Nonlinear Study in Quantifying Effect of Music & Color on Human Body: Development of an Emotion Recognizer

Thesis submitted by

Chandrima Roy

Doctor of Philosophy (Engineering)

Department of Instrumentation & Electronics Engineering,

Faculty Council of Engineering & Technology

Jadavpur University

Kolkata, India

2023

JADAVPUR UNIVERSITY

KOLKATA-700032, INDIA

INDEX NO. D-7/E/297/16

1. *Title of the thesis:*

Nonlinear Study in Quantifying Effect of Music & Color on Human Body: Development of an Emotion Recognizer

2. *Name, Designation & Institution of the Supervisors:*

Prof. (Dr.) Dipak Ghosh
Professor Emeritus,
Sir C. V. Raman Centre for Physics & Music
Jadavpur University, Kolkata-700032, India

Prof. (Dr.) Kumardeb Banerjee
Professor
Department of Instrumentation & Electronics Engineering
Jadavpur University, Kolkata-700098, India

3. *List of Publications:*

A. Journals

1. Roy. S, Roy. C et al, "Chaos based non-linear cognitive study of different stimulus in the cross-modal perspective", Physica A Statistical Mechanics and its Applications, Volume 546, 15 May 2020, 122842.

2. Roy. S, Banerjee. A, Roy. C et al., "Brain response to color stimuli: an EEG study with nonlinear approach",Cognitive Neurodynamics, Volume 15, pages1023–1053 (2021)

3. Roy. C, Roy. S et al, "Neuro-Cognitive Nonlinear Study for Categorization & Quantification of Effect of Colors & Ragas on Human Brain" YMER Digital, ISSN 0044-0477 in Volume 22 Issue 04(April 2023)

B. Conferences:

1. Roy. C, Roy. S. et al, "Categorization & Quantifying Effect of Ragas & Colors on Human Brain: A Neuro-Cognitive Nonlinear Study", Frontiers of Research on Speech & Music (FRSM), Centre for Education Technology, Indian Institute of Technology, Kharagpur, India, 2015.

2. Roy. C, Ghosh. D, "Emotion and Creativity: A Case Study with Specific Art Form (Recitation) using Time Dilation" International Symposium on Social Sciences and Humanities (ISSSH), Sri Lanka, Dec 2019

3. Roy. C, Roy S, Ghosh D, "Chaos Based Study on Association of Color with Music in the Perspective of CrossModal Bias of the Brain, IJCSIS Volume 14 Special Issue October 2016, Proceedings of International Conference on Advances in Computational Intelligence and Communication (CIC 2016)

4. List of Patents: Not Applicable

"STATEMENT OF ORIGINALITY"

I, Chandrima Roy, registered on May, 2016, do hereby declare that this thesis entitled *"**Nonlinear Study in Quantifying Effect of Music & Color on Human Body: Development of an Emotion Recognizer**"* contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I havefully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is 12 %

Signature of Candidate:

Date:

Certified by Supervisor(s):

(Signature with date, seal)

Prof. (Dr.) Dipak Ghosh

Prof. (Dr.) Kumardeb Banerjee

CERTIFICATE FROM THE SUPERVISORS

This is to certify that the thesis entitled "Nonlinear Study in Quantifying Effect of Music & Color on Human Body: Development of an Emotion Recognizer" submitted bySmt. Chandrima Roy, who got her name registered on May, 2016 for the award of Ph. D. (Engg.) degree of Jadavpur University is absolutely based upon his/her own work under the supervision of Prof.(). Dipak Ghosh and Prof. (Dr.) Kumardeb Banerjee and that neither his/her thesis nor any part of the thesis has beensubmitted for any degree/ diploma or any other academic award anywhere before.

Signature of the Supervisors:

……………………………………………………………

1. Prof. (Dr.) Dipak Ghosh
Professor Emeritus,
Sir C. V. Raman Centre for Physics & Music
Jadavpur University, Kolkata-700032, India

……………………………………………………

2. Prof. (Dr.) Kumardeb Banerjee
Professor
Department of Instrumentation & Electronics Engineering
Jadavpur University, Kolkata-700098, India

Dedicated to

My parents

&

My life-mentor, Prof. Dipak Ghosh

ACKNOWLEDGEMENT

Prof. Dipak Ghosh, my co-guide and mentor during this entire academic process, is the first person to whom I would want to convey my most heartfelt appreciation. I am fortunate to work in the world-class laboratory at the Sir C. V. Raman Centre for Physics and Music, where Prof. Ghosh has led ground-breaking research into the neuro-cognitive elements of visual and aural stimulation from the standpoint of hard-core physics. This thesis would not have been achievable without his consistent direction and support. Apart from being a guide and a professor, he is way more my angel friend, philosopher and light house who has always fetched me the right direction. A time when friends, family and perhaps even the cosmos conspired to make me giving up, sir reminded "Yu are enough yourself! You don't need anyone to support". everything! Sir, Thank you, for being whatever you are!

Prof. Kumardeb Banerjee, my guide, an accomplished professor and researcher in the fields of Instrumentation engineering, has been a continuous source of encouragement. In every moment of crisis and hours of need, he has been by my side. He helped me beyond borders in all possible administrative needs. It is needless to mention that his knowledge and experiences have enriched me and my research in several ways for which I will remain forever gratefulto him.

I owe a tremendous amount of gratitude to my juniors and co-researchers, Dr. Shankha Sanyal, Souparno Roy and Medha Basu, for the consistent assistance and support that they provided throughout the course of the research that was included in the thesis. Their contributions improved the quality of the research in a variety of different ways, such as by having in-depth conversations about the issues being investigated as well as by computing statistical analysis. They were more than pals both within and outside of the laboratory where they worked. This continues to be the case.

I would like to offer my sincere gratitude to senior researchers and fellow researchers of the laboratory, including, but not limited to Dr. Archi Banerjee, Dr. Sayantan Chakraborty, Dr. Anuradha Roy and Madhuparna Ganguly. Please accept my sincere gratitude. We are really grateful for their insightful feedback as well as their support in drafting the papers and gathering the experimental data. In addition, I want to express my gratitude to Mr. Sadananda Pramanik, who has helped me out on several times with laboratory-related problems.

I would like to recognize the academic excitement that was offered by a group of young researchers that includes Rahul Laha, Priyam Chaudhury, Ayan Saha, Megha Roy, Riddhi Saha, amongst many others. This group of researchers is comprised of a bunch of incredibly smart young people. Working alongside them and absorbing their contagious enthusiasm made for a very rewarding experience for me. We talked about a number of different concepts and their help and support was indispensable at every bit of it.

I had the privilege to cross paths with nationally and internationally respected scientists and eminent personalities like Prof. Bikash Sinha, Joy Goswami, Pandit Ajoy Chakraborty. Watching them up close and getting to interact with them were some of the highlights of my tenure as a PhD scholar.

I would like to express my extreme gratitude to Professor Chiranjib Bhattacharjee, pro- vice chancellor of Jadavpur University for helping me getting the last minute covid extension for six months. Without his support, submission of this thesis was mere impossible.

I am ever indebted to Dr. Samit Pahari, Sectretary, FET, Jadavpur University for being there for me every moment. His affection, involvement, active support and helpful participation actually sailed me through a very hard time of life!

This work would have not been possible without the effective support of Dr. Anisha Halder Roy of Radio physics Department of Rajabazar Science College, University of Calcutta, and her PhD scholar Prithwijit Mukherjee for helping us executing the last-minute experiments in their laboratory and allowing us to access their instruments and other setups.

Lastly, it is time to remember the people who are ours and can't be thanked. But at this moment I want express my heartfelt gratitude, love and sincere thankfulness to them, as without them, nothing was possible! Rajat Bandyopadhyay, Former Registrar, Jadavpur University is the first name to mention. He has ever been the home since I left home! Solving unprecedented problems, critical administrative issues, raising me up to stand against odds and what not has he done for me! The list will fall short but his to-do-list for me won't even come to a comma! He is one of the instrumental people to inspire me to complete this submission and helped me getting all types of administrative helps that were needed.

Finally, I would want to take this opportunity to thank my parents, Sisir Roy and Kuhu Roy (Bhattacharyya), who have been my rock throughout my life. I grew up in a family where excellence was taught to be a normal deliverable. My mother always reminded me that education and a higher degree of knowledge have no replacement. Not completing this thesis was the biggest irritation to her, and hopefully now these calms her down. Without her constant encouragement and tenacity, this would be really impossible. I have really not seen any other person except my mother, who is so motivated, so willing to learn, and so tenacious! Whatever I am doing today, is all because of her hard work, sacrifices, and dreams!

'Maa, this thesis is for you'!

My father has been 'The Man' in my life who has ever reminded me about the basic virtues of life. The tunnel was truly dark for a very long time with absolutely no ray of hope; even then, he relentlessly believed that sincerity and honest intent would find their way out of all odds, and this time too, they would! I lost hope many times in many instances in life; he did not. Honesty, integrity, and tolerance are his life weapons, and he, as a father, made sure that I followed the path where excellence outshines success, hard work wins over shortcuts, and dignity precedes the key role in the walk of life. Baba, perhaps I now understand what it takes to be a father!

And at times of turbulent tides, one needs sailors to hold onto the ship and drive it to the harbor for a new sunrise, they are called friends. Subhankar, without you, this would be difficult.

Dear Universe, please accept my heartfelt gratitude!

Chandrima Roy

June, 2023.

Table of Contents

Chapter 4

Chapter 5

Methodology

CHAPTER 1

INTRODUCTION

“Biology gives you a brain. Life turns it into a mind.”

Jeffrey Eugenides

1.1 Prologue

It was in the realms of physics and applied mathematics that the study of chaos and nonlinear dynamics first took root. Applications can be found in practically every area of science and technology, and even beyond, because to the extremely generic, multidisciplinary nature of the discoveries obtained during the past few decades. Chaos theory and related methodologies are crucial when quantitatively modeling and analyzing nonlinear, complex processes [Banerjee'2011].

The magnitude of the output in a nonlinear system is not regulated by the magnitude of the input, in contrast to a linear system where this is the case [Boeing'2016]. Linear systems, in contrast to nonlinear ones, make the key assumptions of proportionality and superposition. The term "proportionality" refers to a relationship in which the output exactly matches the size of the input. The term "superposition" is used to describe the ability to completely understand and forecast the behavior of linear systems made up of several components by isolating those components and determining their respective input-output relationships. The final result will be calculated by adding up all of these subtotals. Everything "adds up" in a linear system, and there are no unexpected or unusual actions. While linear systems adhere to the laws of proportionality and superposition, nonlinear systems, even the simplest of them, do not [Goldberger'2006]. Non-linear and complex networks are prevalent in the ecological, social, economic, and human-developed systems that make up our physical world. At a microscopic level, it has been discovered that physical systems are governed by mechanical laws, with precise equations describing the dynamics of their inherent character and the ability to map any future state to a corresponding given initial state at a later time.

Humans interpret nature through their sensory modalities and cognitive capabilities. Nature is a machinery that has an incredibly complex working algorithm. But, at the same time, it presents an elegant face that makes the reality around us worth surviving for. And it is our sensory organs, working in synchrony with the cognitive core, that provide us the quintessential vessel to travel this sea of complexity. From gargantuan celestial bodies to esoteric music-art-poetry, everything makes sense because our intrinsic system makes it sensible. It works acrossscales – from macro to micro – and across time – from polypeptide vibration (hundreds of thousand times per second) to genetic mutation (0.5×10^{-9} per base pair per year) – and even across tangibility – from complex models of architecture to complex models of emotion. Yet, the framework of our guiding system remains elusive to us. Little has been known, even less agreed upon. How does cognition emerge from a biological hot soup called brain? How is visual stimulus perceived – fragmented, or integrated? What happens when different sensory modalities cross paths – does it help or hinder sensory perception? What is emotion and is it actually subjective? How does perceptual ambiguity and uncertainty bode on aesthetic processes and/or creativity? Questions like these are yet to be met with answers conclusive enough. In this introductory chapter, we will discuss the prevailing ideas and debates surrounding both the psychological and physiological correlates of Mind, perception, emotion,cognition, creative aesthetics and ponder upon their complexity. Also, we will discuss different statistical methodologies that will help us in multiple occasions in the thesis to analyze complexsystems like bio-signals and acoustic signals – from power law and related distributions to fractal-based scaling analysis techniques. Indeed, these techniques have been very useful in extracting features from the face of complexity. But, to discuss the emergence of it in cognitivedomain, one needs a theory that is forged in the depths of psychology and involves the same in its interpretations – the quantum theory. Hence, the chapter's concluding notes review all the quantum approaches made in regard to resolve various cognitive conundrums. In due course ofthe thesis, we shall put these methodological aspects - both statistical and quantum – in extensive use to explore emotion's role in multimodal perception, to identify complexity features of visual perception, to categorize as well as classify acoustic information, to recognize non-classical attributes of auditory perception and to hypothesize the emergence of creative cognition. This introductory chapter acts as a preface to the works that follow.

1.2 Motivation

The study of nonlinear dynamics is very important not only in physics and other areas of general science, but also in engineering, since almost all natural phenomena are found to be nonlinear and can be described by nonlinear equations [Yazdi, He, 2010]. For example, most engineering problems and some equations that describe oscillations are not linear. Traditional perturbation methods have many problems because they don't work well for most nonlinear equations and can't be used directly if there isn't a small constant in the equation. To get around these problems, many asymptotic and analytical methods have been used to deal with period solutions of strong nonlinearity. These methods include the Variational Iteration Method (VIM) [He'2010, Fesanghary'2009], the Energy Balance Method (EBM) [He'2002, Ozis'2007], the Hamiltonian approach [Xu'2010, Khan'2010], the Variational approach [Khan'2011a], the amplitude-frequency formulation [Khan

[Singh, 2013] says that the key to understanding many things studied in the natural and social sciences is to figure out how dynamical systems interact with each other by analyzing the signs they send. In recent years, there has been a lot of growth in the study of how different bodily signs change over time [Dutta, 2016]. Analysis of linear statistics (like mean values, Fourier analysis, variability measures, and spectra analysis) of bodily data does not directly show how complicated, irregular, or predictable they are. Methods based on non-linear dynamics and "chaos" theories reveal subtle abnormalities in the physiological signals that may not be found by traditional (i.e. "linear") measures of variability. This makes them a useful tool for a thorough evaluation of the properties of complex physiological systems [Hausdorf, 2001].

With the development of nonlinear dynamics, it is now clear that simple nonlinear systems behave in a way that is highly complex and chaotic [Ikegawa'2000, Liu'2004, Grassberger'1983, Parker'1989, Buczkowski' 1998, Kim'1999]. This is because they are very sensitive to their initial conditions, and any change, no matter how small, will change their future forever. There is a self-similarity effect in complex signals. This means that there is a smaller scale structure that looks like the larger scale structure in complex biological signals like EEG, ECG, and EMG signals, to name a few [Ghosh, 2017].

Complex systems make data sets that change over a wide range of time scales and/or have a "broad distribution" of values. In cases with and without stability, natural changes often follow a scaling relationship over several orders of magnitude. Such scaling rules allow fractal (or multifractal) scaling exponents to be used to describe the data and the complex system that created it. These exponents can be used to compare the systems with other systems and models as if they were fingerprints. Many data sets from experimental physics, geology, medicine, physiology, and even the social sciences and engineering (such as civil, mechanical, electrical, electronics, biotechnology, etc.) have shown fractal scaling behavior. Most of the time, the exact reasons why fractal growth is seen are not known. Fractal or multifractal characterisation can be used to create substitute (test) data, describe the time series, and make predictions about extreme events or future behavior. But the major use is still to describe the different states or phases of a complicated system based on how it scales. For example, the health status and different physiological states of the human cardiovascular system are shown by the fractal scaling behavior of the time series of intervals between successive heartbeats. The coarsening dynamics in metal alloys are shown by the fractal scaling of the time-dependent speckle intensities seen in coherent X-ray spectroscopy [Kantelhardt'2008].

Several tools have been made so that fractal and multifractal scaling behavior in time series can be seen. In addition to older methods that assume the data are stable, there are newer methods that can tell the difference between real fractal dynamics and fake scaling behavior caused by non-stationary data. [Kantelhardt, 2008] Also, it is important to make a clear distinction between short-term and long-term relationships in order to show how fractal scaling works.

1.3 Objective

Human evolution has focused on emotion. "...neurochemical processes by which the body monitors changes in its internal situation and is thereby alerted to the need for certain responses to its ever-changing states" (Johnson, 2001). Emotion and cognition are strongly linked (Pessoa, 2013; Dolcos et al., 2014; Okon-singer, 2015). Emotion's influence in sensory binding is another hot topic of inquiry.

Finally, the idea that all causal mechanisms in neuroscience can be formulated in terms of material particles inside the brain (thus, forsaking all intrinsically psychological contents) has one restriction: the natural laws motivating this idea have been shown to be limited in light of theoretical advancements in basic Physics in the late 20th century. Contemporary basic physical theory differs greatly from classic physics on how human consciousness enters into the structure of empirical phenomena, contradicting the older idea that local mechanical processes alone can explain all observed empirical data (Schwartz et al., 2005). This breakthrough has given neuroscientists and psychologists a new conceptual framework to analyze and characterize neurological and perceptual processes to varying degrees (Busemeyer et al., 2006, 2011; Khrennikov, 2009; Aerts, 2012). This non-classical framework is based on quantum theory, one of the most empirically successful theories of physics, and has introduced subjective and objective psychological constructs, tied by rules that directly specify the causal effects of the subject's choices on the brain without needing to specify how these choices came about. In Ochsner et al. (2002), intention-induced modulation of brain processes is essential for emotional self-regulation in the active cognitive reappraisal condition.

This thesis aims to examine brain dynamics under the impact of external visual and auditory stimuli and the complexity and structural importance of the stimuli in triggering emotional responses in the observer. We emphasize the following aspects:

- we use robust non-linear analysis of brain electrical activity and auditory and visual stimuli to study their neurobiological and cross-modal impacts.
- Comparative study between musician and non-musician using two opposite emotion invoking North Indian Classical Ragas along with color stimuli.
- Nonlinear analysis of cognitive engagements in different lobes of the brain using recitation and color as stimuli.
- Effect of syntax, semantics & prosodic on nonliear analysis of audio and color stimuli with matching and contrasting combination.
- Translating this research into the development of a Automatic Emotion Recognizer.

1.4 Organization of Thesis

Chapter 2

This chapter introspects the the origins of music and its transitions over period of time and the age-old heritage of Natyashastra from where the concept of Rasa has emerged out. It also addresses the performance style and western vs eastern comparison. Later it deeply drives in the correlation between music, color and emotion. The eastern and western model of emotions are also discussed in details. Complex Structure of Music Signals and Role of Color in People's Lives are discussed in details.

Perception, attention, decision-making, and memory were isolated from emotion for a long time. Due to the long-held idea that "feelings" and "reason" were opposites. Even as psychology and neuroscience advanced, the concept that emotion may affect perception or cognition was rejected for most of the 20th century. Recent studies have illuminated how emotional processing affects cognition. Neuropsychological investigations demonstrated emotional dysregulation impairs numerous socially significant cognitive capacities. Neuroimaging studies have shown that brain areas traditionally thought to govern solely emotion or cognition interact complexly. Psychological and evolutionary research show that emotional increase of attention or memory allows preferred processing of environmental inputs, an evolutionary benefit (Dolan, 2002). These studies have highlighted how emotion and mental functioning are closely linked and often inseparable.

Chapter 3

Chaos, Butterfly Effect and Music, Approaching the Complex System: 'Brain' Through Fractal analysis & Chaos Theory and A New Dialogue Between Mankind and Nature through Fractals and Multifractals are majorly discussed here.

The fundamental ideas of fractal systems, geometry, and classification are discussed along with appropriate examples are discussed in this chapter. This is then followed by a discussion of the applications of fractal geometry in various fields such as science and technology, economics, physiology, biomedicine, geothermal systems, and so on. This chapter also contains a concise survey of key publications in the field of chaos-based mono- and multifractal systems, as well as a brief introduction on the ideas of fractals and the various analysis approaches utilized for measurement of fractal dimension.

Chapter 4

This chapter talks about the previous works that have been done in this domain. Though no literature reports to have used recitation as a stimuli, detailed discussion on various EEG related works involving color and music have been reported. Empirical research on color perception has a long history (Elliot & Maier, 2014; Elliot, 2019). Goethe, back in 1810, gave observation-based accounts of color perception and its association with emotional states (or 'feelings') in his book *Theory of colors* (Von Goethe, 2006). Some colors were assigned to induce positive feelings and some induced negative ones.

According to him, Red is associated with both gravity and lightness, Blue with coldness and negativity, Green with calmness, Yellow with warmth and Orange with energy and power. Later in the same century, psychologist and writers like Wilhelm Wundt and Grant Allen addressed this issue in a similar manner and associated color with emotions based on experience and observation. They shared similar ideas such as: White is linked to positive emotions (pleasant, stimulating, cheerful), Black to negative emotions (unpleasant, gravity), Yellow and Red are exciting and arousing, Blue is depressing/relaxing, and Green is linked to tranquillity and calmness (Wundt, 1874; Allen, 1877). Subsequent quantitative researches from Charles Féré (1887) and Hugo Münsterberg et al. (1894), involving color stimulus and physiological signatures – pulse rate, respiratory pattern, head and eye movement – demonstrated that Red (and Yellow, in the latter) had a comparatively higher arousal and attention capturing effect whereas Blue (and Green, to some degrees) is calming/relaxing. Also, in some color preference studies, Blue was reported to be the most preferred color, followed by Red (Cohn, 1894; Jastrow, 1897).

Chapter 5

Chapter 5 provides an explanation of the MFDFA and MFDXA multifractal analysis approaches, both of which I have used in my research work to investigate a variety of non-linear dynamic systems. In this article, the advantages of using these methods as opposed to more traditional non-linear analytic approaches are highlighted as well. It deals with various techniques associated with the analysis of the structures of music signals as well as bio-signals obtained from Encephalography data. A detailed analysis on the following tools of complex data analysis have been presented here which is used later in the thesis for different studies:

i) Empirical mode decomposition (EMD)

ii) Detrended fluctuation analysis (DFA).

iii) Multifractal detrended fluctuation analysis (MFDFA)

iv) Multifractal cross correlation analysis (MFDXA)

These techniques (i-iv) make use of Fractal Dimension (FD) or multifractal spectral width (obtained as an output of the MFDFA technique) as an important parameter with which the affective arousal corresponding to certain cognitive task (visual or auditory) can be quantified. EMD is a decomposition method for non-stationary and nonlinear signals such as EEG. Detrended Fluctuation Analysis (DFA) is used to analyze the long-range temporal correlations (LRTC) of the observed fluctuations in the signal. Advancing from DFA, MFDFAis a fractal analysis technique which is highly scale dependent. Here, signal components of different scaling ratios are analysed together in the form of a multifractal spectral width whichindicates the degree of complexity of the signal. Lastly, MFDXA is an important tool with which the degree of cross correlation between two non-linear EEG signals originating from different lobes of brain can be quantitatively measured during higher order cognitive tasks. With this, we can have a quantitative assessment of how the different lobes is cross-correlatedduring higher order thinking tasks and the perception of external stimulus. A higher degree ofcross-correlation would imply similarity between the signals in certain aspects. This in turn canbe used to obtain a cue for the informational connectivity human brain displays while processing real world stimuli.

Chapter 6

This chapter elaborates on neuro-cognitive research on brain responses to various color stimuli. Red, Green, Blue: three primary colors utilizing the signals of electro-encephalograms and nonlinear multifractal approaches to establish the magnitude of complexity using a quantitative parameter. Color stimuli were imposed to subjects and the EEG readings from the corresponding lobes were taken note of and analyzed. Along with this, two ragas namely Chhayanat and Darbari, were used to study the effect on human brain using exactly the same methodology adopted in case of the colors. Along with this we also explored to correlate whether colors are also associated with Ragas of Indian Classical Music. The experiment reveals new data of extreme interest in color-raga-emotion scenario.

Chapter 7

This chapter examines Rabindranath Tagore, Sankha Ghosh, and Joy Goswami's acoustical and neuro-cognitive recitations. These writers' adorned lyrics have captivated readers for a century. Our 100-year research examines how different eras have created poetry and how they affect the human psyche. The study investigates how different texts affect cognitive engagement. We want to understand the complex interaction between poetry, emotions, and cognition by examining how these recitations affect human emotions and cognitive engagement. We collected over 200 responses from human participants using an online interactive form where they listened to sounds and picked one of nine emotions. Homogeneous data ensured consistency and accurate analysis.

Our goal is to research neuro-cognitive engagements with distinct stimuli-evoked emotions and build a qualitative-to-quantitative parity between art forms and their cognitive engagements. We want physiological measurements. We analyzed human reactions prior to non-linearly quantify and analyze brain alterations generated by these stimuli and used EEG. We analyze the frontal, temporal, occipital, and parietal lobes. EEG lets us analyze cognitive engagement response patterns.

Multifractal Detrended Fluctuation Analysis (MFDFA) is used to analyze brain lobe EEGs non-linearly. This technique, created for the investigation of non-linear and extremely complex systems, allows us study the complicated cognitive responses to inputs during poetry recitation. MFDXA will be used to quantify the association between recitation clips We may establish their association by measuring the cross-correlation between each pair of individual clips with the same mood. These clips' low cross-correlation suggests a greater scientific connection.

This study examines cognitive engagement changes using the Multifractal Width (w) of audio clips and EEG brain waves [23-24]. This metric lets us compare cognitive pattern multifractality. To guarantee a full investigation, we integrate qualitative assessments from human responses to stimuli with technological analysis. This simultaneous evaluation will integrate subjective human perception with objective scientific measurements to better comprehend art and literature's neuro-cognitive impacts.

Chapter 8

This study examines the cognitive engagements evoked by reciting different texts and associates them with matching and contrasting colors based on prior studies' color mappings. We study how these linkages affect human emotions and cognitive engagement to understand poetry, emotions, color, and cognition. We obtained approximately 200 online form answers from real participants for this study. Participants heard and chose one of nine feelings. We collected homogeneous data to guarantee uniformity and trustworthy analysis. Russell's Emotional Circumplex model was developed to characterize human responses. The aforementioned paradigm for baseline emotions in cognitive activities is more widely accepted than Bharata's Natyashastra and Navaras.

Our goal is to research neuro-cognitive engagements seen through distinct stimuli-induced emotions and build a qualitative-to-quantitative relationship between art forms, colors, and cognitive engagements. We quantify these encounters physiologically. We used EEG to analyze human reactions. We may analyze cognitive engagement response patterns by analyzing EEG signals from the frontal, temporal, occipital, and parietal lobes.

EEG signals from these brain lobes are analyzed using Multifractal Detrended Fluctuation Analysis (MFDFA), a well-established method for non-linear and extraordinarily complex systems like the brain. This approach lets us study the cognitive engagements caused by reciting poetry and their color connections. This study uses colors to correlate cognitive reactions with aural stimuli [21-22]. Visual stimuli influence cognitive engagement, which the EEG assesses. This method will reveal how color affects recitation's neuro-cognitive processes.

Chapter 9

This chapter examines Rabindranath Tagore's prosodic variations' auditory and neuro-cognitive effects. Tagore was the greatest poet of his day, if not all time, and his deep lyrics in several languages captivated readers. Our work considers three Tagore works with distinct prosodies; hence it has no temporal frame.

Our stimuli were three compositions by the same poet, with the same syntax and semantics, but with three different prosodies: speech, recitation, and song. We seek to illuminate the complex interaction between diverse renditions and human cognition by examining how these audio samples affect neurocognitive engagement and the mind. Multiple studies have shown that cognitive engagement for stimuli like this one is highest when sung. We want to create a qualitative-to-quantitative equivalency between human psyche and brain cognition.

We also measure bio-physical cognitive engagements and neuro-cognitive processes related to these stimuli-evoked emotions. Electroencephalography (EEG) was used to non-linearly quantify and analyze the brain lobe changes evoked by these stimuli based on human responses recorded previously. We analyze the frontal, temporal, occipital, and parietal lobes. EEG will allow us to study cognitive engagement response patterns.

Multifractal Detrended Fluctuation Analysis (MFDFA) is used to analyze EEG information from the lobes. This approach for non-linear super-complex systems allows us to analyze the brain's complicated reaction to inputs during poem recitation. This study used the Multifractal Width (w) of audio clips and

EEG brain waves to measure cognitive engagement changes. This measure allows neuro-cognitive investigations to quantify and compare multifractality of cognitive processes.

This simultaneous evaluation will help us comprehend the neuro-cognitive consequences of art and literature by bridging subjective human perception with objective scientific measurements.

Chapter 10

This chapter examines how prosodies and colors relate. This study examines the auditory and neuropsychological differences in prosody across Rabindranath Tagore's compositions. Tagore's deep poetry in several languages captivated readers and made him one of the finest poets of his day, if not all time. We investigate three Tagore pieces with diverse prosodic renderings, not a certain chronological period. This study examines how various versions affect cognitive engagement. Three poems by the same poet are presented as speeches, recitations, and songs. Based on studies, stimuli include matching and contrasting colors. By examining the impacts of these audio snippets and their color associations on cognitive engagement and human emotions, we want to reveal the complex link between sounds, colors, and cognition.

We can derive qualitative-to-quantitative generalizations regarding how colors and prosodies affect neurocognitive involvement. Singing renditions have been proven to increase cognitive involvement, supporting our findings. We measure biophysical cognitive activation and neurocognitive processes related to stimuli-evoked emotions. We want to non-linearly quantify and analyze brain lobe changes caused by these stimuli. We used electroencephalography (EEG) to capture brain activity. We analyze the frontal, temporal, occipital, and parietal lobes. EEG can reveal cognitive engagement response patterns.

Multifractal Detrended Fluctuation Analysis (MFDFA), an established technique for researching non-linear complex systems, is used to analyze EEG information from the lobes. This method lets us study the brain's complex reaction to poetry and color connections. This study uses the Multifractal Width (w) of audio samples and EEG brain waves to measure cognitive involvement. This measure allows neurocognitive investigations to quantify and compare the multifractality of the cognitive processes.

We link subjective assessments of human emotions with technological analyses to ensure a complete study. This parallel evaluation will help us understand the neurocognitive impacts of art, color, and literature by bridging human perception with scientific measures.

Chapter 11

Final chapter of the thesis deals with the implementation of detecting emotions out of audio signals using the nonlinear tool MFDFA. Studies report that Emotion recognition in conversations (ERC) is a hard job that has become more popular lately because of the ways it could be used. But until now, there hasn't been a big, multimodal, multi-party collection of emotional conversations with more than two people per discussion. Facial expression mood recognition is a natural way to tell what a person is thinking and feeling, and it is one of the most important ways to communicate with other people. It can be used in a lot of different areas, like psychology. As a famous person in old China, Zeng Guofan knew how to read people's emotions by looking at their faces. In his book Bing Jian, he summarizes eight ways to figure out who someone is, especially how to choose the right one. For example, "look at the eyes and nose for evil and righteousness, the lips for truth and falsehood; the temperament for success and fame, the spirit for wealth and fortune; the fingers and claws for ideas, the hamstrings for setbacks; if you want to know his conviction, you can pay attention to what he has said." People say that a person's face shows his or her attitude, thought, and whether they are good or bad. But because people's facial expressions of emotion are complicated and vary, standard facial expression emotion recognition technology has problems with not being able to pull out enough features and being affected by the outside world. Here we propose a simple yet extremely impactful model for detection customer satisfaction by comparing the complexities of his tone with the company operator. This is an extremely powerful tool that finds extensive applications in Business Intelligence.

Chapter 2

Music–Color-Emotion: Basic Concepts

"The pleasure we obtain from music comes from counting, but counting unconsciously.

Music is nothing but unconscious arithmetic."

Gottfried Leibniz

2.1 The Origins of Music:

The capabilities of music have often been considered among the many unsolved problems of humanity by Aristotle. Referred to as "the greatest mystery." by Charles Darwin, the theories describing musical emotions are attempts to uncover the mysteries of music by unearthing its origins. Research has shown that humans have innate inclinations to music, albeit with no compelling argument of music's shaping by natural selection. Huron discussed social reasons for music origins, but the list of possible uses of music alone cannot explain musical power over the human psyche. Cross suggested that music evolved hand in hand with language, the latter requiring more voluntary neural control over the former, while a less voluntary control had to be kept for music to continue playing the role of an "honest signal." Music's major role is social, serving as a means of creating "shared intentionality." Lengthening of juvenile periods was identified as fundamental for the origin of music. The early forms of musical behavior have been used as a foundation for culture-specific innovations in ritual ceremonies designed to bring people together. These aspects of music evoke strong emotions that activate areas of the brain related to primal mechanisms of motivation and reward. Some have argued that Neanderthals might have had proto-musical ability. Juslin and Västfjäll analyze mechanisms of musical emotions and conclude that musical emotions are no different from other emotions. Levitin suggested that the origin of music was from animal cries and that it functions today essentially with the same purpose: communication of emotions. The reason that music evolved as an "honest signal" is to preserve this property. This is opposed by those who suggest that music is a "dishonest signal." The mechanisms that evolved music from IDS to contemporary music are not clear, and discussions of these mechanisms are lacking or unconvincing. Cross & Morley concluded that the removal of music would be impossible without revoking many of the socially cognitive abilities fundamental to being human.

2.2 The Knowledge Instinct:

The mind needs to perceive objects and understand situations and events to fulfill its instinctual bodily needs like eating or procreation. Matching models based on concepts to the surroundings is necessary for this task, however objects in the world never perfectly match old memories. This has posed challenges for pattern recognition and artificial intelligence since the 1950s, as various works by Perlovsky have discussed. Mental representation-models are therefore deliberately vague and match different objects with minimal precision to overcome these difficulties. The mind then modifies these concepts-representations to fit specific objects and situations. This mechanism aims to satisfy basic understanding, an inborn autonomous characteristic known to man as the knowledge instinct or KI. The said mechanism is brought about by designing concept-models close in appearance to the surroundings. The mind has an inherent capacity to maximise this similarity.

The dissatisfaction or satisfaction of the instinct is felt as emotions that compare the harmony between the world and the knowledge. These emotions are directly related only to the greater thirst for knowledge.

2.3 Differentiation and Synthesis

According to Perlovsky's research, the mind is organized in a hierarchical manner, with each level involving the matching of TD signals generated by representations, concepts, and models with BU signals originating from lower level representations. The hierarchy involves multiple levels ranging from simple elements of perception to complicated and highly regarded concepts. The latter, which are essential for understanding the nature of beauty, are located near the top of the hierarchy.

Perlovsky also discusses the KI, which works mainly on the two mechanisms of differentiation and synthesis. Differentiating creates more specific and detailed concepts and operates descending on the hierarchy, while synthesis creates an understanding of situations and abstract concepts as a unity of constituent notions and operates ascending the hierarchy.

The main mechanism of differentiation is language, which gives the human mind an evolved means of differentiating reality in great detail. Neural rewiring of circuits that control vocalization are required by evolution, allowing for conscious voluntary control over voice that is necessary for language. However, this differentiation destroyed the primordial synthesis of the psyche, separating concepts and emotions from behavior and destroying the feeling of being whole.

The advantage of conceptual differentiation is the development of conceptual culture, science, and technology. However, it comes costly, as the human psyche is not whole by itself, and systemic knowledge contradictions may lead to internal crises and clinical depression. The lost synthesis may also cause wars, cultural calamities, and destruction. So cultural evolution warrants a balance between differentiation and synthesis.

2.4 Summary and Further Directions

Throughout history, from Aristotle to the 20th century, the impact which music has on the human soul and body has been a mysterious topic in cognitive science. Contemporary evolutionary psychologists have acknowledged that music is a powerful cultural universal. However, the underlying function and role of music in cognition, cultural evolution, and consciousness have not been fully understood. In a recent paper, previous scientific hypotheses about the role and function of music are discussed, along with their inadequacies. The paper proposes a new theory that suggests the essential function of musical emotions in cognition is to mediate cognitive differences created by knowledge while enabling the evolution of culture and consciousness.

The new theory explains the mechanisms of musical emotions by correlating them to the old connections between voicing and emotions. It proposes that the purpose of music is to differentiate emotions to restore the unity of self. Music-induced emotions can help one to maintain their drive, their purpose, when stood face to face against the contradictory bellows of knowledge. This is also known as the "synthesis of differentiated consciousness."

The hypothesis proposes that the beginnings of music are linked to the origins of language, which arose as a result of the differentiation of the original unity of primordial self. Our predecessors who could concentrate their will while distinguishing knowledge about the world gained an evolutionary advantage. This led to a selective pressure to enhance the emotional aspect of primordial vocalization, which eventually developed into music.

Empirical evidence supporting this also includes parallel changes observed in musical styles, cultures, and consciousness, with experimental studies confirming the theoretical predictions.

Addressing numerous questions that have remained open for millennia, the proposed musical origin's theory and functions of musical emotions are therefore a program revealing neural mechanisms. In conjunction, studies of the function of music are necessary, along with laboratory tests, empirical ethno-musicological, historical and anthropological studies.

2.5 Functions of Musical Emotions

A critical balance between differentiation and synthesis needs to be struck for the cultural development and emergence of human conscience. Ancestors developing differentiated consciousnesses had an evolutionary advantage if they could maintain the unity of self-necessary for concentrating will. Maintaining this balance is fundamental to music's role in cognition and the evolution of this ability.

The instability between differentiation and synthesis is unique to human evolution due to the pace of differentiation of knowledge vastly exceeding biological evolutionary capacity to maintain synthesis. Language evolved to enhance conceptual differentiation ability, but music evolved for maintaining the balance between differentiation and synthesis.

Originally, language and music were one, and this fused language-music did not threaten synthesis. Language has developed towards increasing differentiability in concepts from ancient emotional and bodily instinctual influences. While language enhanced differentiation, the primordial unity of the psyche was dismantled. But music reconnected the differentiated psyche, bringing back the essence of knowledge and paving the way for evolution of cultures.

Music played a crucial role in cultural evolution by promoting harmony in the midst of growing linguistic diversity. As the knowledge instinct (KI) diversified, emotions associated with knowledge became more specialized as well. Each concept within the KI operates as an individual component and assesses other concepts for their mutual coherence. Since almost every combination of concepts has some level of contradiction, aesthetic emotions evolved for reconciling these contradictions. Synthesis of differentiated consciousness have resulted in the evolution of musical emotions, for reconciling cognitive dissonances, and for creating a unity of differentiated Self.

2.6 Empirical and Experimental Evidence

The accumulation of evidence has shown that culture, consciousness, and music have evolved in parallel. This evidence has revealed that as cultures and consciousness advanced, there was a corresponding advancement in the differentiation of musical emotions. The emergence of contemporary consciousness occurred around 2,500 years ago in Ancient Greece, Israel, and China. The development of antiphony, a type of music where two choruses respond to each other, was a means of reconciling the cognitive dissonances created by these advancements in consciousness. Tonality, a new musical style that was developed during the Renaissance, allowed for the creation of diverse emotions that corresponded to the evolving psyche. The development of a new type of music during the Baroque era was a means of reconciling the tensions in the human soul that had reached their maximum. Pop songs, especially in rap music, play a vital role in unifying the split culture and souls of people today. Experimental laboratory evidence supports the theory that music helps reconcile cognitive dissonances. Music performs a fundamental cognitive function that has enabled human evolution, explaining the mystery of its origin and evolution from animal cries to music of the modern era.

2.7 Background of Indian Classical Music

Originating from South Asia, the world at large is increasingly familiar with the classical music of India. Over six thousand years ago, a system of musical notes and rhythmic cycles was developed with Vedic chanting. The musical moods, known as "ragas," and the numerous time cycles, known as "taals," that are characteristic of Indian classical music are derived, in part, from the natural world, including the changing of the seasons and the hours of the day. The vast majority of the music is improvised within the constraints of the compositions' notes and mathematical formulas. Because of this, the music has an element of spontaneity, and it also helps to distinguish one performer from another. The three main periods of ancient, mediaeval, and modern Indian music history can be distinguished. The transition from Vedic to Sangita Ratnakara music represents the conversion of traditional music to medieval music. During the same time, the Hindustani and Carnatic systems began to develop separately. Both of the branches became robust. During this historical period, a large number of musicologists and composers contributed to the expansion of Raga-a melodic framework for improvisation and composition, Tala-a musical metric cycle with a specific number of beats, anong other forms of music.

2.7.1 ANCIENT PERIOD

There are multiple ancient scriptures, comprising of the Vedas, Agamas, and Upanishads, that allude to the diverse elements of classical music. These include the seven notes, three scales, twenty-one melodies, three tempos, nine emotions, three octaves, and intonations, among other aspects.The For Indian culture, Vedas are thought to be the repositories filled with knowledge. It is said that Sama Veda was the one who first created music. The singing of vedic mantras begins with a single note. The use of two notes, and then subsequently three notes, helped make the recitation more engaging.

2.7.2 MEDIEVAL PERIOD

Before the 13th century, all of ndia shared a same musical tradition. The saptaswaras, octave, sruti, etc. served as the basis. Haripala spread the music of Hindustani and Karnatak. After the Muslim conquest of the North, Indian music had an impact on the music of Arabia and Persia. It was with the support of Muslim kings that Indian music flourished.

2.7.3 THE GOLDEN AGE of 18th Century

This epoch brought about the development and growth of Ragas, Talas, musical instruments, notation systems, and more. Several Kritis, Swarajatis, Varna, Pada, Tillana, Jawali, Ragamalikas, and other scholarly musical genres were written. All these compositions were based on ancient prabandhas. Newer compositions have refined musical and lyrical elements, but only the portions. Music compositions were also preserved in notation, and today's age is lucky to have access to all of them.

2.8 Performance Style of Indian Classical Music

A drone and rhythm accompany the soloist in chamber performances. Melody trumps harmony. Melodic lines are ornamented with glide, vibrato, and oscillation. Performers often start with a sluggish "alaap" and gradually increase the improvisations and tempo with diverse compositions to a rapid crescendo. Throughout decades, Indian classical music has become a sophisticated, beautiful art form. Indian classical music uses ragas, ornamentation, and rhythmic patterns to link artist and listener in bhava. Indian classical music complements folk, religious, dance, opera, light, katha kalakshepa, and other genres. Indian culture includes classical music. India lives through music. It is a spiritual experience and a path to God for intelligent seers and a calming entertainment for the common man. The Puranas contain references to Nada, flute, and veena associated with India deities such as Siva, Saraaswati and Krishna. Some of the musical deities, namely Narada, Tumburu, and Nandi among others have also been mentioned. The inclusion of these elements in Indian classical music made it a sacred art form. Classical music has the ability to harmonize with a wide range of genres including art, folk, sacred, dance, opera, light, Katha Kalakshepa, and more, which complement and enhance classical music.

2.9 Brief introduction to Raga in Hindustani classical music

Ragas are styles of music that are characterized by a certain set of notes and sounds. The term "raga" originates from the “Ranj” in Sanskrit that basically means "to enjoy and take pleasure in". The former term refers to a tonal module that can have various meanings. In order to recognize a Raga, the listener needs to hear more than one piece of the style. To achieve this goal, Hindustani artists focus on effectively expressing musical structure and expression to their audiences. Alap begins a Raga. The Alap is where Hindustani Music (HM) gets its beginnings. During alap phase the raga will be introduced, while its progression will be demonstrated using all of its notes and the appropriate transitions between them. When accompanied by the drone of the tanpura, alap is typically sung slowly or without tempo. The Vilambit bandish introduces the tala and lyrics. A raga-specific melodic and fixed Hindustani vocal or instrumental composition is called a Bandish. It is played in rythm alongside a tabla or pakhawaj, a sarangi, harmonium, or another melodic instrument. Bandishes are typically played with a tabla or pakhawaj (Neuman, 1990). Vilambit is a slow bandish that can range anywhere from 10 to 40 beats per minute in tempo. HM can add a prefix, infix, or suffix to a motive, as well as expand or compress the phrase. Motives or phrases can be split apart into their component parts or telescoped by arranging them in a specific order through a variety of registers (Neuman, 1990). As a direct consequence of this, a performer will gradually become freer during the course of a performance. He doesn't break them, but rather he interprets it in a new way. Thus is the beauty of Hindustani classical music, where we see that a Raga and its associated grammar are merely means. He does not break them, but rather he interprets them in a different way. Every rendition of a raga is one of a kind and exemplifies the spontaneity that is inherent in Hindustani music (HM). Raga, in contrast to symphonies or concertos, is improvisatory in nature and always takes on fresh and exciting forms throughout the course of a performance, essentially what can be classified as "improvisation".

2.10 Improvisation: Hindustani classical v/s Western Music

Regardless of the fact that improvisation is an ubiquitous musical endeavor, scientific musical analysis has done surprisingly little research on it. Hindustani music (HM) depends on an artist's imagination, his or her inventiveness, Talim (learning), Riyaz (hard practice), in addition to Aarohan (ascending), Aborohan (descending), Bandish (composition) as well as Chalan (major phrase). Without using notation, the musician creates music in the HM style. In contrast to Western music, which is based on reproducing written compositions, Indian classical performers and musicologists excel at improvisational music as a form of live oral legacy. Raga is performed by a musician in accordance with his disposition as well as the environment. As a direct result of this, renditions are not identical. Two different interpretations of the same Raga and Bandish should sound distinctively different to the listener. The progression of a raga over the course of several days is an example of improvisation. Studies in ethnomusicology demonstrate how the performers' musical traditions and the relationships between them affect North Indian Classical music's social order (Clayton et al., 2015). Improvisation is often considered to be the antithesis of composition, as well as of a lower quality than art music according to Western music culture, which places an emphasis on pre-composition. The art of improvisation is highly valued in Hindustani classical music. Improvisation is an integral part of Hindustani music (HM), and its success is dependent on the creativity, inventiveness, and ingenuity of the musician performing it (Hamill, 2005). It is possible to find out by analyzing the artist's variance in a number of different interpretations of the same song. Improvisation analysis is gaining popularity in the field of music therapy, particularly in folk and jazz music, the therapeutic process of which is directly influenced by this analysis. An additional investigation using cross wavelet spectral analysis (Walton et al., 2015) sheds light on the musician's spontaneous improvisation with co-performers to produce new musical expressions. All music genres appreciate performative gestures (Thompson et.al, 2005). An examination of the work of B. B. King shows that some specific gestures make the listeners direct their attention to a music's local aspects like the subtlety of notes, or dissuading from the overall framework of melody. Because of this genre's focus on note combinations, gesturing has traditionally been neglected in Indian music (Kendon, 2004; Parrill et al., 2011). Movements that accompany improvisation in Hindustani classical music are never taught officially but seem to imply melody. This is because these movements are never taught apart from the improvisation. There has been a significant amount of research conducted on the gestures used during performances of Hindustani raga (Rahaim, 2008). Wieczorkowska and colleagues (2010) discovered that different parts of the same raga can elicit a wide range of feelings that can be grouped together. Similarities in responses across different cultures are especially significant. According to the findings of a more recent study that focused on human reactions to traditional Indian instrumental music, the alap and gat sections of raga can trigger a wide variety of distinct emotions (Mathur et.al, 2015). In this study, non-linear parameters are used to measure the improvisational cues used in Hindustani music for the first time.

2.11 Basic Emotions

The European culture views its primary feelings as being shared by all people. They consist of feelings such as happiness, sadness, anger, fear, surprise, and disgust. They are often manifested through facial expressions, body language, and vocal signs, and it is believed that they evolved to facilitate the rapid communication of an individual's internal state to others in the context of social settings. These feelings are known to elicit physiological responses such as increased heart rate, perspiration, and dilated pupils, which highlights the significance of these feelings in human connection. Understanding these feelings is necessary for effective communication and social interaction.

In Western countries, identifying fundamental feelings is done in a more overt manner than in Eastern cultures. Emotions felt by humans are still taken into account. The Eastern philosophical perspective on emotions is that they are malleable and cannot be labeled. According to Taoism, feelings are a natural part of the human experience and should be welcomed without criticism. According to Buddhist thought, feelings are fleeting experiences that can be managed by practices such as mindfulness and meditation.

In Confucianism, the proper management of one's feelings is essential to the development of virtue, morality, and harmonious relationships. The practice of self-cultivation and self-discipline is emphasized in Confucianism as a means of bringing about positive character traits such as compassion, respect, and gratitude.

In conclusion, Eastern cultures perceive emotions as fluid and dynamic states, and they place a high priority on the management and modification of emotional states through philosophical and spiritual pursuits. In contrast, Western cultures view emotional states as stable classifications.

2.11.1 Russell's (1980) Circumplex Models

Putting the following emotion words on the line based on how they make you feel and how they make you act, James Russell made a model called the Subjective Circumplex (Figure below). Russell (1980) had people who had put 28 words about emotions into groups based on how similar they seemed. Russell then used a statistical method to circle similar phrases based on how well they fit together. The results of our multidimensional scaling study showed that there are two polar dimensions: valence and activation! So, all emotions have a pleasantness or unpleasantness and a high or low level of arousal (activation).

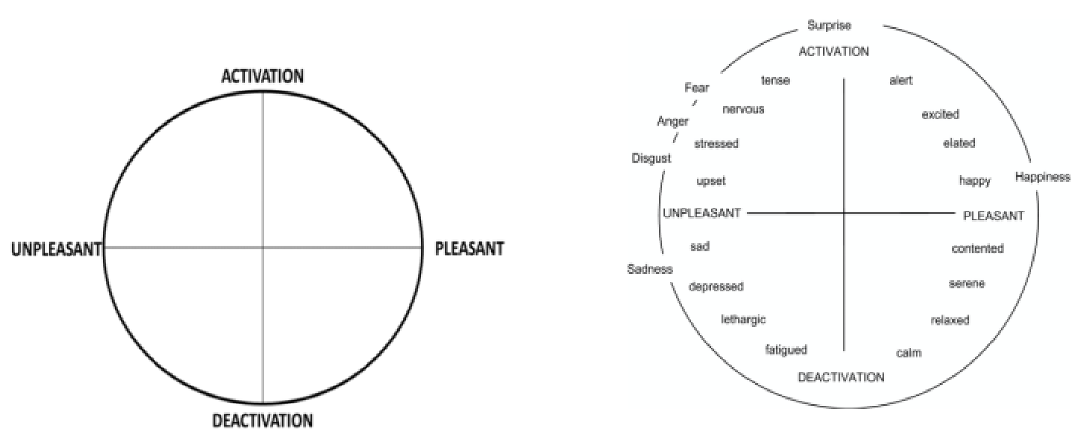


Fig 2.1 A Detailed variant of Russell's Circumplex Model (1980)

In Russell's model, valence and activation as variables are separate, unrelated and bipolar. Bipolar emotions have opposite activation and valence poles. The figure below shows joyful and sad at opposite pleasantness poles. The orange circles in Figure below depict tense and drowsy at opposite ends of the activation dimension. Consequently, tense people cannot sleep. This model concludes that mixed emotions are subjectively comparable. Consequently, a mixed emotion cannot contain sentiments like happiness and despair. Mixed emotions are those in the same quadrant, as seen below.

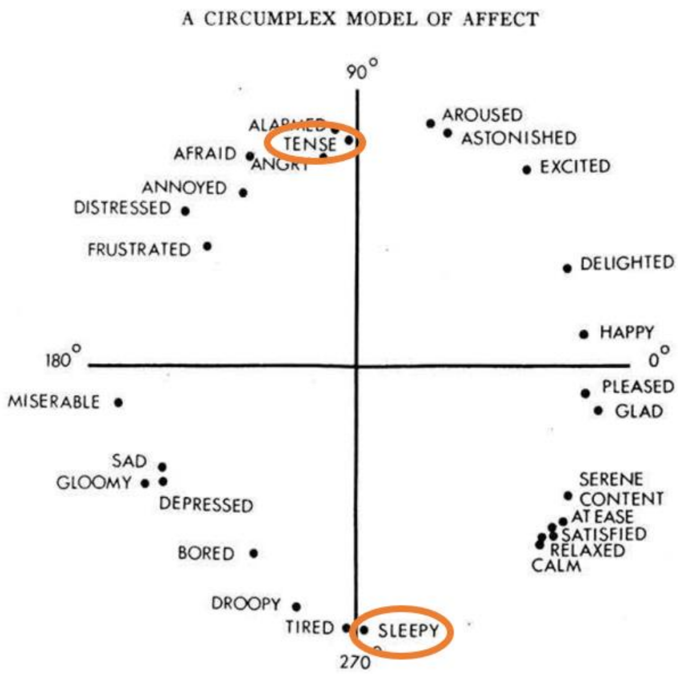


Fig 2.2 Adaptation of the “Independence and bipolarity in the structure of current affect,” by L. Feldman Barrett and J.A. Russell, 1998, Journal of Personality and Social Psychology, 74(4). Copyright 1998 by the American Psychological Association.

2.11.2 Emotions & Neuro Science:

Affective neuroscience is a field that aims at understanding the underlying emotional processes of neural networks and their effects on cognition, physiology, and behavior. The historical focus has been on describing human emotions universally, clearly defining the cause of emotional processes, and also the role of the body and interoception of feelings and emotions.

Within this domain, it is possible to differentiate emotions from other concepts, such as moods, affects, and feelings. Personal experiences linked to emotions are known as feelings, whereas moods tend to persist for longer durations than emotions and are less intense diffuse affective states. Affect, on the other hand, encompasses emotions, moods, and feelings.

Emotions have a social, or motivational, or adaptive role in human life, producing different characteristics which are indicative of human behavior. Decision-making, perception, human interactions, and human intelligence, as well as human health and work efficiency - are all affected by emotions. There are three components that influence the psychological behavior of humans: personal experiences, physiological responses, and behavioral or expressive responses.

Emotions are consistent or discrete responses to events that are considerable for a being, corresponding to a coordinated set of responses that are brief in duration. To better understand emotions expressed daily, they can be analyzed from a dimensional or categorical point of view.

The categorical point of view is based on the idea of basic emotions that are implanted in human physiology. There are different proposals for the number and type of basic emotions, ranging from six to ten. From the dimensional perspective, emotions are mapped into valence, arousal, and dominance.

Understanding emotional signals in everyday life environments is essential for communication through verbal and nonverbal behavior. Facial expressions are one example of emotional signals that are the most immediate means of communication of emotions and intentions. With advancements in brain-computer interface and neuroimaging technology, it is possible to record brainwave signals non-intrusively and measure or control device motions virtually or physically.

New applications, including neuroinformatics, which is the study of classification of emotions by collecting brainware signals are being actively developed using Artificial Intelligence and Machine Learning. This would in-turn aid in the development of Human Computer Interfaces (HCI) that cater to niche human needs.

2.11.3 Music & Color Association

People have long been fascinated by the relationship between certain sounds and colors. Individuals with sound-color synesthesia experience a conscious perception of a particular color when hearing a specific sound. A strong intuition about which sounds and colors complement each other is also possessed by non-synesthetes, although the extent to which these cross-modal correspondences share mechanisms with synesthesia is still debated. These correspondences influence perception and language, with metaphors such as referring to high-frequency sounds as "bright" being a common example.

The cross-modal correspondences and its importance for both human and language perceptions is highlighted by their pervasiveness in various fields. Iconicity, or the association between sound and meaning, provides insight into the evolution of cognition and human language, as well as into how language continues to culturally evolve. Cross-modal sound-color associations provide evidence of sound symbolism, which affects lexical iconicity and word formation, especially in relation to description and perception.

The present article examines the psychological aspect of the relationship between sound and color, specifically how different properties of color such as saturation, luminance and hue, correspond to acoustic characteristics such as loudness, pitch, and spectral elements.

One of the most straightforward examples of cross-modal correspondences is the association between auditory loudness and visual luminance. This association is based on the amount of sensory experience in both modalities and is known as a prothetic cross-modal correspondence. Loud sounds and bright colors are grouped together as they are high on their respective prothetic dimensions.

Pitch, which describes whether a tonal sound is of the high or low nature, is associated with luminance and possibly saturation. Unlike loudness, pitch is a metathetic dimension and is not considered larger or greater at higher levels but is qualitatively different. According to some theories, there is a mapping of pitch onto sensory dimensions in other modalities, such as luminance, which is based on a qualitative correspondence between them. Although some previous studies have reported links between pitch and color that could be attributed to changes in loudness, recent evidence suggests that cross-modal correspondences involving pitch are not solely influenced by loudness.

2.12 Natyashastra & Aesthetic Emotion Underlying Unity of all Arts

From 200BC and 200AD, works of dance and theater from Bharata's Natyashastra can be found to include the aesthetic sensation of rasa. In order to provide a methodology for the production of art as well as the study of it, Rasa unites all fields of study. Natyashastra, a field of study that focuses on Indian culture, art, fine arts, and education, is underpinned by psychology. The final passages of the book make references to Bharata in the role of the performing leader, who is full in knowledge and art. Both the identity of Bharata and his era are unknown.

The word "Bharata" is an acronym that stands for the Indian musical terms "Bhava," "Raga," and "Tala" (rhythm). Academics from the West contend that the Natyashastra was not written by a single person, group, or school and that it was instead a collaborative effort. They believe that other authors contributed to the book at various times. A detailed reading of the Natyashasthra exposes its unified purpose and suggests that it was written by a single author, as stated by the well-known Indian historian Professor Kapila Vatsayan. The Natyashastra was written even earlier than Valmiki's Ramayana. From the Natyashastra in Sunder and Yuddha Khandas, Valmiki took the nomenclature that Bharat Muni had established for a number of different aspects of Indian classical music.

Bharat's Natyashastra starts with an address to Maheshwara (Shiva) and Pitamaha (Brahma), while attributing everything to Brahma. After all, it was Brahma who established the Natyaveda, the fifth of the Vedas. "O, the sinless one, you will have to put "Natyaveda" to use," Brahma stated to Bharata. "Natyaveda" stands for the performing arts veda. Bharata along with the other sages explored the origin, method and theory of play and theater in the Natyashastra. These topics include speech, word, body language, gestures, costumes, decor, as well as interior states and temperaments. The oral transmission of the Natya Veda resulted in the compilation of 36,000 slokas.

Sanskrit critics such as Abhinav Gupta, Manmohan, and Vishwanath all cite Bharata as an important influence on Indian aesthetics. The most reliable source for information regarding the Natyashastra is "Abhinava Bharati," which was written by Abhinava Gupta. While constructing a corresponding system between the various realms of the material, psychical, physical, ethical, and the spiritual, Bharata envisioned all categories of arts, particularly drama, dance, poetry, and music. He did this with a degree of precision that was inexplicable. According to Bharata, the arts not only deliver pleasure and education but also teach about beauty, duty, and behavior.

Natyashastra is a text that represents and transmits the feelings associated with all parts of life, such as knowledge, lore, art and fine art, lore, design, as well as feelings and behaviors. According to Bharata, human nature is inextricably linked to the experience of happiness or misery, which can be shown through histrionics (Abhinaya) and Natya, which is a form of acting that combines physical and emotional performance. Even though Bharata is speaking in the context of theater, which is achieved through honing the senses, most notably the ear and the eye, that provided a groundwork for a notion irrespective of any singular form of artistic expression.

In Natyashastra, Bharata makes the audacious claim that play incorporates all aspects of the arts, sciences, crafts, and abilities.

The concept of 'Rasa' was initially implemented in Natya, which refers to theater; subsequently, it was utilized in Kavya, which refers to poetry; Alekhya, which refers to drawing and painting; Sangita, which refers to music; Murtishilpa, which refers to sculpture; Nritya, which refers to dance and drama; and Vastu Shilpa, which refers to architecture. Divine worship brings together each of these expressions. Rasa, according to Bharata, is the one-of-a-kind delight that comes through self-revelation through realization of the cosmic spirit of Anand (Aesthetic Bliss or Ecstasy).

All of the fine arts share common characteristics, including themes, contents, displays of sentiments and emotions, skillfulness, and control. Ragas, which are used in Indian classical music, are believed to have an emotional significance, and they have the capacity to induce a variety of different mental effects. Hence, the Raga reflects the many manifestations of the soul under the Nayika's sufferings of separation in a Bandish displaying Karuna Rasa, Vipralambh Sringara or the effervescence of passion. This takes place in the context of the Nayika (Sambhog Shringara Rasa). These feelings can be conveyed through any of the fine arts. As a result, Rasa connects all of India's artistic achievements—from the mesmerising strokes of the Ajanta caves and the artfully sculptured Konark and Khajuraho, to the pristine marbles of Taj Mahal.

2.13 Music & Emotion: Indian Concept

The musical experience known as Rasanubhava has been shown to have a significant impact on a listener's psyche. The concept of "rasa" is considered to be one of the most fundamental aspects of Hindu aesthetics (essence). The persistent esthetic sentiments of love (rati), laughing (hasa), pathos (soka), rage (krodha), enthusiasm (utsaha), fear (bhayam), disgust (jugupsa), and amazement correlate to the rasas sringara, hasya, karuna, raudra, vira, bhayanaka, bibhatsa, and adbhuta (vismaya). [14] It is thought that the seven tonal centers in the human vocal range correlate to each of these eight "rasas," which are also known as fundamental emotions. [15]

Listening to music is primarily motivated by its emotional impact, ability to provide diversion, and evoke memories. Research indicates that listeners, including children as young as three, can accurately recognize the emotional intent of a musical performer. Although some scientists have argued that music not having the capacity to generate actual emotional states, other experiments have demonstrated that music can cause specific changes in heart rate, blood pressure, and other autonomic bodily reactions that are associated with different emotions. There are two primary schools of thought regarding musical emotions: emotivists suggest that music garners emotions similar to non-musical emotions, whereas cognitivists propose that emotions are expressed by the music recognized by the listeners but do not necessarily experience themselves.

According to Meyer's theory on musical emotions, emotions are closely tied to specific moments in the music, and expectations play a crucial role in creating these emotions, based on both general psychological principles and familiarity with the music style. Recently, numerous empirical studies have provided evidence that music is a powerful stimulus that can elicit strong emotions accompanied by changes in the autonomic nervous system (ANS). For instance, in one study, participants listened to the leitmotivs of several Wagner operas, and their electrodermal response and respiratory activity were recorded and analyzed based on emotional arousal ratings. The results showed distinct changes in physiological measures in response to the different leitmotivs and their musical features. Additionally, research conducted in clinical and therapeutic contexts suggests that music can induce ANS responses even when individuals report feeling less anxious and more relaxed.

Music has the ability to express basic and discrete emotions that we experience in our daily lives, given that it has the capacity to express traditional emotions. Krumhansl conducted a study in which listeners heard music that had been previously rated as one of happy, sad, or fearful. Physiological measures were recorded during the listening sessions and analyzed to determine the relationship between physiological changes and dynamic ratings of emotions. The results showed that the physiological changes were similar for all three emotions, convincingly suggesting that music is capable of inducing genuine emotions in the listener. However, it is still unclear whether the changes in the listener's ANS and differentiation of emotions in music correspond to those observed in non-musical emotions.

2.13.1 Modeling of Discrete Emotions

Human emotions are difficult to judge or model as they are expressed differently by different people. Researchers mainly use two procedures to model emotions: One where emotions are labelled in categories and human judges are required to choose from the prescribed list of labels, namely joy, surprise, anger, sadness, love, fear, etc. Although, this method has its limitations, including the aspect of the stimuli containing blended emotions inexpressible in words. The other method makes the use of multiple dimensions and sales to map emotions where the subjects are required to indicate the impression left over by each stimulus in continuous scales. Two common scales used to model emotions are valence and arousal, the former in its axis representing the extremes of pleasantness of a stimuli, while arousal represents the level of activation. For example, happiness has a positive valence, whereas sadness is associated with a low arousal, yet surprise comes hand in hand with a very high arousal level.

A 2D emotion model can be created by plotting different emotional labels on a plane consisting of two axes. However, recent studies have found low consistency of physiological configurations during emotions, indicating that ANS activation is more related to specific action tendencies and dispositions rather than the emotions themselves. As a result, Scholsberg proposed a 3D model that also involved attention-rejection to the previous model. These associated action tendencies referred to as "stance" in a 3D emotion model that incorporates the conglomerate of arousal, valence, and stance. For example, fear is associated with the action pattern of “flight,” anger with “fight,” and so on. still it is not known what elemental problem is solved by happiness and what type of action pattern or motor program this emotion is connected to.

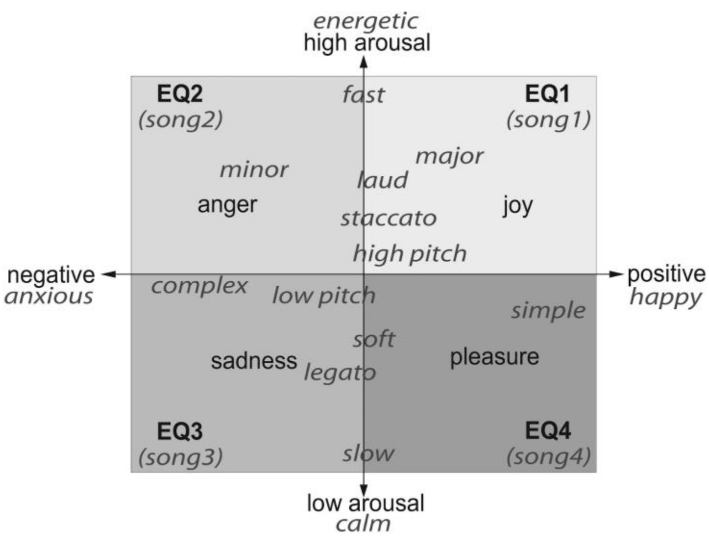


Fig. 2. 3D emotion model based reference emotional cues in music. EQ1 = positive/high arousal, EQ2 = negative/high arousal, EQ3 = negative/low arousal, and EQ4 = positive/low arousal.

Positive emotions appear to be characterized by minimal autonomic activation, which may be a contributing factor to the relatively slower pace of research on positive emotions compared to negative emotions. An interesting finding by Fredricson and Levenson is the "undoing" effect brought along by positive emotions, wherein certain positive emotions aid in faster recovery from the cardiovascular consequences of negative emotions. This observation supports the notion of a balanced process forming the basis of the emotion system, where negative emotions enable the organism to break free from homeostasis, while positive emotions such as contentment and amusement expedite the return to a homeostatic level.

2.14 Complex Structure of Music Signals

Micro and macro kinds of musical signals are approximately periodic from a physical standpoint. According to this theory, musical signals appear to exhibit deterministic behavior, but that has not been observed as music would then be a deterministic problem rendered out of rational human thought. In linguistic, aesthetic, and cognitive philosophy, however, it is widely held that music is a complex nonlinear system of many facets. Numerous researches are based on Musical notes' rhythmic and harmonic structures. However, the realistic dynamics of polyphonic recordings might not be able to be determined by frequency analysis. Several researches have attempted to associate human actions with musical sequences that are complex and rhythmic. In accordance to one such study, a stable pattern with a multi-periodicity is observed to emerge when listeners are exposed to a rhythmic music structure, which is a demonstration of the temporal structureof the rhythm. The purpose of this study is to describe some characteristics that will enable for the quantification of cues with improvisation in the four alternative interpretations of one particular "raga" performed by a Hindustani musician.

2.15 Role of Color in People's Lives

Colors have been highly regarded by humans for many years. Color meanings substantially influence people's displays of moods and emotions, therefore modern scientists explore color psychology across cultures. To convey meaning and evoke responses from their target audiences, businesses often use color psychology.

Color has psychological and aesthetic effects. Colors have psychological and physiological effects. The colors red and yellow are linked to vivacity and energy, while the colors blue and green are associated with calm and repose. A person's reaction to a color can be affected by their upbringing, their environment, and their personal history, therefore its meaning will change depending on who you ask. Feelings can also be influenced by how colors are combined, how intense they are, and how saturated they are.

2.15.1 Color Symbolisms

Colors have a lot of cultural significance. There's a chance they'll bring back memories of exotic rituals, times of year, or locations. The psychological impact of color theory. Color meanings can be culturally specific. We can trace the evolution of ideas, feelings, and even entire eras back to the impact of color. Moods can be described by their associated colors, such as being "green with envy," "tickled pink," "blue," and so on.

Colors are categorized in remarkably different ways between cultural groups. The Bassa of Liberia have two different words for each primary color: hui for violet, blue, and green, and ziza for sunshine, tango, and crimson. Several kinds of snow require different Inuit words meaning white.

Color psychology affects cultures everywhere. Colors have good and bad associations. In one culture, a hue means happiness and warmth, in another, betrayal and envy. Based on cultural color psychology, below are some colors and their meanings.

Blue

Blue, the safest color, is positive. Blue represents authority, security, and trust in Europe and North America. In certain cultures, it symbolizes grief, loneliness, and depression, resulting in "the blues."

Yellow

Sunshine-yellow makes many people happy. Its significance is darker in various cultures. It symbolizes jealousy in Germany. Yellow symbolizes jealousy, conflict, weakness, and betrayal in France.

Green

Green symbolizes jealousy, greed, inexperience (green horn), prosperity, environmental consciousness, spring, freshness, nature, and luck in the West. Military color. Ireland's greenery earned it the nickname The Emerald Island.

Red

Red symbolizes danger, love, action, passion, energy, and excitement in Western cultures but revolution and communism in Russia.

Orange

Westerners connect orange with visibility, warmth, harvest, and fall. Orange represents health, happiness, love, and humility in Eastern civilizations.

Purple

Purple symbolizes nobility, spirituality, religion, piety, wealth, and majesty. Japan only allows high-ranking Buddhist monks to wear purple robes. Catholic penitence is this color.

White

Western brides wear white to symbolize cleanliness, purity, serenity, and grace.

Black

Most cultures connect black with formality and sophistication in color psychology studies. Black symbolizes mystery, bad luck (black cat), disease, fierceness, magic, mourning, evil, and death.

Western cultures equate pink with infant girls, compassion, caring, romance, love, and femininity. Eastern countries associate these phrases with pink.

2.15.2 Color & Emotion:

Recognizing objects relies heavily on the perception of color. Furthermore, color can evoke emotions and feelings within an observer. Given that colors are inherent to objects and have a significant impact on our everyday lives, the emotional associations attached to colors are consequential. In the field of marketing, the impact of hues on emotions and preferences plays a crucial role since the color of products can have either a positive or negative effect on how viewers perceive them, and can also aid in distinguishing products and brand or corporate images. Various studies have examined the emotional connections linked to colors, utilizing distinct measuring approaches and populations. For example, Wexner examined hues linked to 11 tonal moods, including comfort and stimulation. Schaie investigated the mood-color associations to a certain degree using a paired comparison and sorting method. Deabler and Murray carried out a study on the correlation between color and mood in different populations, including university students from two distinct areas, neuropsychiatric patients as well as nursing assistants, and found differences in color-mood associations based on socio-economic and regional factors. In another study, Odbert et al. examined the music-induced associations between color and moods. Hupka et al. conducted an examination involving multiple cultures, regarding the color associations with 4 major emotions (anger, fear, envy, and jealousy). Kaya objectively investigated the associations between color and emotions using specified colors, while Costall and Clarke explored the connotations of colors regarding emotions using semi-structured interviews. Various associations were observed across these studies, as for instance, red is usually associated with excitement and anger while green goes with peacefulness and calmness; yellow is associated with happiness & cheerfulness, blue with calmness, and similarly black and gray with sadness and depression. While these associations can be found throughout multiple cultures, characteristic associations are also evident (example: the association of blue with depression in some contexts). On similar lines, white is also often associated with both cleanliness and purity but at the same time with emptiness, with these associations varying across cultures. Furthermore, Hupka et al. observed less consistent color associations with jealousy and envy than with anger and fear. Some studies have even determined similarities in color-emotion associations across different cultural backgrounds. The associations between emotions and colors were found to be similar in US college students, Tzeltal-speaking people in Chiapas, and the Arawakan-speaking Machiguenga community in Peru. However, it is unclear whether or not color-emotion associations are culture-specific or universal across cultures, but with minimal cross-cultural color-emotion variations. Although studies have reported sex biases in color preferences, few have also reported sex differences in color-emotion associations in adults. However, significant sex-bias in color-emotion associations have been observed in children, as in girls have been found to associate pink with happiness more than boys, while the latter associating blue with the same. These differences may be attributed to stereotypical color associations of girls and boys (pink and blue respectively), leading to color preference differences and subsequently the association of preferred colors with positive emotions. Differences aside, the overall pattern of associations was similar for both girls and boys with Lawler and Lawler's study reaffirming this finding.

Psychological scales such as semantic-differential (SD) scales have indirectly examined color-emotion associations in various cultures. Tanaka et al. used SD scales to assess the affective meanings of colors in Japanese and US college students and found that the results were similar for both groups. Adams and Osgood employed SD scales to measure the colors' meanings in twenty-three groups of high school male students spread across 20 countries and concluded high consistency in affective meanings among the different countries. Red was associated with high potency and activity, white and yellow were associated the other way around; Blue and green with high evaluation, & black with low activity and high potency . Ou & Gao and company have used a similar semantic differential technique to examine the affective meanings of colors and found British and Chinese participants having similarities with small differences among 7 other regional groups. Furthermore, Ou. found no major differences between male and female responses regarding associations, and not many studies examining SD ratings of colors have reported any sex dissimilarities. Therefore, sex differences in SD ratings for colors appear to be minimal.

Although emotional connections to colors are often noticed, there are substantial differences between various cultures. This suggests that color-emotion connections are created by customs that represent shared experiences. Children have diverse experiences with colors that are linked to their emotions. As these experiences accumulate, people's color-emotion connections are formed. Cultural customs of color-emotion associations could be established through shared experiences because people living near each other usually have common experiences, and individuals in the same culture likely have numerous opportunities to communicate and interact with each other. Many research studies, such as Kaya and Epps' work, support this hypothesis. They found that college students in the US correlate yellow-green with disgust and sickness, but green with relaxation and comfort associated with nature. However this hypothesis cannot entirely explain the similarity between data from 3-4 year old children and adults, as the former wouldn't have had as much of an opportunity to be exposed to the common cultural norms as the latter. Additionally, the universality of certain color-emotion associations across vastly different cultures challenges this hypothesis.

However, this hypothesis cannot define the consistency observed between 3 and 4-year-old children and adults' color-emotion associations since 3-year-old children would not have had as many chances to have enough common experiences with others.

An alternative explanation is that colors can induce emotions directly through a physiological mechanism. Supporting this notion, studies have found that colors can elicit consistent physiological responses, with red and violet generally increasing participants' arousal and blue and green decreasing it. However, these effects have not always been significant and appear to depend on various experimental conditions such as the duration of stimulation and size of the stimuli.

Studies in the past have investigated the impact of colors on emotions through psychological scales, with or without physiological measurements. Warm colors, such as red and yellow, have been found to cause more anxiety compared to cool colors like blue and green. This has been observed in previous research.

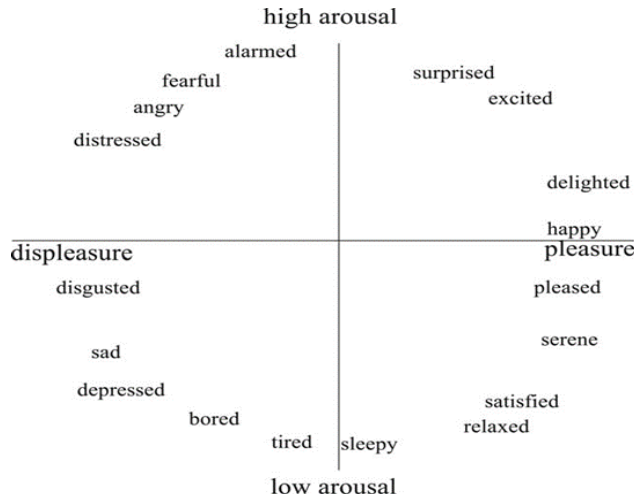


Fig 2.4: Detailed Circumplex Model of Russell's Emotion

The circumplex model of emotion/affect by Russell, which represents emotions, is shown in FIGURE 3. It has been modified to incorporate the baseline human emotions of happiness, anger, surprise, sadness, fear and disgust.

The color blue has been found to have a greater impact on inducing feelings of relaxation and calmness compared to other colors. However, studies have shown that the effects of color on emotional states or moods are not always significant or straightforward, and some studies have suggested that factors such as saturation and lightness may have more influence than hue. These studies support the idea that colors can affect emotions, but it is unclear whether the effects are caused by the color itself or by the association between color and emotion. The physiological effects of colors may be mediated by cognitive processes, as emotional associations with specific colors can influence arousal levels.

This study aimed to investigate whether emotional and color space configurations correspond to each other. Tools such as the Munsell color system and the CIELAB color space can be used to represent colors using a three-dimensional space, incorporating hue, saturation, and brightness. Hue is often depicted as circular figures in the hue-saturation plane at a given brightness. In a similar fashion, only a 2-dimensional space is required to represent emotions. Case in point, a study conducted by Schlosberg analyzed facial expressions, obtaining a two-dimensional mapping of facial expression characterized by arousal and pleasantness. Russell presented a circumplex model of emotion/affect that incorporated scaling techniques such as multidimensional scaling. This model represented emotions in a two-dimensional space with the two axes signifying pleasantness and arousal while representative emotions being arranged in a circle as shown in Figure 1. Other studies have also come up with slight variations of similar circular patterns of emotions.

This study hypothesizes that emotions and hues are linked by matching their respective circular representations in a two-dimensional space. Prior research in psychophysics and cognitive psychology has demonstrated that humans can match completely different dimensions with ease, such as the severity of crimes and music, through fast, intuitive, emotional, and automatic thinking. This suggests that the matching of unrelated dimensions may occur between the emotion and color circular orders.

Efforts have been made to explain these associations by matching circles of hue and mood. For instance, Ross investigated the appropriate illumination colors for theatre plays and discovered that comedy suited warm colors while tragedy suited cool colors. Additionally, Hevner's mood and hue circles were aligned, following which Odbert et al. tried correlating the former's mood with the hue circle using associations of music and color, each with mood. However, several problems were observed to have arisen from these studies. The mood circle was founded on music-induced moods while excluding basic emotions such as anger, surprise, fear and disgust, which music may not be able to elicit as intensely as other emotions. The mood circle presented by Hevner was introduced long before the emotion circumplex model and did not gather as much support. Secondly, the mood-color relationship was established indirectly through music or theatre as a mediator. Finally, advanced statistical methods were not employed in matching colors with moods.

Plutchik proposed a circular model of emotions based on the opponent-color theory, which consists of eight primary emotions, with four pairs of opposite emotions like complementary colors. Other emotions are mixtures of primary emotions, similar to non-primary colors. He did not argue that his emotion circle matches the color circle despite implications of similarities between those circles. However, Fromme and O'Brien had concluded experimental evidence partially supporting Plutchik's emotion & hue circles corresponding. In arts and interactive systems, colors, shapes and animations are often used to represent emotions. In such a system, the aforementioned correspondence is assumed, though there is no firm empirical evidence backing it in information and communication technology.

This study aimed to investigate whether there is a correspondence between the hue circle and the emotion circle using direct color-emotion associations data and a data visualization method called correspondence analysis. Previous studies have been criticized for using color names or imperfect color specifications, so colors specified in the CIE color space were used, and participants reported their emotions associated with these stimuli. Correspondence analysis was conducted to visualize the degree of association between the colors and emotions in a biplot. The distance between the colors and emotions in the biplot reflects the degree of association between them, and if there is a correspondence between emotion and hue circles, they should have a biplot overlap. The study also highlights that correspondence analysis can be used for exploratory data analysis and to gain useful insights into the statistical structures of color-emotion associations.

2.16 Human Brain:

It is said to be the most complicated system in the entire Universe and its Chaotic Dynamics. Because it can make things happen on its own, the brain doesn't just process information; it also makes information. So, the outside world is not just "coded" by meaningless "bits" of neuronal spikes. Instead, it is put into a context, of which time is an important part. In neuroscience, this is a fairly new way of thinking, and it's hard to defend it if you agree with Aristotle's idea that nothing moves or changes itself.

The new idea of a principle that is driven by "self-cause" has come up in a number of fields. People often call systems with these kinds of parts "complex." "Complex" doesn't just mean "hard to understand," though. It also means that the parts don't relate to each other in a straight line, that they depend on the past, that their boundaries are fuzzy, and that there are both positive and negative feedback loops. Because of this, very small changes can have big effects or none at all. Balanced systems are easier to comprehend and it is difficult to make any changes. Complex systems are usually open, and the information contained can always flow between them. Complex systems are marked by the fact that they are always changing, even if they look calm and stable for long periods of time. Complexity is often not only a trait of the system as a whole, but also of the parts that make it up. For example, some complex systems that are adaptive in nature like neurons form hierarchies at different levels. These things comprises of how the brain works because it is also a complex system or network where mental states are created by the interaction of many physical and functional levels.

It all starts with the idea of open systems in physics, which can trade energy, matter, and entropy and are not thermodynamic equilibrium with their surroundings. Few examples are: Galaxies, Avalanches, earthquakes.Ilya Prigogine, a Belgian-American chemist, came up with the term "dissipative structures" to describe patterns that form on their own in states that are far from equilibrium. When a system is "far from equilibrium," it means that standard linear mathematical methods cannot be used to describe it. Nonlinear differential equations are used to describe dissipative systems because there are no universal solutions. Chaos theory says that these complicated systems follow the rules of nonlinear dynamics (Prigogine, Stengers & Prigogine, 1984; Glass & Mackey, 1988; Gleick & Berry, 1987). Mathematically, chaos is when a system depends on its initial conditions in an exponentially sensitive way. This means that there is a fundamental limit to how well the system can be predicted. Entropy is a measure of how predictable (or not) a system is.

Multidimensional motion vectors are the means by which complex systems evolve. Due to their intricacy, nonlinear equations sometimes lead to unexpected results. Therefore,the prediction of a dynamic system is difficult. The result is independent of the summing of the agents. Order and structure develop from the interactions of many parts. As in a rhythm, the emergent self-organized dynamic imposes constraints on its components' freedom of action. Members of complex systems are interconnected at more than one level, allowing them to evolve beyond the effects of local interactions. Collaboration and competition between its components fuel its rise to the top. According to chaos theory, this preeminence is referred to as the attractor property and might decrease the system's inherent flexibility. Collectively, the degrees of freedom in a complex system can be compressed by an increase in entropy. The dynamics of the brain and chaos theory are a contentious topic. Despite the importance of nonlinear dynamics in the nervous system, efforts to detect strange attractors in brain signals using estimations of their fractal dimensions and by Lyapunov exponents, and other metrics have caused debate and controversy in the scientific community. Research into dynamics of the brain is primarily done using linear models and Fourier spectra. Notwithstanding the peculiar attractors of brain activity, the new methods of nonlinear and chaotic behavior analysis that have emerged in recent years might prove useful to the field of neuroscience. An electroencephalogram (EEG) uses electrodes placed on the scalp to record the electrical activity of the brain. The flexibility and coherence with which our brains adapt to perceptual stimuli is made possible, according to EEG studies, by the presence of chaos in cortical neurodynamics (Freeman, 1994; 2000). A large network of nonlinear devices, like neurons, should exhibit nonlinear behavior.

A linear reaction is impossible due to the complexity of the brain's needs. Due to the great unpredictability of brain electrical activity, nonlinear methods are more likely to be used for evaluation. In this dissertation, we use powerful nonlinear algorithms to assess brain signals from various lobes in response to musical stimuli.

2.17 Neuro-cognitive Application of Bio-Sensors

Investigation into human behavior is a significant area of research in the field of neuroscience. It is widely accepted that human behavior is linked to brain activity. Therefore, the analysis of human behavior begins with analyzing brain activity. Electroencephalography (EEG) is a widely recognized method for measuring brain activity, which produces a disorderly signal that displays fractal features. This research exposes the correlation between the complexity (fractal structure) of human EEG signals and auditory stimuli. We selected a variety of auditory stimuli with different rhythmic patterns to examine the impact on the fractal structure of human EEG signals. Our findings reveal that the fractal structure of human EEG signals changes significantly in response to various rhythmic patterns. This study's potential can be used to categorize the brain's response to different stimuli by stimulus type.

Behavior is the primary area of study for neuroscientists. Behavior can be influenced by neural activity. So, the examination of brain activity is absolutely necessary for behavior comprehension. Electroencephalography, often known as EEG, is frequently used to analyze the activity of the brain, and the results of this analysis can be chaotic and fractal. This study demonstrates how the fractal pattern of human EEG data is affected when aural stimuli are present. This was accomplished by picking a broad variety of rhythmic auditory stimuli from the available options. The fractal structure of human EEG data can be altered by a variety of rhythmic patterns. This information can be used to categorize how the brain reacts to a variety of stimuli that are fed into it.

Research in neuroscience focuses on behavior. The activity in the brain has an effect on behavior. As a result, examination of brain activity serves as the basis for behavior analysis. Electroencephalography, sometimes known as EEG, is a common technique for measuring brain activity. The output of this technique is chaotic and fractal. This study demonstrates how different aural stimuli influence the fractal structure of human EEG signals. In order to accomplish this, we made use of a variety of rhythmic auditory cues. The fractal structure of human EEG signals can be altered by a variety of rhythmic patterns. The findings of this research can be applied to the classification of brain responses to various stimuli.

1. Without any prior training, we have the intrinsic ability to synchronize our tapping to both simple and complex rhythmic sequences, which is an essential component in music perception.

Children aged seven to nine months have the ability to differentiate between rhythmic structures that have different patterns and to recognize downbeats, which are the opening note of rhythmic cycles, even when they are absent or unstressed.

2. The note lengths in a melody rhythm are all different from one another. As a result, rhythm can be defined as a temporal sequence of events with varying intensities. The terms rhythmic pattern, tempo, meter, and timing are all possible components of rhythm.

3. Rhythm, as referred to within the context of music theory, most frequently refers to a rhythmic pattern. As a result, the rhythmic pattern of the research constitutes a distinct symbolic scale of durations. There hasn't been a lot of research done in the past few decades to figure out how the human brain interprets musical rhythm and how it reacts to it. The cortical motor system is affected when one is able to perceive musical rhythm. Including the Supplementary Motor Area (SMA), the Pre-Motor Cortex (PMC), as well as the basal ganglia and the cerebellum.

4.In(8–10) The putamen, the supplementary motor region, the premotor cortex, and the auditory cortex all revealed greater functional connectivity when fMRI investigations were conducted using beat-based rhythms. A direct relationship exists between the functional connectivity of the premotor and auditory cortexes, and the intensity of isochronous tones.

5. Electroencephalography (EEG) and magnetoencephalography (MEG) have been utilized in the research of brain responses to auditory rhythms, specifically for the purpose of measuring neural activity entrainment to the beat and meter of the music. In one study, the researchers found that the level of induced (non-phase-locked) gamma band activity (GBA) was greater when the participants were asked to listen to isochronous beats that alternated between strong and weak beats. This was the case even when the participants were not exposed to any predicted tones. The

participants' upper beta band oscillatory activity rose again when they envisioned a downbeat occurring at varied positions on an equal time interval with imprecise rhythmic phrase (Containing two tones and ending with a rest gap).

6. The influence of fictional accented beat on entrained oscillations has been investigated in a number of different research. In another piece of research, beta activity was linked to isochronous rhythmic processes that occurred at variable rates. 17 The scaling of biological time series and patterns is an important application of fractal theory. Fractals are basically repeating patterns found in nature or sometimes in mathematics that may be observed at any partricular scale (also, self-similar).

7. Scaling exponents (dimensions) are what govern the scaling laws. Simple fractals are scaled on integers. Complex entities that are identical to themselves are not integers. 19 Fractals are geometric objects that have a scaling exponent (dimension) that satisfies the Szpilrajn inequality 20: DT,(1), where and are the object's topological dimension and the scaling exponent (dimension) of the object, respectively (Euclidean dimension of units from which the fractal object is created). The fractal dimension is a measure of complexity that illustrates how the details of a pattern change as the scale changes. 21 The fractal technique has been utilized extensively in order to investigate the complexity of various biomedical signals and patterns, including DNA,(22 to 25) in the human face, 26, the signal for respiration, (27 and 28) the movement of eye timeseries, (29 and 30) the structure of bone ,31 the heart-rate,32 the signal containing s-ABR, (33 and 34) the brain signal of spider, (35 and 36) and the behaviour of animal foraging. 37 Fractal theory was applied in a few of the research that analyzed EEG signals. EEG signals from visual, (38 and 40) auditory, (41 and 42), and olfactory stimuli were analyzed using fractal theory in both healthy and ill individuals.

8. It is noteworthy that all the studies reported that external stimuli created a shift in the fractal structure of the EEG signal. None of the cited research papers, has established any relationship between the structure of an EEG signal and the auditory stimulus in the form of rhythmic patterns. In this study, we look at how the complexity of the EEG signal changes when there are different rhythmic patterns for the first time. Since the pattern of a person's EEG signal looks like a fractal, we can use fractal theory to learn more about how complicated an EEG signal is. We think that the fractal structure of the EEG signal is affected by changes in the rhythmic patterns of the auditory stimuli.

A parametric difference in the activation patterns of the brain cortex was observed in an early EEG study: a left fronto-temporal cortex bias was noticed in a more significant lateralisation was produced by musical excerpts that imbided a positive note, whereas a right fronto-temporal bias was observed to be induced by musical excerpts of a negative note. Recent studies corroborate the results in a way that the left frontal and right frontal areas are involved with the processing of positive and negative music respectively. For the processing of an affective visual stimuli, the same frontal asymmetry is reported.

Hence, it is justified that there are cross overs between visual and musical emotions. But the question arises whether these emotions that are from the auditory channel can influence the emotions arising from other sensory channels (in this case visual)? Research work conducted on crossmodal integration of visual and auditory emotions depict that the rating od affective information in one sensory modality can be biased towards the direction of the emotional valence of information in another modality. Therefore, we can conclude that visual emotions can be interacted with musical emotion for simultaneously processing music and visuals.

2.17.1 Several Biosensors

The research gathered physiological data utilizing the Pro-Comp 2 Infiniti, equipped with four biosensors, namely the Electromyogram (EMG), Respiration (RSP), Skin Conductance (SC), Electrocardiogram (ECG). The rates at which they were sampled are as follows: 32Hz for EMG, RSP and SC while 256 Hz for ECG. The waveforms along with the biosensors' positions used in the study are shown in Fig. 3.

The subjects individually selected four songs intended to evoke emotional memories and certain moods corresponding to the four target emotions. The songs were chosen based on a musical emotion model (Fig. 21) and metaphoric cues, such as positively stimulating, delightful, euphoric, energizing, noisy, loud, melancholic, sad memory, irritating, blissful, pleasurable, slumberous, and tender.

The study used an 8-channel 14-bit multimodal Biofeedback system conjuncted to a fiber optic connection to the computer. The experiment setup was envisioned as a quiet listening room, and the subjects were demonstrated the procedure to prepare their skin using an antiseptic and an electrode impedance-reducing skin preparation gel, as well as being directed as to the correct position of sensors.

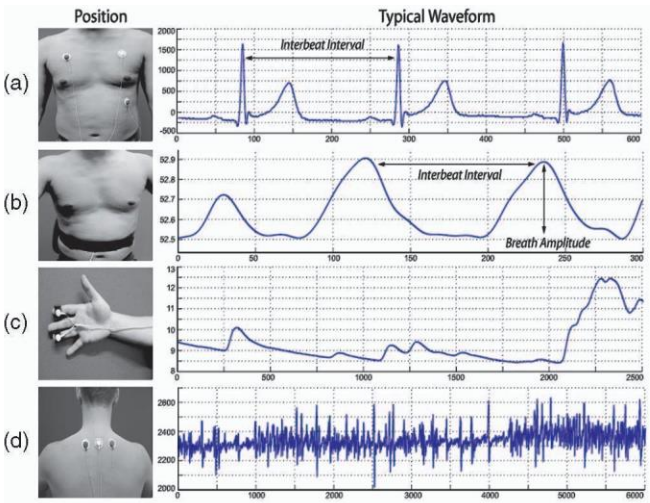


Fig. 2.5. Position and typical waveforms of the biosensors. (a) ECG (b) RSP. (c) SC. (d) EMG.

Electrocardiogram

A pre-amplified electrocardiograph sensor with a bandwidth of 0.05 Hz-1 KHz was used, connected with pre-gelled single Ag/AgCl electrodes, to measure the average action potential on the skin since it is not possible to measure individual action potentials directly in the heart. Starting high in the right atrium, the action potential moves towards the centre, followed by a downward shift towards the apex. The mean movement was essentially along the "electrical axis" of the heart.

The ECG machine measures heart rate, inter-beat interval, and heart rate variability (HRV). Heart rate can determine the difference between positive and negative emotions with further differences being made possible with finger temperature. The measurement of HRV pertains to the cyclical variation between successive heartbeats and has been utilized to gauge mental exertion and tension in adults, and as a metric has been established as a valuable tool in assessing situations potentially imbibing stress.

Electromyogram

The research utilized a Myoscan-Pro sensor that had pre-gelled single Ag/AgCl electrodes and an active range of 20-500 Hz to record electromyography (EMG) signals up to 1,600 µV. The purpose of EMG is to measure any activity from the muscles by detecting the change in surface voltages induced by muscle contractions. To obtain optimal data, the sensor is meant to be placed on the belly of the muscle, with a parallel placement of the negative and positive electrodes to the fibres. The strength of the obtained electrical signal varies proportionally to the strength of the contraction. EMG has been widely used already in psychophysiology establishing the correlation between the cognitive emotion and physiological reactions. In their experiment, bipolar electrodes were placed at the upper trapezius muscle to measure the mental stress levels of the subjects.

Respiration

The participants' breathing activity was measured using a latex-clad stretched sensor fixed with a Velcro belt. The sensor could be worn over clothing and recorded the voltage change corresponding to the magnitude of elastic stretch. RSP rate and depth were the most commonly used measures, with a decrease in rate typically indicating relaxation. However, momentary cessation could occur in response to startling events or tense situations, and negative emotions were found to cause irregularities in the RSP pattern. As RSP and cardiac functions are closely intertwined, even a deep breath could affect other measurements such as EMG and skin conductivity. RSP cycle was also observed to be irregular during talking. Additionally, capnography, which monitors the CO2 content in inhaled/exhaled air, or measuring the chest cavity expansion, could be used to obtain the cyclic repetition of RSP data.

Skin Conductivity

Skin Conductivity is a commonly used characteristic to understand an user's emotional state, specifically in case of a difference in arousal. Studies have shown that the intensity of emotional experience is almost linearly associated with the magnitude of electrodermal change in the arousal dimension. The SC sensor measures the skin's conductivity, which is an activity function of the eccrine sweat glands and the skin's pore size. The sensor consists of Ag/AgCl electrodes fixed with a two-finger band and positioned at the ring and index fingers of the non-preferred hand. The skin conductance signal consists of a gradual tonic component reflecting the overall activity of the sweat glands that are affected by temperature or other factor in addition to a rapid phasic component that is impacted by the intensity of emotions and level of arousal. When a person experiences sudden fear or anxiety, there will be a rapid increase in skin conductance caused by heightened activity in the sweat glands.

2.18 Crossmodal Association

The article discusses how people associate color with music or natural soundscapes using different strategies, which have been studied by researchers for over a century, as reported in. Crossmodal associations can arise through at least four mechanisms, corresponding to various levels of neural processing in the brain, as outlined in Spence's tutorial. An overview is explained of three seperate types of crossmodal correspondence: structural, statistical, and semantic. The structural correspondences are rooted in similarities in the way neurons encode sensory information, and are typically observed in the initial stages of neural processing. Statistical occurrence and ecological perception, the second type of crossmodal association, occurs when the stimuli has been perceived simultaneously through varied sensory organs and parallel neurons; these might get associated at a random intermediate point in the neural processing path. The third type of crossmodal association is based on learned conscious associations, which are available to the individual for inspection and training, and solely rely on a terminology that is descriptive as well as common between different modalities. Finally, a fourth way in which crossmodal association might arise is through emotion at a pre-cognitive level. Certain crossmodal correspondences may be rooted in psychobiological factors, whereas others could be influenced by individual gender, cultural upbringing, or personal experience. The article cites various sources to support its claims and provides a brief overview of the mechanisms of crossmodal associations.

2.19 References

Aerts, D. (2012). Quantum interference and superposition in cognition: A theory for the disjunction of concepts. In *Worldviews, science and us: Bridging knowledge and its implications for our perspectives of the world* (pp. 169-211).

Armstrong, A. H. (1968). Plotinus. *The Classical Review*, *18*(02).

Atreya, J. P. (1985). *Mind and its function in Indian thought*. Classical Publ. Company.

Bala, S. (2009). *The Concept of Mind* (Doctoral dissertation, Guru Nanak Dev University Amritsar). Berkeley, G. (1948). An essay toward a new theory of vision, 1709.

Busemeyer, J. R., Pothos, E. M., Franco, R., & Trueblood, J. S. (2011). A quantum theoretical explanation for probability judgment errors. *Psychological review*, *118*(2), 193.

Busemeyer, J. R., Wang, Z., & Townsend, J. T. (2006). Quantum dynamics of human decision- making. *Journal of Mathematical Psychology*, *50*(3), 220-241.

Churchland, P. S. (1980). A perspective on mind-brain research. *The Journal of Philosophy*, *77*(4), 185-207.

Chakrabarti, K. K. (1999). *Classical Indian philosophy of mind: The Nyaya dualist tradition*. SUNY Press.

Churchland, P. M. (1981). Eliminative materialism and propositional attitudes. *the Journal of Philosophy*, *78*(2), 67-90.

Davidson, D. (2001). *Essays on Actions and Events: Philosophical Essays Volume 1*. Clarendon Press.

Descartes, R. (1988). *Descartes: Selected philosophical writings*. Cambridge University Press.

Damasio, A. R. (2000). A second chance for emotion. *Cognitive neuroscience of emotion*, *12*, 23.

Dolcos, F., Wang, L., & Mather, M. (2014). Current research and emerging directions in emotion- cognition interactions. *Frontiers in Integrative Neuroscience*, *8*, 83.

Durant, W. (1961). *Story of philosophy*. Simon and Schuster. New York: Washington Square Press Publication of Pocket Books.

Feigl, H. (1958). The ‘mental’and the ‘physical’. *Minnesota studies in the philosophy of science*, *2*(2), 370-497.

Feyerabend, P. (1963). Mental Events and the Brain. *Journal of Philosophy*, 40, 295–296. Fichte, J. G. (1993). *Fichte: Early philosophical writings*. Cornell University Press.

Hansotia, P. (2003). A neurologist looks at mind and brain:“The enchanted loom”. *Clinical medicine & research*, *1*(4), 327-332.

Johnson, M. L. (2001). The feeling of what happens: body and emotion in the making of consciousness.

Khrennikov, A. (2009). Quantum-like model of cognitive decision making and information processing. *Biosystems*, *95*(3), 179-187.

Ochsner, K. N., Bunge, S. A., Gross, J. J., & Gabrieli, J. D. (2002). Rethinking feelings: an FMRI study of the cognitive regulation of emotion. *Journal of cognitive neuroscience*, *14*(8), 1215-1229.

Okon-Singer, H., Hendler, T., Pessoa, L., & Shackman, A. J. (2015). The neurobiology of emotion– cognition interactions: fundamental questions and strategies for future research. *Frontiers in human neuroscience*, *9*, 58.

Pessoa, L. (2013). *The cognitive-emotional brain: From interactions to integration*. MIT press.

Pinchot, R. B., & Gersten, J. (1930). *The brain: mystery of matter and mind.* Washington DC: US New Books.

Russell, B. (2022). *My philosophical development*. Taylor & Francis. (Originally published by London: George Allen and Unwin, Ltd., 1959.)

Schifferstein, H. N., & Spence, C. (2008). Multisensory product experience. In *Product experience*

(pp. 133-161). Elsevier.

Schwartz, J. M., & Begley, S. (2009). *The mind and the brain*. Springer Science & Business Media.

Schwartz, J. M., Stapp, H. P., & Beauregard, M. (2005). Quantum physics in neuroscience and psychology: a neurophysical model of mind–brain interaction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1458), 1309-1327.

York III, G. K., & Steinberg, D. A. (2011). Hughlings Jackson's neurological ideas. *Brain*, *134*(10), 3106-3113.

Hegel, G. W. F. (1977). *Difference Between Fichte's and Schelling's System of Philosophy, The: An English Translation of GWF Hegel s Differenz des Fichte schen und Schelling schen Systems der Philosophie*. Suny Press.

Horgan, T. (1982). 1 982: Supervenience and micro-physics. *Pacific Philosophical Quarterly*, *63*, 27-43.

Jackson, F. (1982). Epiphenomenal qualia. The Philosophical Quarterly 32 (127), 127–136. Jackson, F. (1998). Postscript on Qualia, in his mind, method and conditionals (pp. 76–79).

Kant, I. (1998). Critique of Pure Reason. *Trans. and ed. P. Guyer and AW Wood. Cambridge: Cambridge University Press*.

Kripke, S. A. (1972). Naming and necessity. In *Semantics of natural language* (pp. 253-355). Springer, Dordrecht.

Lange, F. A. (1865). The History of Materialism and Criticism of its Present Importance, trans. E. Thomas. *New York: The Humanities Press*, *75*, 1950.

Larmer, R. (1986). Mind-body interaction and the conservation of energy. *International philosophical quarterly*, *26*(3), 277-285.

Loptson, P. (2006). Leibniz's body realism: Two interpretations. *The Leibniz Review*, *16*, 1-42.

McLaughlin, B. P. (1984). Perception, causation, and supervenience. *Midwest Studies in Philosophy*, *9*(1), 569-591.

Place, U. T. (1970). Materialism as a scientific hypothesis. In *The Mind-Brain Identity Theory* (pp. 83-86). Palgrave, London.

Radhakrishnan, M. (2009). Indian Philosophy of Mind: A Comparative Study. فلسفه, *37*(1), 1-19.

Radhakrishnan, S. (1953). *History of Philosophy, Eastern and Western*. Geoge Allen & Unwin, London.

Reichenbach, H. (1938). Experience and prediction: An analysis of the foundations and the structure of knowledge.

Vidyabhusana, S., Basu, B. (1913). *The Nyaya Sutras of Gotama: The sacred book of Hindus.* In Basu, M.D. (Ed.), The sacred books of the Hindus (pp. 1–175). Allahabad: Panini office, Bhuvaneswari Asrama.

Von Schelling, F. W. J. (1988). *Ideas for a Philosophy of Nature*. Cambridge University Press.

Whitney, W. D. (1890). Translation of the Katha-Upanishad. *Transactions of the American Philological Association (1869-1896)*, *21*, 88-112.

Anderson, D. J., & Adolphs, R. (2014). A framework for studying emotions across species. *Cell*, *157*(1), 187-200.

Arnold, M. B. (1960). *Emotion and personality.* Columbia University Press.

Barrett, L. F. (2009). The future of psychology: Connecting mind to brain. *Perspectives on psychological science*, *4*(4), 326-339.

Barrett, L. F. (2017). The theory of constructed emotion: an active inference account of interoception and categorization. *Social cognitive and affective neuroscience*, *12*(1), 1-23.

Bedford, E. (1956, January). Emotions. In *Proceedings of the Aristotelian Society* (Vol. 57, pp. 281- 304). Aristotelian Society, Wiley.

Berridge, K. C. (2018). Evolving concepts of emotion and motivation. *Frontiers in Psychology*, 1647.

Cannon, W. B. (1927). The James-Lange theory of emotions: A critical examination and an alternative theory. *The American journal of psychology*, *39*(1/4), 106-124.

Damasio, A. R. (2004, April). Emotions and feelings. In *Feelings and emotions: The Amsterdam symposium* (pp. 49-57). Cambridge: Cambridge University Press.

Darwin, C., & Prodger, P. (1998). *The expression of the emotions in man and animals*. Oxford University Press, USA.

Descartes, R. (1989). The passions of the soul (S. Voss, Trans.). Indianapolis, IN: Hackett Publishing. (Original work published 1649).

Dewey, J. (1894). The theory of emotion: I: Emotional attitudes. *Psychological review*, *1*(6), 553. Dewey, J. (1895). The theory of emotion. *Psychological review*, *2*(1), 13.

Ekman, P. (1977). Biological and cultural contributions to body and facial movement. *The anthropology of the body*.

Ekman, P. (1999a). Basic emotions. *Handbook of cognition and emotion*, *98*(45-60), 16. Ekman, P. (1999b). Facial expressions. *Handbook of cognition and emotion*, *16*(301), e320.

Ekman, P., Freisen, W. V., & Ancoli, S. (1980). Facial signs of emotional experience. *Journal of personality and social psychology*, *39*(6), 1125.

Fortenbaugh, W. W. (1975). Aristotle on emotion: a contribution to philosophical psychology, rhetoric, poetics, politics, and ethics.

Frijda, N. H. (2007). What might emotions be? Comments on the Comments. *Social Science Information*, *46*(3), 433-443.

Gendron, M., & Feldman Barrett, L. (2009). Reconstructing the past: A century of ideas about emotion in psychology. *Emotion review*, *1*(4), 316-339.

Ghose, P. (2012). Nonquantum Cognition. *arXiv preprint arXiv:1210.4473*.

Greenwald, A. G., & Banaji, M. R. (2017). The implicit revolution: Reconceiving the relation between conscious and unconscious. *American Psychologist*, *72*(9), 861.

Hume, D. (2003). *A treatise of human nature*. Courier Corporation. Izard, C. E. (1971). *The face of emotion.* Appleton-Century-Crofts.

Izard, C. E. (1992). Basic emotions, relations among emotions, and emotion-cognition relations.

Psychological Review, 99(3), 561–565.

James, W. (1984). *Psychology, briefer course* (Vol. 14). Harvard University Press. Kenny, A. (2003). *Action, emotion and will*. Routledge.

Lazarus, R. S. (1991). Cognition and motivation in emotion. *American psychologist*, *46*(4), 352.

LeDoux, J. E. (2014). Coming to terms with fear. *Proceedings of the National Academy of Sciences*, *111*(8), 2871-2878.

LeDoux, J. E., & Hofmann, S. G. (2018). The subjective experience of emotion: a fearful view.

Current Opinion in Behavioral Sciences, *19*, 67-72.

Morris, J. S., Öhman, A., & Dolan, R. J. (1998). Conscious and unconscious emotional learning in the human amygdala. *Nature*, *393*(6684), 467-470.

Nussbaum, M. (1996). Compassion: The basic social emotion. *Social Philosophy and Policy*, *13*(1), 27-58.

Nussbaum, M. (2001). Upheavals of thought: the intelligence of emotions Cambridge University Press.

Panksepp, J. (2011). The basic emotional circuits of mammalian brains: do animals have affective lives?. *Neuroscience & Biobehavioral Reviews*, *35*(9), 1791-1804.

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological review*, *110*(1), 145.

Scarantino, A. (2014). The motivational theory of emotions. In J. D'Arms & D. Jacobson (Eds.), *Moral psychology and human agency: Philosophical essays on the science of ethics* (pp. 156–185). Oxford University Press.

Scherer, K. R., Schorr, A., & Johnstone, T. (Eds.). (2001). *Appraisal processes in emotion: Theory, methods, research*. Oxford University Press.

Solomon, R. C. (1993). *The passions: Emotions and the meaning of life*. Hackett Publishing.

Solomon, R. L. (1980). The opponent-process theory of acquired motivation: the costs of pleasure and the benefits of pain. *American psychologist*, *35*(8), 691.

Tomkins, S. S. (2008). *Affect imagery consciousness: the complete edition: two volumes*. Springer publishing company.

Winkielman, P., Berridge, K. C., & Wilbarger, J. L. (2005). Unconscious affective reactions to masked happy versus angry faces influence consumption behavior and judgments of value.

Personality and social psychology bulletin, *31*(1), 121-135.

Armony, J. L., & Dolan, R. J. (2001). Modulation of auditory neural responses by a visual context in human fear conditioning. *Neuroreport*, *12*(15), 3407-3411.

Baumgartner, T., Esslen, M., & Jäncke, L. (2006). From emotion perception to emotion experience: Emotions evoked by pictures and classical music. *International journal of psychophysiology*, *60*(1), 34-43.

Björk, E. A. (1985). The perceived quality of natural sounds. *Acustica*, *57*(3), 185-188.

Bradley, M. M., & Lang, P. J. (2000). Affective reactions to acoustic stimuli. *Psychophysiology*, *37*(2), 204-215.

Bresciani, J. P., Ernst, M. O., Drewing, K., Bouyer, G., Maury, V., & Kheddar, A. (2005). Feeling what you hear: auditory signals can modulate tactile tap perception. *Experimental brain research*, *162*(2), 172-180.

Brosch, T., Pourtois, G., & Sander, D. (2010). *The perception and categorisation of emotional stimuli: A review* (pp. 76-108). Psychology Press.

Brosch, T., Scherer, K. R., Grandjean, D. M., & Sander, D. (2013). The impact of emotion on perception, attention, memory, and decision-making. *Swiss medical weekly*, *143*, w13786.

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature reviews neuroscience*, *3*(3), 201-215.

De Gelder, B., Morris, J. S., & Dolan, R. J. (2005). Unconscious fear influences emotional awareness of faces and voices. *Proceedings of the National Academy of Sciences*, *102*(51), 18682-18687.

De Gelder, B., Pourtois, G., & Weiskrantz, L. (2002). Fear recognition in the voice is modulated by unconsciously recognized facial expressions but not by unconsciously recognized affective pictures. *Proceedings of the National Academy of Sciences*, *99*(6), 4121-4126.

Dolan, R. J. (2002). Emotion, cognition, and behavior. *science*, *298*(5596), 1191-1194.

Driver, J. (2001). A selective review of selective attention research from the past century. *British journal of psychology*, *92*(1), 53-78.

Driver, J., & Noesselt, T. (2008). Multisensory interplay reveals crossmodal influences on 'sensory- specific' brain regions, neural responses, and judgments. *Neuron*, *57*(1), 11-23.

Fan, J. (2014). An information theory account of cognitive control. *Frontiers in human neuroscience*, *8*, 680.

Gayet, S., Paffen, C. L., Belopolsky, A. V., Theeuwes, J., & Van der Stigchel, S. (2016). Visual input signaling threat gains preferential access to awareness in a breaking continuous flash suppression paradigm. *Cognition*, *149*, 77-83.

Gerdes, A. B., Wieser, M. J., & Alpers, G. W. (2014). Emotional pictures and sounds: a review of multimodal interactions of emotion cues in multiple domains. *Frontiers in psychology*, *5*, 1351.

Ghosh, D., Sengupta, R., Sanyal, S., & Banerjee, A. (2018). *Musicality of human brain through fractal analytics*. Springer Singapore.

Grandjean, D., Sander, D., Pourtois, G., Schwartz, S., Seghier, M. L., Scherer, K. R., & Vuilleumier,

P. (2005). The voices of wrath: brain responses to angry prosody in meaningless speech. *Nature neuroscience*, *8*(2), 145-146.

Guski, R. (1999). Personal and social variables as co-determinants of noise annoyance. *Noise and health*, *1*(3), 45.

Hietanen, J. K., Surakka, V., & Linnankoski, I. (1998). Facial electromyographic responses to vocal affect expressions. *Psychophysiology*, *35*(5), 530-536.

Juslin, P. N., & Sloboda, J. A. (2001). Music and emotion. *Theory and research*.

Juslin, P. N., & Västfjäll, D. (2008). Emotional responses to music: The need to consider underlying mechanisms. *Behavioral and brain sciences*, *31*(5), 559-575.

Klasen, M., Kreifelts, B., Chen, Y. H., Seubert, J., & Mathiak, K. (2014). Neural processing of emotion in multimodal settings. *Frontiers in human neuroscience*, *8*, 822.

Krishna, A. (2012). An integrative review of sensory marketing: Engaging the senses to affect perception, judgment and behavior. *Journal of consumer psychology*, *22*(3), 332-351.

Kuwano, S., Namba, S., Hayashi, Y., Komatsu, M., & Kato, T. (2001). Auditory and visual interaction in the aesthetic evaluation of environment. *Empirical Studies of the Arts*, *19*(2), 191-200.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1990). Emotion, attention, and the startle reflex.

Psychological review, *97*(3), 377.

Levenson, R. W. (1999). The intrapersonal functions of emotion. *Cognition & Emotion*, *13*(5), 481- 504.

Ludden, G. D., Schifferstein, H. N., & Hekkert, P. (2009). Visual–tactual incongruities in products as sources of surprise. *Empirical Studies of the Arts*, *27*(1), 61-87.

Mogg, K., Bradley, B. P., De Bono, J. O., & Painter, M. (1997). Time course of attentional bias for threat information in non-clinical anxiety. *Behaviour research and therapy*, *35*(4), 297-303.

Müller, V. I., Cieslik, E. C., Turetsky, B. I., & Eickhoff, S. B. (2012). Crossmodal interactions in audiovisual emotion processing. *Neuroimage*, *60*(1), 553-561.

Niedenthal, P. M., & Wood, A. (2019). Does emotion influence visual perception? Depends on how you look at it. *Cognition and Emotion*, *33*(1), 77-84.

Niedenthal, P. M., Halberstadt, J. B., Margolin, J., & Innes-Ker, Å. H. (2000). Emotional state and the detection of change in facial expression of emotion. *European journal of social psychology*, *30*(2), 211-222.

Öhman, A., Flykt, A., & Esteves, F. (2001). Emotion drives attention: detecting the snake in the grass.

Journal of experimental psychology: general, *130*(3), 466.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The measurement of meaning* (No. 47). University of Illinois press.

Phelps, E. A., Ling, S., & Carrasco, M. (2006). Emotion facilitates perception and potentiates the perceptual benefits of attention. *Psychological science*, *17*(4), 292-299.

Phelps, E. A., Ling, S., & Carrasco, M. (2006). Emotion facilitates perception and potentiates the perceptual benefits of attention. *Psychological science*, *17*(4), 292-299.

Riener, C. R., Stefanucci, J. K., Proffitt, D. R., & Clore, G. (2011). An effect of mood on the perception of geographical slant. *Cognition and Emotion*, *25*(1), 174-182.

Roy, S., Roy, C., Nag, S., Banerjee, A., Sengupta, R., & Ghosh, D. (2020). Chaos based non-linear cognitive study of different stimulus in the cross-modal perspective. *Physica A: Statistical Mechanics and its Applications*, *546*, 122842.

Russell, C. A. (2002). Investigating the effectiveness of product placements in television shows: The role of modality and plot connection congruence on brand memory and attitude. *Journal of consumer research*, *29*(3), 306-318.

Sander, D. (2013). Models of emotion: The affective neuroscience approach. In J. Armony & P. Vuilleumier (Eds.), *The Cambridge handbook of human affective neuroscience* (pp. 5–53). Cambridge University Press.

Schafer, R., & Murphy, G. (1943). The role of autism in a visual figure-ground relationship. *Journal of Experimental Psychology*, *32*(4), 335.

Scherer, K. R., & Wallbott, H. G. (1994). Evidence for universality and cultural variation of differential emotion response patterning. *Journal of personality and social psychology*, *66*(2), 310.

Schreuder, E., Van Erp, J., Toet, A., & Kallen, V. L. (2016). Emotional responses to multisensory environmental stimuli: A conceptual framework and literature review. *Sage Open*, *6*(1), 2158244016630591.

Seigneuric, A., Durand, K., Jiang, T., Baudouin, J. Y., & Schaal, B. (2010). The nose tells it to the eyes: crossmodal associations between olfaction and vision. *Perception*, *39*(11), 1541-1554.

Shimojo, S., & Shams, L. (2001). Sensory modalities are not separate modalities: plasticity and interactions. *Current opinion in neurobiology*, *11*(4), 505-509.

Siegel, E. H., Wormwood, J. B., Quigley, K. S., & Barrett, L. F. (2018). Seeing what you feel: Affect drives visual perception of structurally neutral faces. *Psychological science*, *29*(4), 496-503.

Siemer, M., Mauss, I., & Gross, J. J. (2007). Same situation--different emotions: how appraisals shape our emotions. *Emotion*, *7*(3), 592.

Tajadura-Jiménez, A., & Västfjäll, D. (2008). Auditory-induced emotion: A neglected channel for communication in human-computer interaction. In *Affect and Emotion in Human-Computer Interaction* (pp. 63-74). Springer, Berlin, Heidelberg.

Vines, B. W., Krumhansl, C. L., Wanderley, M. M., & Levitin, D. J. (2006). Cross-modal interactions in the perception of musical performance. *Cognition*, *101*(1), 80-113.

Voss, A., Rothermund, K., & Brandtstädter, J. (2008). Interpreting ambiguous stimuli: Separating perceptual and judgmental biases. *Journal of Experimental Social Psychology*, *44*(4), 1048-1056.

Vuilleumier, P. (2005). How brains beware: neural mechanisms of emotional attention. *Trends in cognitive sciences*, *9*(12), 585-594.

Vuilleumier, P., Armony, J. L., Driver, J., & Dolan, R. J. (2001). Effects of attention and emotion on face processing in the human brain: an event-related fMRI study. *Neuron*, *30*(3), 829-841.

Vuilleumier, P., Richardson, M. P., Armony, J. L., Driver, J., & Dolan, R. J. (2004). Distant influences of amygdala lesion on visual cortical activation during emotional face processing. *Nature neuroscience*, *7*(11), 1271-1278.

Zadra, J. R., & Clore, G. L. (2011). Emotion and perception: The role of affective information. *Wiley interdisciplinary reviews: cognitive science*, *2*(6), 676-685.

Ballard, L., & Bengtson, M. (2017). *The Alexander Scriabin companion: History, performance, and lore*. Rowman & Littlefield.

Beattie, L. A. (1998). *Color and sound interrelated*. San Jose State University.

Bresin, R. (2005, September). What is the color of that music performance?. In *ICMC*.

Caivano, J. L. (1994). Color and sound: Physical and psychophysical relations. *Color Research & Application*, *19*(2), 126-133.

Cajochen, C., Munch, M., Kobialka, S., Krauchi, K., Steiner, R., Oelhafen, P., ... & Wirz-Justice, A. (2005). High sensitivity of human melatonin, alertness, thermoregulation, and heart rate to short wavelength light. *The journal of clinical endocrinology & metabolism*, *90*(3), 1311-1316.

Campos, J. J., Mumme, D., Kermoian, R., & Campos, R. G. (1994). A functionalist perspective on the nature of emotion. *Japanese Journal of Research on Emotions*, *2*(1), 1-20.

Cheriyan, L. B. (2017). The Psychological and Physiological Relevance of Bharathamuni's Theory of Rasa: A Study on the Basis of Colorgenics.

Clayton, M. (2001). Introduction: Towards a theory of musical meaning (in India and elsewhere).

British Journal of Ethnomusicology, *10*(1), 1-17.

Collier, W. G., & Hubbard, T. L. (2004). Musical scales and brightness evaluations: Effects of pitch, direction, and scale mode. *Musicae Scientiae*, *8*(2), 151-173.

Davidoff, J. (1991). *Cognition through color.* The MIT Press.

Doczi, G. (1981). *The power of limits: Proportional harmonies in nature, art, and architecture* (p. 150). Boulder, CO: Shambhala.

Ekman, P. (1992). An argument for basic emotions. *Cognition & emotion*, *6*(3-4), 169-200.

Ekman, P., Friesen, W. V., O'sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., ... & Tzavaras, A. (1987). Universals and cultural differences in the judgments of facial expressions of emotion. *Journal of personality and social psychology*, *53*(4), 712.

Franssen, M. (1991). The ocular harpsichord of louis-bertrand castel. *Tractrix*, *3*(1991), 15-77.

Hejmadi, A., Davidson, R. J., & Rozin, P. (2000). Exploring Hindu Indian emotion expressions: Evidence for accurate recognition by Americans and Indians. *Psychological Science*, *11*(3), 183-187.

Higgins, K. M. (2007). An alchemy of emotion: Rasa and aesthetic breakthroughs. *The Journal of Aesthetics and Art Criticism*, *65*(1), 43-54.

Isbilen, E. S., & Krumhansl, C. L. (2016). The color of music: Emotion-mediated associations to Bach's Well-tempered Clavier. *Psychomusicology: Music, Mind, and Brain*, *26*(2), 149.

Itten, J. (1970). *The elements of color* (Vol. 4). John Wiley & Sons.

Izard, C. E. (1992). Basic emotions, relations among emotions, and emotion-cognition relations. Kaufmann, W. (1965). Rasa, rāga-mālā and performance times in North Indian rāgas.

Ethnomusicology, 272-291.

Kavi, R. (1934). *NATYASHASTRA with Commentary of ABHINAVAGUPTA*. Рипол Классик.

Lakoff, G., & Johnson, M. (1999). *Philosophy in the flesh: The cognitive unconscious and the embodied mind: How the embodied mind creates philosophy*. Basic Books.

Lindborg, P., & Friberg, A. K. (2015). Colour association with music is mediated by emotion: Evidence from an experiment using a CIE Lab interface and interviews. *PloS one*, *10*(12), e0144013.

Newton, I. (1952). *Opticks, or, a treatise of the reflections, refractions, inflections & colours of light*. Courier Corporation.

Palmer, S. E., Langlois, T. A., & Schloss, K. B. (2016). Music-to-color associations of single-line piano melodies in non-synesthetes. *Multisensory Research*, *29*(1-3), 157-193.

Palmer, S. E., Schloss, K. B., Xu, Z., & Prado-León, L. R. (2013). Music–color associations are mediated by emotion. *Proceedings of the National Academy of Sciences*, *110*(22), 8836-8841.

Polzella, D. J., & Biers, D. W. (1987). Chromesthetic responses to music: Replication and extension.

Perceptual and Motor Skills, *65*(2), 439-443.

Polzella, D. J., & Hassen, J. L. (1997). Aesthetic preferences for combinations of color and music.

Perceptual and motor skills, *85*(3), 960-962.

Polzella, D. J., Kuna, A. M., Biers, D. W., & DaPolito, F. (1982). Hemispheric asymmetry in musically-induced color imagery. *Psychomusicology: A Journal of Research in Music Cognition*, *2*(2), 64.

Pridmore, R. W. (1992). Music and color: Relations in the psychophysical perspective. *Color Research & Application*, *17*(1), 57-61.

Rachman, S. (1983). Fear and courage among military bomb-disposal operators. A*dvances in Behaviour Research and Therapy*, 4(3), 97-175.

Ramaprasad, D. (2013). Emotions: an Indian perspective. *Indian Journal of Psychiatry*, *55*(Suppl 2), S153.

Roy, S., Roy, C., Nag, S., Banerjee, A., Sengupta, R., & Ghosh, D. (2020). Chaos based non-linear cognitive study of different stimulus in the cross-modal perspective. *Physica A: Statistical Mechanics and its Applications*, *546*, 122842.

Russell, J. A. (1991). In defense of a prototype approach to emotion concepts. *Journal of personality and social psychology*, *60*(1), 37.

Schechner, R. (2003). *Performance theory*. Routledge.

Shaffer, L. F. (1947). Fear and courage in aerial combat. *Journal of consulting psychology, 11*(3), 137.

Tripathi, R., Mukhopadhyay, D., Singh, C. K., Miyapuram, K. P., & Jolad, S. (2018). Characterizing functional brain networks and emotional centers based on Rasa theory of Indian aesthetics. *arXiv preprint arXiv:1809.05336*.

von Goethe, J. W. (2006). Theory of colours (trans: Eastlake, CL). *Mineola: Dover (Original work published 1810)*.

Walz, R. (2013). Wassily Kandinsky, Concerning the spiritual in art. In *Modernism* (pp. 146-147). Routledge.

Ward, J., Huckstep, B., & Tsakanikos, E. (2006). Sound-colour synaesthesia: To what extent does it use cross-modal mechanisms common to us all?. *Cortex*, *42*(2), 264-280.

Wexner, L. B. (1954). The degree to which colors (hues) are associated with mood-tones. *Journal of applied psychology*, *38*(6), 432.

Whiteford, K. L., Schloss, K. B., Helwig, N. E., & Palmer, S. E. (2018). Color, music, and emotion: Bach to the blues. *i-Perception*, *9*(6), 2041669518808535.

Wieczorkowska, A. A., Datta, A. K., Sengupta, R., Dey, N., & Mukherjee, B. (2010). On search for emotion in Hindusthani vocal music. In *Advances in music information retrieval* (pp. 285-304).

Springer, Berlin, Heidelberg.

Ainsworth, R. A., Simpson, L., & Cassell, D. (1993). Effects of three colors in an office interior on mood and performance. *Perceptual and motor skills*, *76*(1), 235-241.

AL-Ayash, A., Kane, R. T., Smith, D., & Green-Armytage, P. (2016). The influence of color on student emotion, heart rate, and performance in learning environments. *Color Research & Application*, *41*(2), 196-205.

Ali, M. R. (1972). Pattern of EEG recovery under photic stimulation by light of different colors.

Electroencephalography and Clinical Neurophysiology, *33*(3), 332-335. Allen, G. (1877). *Physiological aesthetics*. New York: D. Appleton.

Briki, W., & Hue, O. (2016). How red, blue, and green are affectively judged. *Applied Cognitive Psychology*, *30*(2), 301-304.

Brown, B. (1966). Specificity of EEG photic flicker responses to color as related to visual imagery ability. *Psychophysiology*, *2*(3), 197-207.

Buechner, V. L., & Maier, M. A. (2016). Not always a matter of context: direct effects of red on arousal but context-dependent moderations on valence. *PeerJ*, *4*, e2515.

Choi, Y., Kim, M., & Chun, C. (2015). Measurement of occupants' stress based on electroencephalograms (EEG) in twelve combined environments. *Building and Environment*, *88*, 65- 72.

Cohn, J. (1894). *Experimentelle Untersuchungen über die Gefühlsbetonung der Farben, Helligkeiten und ihrer Combinationen*. Engelmann.

Deutsch, F. (1937). Psycho-physical Reactions of the Vascular System to Influence of Light and Impressions Gained through Light. *Folia Clinica Orientalia*, *1*(3).

Dreiskaemper, D., Strauss, B., Hagemann, N., & Büsch, D. (2013). Influence of red jersey color on physical parameters in combat sports. *Journal of Sport and Exercise Psychology*, *35*(1), 44-49.

Elliot, A. J. (2019). A historically based review of empirical work on color and psychological functioning: Content, methods, and recommendations for future research. *Review of General Psychology*, *23*(2), 177-200.

Elliot, A. J., & Maier, M. A. (2014). Color psychology: Effects of perceiving color on psychological functioning in humans. *Annual review of psychology*, *65*(1), 95-120.

Elliot, A. J., & Niesta, D. (2008). Romantic red: red enhances men's attraction to women. *Journal of personality and social psychology*, *95*(5), 1150.

Erwin, C. W., Lerner, M., Wilson, N. J., & Wilson, W. P. (1961). Some further observations on the photically elicited arousal response. *Electroencephalography and Clinical Neurophysiology*, *13*(3), 391-394.

Féré, C. (1887). Note sur les conditions physiologiques des émotions [Note on the physiological conditions of emotions]. *Revue Philosophique de la France et de l'Étranger*, *24*, 561-581.

Frank, M. G., & Gilovich, T. (1988). The dark side of self-and social perception: black uniforms and aggression in professional sports. *Journal of personality and social psychology*, *54*(1), 74.

Gerard, K. (1958). Differential effects of colored lights on psycho-physiological functions.

Unpublished doctoral dissertation, University of California, Los Angeles.

Goldstein, K. (1942). Some experimental observations concerning the influence of colors on the function of the organism. *Occupational Therapy*.

Hill, R. A., & Barton, R. A. (2005). Red enhances human performance in contests. *Nature*, *435*(7040), 293-293.

Jastrow, J. (1897). The popular aesthetics of color. *Popular Science Monthly, 50,* 361–368.

Kaiser, P. K. (1984). Physiological response to color: A critical review. *Color research & application, 9*(1), 29-36.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain research reviews*, *29*(2-3), 169-195.

Lee, S., & Rao, V. S. (2010). Color and store choice in electronic commerce: The explanatory role of trust. *Journal of Electronic Commerce Research*, *11*(2).

Linhares, J. M. M., Pinto, P. D., & Nascimento, S. M. C. (2008). The number of discernible colors in natural scenes. *JOSA A*, *25*(12), 2918-2924.

Mehta, R., & Zhu, R. (2009). Blue or red? Exploring the effect of color on cognitive task performances. *Science*, *323*(5918), 1226-1229.

Münsterberg, H., Campbell, W. W., Bigham, J., Pierce, A. H., Calkins, M. W., & Pierce, E. (1894). Studies from the Harvard Psychological Laboratory (II). *Psychological Review*, *1*(5), 441.

Nakshian, J. S. (1964). The effects of red and green surroundings on behavior. *The Journal of General Psychology*, *70*(1), 143-161.

Nourse, J. C., & Welch, R. B. (1971). Emotional attributes of color: A comparison of violet and green. *Perceptual and motor skills*, *32*(2), 403-406.

Ou, L. C., Luo, M. R., Woodcock, A., & Wright, A. (2004). A study of colour emotion and colour preference. Part I: Colour emotions for single colours. *Color Research & Application*, *29*(3), 232-240.

Sakuragi, S., & Sugiyama, Y. (2011). Effect of partition board color on mood and autonomic nervous function. *Perceptual and motor skills*, *113*(3), 941-956.

Suk, H. J., & Irtel, H. (2010). Emotional response to color across media. *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de la Couleur*, *35*(1), 64-77.

Vandewalle, G., Schmidt, C., Albouy, G., Sterpenich, V., Darsaud, A., Rauchs, G., ... & Dijk, D. J. (2007). Brain responses to violet, blue, and green monochromatic light exposures in humans: prominent role of blue light and the brainstem. *PloS one*, *2*(11), e1247.

von Goethe, J. W. (2006). Theory of colours (trans: Eastlake, CL). *Mineola: Dover (Original work published 1810)*.

Wilms, L., & Oberfeld, D. (2018). Color and emotion: effects of hue, saturation, and brightness.

Psychological research, *82*(5), 896-914.

Wilson, G. D. (1966). Arousal properties of red versus green. *Perceptual and motor skills*.

Wundt, W. (1874). *Grundzuge der physiologischen Psychologie*. [Main features of physiological psychology]. Leipzig, Germany: Wilhelm Engelmann.

Albertazzi, L., Canal, L., & Micciolo, R. (2015). Cross-modal associations between materic painting and classical Spanish music. *Frontiers in Psychology*, *6*, 424.

Baier, B., Kleinschmidt, A., & Müller, N. G. (2006). Cross-modal processing in early visual and auditory cortices depends on expected statistical relationship of multisensory information. *Journal of Neuroscience*, *26*(47), 12260-12265.

Barbiere, J. M., Vidal, A., & Zellner, D. A. (2007). The color of music: Correspondence through emotion. *Empirical studies of the arts*, *25*(2), 193-208.

Beauchamp, M. S., Argall, B. D., Bodurka, J., Duyn, J. H., & Martin, A. (2004b). Unraveling multisensory integration: patchy organization within human STS multisensory cortex. *Nature neuroscience*, *7*(11), 1190-1192.

Beauchamp, M. S., Lee, K. E., Argall, B. D., & Martin, A. (2004a). Integration of auditory and visual information about objects in superior temporal sulcus. *Neuron*, *41*(5), 809-823.

Bernstein, I. H., & Edelstein, B. A. (1971). Effects of some variations in auditory input upon visual choice reaction time. *Journal of experimental psychology*, *87*(2), 241.

Bond, B., & Stevens, S. S. (1969). Cross-modality matching of brightness to loudness by 5-year-olds.

Perception & Psychophysics, *6*(6), 337-339.

Chen, Y. C., & Spence, C. (2010). When hearing the bark helps to identify the dog: Semantically- congruent sounds modulate the identification of masked pictures. *Cognition*, *114*(3), 389-404.

Crisinel, A. S., & Spence, C. (2009). Implicit association between basic tastes and pitch.

Neuroscience letters, *464*(1), 39-42.

Cutietta, R. A., & Haggerty, K. J. (1987). A comparative study of color association with music at various age levels. *Journal of research in music education*, *35*(2), 78-91.

Doehrmann, O., & Naumer, M. J. (2008). Semantics and the multisensory brain: how meaning modulates processes of audio-visual integration. *Brain research*, *1242*, 136-150.

Ernst, M. O. (2006). A Bayesian View on Multimodal. *Human body perception from the inside out*, 105.

Ernst, M. O., Lange, C., & Newell, F. N. (2007). Multisensory recognition of actively explored objects. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *61*(3), 242.

Evans, K. K., & Treisman, A. (2010). Natural cross-modal mappings between visual and auditory features. *Journal of vision*, *10*(1), 6-6.

Frens, M. A., Van Opstal, A. J., & Van der Willigen, R. F. (1995). Spatial and temporal factors determine auditory-visual interactions in human saccadic eye movements. *Perception & psychophysics*, *57*(6), 802-816.

Gal, D., Wheeler, S. C., & Shiv, B. (2007). Cross-modal influences on gustatory perception. *Available at SSRN 1030197*.

Gallace, A., & Spence, C. (2006). Multisensory synesthetic interactions in the speeded classification of visual size. *Perception & psychophysics*, *68*(7), 1191-1203.

Grassi, M., & Casco, C. (2010). Audiovisual bounce-inducing effect: When sound congruence affects grouping in vision. *Attention, Perception, & Psychophysics*, *72*(2), 378-386.

Helbig, H. B., & Ernst, M. O. (2007). Optimal integration of shape information from vision and touch.

Experimental brain research, *179*(4), 595-606.

Isbilen, E. S., & Krumhansl, C. L. (2016). The color of music: Emotion-mediated associations to Bach's Well-tempered Clavier. *Psychomusicology: Music, Mind, and Brain*, *26*(2), 149.

Jones, M. R., Johnston, H. M., & Puente, J. (2006). Effects of auditory pattern structure on anticipatory and reactive attending. *Cognitive psychology, 53*(1), 59-96.

Kemp, S. E., & Gilbert, A. N. (1997). Odor Intensity and Color Lightness Are Correlated Sensory Dimensions. *The American Journal of Psychology*, 35-46.

Köhler, W. (1929). *Gestalt psychology*. New York: Liveright.

Lindborg, P., & Friberg, A. K. (2015). Colour association with music is mediated by emotion: Evidence from an experiment using a CIE Lab interface and interviews. *PloS one*, *10*(12), e0144013.

Marin, M. M., & Bhattacharya, J. (2010). Music induced emotions: some current issues and cross- modal comparisons. *Music education*, 1-38.

Marks, L. E. (1974). On associations of light and sound: The mediation of brightness, pitch, and loudness. *The American journal of psychology*, 173-188.

Marks, L. E. (2004). 6 Cross-Modal Interactions. *The handbook of multisensory processes*, 85.

Martino, G., & Marks, L. E. (2000). Cross-modal interaction between vision and touch: the role of synesthetic correspondence. *Perception*, *29*(6), 745-754.

Nuckolls, J. B. (2003, April). To be or not to be ideophonically impoverished. In *Proceedings of the Eleventh Annual Symposium about Language and Society—Austin*.

Palmer, S. E., Langlois, T. A., & Schloss, K. B. (2016). Music-to-color associations of single-line piano melodies in non-synesthetes. *Multisensory Research*, *29*(1-3), 157-193.

Palmer, S. E., Schloss, K. B., Xu, Z., & Prado-León, L. R. (2013). Music–color associations are mediated by emotion. *Proceedings of the National Academy of Sciences*, *110*(22), 8836-8841.

Parrott, A. C. (1982). Effects of paintings and music, both alone and in combination, on emotional judgments. *Perceptual and Motor Skills*, *54*(2), 635-641.

Ramachandran, V. S., & Hubbard, E. M. (2001). Synaesthesia--a window into perception, thought and language. *Journal of consciousness studies*, *8*(12), 3-34.

Ramachandran, V. S., & Hubbard, E. M. (2003). Hearing colors, tasting shapes. *Scientific American*, *288*(5), 52-59.

Ramachandran, V. S., & Hubbard, E. M. (2003). Hearing colors, tasting shapes. *Scientific American*, *288*(5), 52-59.

Ramachandran, V. S., & Oberman, L. M. (2006). Broken mirrors. *Scientific American*, *295*(5), 62-69.

Roffler, S. K., & Butler, R. A. (1968). Factors that influence the localization of sound in the vertical plane. *The Journal of the Acoustical Society of America*, *43*(6), 1255-1259.

Sapir, E. (1929). A study in phonetic symbolism. *Journal of experimental psychology*, *12*(3), 225.

Seo, H. S., Arshamian, A., Schemmer, K., Scheer, I., Sander, T., Ritter, G., & Hummel, T. (2010). Cross-modal integration between odors and abstract symbols. *Neuroscience letters*, *478*(3), 175-178.

Shore, D. I., Barnes, M. E., & Spence, C. (2006). Temporal aspects of the visuotactile congruency effect. *Neuroscience letters*, *392*(1-2), 96-100.

Slutsky, D. A., & Recanzone, G. H. (2001). Temporal and spatial dependency of the ventriloquism effect. *Neuroreport*, *12*(1), 7-10.

Smith, L. B., & Sera, M. D. (1992). A developmental analysis of the polar structure of dimensions.

Cognitive psychology, *24*(1), 99-142.

Spence, C. (2011). Crossmodal correspondences: A tutorial review. *Attention, Perception, & Psychophysics*, *73*(4), 971-995.

Spence, C. (2011). Crossmodal correspondences: A tutorial review. *Attention, Perception, & Psychophysics*, *73*(4), 971-995.

Spence, C. (2019). On the relative nature of (pitch-based) crossmodal correspondences. *Multisensory Research*, *32*(3), 235-265.

Vatakis, A., Ghazanfar, A. A., & Spence, C. (2008). Facilitation of multisensory integration by the “unity effect” reveals that speech is special. *Journal of Vision*, *8*(9), 14-14.

Walker, P., Bremner, J. G., Mason, U., Spring, J., Mattock, K., Slater, A., & Johnson, S. P. (2010). Preverbal infants’ sensitivity to synaesthetic cross-modality correspondences. *Psychological Science*, *21*(1), 21-25.

Whiteford, K. L., Schloss, K. B., Helwig, N. E., & Palmer, S. E. (2018). Color, music, and emotion: Bach to the blues. *i-Perception*, *9*(6), 2041669518808535.

Wicker, F. W. (1968). Mapping the intersensory regions of perceptual space. *The American Journal of Psychology*, *81*(2), 178-188.

Zangenehpour, S., & Zatorre, R. J. (2010). Crossmodal recruitment of primary visual cortex following brief exposure to bimodal audiovisual stimuli. *Neuropsychologia*, *48*(2), 591-600.

Gleick, J., & Berry, M. (1987). Chaos-making a new science. *Nature*, *330*, 293.

Ilya, P., & Stengers, I. (1984). Order out of chaos: man’s new dialogue with nature. *New York, Bantam*.

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of atmospheric sciences*, *20*(2), 130- 141.

Pool, R. (1989). Is It Healthy to Be Chaotic? Chaos may provide a healthy flexibility to the heart, brain, and other parts of the body. Conversely, many ailments may be associated with a loss of this chaotic flexibility. *Science*, *243*(4891), 604-607.

Ahmadlou, M., & Adeli, H. (2011). Functional community analysis of brain: A new approach for EEG-based investigation of the brain pathology. *Neuroimage*, *58*(2), 401-408.

Ahmadlou, M., Adeli, H., & Adeli, A. (2010). New diagnostic EEG markers of the Alzheimer’s disease using visibility graph. *Journal of neural transmission*, *117*(9), 1099-1109.

Ahmadlou, M., Adeli, H., & Adeli, A. (2012). Fractality analysis of frontal brain in major depressive disorder. *International Journal of Psychophysiology*, *85*(2), 206-211.

Banerjee, A., Sanyal, S., Patranabis, A., Banerjee, K., Guhathakurta, T., Sengupta, R., ... & Ghose, P. (2016). Study on brain dynamics by non linear analysis of music induced EEG signals. *Physica A: Statistical Mechanics and its Applications*, *444*, 110-120.

Bigerelle, M., & Iost, A. (2000). Fractal dimension and classification of music. *Chaos, Solitons & Fractals*, *11*(14), 2179-2192.

Gao, T. T., Wu, D., Huang, Y. L., & Yao, D. Z. (2007). Detrended fluctuation analysis of the human EEG during listening to emotional music. *Journal of Electronic Science and Technology*, *5*(3), 272- 277.

Hsü, K. J., & Hsü, A. J. (1990). Fractal geometry of music. *Proceedings of the National Academy of Sciences*, *87*(3), 938-941.

Hwa, R. C., & Ferree, T. C. (2002). Scaling properties of fluctuations in the human electroencephalogram. *Physical Review E*, *66*(2), 021901.

Kiselev, V. G., Hahn, K. R., & Auer, D. P. (2003). Is the brain cortex a fractal?. *Neuroimage*, *20*(3), 1765-1774.

Kumar, A., & Mullick, S. K. (1996). Nonlinear dynamical analysis of speech. *The Journal of the Acoustical Society of America*, *100*(1), 615-629.

Lee, J. M., Kim, D. J., Kim, I. Y., Park, K. S., & Kim, S. I. (2002). Detrended fluctuation analysis of EEG in sleep apnea using MIT/BIH polysomnography data. *Computers in biology and medicine*, *32*(1), 37-47.

Lee, M. (2015). *György Ligeti's" Désordre" and" L'escalier du Diable": Compositional style and method of practice*. The Ohio State University.

Ligeti, G. (2003). *Etudes, books I and II*. Naxos.

Linkenkaer-Hansen, K., Nikouline, V. V., Palva, J. M., & Ilmoniemi, R. J. (2001). Long-range temporal correlations and scaling behavior in human brain oscillations. *Journal of Neuroscience*, *21*(4), 1370-1377.

Lochhead, J. (2001). Hearing Chaos. *American Music*, 210-246.

Lopes, R., & Betrouni, N. (2009). Fractal and multifractal analysis: a review. *Medical image analysis*, *13*(4), 634-649.

Maity, A. K., Pratihar, R., Mitra, A., Dey, S., Agrawal, V., Sanyal, S., ... & Ghosh, D. (2015). Multifractal detrended fluctuation analysis of alpha and theta EEG rhythms with musical stimuli. *Chaos, Solitons & Fractals*, *81*, 52-67.

Mandelbrot, B. (1967). How long is the coast of Britain? Statistical self-similarity and fractional dimension. *science*, *156*(3775), 636-638.

Mölle, M., Marshall, L., Lutzenberger, W., Pietrowsky, R., Fehm, H. L., & Born, J. (1996). Enhanced dynamic complexity in the human EEG during creative thinking. *Neuroscience Letters*, *208*(1), 61-64.

Natarajan, K., Acharya U, R., Alias, F., Tiboleng, T., & Puthusserypady, S. K. (2004). Nonlinear analysis of EEG signals at different mental states. *Biomedical engineering online*, *3*(1), 1-11.

Pressing, J. (1988). Improvisation: methods and models. *Generative processes in music*, 129-178.

Salter, J. R. (2009). *Chaos in music: Historical developments and applications to music theory and composition*. The University of North Carolina at Greensboro.

Sengupta, R., Dey, N., Datta, A. K., Ghosh, D., & Patranabis, A. (2010). Analysis of the signal complexity in sitar performances. *Fractals*, *18*(02), 265-270.

Su, Z. Y., & Wu, T. (2006). Multifractal analyses of music sequences. *Physica D: Nonlinear Phenomena*, *221*(2), 188-194.

Tong, S., Huang, H., Luan, J., & Chen, H. (2005). Dimensional complexity analysis of human EEG in visual processing. *Neurocomputing*, *67*, 297-305.

Voss, R. F., & Clarke, J. (1975). '1/f noise in music and speech. *Nature*, *258*(5533), 317-318.

Weiss, B., Clemens, Z., Bódizs, R., & Halász, P. (2011). Comparison of fractal and power spectral EEG features: Effects of topography and sleep stages. *Brain research bulletin*, *84*(6), 359-375.

Adamic, L. A. (2000). Zipf, power-laws, and pareto-a ranking tutorial. *Xerox Palo Alto Research Center, Palo Alto, CA, http://ginger. hpl. hp. com/shl/papers/ranking/ranking. html*.

Bak, P., Tang, C., & Wiesenfeld, K. (1987). Self-organized criticality: An explanation of the 1/f noise.

Physical review letters, *59*(4), 381.

Brothers, H. J. (2007). Structural scaling in Bach's Cello Suite no. 3. *Fractals*, *15*(01), 89-95.

Chang, M. C., Yang, A. C. C., Stanley, H. E., & Peng, C. K. (2017). Measuring information-based energy and temperature of literary texts. *Physica A: Statistical Mechanics and its Applications*, *468*, 783-789.

Cox, R. A., Felton, J. M., & Chung, K. H. (1995). The concentration of commercial success in popular music: an analysis of the distribution of gold records. *Journal of cultural economics*, *19*(4), 333-340.

Cramer, I. (2005). The parameters of the Altmann-Menzerath law. *Journal of Quantitative Linguistics*, *12*(1), 41-52.

Crovella, M. E., & Bestavros, A. (1997). Self-similarity in World Wide Web traffic: Evidence and possible causes. *IEEE/ACM Transactions on networking*, *5*(6), 835-846.

De Campos, H., & Tolman, J. M. (1982). The informational temperature of the text. *Poetics Today*, *3*(3), 177-187.

De Souza, N. M., Vanderlei, L. C. M., & Garner, D. M. (2015). Risk evaluation of diabetes mellitus by relation of chaotic globals to HRV. *Complexity*, *20*(3), 84-92.

Gabaix, X. (1999). Zipf's law for cities: an explanation. *The Quarterly journal of economics*, *114*(3), 739-767.

Gutenberg, B., & Richter, C. F. (1944). Frequency of earthquakes in California. *Bulletin of the Seismological society of America*, *34*(4), 185-188.

i Cancho, R. F. (2010). Network theory. In *The Cambridge encyclopedia of the language sciences* (pp. 555-557). Cambridge University Press.

i Cancho, R. F., & Solé, R. V. (2003). Statistical mechanics of complex networks. *Lecture notes in Physics*, *625*, 114-125.

Jackendoff, R. (2009). Parallels and nonparallels between language and music. *Music perception*, *26*(3), 195-204.

Kello, C. T., Brown, G. D., Ferrer-i-Cancho, R., Holden, J. G., Linkenkaer-Hansen, K., Rhodes, T., & Van Orden, G. C. (2010). Scaling laws in cognitive sciences. *Trends in cognitive sciences*, *14*(5), 223- 232.

Kim, S. (2006). Player's positional dependence of fractal behaviors in a soccer game. *Fractals*, *14*(01), 71-76.

Kosmidis, K., Kalampokis, A., & Argyrakis, P. (2006). Language time series analysis. *Physica A: Statistical Mechanics and its Applications*, *370*(2), 808-816.

Li, W. (2002). Zipf's Law everywhere. *Glottometrics*, *5*(2002), 14-21.

Lotka, A. J. (1926). The frequency distribution of scientific productivity. *Journal of the Washington academy of sciences*, *16*(12), 317-323.

Lu, E. T., & Hamilton, R. J. (1991). Avalanches and the distribution of solar flares. *The astrophysical journal*, *380*, L89-L92.

Mandelbrot, B. (1953). An informational theory of the statistical structure of language. *Communication theory*, *84*, 486-502.

Mandelbrot, B. (1965). Self-similar error clusters in communication systems and the concept of conditional stationarity. *IEEE Transactions on Communication Technology*, *13*(1), 71-90.

Mitzenmacher, M. (2004). A brief history of generative models for power law and lognormal distributions. *Internet mathematics*, *1*(2), 226-251.

Miyazima, S., & Yamamoto, K. (2008). Measuring the temperature of texts. *Fractals*, *16*(01), 25-32.

Newman, M. E. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary physics*, *46*(5), 323-351.

Newman, M. E. (2011). Complex systems: A survey. *arXiv preprint arXiv:1112.1440*. Pareto, V. (1964). *Cours d'économie politique* (Vol. 1). Librairie Droz.

Patel, A. D. (2003). Language, music, syntax and the brain. *Nature neuroscience*, *6*(7), 674-681. Patel, A. D. (2008). *Music, language, and the brain*. Oxford University Press.

Reˆgo, H. H. A., Braunstein, L. A., D′ Agostino, G., Stanley, H. E., & Miyazima, S. (2014). When a text is translated does the complexity of its vocabulary change? Translations and target

readerships. *PloS one*, *9*(10), e110213.

Rovenchak, A. (2014). Trends in language evolution found from the frequency structure of texts mapped against the Bose-distribution. *Journal of Quantitative Linguistics*, *21*(3), 281-294.

Rovenchak, A., & Buk, S. (2011). Application of a quantum ensemble model to linguistic analysis. *Physica A: Statistical Mechanics and its Applications*, *390*(7), 1326-1331.

Sengupta, R., Dey, N., Datta, A. K., & Ghosh, D. (2005). Assessment of musical quality of tanpura by fractal-dimensional analysis. *Fractals*, *13*(03), 245-252.

Simon, H. A. (1955). On a class of skew distribution functions. *Biometrika*, *42*(3/4), 425-440.

Willis, J. C., & Yule, G. U. (1922). Some statistics of evolution and geographical distribution in plants and animals, and their significance. *Nature*, *109*(2728), 177-179.

Zanette, D. H., & Manrubia, S. C. (2001). Vertical transmission of culture and the distribution of family names. Physica A: Statistical Mechanics and its Applications, 295(1-2), 1-8.

Zipf, G. K. (1949). Human behavior and the principle of least effort: an introduction to human ecology.

Bhushan, L. I., & Amal, S. B. (1986). A situational test of intolerance of ambiguity. *Psychologia: An International Journal of Psychology in the Orient*.

Blanchette, I., & Richards, A. (2010). The influence of affect on higher level cognition: A review of research on interpretation, judgment, decision making and reasoning. *Cognition & Emotion*, *24*(4), 561-595.

Bode, C. (1991). The aesthetics of ambiguity.

Brainerd, C. J. (2018). The emotional-ambiguity hypothesis: A large-scale test. *Psychological science*, *29*(10), 1706-1715.

Comadena, M. E. (1984). Brainstorming groups: Ambiguity tolerance, communication apprehension, task attraction, and individual productivity. *Small Group Behavior*, *15*(2), 251-264.

Cowen, A. S., Fang, X., Sauter, D., & Keltner, D. (2020). What music makes us feel: At least 13 dimensions organize subjective experiences associated with music across different

cultures. *Proceedings of the National Academy of Sciences*, *117*(4), 1924-1934.

Frenkel-Brunswick, E. (1949). Intolerance of ambiguity as emotional and perceptual personality disposition. *Journal of Personality*, *18*, 103-143.

Frenkel-Brunswick, E. (1951). Personality theory and perception. Perception. An approach to personality Blake, R., Ramsay, C.

Furnham, A., & Marks, J. (2013). Tolerance of ambiguity: A review of the recent literature. *Psychology*, *4*(09), 717-728.

Furnham, A., & Ribchester, T. (1995). Tolerance of ambiguity: A review of the concept, its measurement and applications. *Current psychology*, *14*(3), 179-199.

Kensinger, E. A. (2004). Remembering emotional experiences: The contribution of valence and arousal. *Reviews in the Neurosciences*, *15*(4), 241-252.

Kuppens, P., Tuerlinckx, F., Russell, J. A., & Barrett, L. F. (2013). The relation between valence and arousal in subjective experience. *Psychological bulletin*, *139*(4), 917.

Lang, P. J., Bradley, M. M., Fitzsimmons, J. R., Cuthbert, B. N., Scott, J. D., Moulder, B., & Nangia,

V. (1998). Emotional arousal and activation of the visual cortex: an fMRI analysis. *Psychophysiology*, *35*(2), 199-210.

Liu, C. (2015). Relevant researches on tolerance of ambiguity. *Theory and Practice in Language Studies*, *5*(9), 1874.

Mattek, A. M., Wolford, G. L., & Whalen, P. J. (2017). A mathematical model captures the structure of subjective affect. *Perspectives on Psychological Science*, *12*(3), 508-526.

Russell, J. A. (1980). A circumplex model of affect. *Journal of personality and social psychology*, *39*(6), 1161.

Sternberg, R. J., & Lubart, T. I. (1995). *Defying the crowd: Cultivating creativity in a culture of conformity*. Free press.

Stoycheva, K. (1998). Ambiguity Tolerance: Adolescents' Responses to Uncertainty in Life. Research Report, September 1996-December 1997.

Stoycheva, K. (2003). Talent, science and education: How do we cope with uncertainty and ambiguities?

Tegano, D. W. (1990). Relationship of tolerance of ambiguity and playfulness to creativity. *Psychological reports*, *66*(3), 1047-1056.

Urban, K. K. (2003). Toward a componential model of creativity,[w:]: Creative Intelligence. Toward Theoretic Integration,(red.) D. Ambros, LM Cohen, AJ Tennenbaum.

Vernon, P. E. (1970). Creativity. *Modern Psychology Readings. First edn. Baltimore: Penguin*.

Yik, M., Russell, J. A., & Steiger, J. H. (2011). A 12-point circumplex structure of core affect. *Emotion*, *11*(4), 705.

Zenasni, F., Besançon, M., & Lubart, T. (2008). Creativity and tolerance of ambiguity: An empirical study. *The Journal of Creative Behavior*, *42*(1), 61-73.

Aerts, D., & Aerts, S. (1995). Applications of quantum statistics in psychological studies of decision processes. *Foundations of Science*, *1*(1), 85-97.

Aerts, D., Durt, T., Grib, A. A., Van Bogaert, B., & Zapatrin, R. R. (1993). Quantum structures in macroscopic reality. *International Journal of Theoretical Physics*, *32*(3), 489-498.

Atmanspacher, H. (2017). Quantum approaches to brain and mind. *The Blackwell companion to consciousness*, 298-313.

Atmanspacher, H., & Filk, T. (2010). A proposed test of temporal nonlocality in bistable perception. *Journal of Mathematical Psychology*, *54*(3), 314-321.

Atmanspacher, H., & Filk, T. (2013). The Necker–Zeno model for bistable perception. *Topics in cognitive science*, *5*(4), 800-817.

Atmanspacher, H., Filk, T., & Foundation, P. (2006). Complexity and non-commutativity of learning operations on graphs. *BioSystems*, *85*(1), 84-93.

Atmanspacher, H., Römer, H., & Walach, H. (2002). Weak quantum theory: Complementarity and entanglement in physics and beyond. *Foundations of physics*, *32*(3), 379-406.

Bruza, P. D., Wang, Z., & Busemeyer, J. R. (2015). Quantum cognition: a new theoretical approach to psychology. *Trends in cognitive sciences*, *19*(7), 383-393.

Busemeyer, J. R., Wang, Z., & Townsend, J. T. (2006). Quantum dynamics of human decision- making. *Journal of Mathematical Psychology*, *50*(3), 220-241.

Gabora, L., & Aerts, D. (2002). Contextualizing concepts using a mathematical generalization of the quantum formalism. *Journal of Experimental & Theoretical Artificial Intelligence*, *14*(4), 327-358.

Hameroff, S., & Penrose, R. (1996). Orchestrated reduction of quantum coherence in brain microtubules: A model for consciousness. *Mathematics and computers in simulation*, *40*(3-4), 453- 480.

Hartmann, L., Dür, W., & Briegel, H. J. (2006). Steady-state entanglement in open and noisy quantum systems. *Physical Review A*, *74*(5), 052304.

Huelga, S. F., & Plenio, M. B. (2013). Vibrations, quanta and biology. *Contemporary Physics*, *54*(4), 181-207.

Khrennivov, A. (1999). Classical and quantum mechanics on information spaces with applications to cognitive, psychological, social, and anomalous phenomena. *Foundations of Physics*, *29*(7), 1065- 1098.

London, F., & Bauer, E. (1939). La theorie de l'observation en mecanique quantique. Hermann, Paris. English translation in Wheeler, JA and Zurek, WH eds. 1983. Quantum Theory and Measurement.

Manousakis, E. (2009). Quantum formalism to describe binocular rivalry. *Biosystems*, *98*(2), 57-66. Penrose, R. (1994). *Shadows of the Mind* (Vol. 4). Oxford: Oxford University Press.

Pothos, E. M., & Busemeyer, J. R. (2009). A quantum probability explanation for violations of 'rational'decision theory. *Proceedings of the Royal Society B: Biological Sciences*, *276*(1665), 2171- 2178.

Pothos, E. M., Busemeyer, J. R., & Trueblood, J. S. (2013). A quantum geometric model of similarity. *Psychological Review*, *120*(3), 679.

Ricciardi, L. M., & Umezawa, H. (1967). Brain and physics of many-body problems. *Kybernetik*, *4*(2), 44-48.

Sahu, S., Ghosh, S., Hirata, K., Fujita, D., & Bandyopadhyay, A. (2013). Multi-level memory- switching properties of a single brain microtubule. *Applied Physics Letters*, *102*(12), 123701.

Stapp, H. P. (1999). Attention, intention, and will in quantum physics. *Journal of Consciousness studies*, *6*(8-9), 143-143.

Stapp, H. P. (2004). Mind, matter, and quantum mechanics. In *Mind, matter and quantum mechanics* (pp. 81-118). Springer, Berlin, Heidelberg.

Stapp, H. P. (2015). A quantum-mechanical theory of the mind-brain connection. *Beyond Physicalism*, 157-193.

Tegmark, M. (2000). Importance of quantum decoherence in brain processes. *Physical review E*, *61*(4), 4194.

Vitiello, G. (1995). Dissipation and memory capacity in the quantum brain model. *International Journal of Modern Physics B*, *9*(08), 973-989.

Vitiello, G. (2012). Fractals, coherent states and self-similarity induced noncommutative geometry. *Physics Letters A*, *376*(37), 2527-2532.

Von Neumann, J. (2018). *Mathematical foundations of quantum mechanics*. Princeton university press.

Wigner, E. P. (1967). Explaining Consciousness: Of Molecules and Men. Francis Crick. University of Washington Press, Seattle, 1966. 115 pp. $3.95. John Danz Lecture Series. *Science*, *156*(3776), 798- 799.

CHAPTER 3

COMPLEX SYSTEM,

CHAOS

&

FRACTAL

"Clouds are not spheres; mountains are not cones … Nature exhibits not simply a higher degree but an altogether different level of complexity."

Benoît Mandelbröt

3.1 INTRODUCTION

Chaos theory is a delicious mix of science, contradiction and unpredictability. And if one intends to extract hidden ordered patterns among nature’s apparent disorganization and randomness, this scientific tool will certainly be his most trustworthy aid. Chaos theory was synthesized theoretically by Prigogine & Stengers (1984) and popularized by James Gleick & Michael Berry (1987). Unlike The traditional scientific approach which deals with supposedly deterministic physical phenomena like gravity, electricity, or chemical reactions, Chaos, a simplification of the theoretical construct, can be defined as an event, behavior, or process which is variable, nonlinear, and unpredictable, like turbulence, weather, stock market, human brain and cognitive states etc. What was, through observation and experimentation, considered random and unpredictable and, therefore, categorized as error or divergence, Chaos theory helps those to be understood as representative of patterned behavior. These patterns as well as the boundaries are flexible and non-deterministic, changing unpredictably (Pool, 1989). Such phenomena are often described by *fractal* mathematics, which captures the infinite complexity of nature. Almost all natural objects surrounding us exhibit fractal properties and complex chaotic behavior, including landscapes, clouds, trees, organs, rivers etc. To gain an insight into the inner workings of both the physical and biological world, one needs to recognize their chaotic nature. The importance of chaos theory lies in its explanatory power to understand the behavior of diverse complex systems.

In chaotic systems, an attractor is not a point or a simple, smooth, continuous curve, like in case of Moon’s orbit around the earth. The attractor — often called a *strange attractor* or sometimes a *fractal* — could be an infinite set of unconnected points (e.g., a Cantor dust), or a smooth curve with mathematical discontinuities, or a curve that is fully connected but discontinuous everywhere. The term fractal in this sense refers to a space of fractional dimensions: not 1-dimensional or 2- dimensional or n-dimensional, but 1.23, or 2.78 or π, or any positive non-integer number. The attractor cannot fit in X dimensions, but also cannot fill up X+1 dimensions. Any system that tries to conform to such a curve will behave chaotically, for the same reason that trying to roll a tennis ball on a pebbly beach ends up with the ball bouncing and jumping all over the place; the pebbly surface is something more than 2 dimensional and something less than 3.

Another one of the hallmarks of a chaotic dynamical system is sensitive dependence on initial conditions, more commonly known as the ‘Butterfly Effect’ - the idea that a small change in initial conditions can lead to a large change in the behavior of a system. *“Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?"* Edward Lorenz, an MIT meteorologist, accidentally discovered (and coined the term) Butterfly effect while trying to model the weather in 1961 (Lorenz, 1963). Lorenz truncated his data in one run-through, entering 0.506 instead of 0.506127. That tiny alteration in a single variable among more than a dozen representing atmospheric conditions in his model dramatically changed the long-term forecast he was working on. Hence, introduction of the Butterfly effect: the flap of a butterfly’s wings, a miniscule perturbation in the atmosphere, might be the small change necessary at the beginning of a very long and convoluted chain of events that leads to the formation of a tornado somewhere else.

Theory of Complex systems represents an umbrella term for various fields of research that include dynamical systems, discrete dynamical systems and cellular automata, game theory, information theory, networks, computational complexity, numerical methods and many more (Newman, 2011). Organizational clusters of complex systems hold within themselves dozens of thematic frameworks, since each of these covers several of such themes. They include topics that are not readily identified with complex systems and not always studied within mainstream scientific disciplines. Some of these topics are: structural scaling of Johann Sebastian Bach's Cello Suite No. 3 (Brothers, 2007), fractal properties of player’s positional dependence in a soccer game (Kim, 2006), measuring temperature of texts (Miyazima & Yamamoto, 2008), complexity perturbations in tanpura signals (Sengupta et al., 2005), risk evaluation of diabetesmellitus by relation of chaotic globals to HRV (De Souza et al., 2015) among others. The diversity of the topics illustrates the impact as well as the width complexity garnered in recentscientific research.

Among the fundamental tools in the theory of complex systems, some of the most important have been the physical ideas of scaling, phase transitions, and criticality. One startling phenomenon observed in a number of complex systems is the appearance of ‘power-law’ distributions of measured quantities (Newman, 2011). Power-law distributions are said to ‘scale’ or exhibit ‘scaling’ behaviour, because they retain their shape even when the measuredquantity is ‘rescaled’, i.e., multiplied by a constant. The observation and origin of power lawsand scaling in complex systems has been a subject of discussion and research for many decades(Mitzenmacher, 2004), going back as far as the 1890s. Mechanisms of such power law behaviours are studied with interest. The ubiquitous nature of power laws in the natural worldhas led to claims that advocate for a single underlying mathematical mechanism responsible for all power laws, essentially indicating towards grand unification of the complex systems theory. ‘Self-organised criticality’ is one such candidate (Bak et al., 1987).

In this context, the basics of scaling and power law distributions mentioned above, needs to beaddressed. Most of the quantities measured in scientific investigations have a ‘scale’, a typicalvalue around which individual measurements are centred (Bell curve). For example: distribution of heights (in centimetres) of American males or distribution of speeds (in miles per hour) of cars on UK motorways (Newman, 2005). But not always this idea holds. Some cases vary over an enormous dynamic range, sometimes many orders of magnitude. Those distributions show high skewness, that is, asymmetry or distortion from the bell-like mean. Interestingly, when they are replotted in logarithmic scales (log-log scale), the distribution closely follows a straight line with negative slope. Hence, the equation describing the line lookslike: $\ln y(x) = -\alpha \ln(x) + c$, where α and c are constants. Taking exponentials on both sides, it changes into:

$y(x) = Cx^{-\alpha}$, where $C = e^{c}$ (1)

Distributions of the form (1) are said to follow a power law, with α being the exponent (Newman, 2005).

Power law distributions can be observed in a diverse range of fields – city population (Gabaix,1999), seismological frequency (Gutenberg & Richter, 1944), solar flare distributions (Lu & Hamilton, 1991), internet network traffic (Crovella & Bestavros, 1997), word usage frequencyin human languages (Zipf, 1949), distribution of family names (Zanette & Manrubia, 2001), distribution of scientific papers (Lotka, 1926), number of hits on web pages (Adamic, 2000), recording sales (Cox et al., 1995), geographical distribution of plants and animals (Willis & Yule, 1922), annual incomes (Pareto, 1964) and in human cognitive functioning as well (Kelloet al., 2010).

In linguistic behaviour, a power law distribution that has been studied for almost 70 years is Zipf’s law, named after G.K. Zipf who described it in his pioneering study in 1949. Zipf’s law,as originally formulated, states that the frequency of a word (f) in a given corpus is proportionalto the inverse of its frequency rank (r), $f \sim 1/r$ (which is a distribution of the form (1), with theexponent α being 1). Zipf originally explained his law in terms of the principle of least effort, that is, the distribution appears as a result of the optimization between speakers’ preference ofhigh-frequency words and listeners’ preference of low-frequency words. Same basic principlecan also be applied at other linguistic scales, which suggests Zipf’s law is an adaptive propertyof communication. Evidently, this law has been found to be universal and nontrivial in the fieldof human languages (i Cancho & Solé, 2003; i Cancho, 2010). Over the years, Zipf’s law, its modifications and altercations gave a plethora of distribution laws, which are applied to different complex systems. These include Zipf-Mandelbröt law (Mandelbröt, 1965), Yule- Simon distribution (Simon, 1955), Menzerath-Altmann law (Cramer, 2005), and Pareto law (Pareto, 1964) among others. These Zipf and Zipf-like distributions have been claimed to be present in a diverse range of physical phenomena (Li, 2002): word usage in human languages,city population, Webpage

Since music and language both are embedded in human social construct for communicative aswell as entertainment purposes, it is only natural to attempt to seek commonalities between thetwo. Language and music share more than one aspect, cognitively and structurally (Jackendoff,2009). Both require memory capacity for storing representations which is later integrated in a combinatorial manner by means of a set of structural rules. The processing of both language and music involves creating expectations of what is to come. Fine-scale voluntary vocal production and the ability to imitate it are involved in the learning and producing of both. Andmost importantly, they share the characteristic of individual's ability to create and improvise, in order to be emotionally meaningful and also, distinct. Structurally, both phonology and music share similar metric system, based on a hierarchical metrical grid (although the grid appears far more isochronous for latter). In some languages (West African, Chinese) a discretetonal feature is found, as in, tones do not drift downward throughout the utterance. Patel arguesthat such languages provide a closer parallel to musical pitch (Patel, 2008). Syntactic structureof language and prolongational structure in music could also provide a parallel since they are both recursive headed hierarchies. Neuroimaging studies have indicated that Broca's area in brain is responsible for both the syntactic comprehension and music perception (Patel, 2003).

In view of this, the structural complexity of music, a congregation of informative symbolic sequences similar to the human language, is analysed in this thesis using the derived statisticaldistributions. The parameters developed helps to categorise Indian Classical Music (ICM) according to their information content, dynamic nature and improvisation patterns, somethingthat could provide a stepping stone towards understanding their cognitive distinction due to hidden emotional attributes, at least in ICM scenario.

Chaos is somewhat defined. Chaos involves deterministic systems whose courses diverge rapidly. Complex systems should exhibit this tendency. Its relationship to complex system properties remains a study topic.Chaos models describe the dynamics of one or more real (decimal) variables. These models reveal dynamical characteristics.

Complex systems may not naturally exhibit certain forms or behaviors. Complex systems have numerous degrees of freedom—partially autonomous parts. These systems' behavior is called "high-dimensional chaos" to distinguish them from low-dimensional chaos. High-dimensional chaos is an alternative word for complex systems, relying on chaos theory to improve our knowledge of complex systems.

Chaos models system-environment interaction in unclear ways. Deterministic chaos equations describe a closed system. However, such models incorporate system-environment interactions, which may be crucial to accomplish their non-linear dynamics.Thus, chaos is concerned with a few parameters and their dynamics, while complex systems examine the structure, dynamics, and environment of systems.

Chaos also means disorder and randomness. Complex systems explore chaos and unpredictability. Avoid confusing them with deterministic chaos. Since complex can relate to both deterministic chaos and random disorder, "chaotic environment" should probably be replaced by "complex environment" most of the time.

3.1.1 Chaos, Butterfly Effect and Music

The Butterfly Effect is a feature that is present in dynamical systems that exhibit chaotic behavior. A seemingly insignificant modification in the initial conditions might result in a dramatic difference in how the system behaves. Is it possible for a butterfly in Brazil to be responsible for a tornado in Texas? Ed Lorenz, a meteorologist at MIT, made the unintentional discovery of the "Butterfly effect" in 1961 while modeling the weather. Lorenz mistyped the number and put 0.506 rather than 0.506127. To his utter astonishment, this negligible shift in one of the variables caused a substantial shift in the outcomes. The sun was replaced by rain, the wind died down, etc. Steve Reich discovered that very minor alterations to the music's rhythmic framework, like as shifting the phase, could result in significant transformations (e.g., Clapping Music, Violin Phase, Six Marimbas, etc.). The butterfly effect is shown in the piece Désordre (Boudon, 1985), which is the first of 18 technically challenging piano works titled Études. The right hand is responsible for all white keys (C major), whereas the left hand is responsible for all black keys (a pentatonic scale).

Many natural phenomena, such as the weather, animal population cycles, coastlines, trees, leaves, bubble-fields, water pouring, biological systems like pulse rates, and acoustical systems like woodwind multiphonics, have been observed to exhibit chaotic behavior. Other natural phenomena that have been observed to exhibit chaotic behavior include: In addition to this, these effects are beginning to have an impact on musical composition, in particular on computer-generated composition over the course of the past ten years or more. Mathematical and scientific breakthroughs frequently have an impact on other creative fields, including music and art. The presence of fractal geometry and chaotic nonlinear systems in the intellectual landscape will inevitably lead to the emergence of novel music models in the future. (15). For the purpose of studying chaos, nonlinear dynamic systems (or mathematical equations with an unpredictable extent of evolution) and whose behavior can either possess characteristics of chaos or order yet depend on the initial parameters, are utilized. Non-scientists have become interested in these dynamic systems due to the presence of fractal properties and multi-level self-similarity (Pressing, 1988). Some forms of computer-generated nonlinear and fractal visual arts make use of disorderly patterns (Pressing, 1988; Traux, 1990). Musicians are utilizing the fractal properties of nonlinear dynamic systems in order to autonomously build chaotic and unpredictable musical patterns with the computer. Therefore, nonlinear dynamical source modelling shows the usefulness of non-deterministic and chaotic techniques in speech and music signal comprehension (Behrman, 1999; Kumar & Mullick, 1996; Sengupta et.al, 2001; Bigerelle & Iost, 2001; Hsü & Hsü, 1990; Sengupta, 2005; Sengupta, 2010; Sengupta, 2005). In this circumstance, fractal analysis of the signal geometry is quite significant. Voss and Clarke (1975) were the first people to perform fractal analysis on audio signals. They did this by analyzing amplitude spectra in order to find a characteristic frequency called fc. This particular frequency is used to separate white noise, which can be used to measure power spectrum flatness, from co-related behavior (1/f2) at the frequencies which are much higher than fc. Changes in the quality of the music can be quantified using data. The organization of data into conceptual categories is facilitated by geometric features (Devaney, 1989). On the other hand, naturally occurring geometries and phenomena frequently have several scaling ratios. The pattern of clustering is not consistent throughout the system. It's multifractal (Lopes & Betrouni, 2009). The local fractal dimensions of the subsets that make up a multifractal might change from instance to instance. The majority of systems in the real world are multifractal. The rhythms of the music are not uniform (Su & Wu, 2006; Telesca & Lovallo, 2011).

3.2 Approaching the Complex System: 'Brain' Through Fractal analysis & Chaos Theory

Complex systems possess such intricate characters that they are not likely to get split into less complicated subsystems. But this process of doesn't tamper its dynamical properties; which actually makes them really difficult to characterize or understand. Attempts are made in studying such systems by recording of time series datasets based over longer periods of selected variables i.e. observables, in which the state of the systems are reflected in a dimensionally simplified representation.

Chaos:

The branch of mathematics that deals with systems that are nonlinear as well as dynamical is known as Chaos theory. A system may be defined as a set of interacting components that form a larger whole. Nonlinear refers to the multiplicative effects between the components resulting in making the whole something greater than simply a summation of individual parts. Lastly, dynamical refers to the over-time system changes due to its current state.

Almost every real-world system can be considered as a dynamical system with nonlinear properties. Chaotic systems possess such characteristics composed of very few parts which are interacting and it follows simple rules, however they all are very sensitively dependent on their initial conditions. Despite their simple and deterministic nature, these systems have the potential to generate highly divergent, fractal, and unpredictable behavior due to their sensitivity over time. Predicting the future of such systems requires an unimaginable level of precision in measurement and computation. Chaos theory implies that certain futures are inherently unknowable regardless of the level of precision applied to prediction. Additionally, interventions within a system may lead to unpredictable outcomes, even if the intervention is small, as the effects may be nonlinearly damped over time.

The chaotic response of a system is highly dependent on its initial conditions, implying that small changes may alter its evolution. Additionally, the structure of chaos is linked to an abundance of unstable periodic orbits, showcasing ergodic properties where the system frequently visits the vicinity of each one. In such circumstances, it becomes possible to control chaos with slight perturbations by stabilizing an unstable periodic orbit that's a part of a chaotic attractor. This makes the behavior of the system very adaptable. Chaos regulates the dynamics of living systems through various mechanisms, including the regulation of voltage-dependent ion channels, enzyme activity, receptor activity or transport processes, and even circadian rhythms.

Real-world examples of fractal and chaotic systems traverse a varied array from leaky faucets [*Suetani'2012*], to ferns [*Singh'2012*], to heart rates [*Hoshi'2013, Babbs'2014, Glass'2009*], to cryptography [*Hong'2010, Makris'2012*]. Numerous scholars have delved deep into nonlinearity, fractal and chaos theory in order to understand the intricacies of social sciences, urban studies, economics, architecture and city planning.Nonlinear dynamical systems have been difficult to solve analytically due to their inability to be broken down into parts, solved separately, and then combined into a solution. Instead, scientists have historically relied on qualitative and visual approaches, which were first developed by Henri Poincaré in the late 1800s, to explore and analyze the captivating dynamics of nonlinearity. Information visualization has played a significant role in discovering and examining hidden structures in complex datasets. Nonlinear dynamics and chaos, in particular, have benefited greatly from visualization for their pivotal discoveries, such as Lorenz's initial observation of strange attractors, May's influential bifurcation diagrams, and phase diagrams that reveal higher-dimensional hidden structures in data. Nonlinear analysis, which is particularly useful but underutilized, can be used to explore time series data.

Chaos embodies four important properties:

- **Non-linearity:** Linear systems do not contain chaos. Though non-linearity is a necessary condition but it is not sufficient for chaos to occur. All realistic systems show some amount of non-linearity.

- **Determinism:** It is necessary for chaos to follow one or more deterministic equations devoid of random factors. Basically the boundary between probabilistic and deterministic systems might not be clear since a random process might underlying deterministic rules yet to be discovered.

- **Sensitive dependence on initial conditions:** Even small changes in the initial state of the system can cause the final state to behave differently. So the prediction of the long term behaviour of the system is practically impossible.

- **Aperiodicity:** Chaotic orbits are aperiodic, but not all aperiodic orbits are chaotic. Almost-periodic and quasi-periodic orbits are aperiodic, but not chaotic.

3.3 A New Dialogue Between Mankind and Nature: Fractals and Multifractals:

A fractal is a fragmented geometrical object, which when sub-divided; the parts turn out to be proportionally shrinked copies of the whole. Usually fractals are scale independent and self-similar. Fractal dimension refers to the extent of brokenness of the shape. Created with a feedback loop of a recursive process. the metric properties of length or area are a function of the scale of measurement.

The example of the measurement of the coastline of any country (Britain for the case in hand) is very well explicable of the phenomenon of fractcality. When measured with a certain scale, the cumulative length of the crooked coastline is a measure of 'N' line segments each of length 'd'. Subsequently, with a higher resolution of measurement, the small intricate details are measured, thereby increasing the costal length as the measurement scale 'd' keeps on increasing.

Fig.3 1. The coastline of Britain in different scales
(Source: http://www.duke.edu/~mjd/chaos/chaos.html)

Fig. 1 gives an assessment and representation of the change of the coastline of Great Britain with a varied albeit small scale of measurement. The concept of fractal dimension works similarly, as we go on increasing the scale of measurement the more intricate geometry of the signals come into focus. Essentially, the fractal techniques act as a mathematical microscope magnifying such finer details of the complex time series signal which is not possible by any other methods.

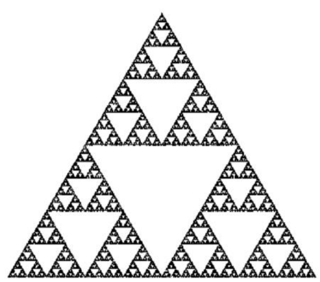


Fig3.2. The Sierpenski triangle
(Source: http://www.duke.edu/~mjd/chaos/chaos.html)

Fig 2: A very common example of fractal image, called Sierpinski triangle. The large triangle comprise of three smaller triangles with side-length half of the original one, the latter subsequently made up of three smaller triangles, and so on. The resultant Sierpenski triangles on all scales are self-similar, and this fractal tool also acts as a mathematical viewfinder to magnify its way into the intricacies of a naturally random object/image/signal.

The field of fractal geometry allows for infinitely long confined curves as well as infinitely wide closed surfaces. It is able to accommodate both curves with real volume and a random large grouping of adjacent forms. This is how our lungs maximize the use of available surface area. When compressed into our lungs, a tennis court is equivalent to a few tennis balls. The laws of fractal self-similarity are followed by the kidneys, liver, and pancreas (Fig. 1.4.3-1.4.6).

Fig 3.3. Influenza Virus

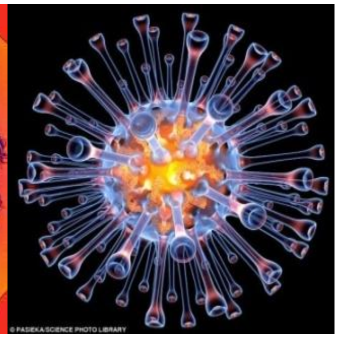


Fig 3.4. Swine Flu Virus

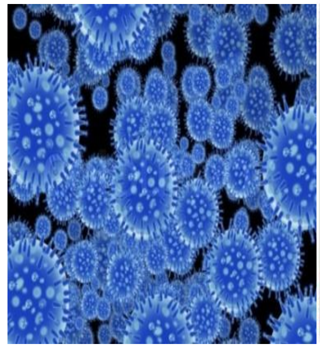


Fig 3.5. Bacteria

Fig 3.6 Blood Vessels

(Source: www.sciencephoto.com)

Multifractals are intertwined fractals. Many scales of multifractal self-similarity (spectrum of dimensions). As spontaneously developing geometries and phenomena occur, it's possible that distinct components of a system will scale differently. The pattern of clustering is not consistent throughout the system. It's multifractal (Lopes & Bertouni, 2009). The local fractal dimensions of the subsets that make up a multifractal might change from instance to instance. The majority of systems in the real world are multifractal. Many complex occurrences in today's world can be explained using fractal geometry. The beginning and progression of turbulence can both be explained by fractals. Fractals can also be blood vessels. There was a mathematical distribution to the earthquakes. Fractal was identified by geologists to be this pattern. The surface fractal dimensions of a metal are an indication of its strength. Since its inception, the MFDFA has been utilized in umpteen number of fields: turbulence analysis (Telesca & Lovallo, 2011), faults and joint systems (Lin & Chen, 2013, traffic movements (Shang, Lu & Kamae, 2008), geological time series, blood flow oscillations (Liao & Jan, 2011), as well as stock exchange. Recent articles by the authors center on the distinction of brain state as a result of the influence of two separate sets of emotional music. Fractals and multifractals can be used to determine the change in condition of a person's brain to quantify feelings using musical samples.

Fractals are considered as the geometry of chaos. An object which is chaotic in space is called a fractal. Thus fractals can help detect chaos. Systems exhibiting periodicity or a very close approach to that, might be the cause of oscillatory components or closed-loop regulation chains, which are usually not limited to one or two characteristic frequencies or frequency bands. They are rather extended over a wide spectrum, from which fluctuations on many time scales as well as broad distributions of the values are found. In such systems quite often there are no specific lower frequency limits and/or upper characteristic time scales; there the dynamics can be characterized by scaling laws which are valid over a wide or possibly unlimited range of time scales or frequencies, at least over orders of magnitude. Such dynamics are usually defined as fractal or multifractal, depending on whether they are characterized by one scaling exponent or by a multitude of scaling exponents [*Kantelhardt'2008*].

Fractal and multifractal scaling behaviour has been reported in many time series of natural / human developed complex systems. These include

- Geological and Geophysical systems,
- Medical and Physiological systems,

- DNA sequences (not actually time series),
- Astrophysical systems (X-ray light sources &sunspot numbers etc.),
- Social systems (finance and economy, language characteristics), as well as
- Technological systems (control systems, internet congestion, neutronic power from a reactor, fault detection, lightning modelling, load scheduling, antenna multiband miniaturization, encoding in communication, image compression, impedance transformer, artificial life (computer graphics), radio and radar etc.) and
- Physics (surface roughness, chaotic spectra of atoms, and photon correlation spectroscopy recordings etc.)[*Kantelhardt'2008*].

The following sections describe the methodology developed so far for fractal as well as multifractal analysis of different complex systems with short discussions of advantages and limitations of different techniques to give a comprehensive scenario of fractal analysis. The applications of the major techniques have also been discussed next to the methodology section followed by a brief review about them. The chapter ends with the state of the art scenario of multifractal analysis including correlation study of two multifractal time series.

3.3.1 Basic notions concerning Fractals

The two basic notions of fractals are about *self-similarity* and *self-affinity*.The term "similar" is defined here asthe objects with same shape but different size, and"self-similar",as a largerobject, composed of smaller-scale copies of such "similar" objects. Thus, the term "self-similarity" can be visualized as an infinite regression of smaller and even smaller images,which constitutes a complete item that is similar to its parts.

For an example, as illustrated in Figure 2.1, a fern exhibits a recursive structure in which the branches resemble miniature versions of the whole fern.The 'self-similar' character of fractals can also be termed as "scale invariant", since during observation they appear similar mathematically at all scales.Another example could be Rocks. They appear the same at all and any scales of observation. A scaled cannot be determined by just looking at a photograph, unless an object of known size is present in the picture [*Brown'2003*].

Fig. 3.7: A Fractal Fern (https://www.flickr.com/photos/roddh/307187374)

Fractals can be considered as “self-affine” if they are broken down into subsets that can be mapped linearly to form a full figure. When this map involves only dilation, rotation and translation, then we can say that the object is self similar. The difference between self-affine and self-similar objects cannot always be made in practice. This process is useful in cases where there are preferable global directions in fractal surfaces.

Another crucial concept of fractals is that they possess a fractional dimension, which means that their dimension is expressed as a fraction rather than a whole number. This implies that a fractal object must not only exhibit self-similarity, but also that the self-similar elements are related in scale through a non-integral power-law. The fractal dimension of a pattern characterizes the scaling relationship through the power-law. Euclidean dimensions only involve integers i.e, 0 for a point, 1 for a line, and so on. New-age mathematics have developed other methods for the measurement of dimensions which are in turn non-Euclidean. Some of these methods are information dimension, capacity dimension, correlation dimension, which will be discussed in the preceding section. In general fractal objects have dimensions which exceed their topological dimension [*Mandelbrot’1977, Brown’2003*].

3.3.2Properties of Fractals:

A fractal is a natural object or geometric figure that displays a combination of the following characteristics:

a) Parts of the fractal will have the same structure as the whole, albeit at a slightly different scale.
b) Its form is irregular or fragmented, and continues to be so at every scale of observation.
c) It contains "distinct elements" whose scales vary and cover a large range of variations
d) Formed by iteration;
e) Possesses an element of fractal dimension.

3.3.3 Types of Fractals:

Fractals can be of three types namely: (i) Natural, (ii) Geometric and (iii) Complex and Random.

3.3.3.1Fractal Geometry in ‘Nature’:

If we were to zoom in on any one part of the object, we would be looking at the original picture, which is the basic definition of a fractal: something with a shape that becomes smaller and repeats eternally. There are many different types of fractals. Approximate fractals can be seen all around us in nature and the surroundings, even in some of the vegetables we eat. Here are a few instances of fractals in nature:

- The quartz stone is one example of a fractal image in nature. It has triangular points and would look similar if you were to zoom in on any part of the stone.

Fig.3.8: A quartz stone (https://upload.wikimedia.org/wikipedia/commons/9/9c/Quartz-159385.jpg)

- Thenext example is a Romanesco Broccoli, which is a cross between Broccoli and Cauliflower with a nice fractal structure.

Fig.3.9 Romanesco Broccoli (http://www.laurieconstantino.com/wp-content/uploads/Brassicas.jpg)

The concept of fractals are also shown by trees. Their branches grow and split following a pattern and they continue this way…

Fig.3.10 Oak tree (https://findingourwayhomeblog.files.wordpress.com/2014/05/oak-mj-dsc03499.jpg)

- Our lungs consist of branching fractals with a surface area ~100 m^2

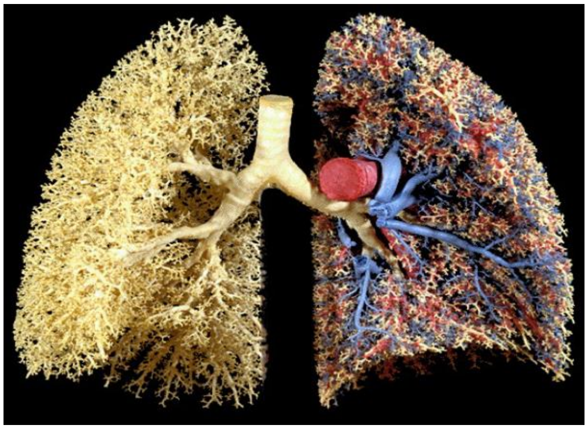


Fig.3.11 Lungs (https://fractalfoundation.org/OFC/OFC-1-2.html)

- Lightning is another example of fractals. Like tree branches lightning branches also continue to grow and split till fully discharged.

Fig.3.12: Lightning (https://originalbeauty.wordpress.com/2009/02/27/fractals-in-nature/)

3.3.3.2 'Geometric' Fractals:

Geometric fractals, as their name implies, are constructed using mathematical rules to create intricate shapes and patterns. These fractals are typically considered to be perfect systems that are not subject to internal deviations or changes due to external influences, except for the possibility of human error during their construction.

3.3.3.2.1 Cantor Set:

The following Fig.13 shows the first five iterations of the construction of the cantor set. The Cantor set is initially constructed using unit interval, or all the points on the line between 0 and 1. The unit interval is shown by the filled bar at the top of the fig. By eliminating all points that fall within the middle third, or all points between 1/3 and 2/3, the first level can be obtained from the zeroth level. The middle third of each remaining interval at the first level, i.e., all points from 1/9 to 2/9, and 7/9 to 8/9, is deleted in order to attain the second level. The middle third of all intervals received from the previous level is typically deleted to obtain the following level from the previous level. An endless number of times, this process is repeated, and the end result is a collection of points that are just barely cut off from the unit interval. The set has N= 2n segments at level n, each with a length of 1n= 13n, making the total length of the Cantor set across all segments (2/3)n.A fractal set exhibits this result: as n+, the number of segments increases exponentially to infinity but the overall mass decreases exponentially. It is demonstrated that the Cantor set consists of an endless number of dots of size zero in the scenario where there are an infinite number of recursions.

Fig.3.13: The initial unit interval and the first five iterations of the construction of the Cantor set are shown from top to bottom (http://hyperspacewiki.org/images/a/a9/Cantor_set.png)

3.3.3.2.2 Iterated Function System Fractals:

Scaling, dislocation, and rotation of the plane's axes serve as the foundation for Iterated Function System (IFS) fractals. The stages involved in creating an IFS fractal are as follows:

Specifying a set of transformations for planes, firstly tracing a pattern onto the plane (any pattern),using the modifications outlined in the first step, changing the initial pattern, Using the same set of transformations to change the new image (a combination of the original and altered patterns),Step four should be repeated as many times as feasible. (In theory, this procedure can be repeated an infinite number of times).

The Sierpinski Triangle and the Koch Snowflake are the two most well-known ISF fractals.

3.3.3.2.3 The Sierpinski Triangle (A detailed overview):

The Sierpinski's Triangle, named after the Polish mathematician WaclawSierpinski, is one of the simplest examples of fractal shapes in existence. Its generation can be brought about by infinitely connecting the midpoints of each side of the triangle to form four separate triangles, and cutting out the triangle in the centre, and repeating the same for each resultant triangle.

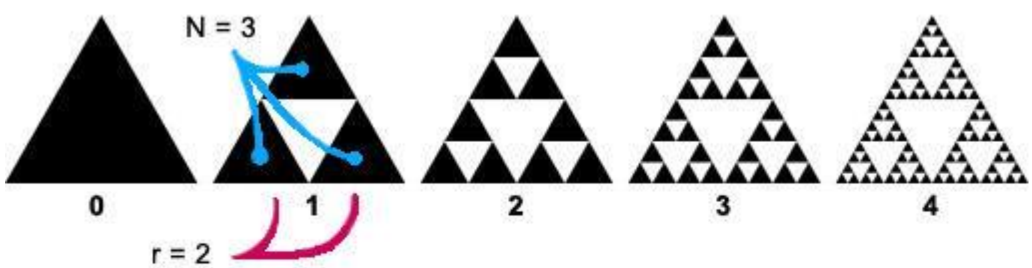


Fig. 3.14 Formation of Sierpinski Triangle (http://fractalfoundation.org/OFC/OFC-10-3.html)

Step 1. We first take an equilateral triangle as the 0 order triangle in the Fig. above.

Step 2. Next, the midpoint of each triangle are connected to form 4 separate 'trianglets'

Step 3. Next the triangle is cut out in the centre.

Step 4. Now we repeat steps 1, 2, and 3 on the three black triangles left behind.Thecenter triangle of each black triangle was cut out as well. i.e., order 2 is made up of 9 triangles.

So each iteration of the fractal has 3 times as many triangles, and N=3. Next we need to Fig. out the scaling factor, r. How much smaller is each triangle in order 1 than order 0? Looking at the edge of each triangle in order 1, we can see that the edge of each triangle is half the length of the edge of the triangle in order 0. So the scaling factor r=2.

Step 5. Finally by using the formula, we can find the dimension:

$$D = \frac{log\ logN}{log\ logr} = \frac{log\ log3}{log\ log2} = 1.585$$

From the above Fig.s we can see that, after the first iteration, with one quarter of the triangle removed, three quarters of the area of the original triangle is left after the first iteration. Thus after n iterations, the area of the Sierpinski's Triangle would result to $(0.75)^n$times the area of the original triangle, while subsequently after an infinite number of iterations, there would be no area at all..

3.3.3.2.4 The Von Koch Curve:

The Von Koch curve is created through a basic geometric process that can be repeated an unlimited number of times. This process involves dividing a straight line segment into three equal parts and replacing the middle portion with two segments of identical length. Despite its simplicity, the Von Koch curve is a well-known example of a fractal, demonstrating self-similarity through its repeated construction according to a straightforward rule.

- **Koch Edge:**

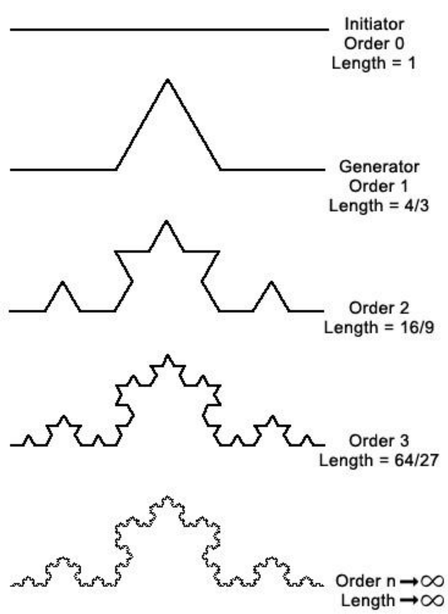


Fig 3.15: Formation of Koch Edge (http://fractalfoundation.org/OFC/OFC-10-2.html)

Step 1. Let us take a straight line for starters.

Step 2. Then, the straight line is divided into 3 equal parts with the middle part replaced by two linear segments at angles 60º and 120º.

Step 3. Now we repeat the steps 1 and 2 to the four-line segments generated in two.

Step 4. On further iterations with the dimension $D = \frac{loglogN}{loglogr} = \frac{loglog4}{loglog3} = 1.262$ we can easily construct the above curves.

It is the self similarity of the fractal that gets presented by the Von Koch Curve. The same patterns appear along the curve in different scales. Although not undertaken in practice, the iteration process should be rendered indefinitely.

In each iteration, the size's length is multiplied by 4/3 in order to keep the distance between the two points constant. We may get a formula for the entire length of the Koch Edge in the nth iteration, L= (4/3)n, using this straightforward iteration rule.Other types of Koch curve can also be constructed with the help of the above method namely: Koch snowflake and Koch star.

- **Koch Snowflake:**

To create the Koch Snowflake, we must start with an equilateral triangle with length sides, such as 1. We will place a new triangle, one-third its size, in the centre of each side, then repeat the operation an unlimited number of times. The boundary's length is 3, 4/3, 4/3, 4/3,..infinity. The region is still less than a circle drawn around the initial triangle, though.This implies that a finite area is surrounded by an indefinitely long line. A Koch Snowflake's final structure resembles a shore's coastline.

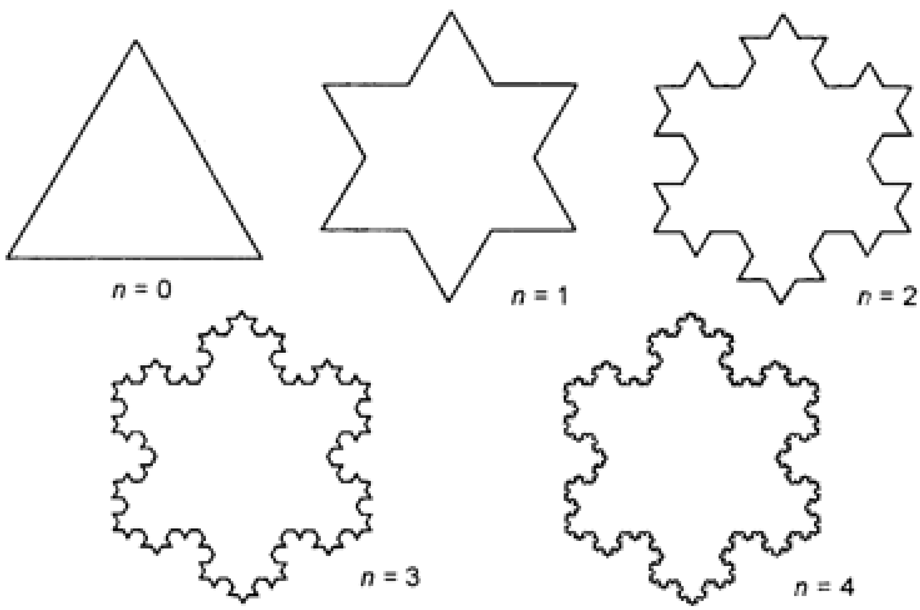


Fig. 3.16: Formation of Koch Snowflake(https://www.researchgate.net/publication/320834110_Modeling_the_External_Structure_of_a_Fractals/Fig.s?lo=1)

- **Koch Star:**

Instead of an equilateral triangle, the similar fractal iteration can be performed on polygons of any size. For example on a hexagram, when the algorithm is processed, the six vertices of the hexagram generate smaller new hexagrams, with the newly generated hexagrams being similar to the original one.

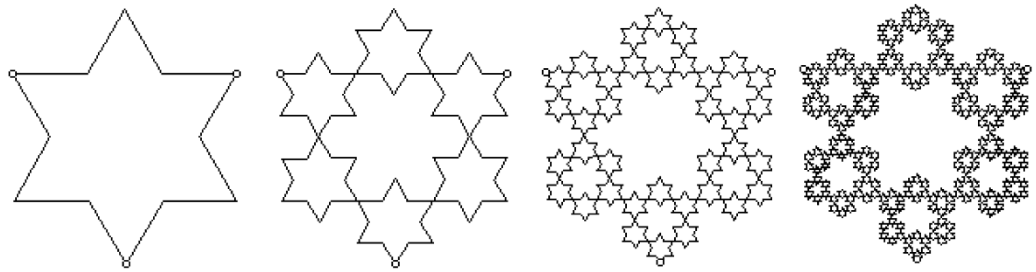


Fig. 3.17: Formation of Koch Star (https://creativiteach.files.wordpress.com/2014/01/fractals2.jpg)

3.3.3.2.5 The Hilbert Curve:

The Hilbert Curve was first introduced by David Hilbert (1862–1943). This curve is called a space-filling curve, as it will eventually cover the entire plane after several iterations.

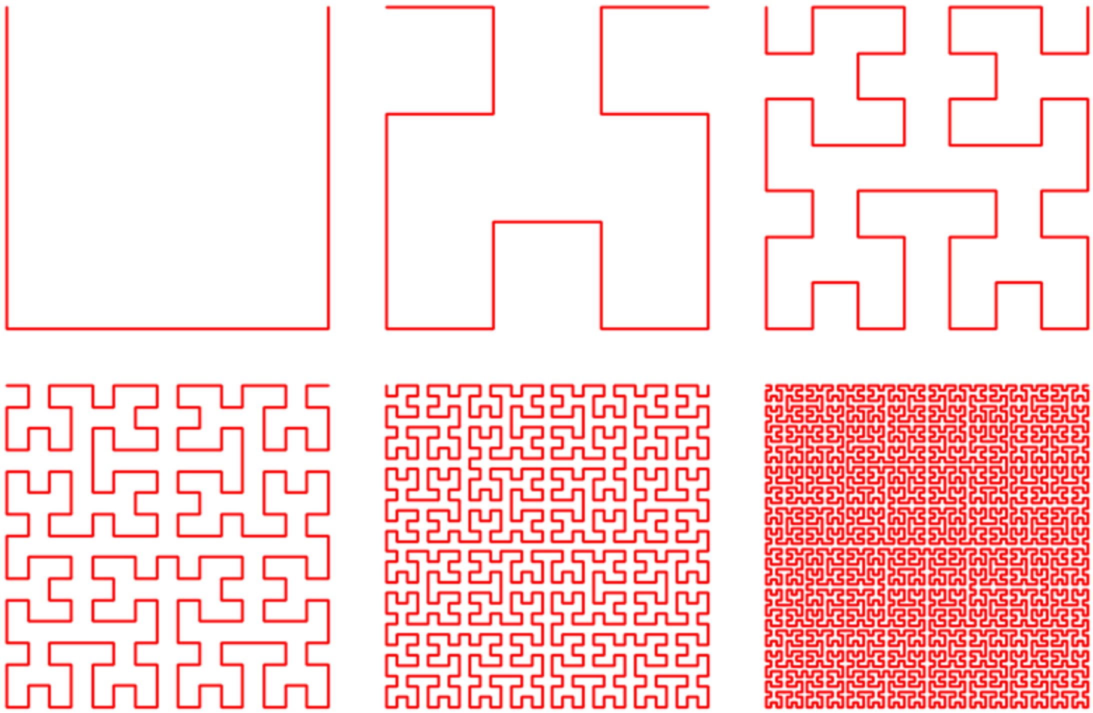


Fig. 3.18: Formation of Hilbert Curve (http://datagenetics.com/blog/march22013/index.html)

Step 1. Firstly, a basic shape is taken into consideration, like the one shown in the figure.

Step 2. Next we reduce the size of the previous curve by half and also reduce the grid size by half. After that, 4 identical copies of the curve are placed on the grid. The bottom two copies remain in their original position while the top two are rotated by a quarter turn, one to the left and the other to the right. Finally, we connect the four pieces using short straight lines (horizontal or vertical) to form the next iteration of the curve.

Step 3. All the rest of the curves are created sequentially one from another using the same algorithm

The Hilbert Curve construction process involves a unique feature where a staple-like shape shrinks and transforms into other positions, distinguishing it from the Von Koch Curve &Sierpinski Triangle. This transformation is achieved using the Lindenmayer System (L-system), a string rewriting system commonly utilized for generating fractals with a dimension ranging between 1 and 2. To complete the curve, it is necessary to link the transformed shapes with additional line segments. As a result of this iterative process, the curve eventually covers the entire plane, typically after 7 to 9 iterations.

[*http://www.math.nus.edu.sg/aslaksen/gemprojects/maa/World of Fractal.pdf*].

At every iteration, the fractal becomes 2 units longer. After n iterations the length of the curve will grow up to 2n units longer.

3.3.3.2 'Complex' Fractals:

Mandelbrot Sets are famous fractals. Benoit Mandelbrot studied self-similarity in the 1960s and graphed complex numbers by 1980. He utilized the recursive formula Z=Z (n-1)^2+ C, where C is a real integer and Z is a complex number like (a+ib). Mandelbrot found that some grow larger and reach infinity, while others shrink and approach zero. Mandelbrot then programmed the computer to color pixels for each number or complex plane point. The computer-colored numbers closer to zero black. It would change color if larger. How fast the number reached infinity determined the colors. He got the most renowned fractal geometry picture [Patrzalek'2006].

3.3.3.2.1 Mandelbrot Set:

A set of points on a complex plane is called the Mandelbrot set. In order to build the same, a recursive formula is used [*Mandelbrot'1983*]:

$$Z_n = Z_{n-1}^2 + C$$

Separating the points of the complex plane into two categories:

1) Points lying inside the Mandelbrot set,
2) Points lying outside the Mandelbrot set.

Fig. 2.13 shows a portion of the complex plane.

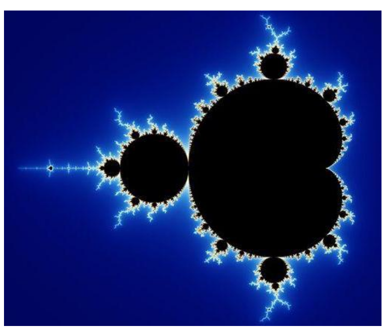


Fig.3.19: Mandelbrot'sset
(https://en.wikipedia.org/wiki/Mandelbrot_set#/media/File:Mandel_zoom_00_mandelbrot_set.jpg)

We can possibly assign a colour to the points outside the Mandelbrot set and their colours are decided by the number of iterations that are required to determine that they are outside the Mandelbrot set.

Creation of the Mandelbrot Set:

To create the Mandelbrot set we have to pick a point (*C*) on the complex plane. The complex number corresponding with this point has the form: $C = (a + i.b)$

After calculating the value of previous expression:

$$Z_1 = Z_0^2 + C$$

With $Z_0 = 0$, we obtain C (Fig. 2.13b). Next is to assign the result to Z_1 and reiterate, repeating the process again and again. [*Patrzalek'2006*].

One way to express this process is by referring to the movement of the starting point C on the plane as a "migration". When reiterated multiple times, if the point stays near the origin, it is considered part of the Mandelbrot set and represented as a black point in the image. If the point moves away from the origin, it is said to "escape" to infinity and is assigned a color based on the speed of its departure.

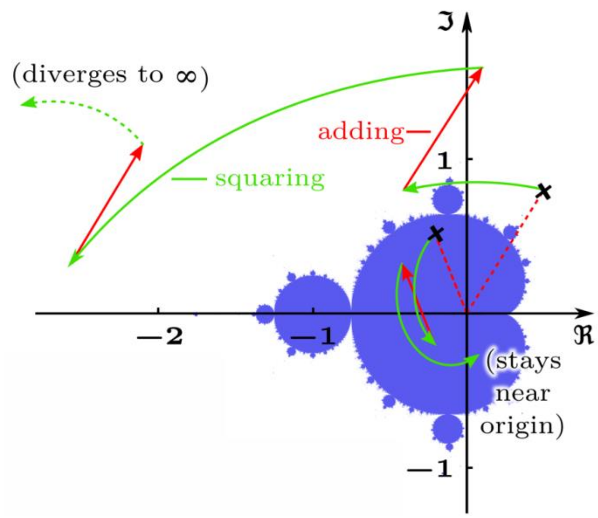


Fig 3.20: Mandelbrot's phase plane model
(https://ianwitham.files.wordpress.com/2009/12/complex_mandelbrot_illustration.png)

Now let us look at the algorithm from a different perspective. Let all the points on the plane be attracted by both the infinity and Mandelbrot sets. This makes it easy to understand why:

- points that are away from the Mandelbrot set rapidly move towards infinity,
- points that are closer to the Mandelbrot set slowly escape to infinity,
- but the points that are inside the Mandelbrot set never escape to infinity.

In the Mandelbrot set, we square the value and add Z.

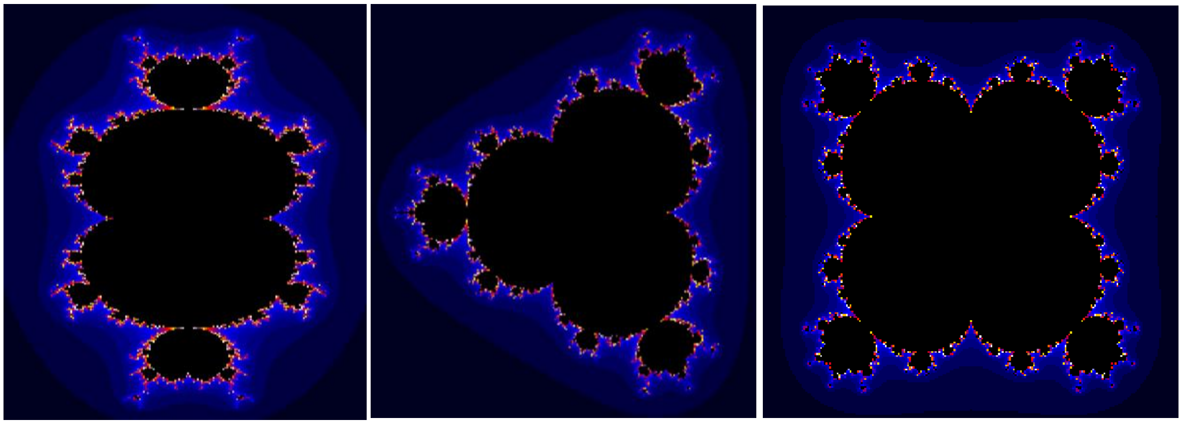


Fig.3.21: Mandelbrot's phase plane model with power 3–5
(http://www.relativitybook.com/CoolStuff/erkfractals_powers.html)

Here we notice how the shape tends to have n-1 'bulbs' to it – which is quite strange and mind boggling, as the value of n affects the colour at only a point wise level, so the fact that in can be seen in the general shape[*Patrzalek'2006*].

3.3.3.2.2 Julia Set:

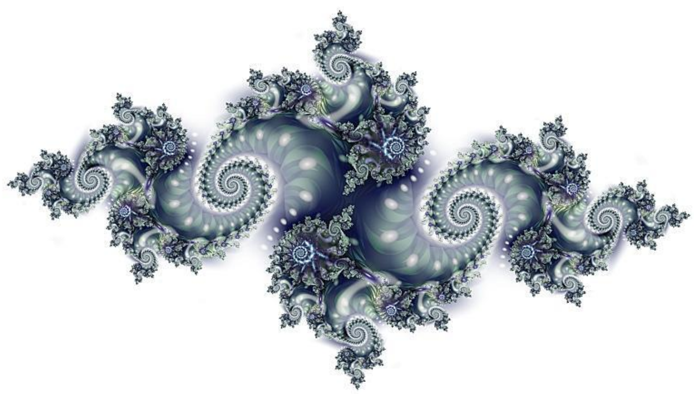


Fig. 3.22: Julia Set (https://orderinchoas.files.wordpress.com/2013/05/julia_set.jpg)

There is a direct connection between Julia sets and the Mandelbrot set. They are created using the same iterative function that created the Mandelbrot set. The application of this formula is the only distinction. We iterate the formula for each point C on the complex plane in order to create a Mandelbrot set image, always beginning with Z0 = 0. In order to create an image of a Julia set, C must remain constant throughout generation while Z0's value changes. Each complex plane point is connected with a certain Julia set depending on the value of C, which affects the geometry of the Julia set [*Patrzalek'2006*].

- **Creation of a Julia set:**

We must select point C on the complicated plane. The following algorithm determines what colour a point on the complex plane Z should be and if it belongs to the Julia set connected to C. To find out if Z is in the set, we have to keep running the function $Z_1 = Z_0^2 + C$using $Z_0 = Z$. Next, we'll look at what happens to the starting point Z as the formula is repeated. Does it stay close to the source, or does it move away and keep getting farther away from the source? Similarly as in the case of the Mandelbrot set, points close to the source belong to the Julia set, while drift towards infinity, and we give Z a color based on how fast the point "escapes" from the origin. To make an image of the whole Julia set associated with C, the process is repeated with all the points whose coordinates are in the range: $-2 < a < 2$; $-1.5 < y < 1.5$(Fig. 2.17).

Figure 2.17 shows how the set gets gradually more complex as the values of "Z" and "C" go up. This is due to the reason Julia sets, "C" is the common complex number for all the pixels, and different values of "C" lead to many different Julia sets. By changing c in a smooth way, we can obtain another set from one Julia set over time, making fractal shapes that move. But the most important thing to know about Julia sets and Mandelbrot sets is that a Mandelbrot set is connected (it is one piece), but a Julia set is only connected if it is linked to a point in a Mandelbrot set.

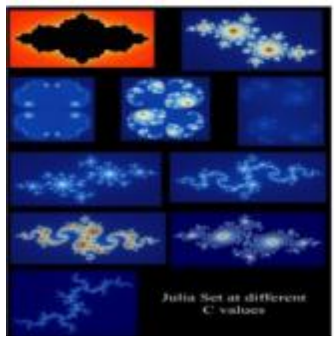


Fig.3.23: Examples of Julia Set (https://en.wikipedia.org/wiki/Julia_set)

Put in a simple way, a particular Julia set can be described by a point in the Mandelbrot set which matches its constant c value, and the appearance of a whole Julia set often resembles the Mandelbrot set in that same spot. Julia sets that are most fascinating are usually found near the boundaries of the Mandelbrot set.. [*Patrzalek'2006*] (shown in the Fig. 2.18).

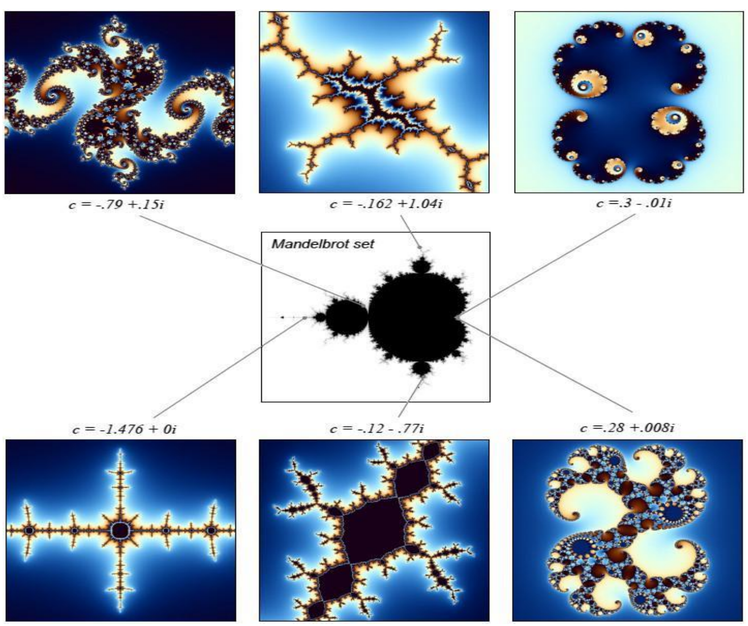


Fig.3.24: Julia-Mandelbrot Set with different 'C' values [http://www.karlsims.com/julia.html]

In fig 2.18, Different values corresponding to six Julia sets and their respective locations in the Mandelbrot set are displayed. of '*C*'.

3.3.4 Fractal Dimension:

Dimension (latin:*dimensio; to measure)*. Traditionally, objects and phenomena are described by using different measurements, called *dimensions.*

A point can be dimensionless, since the point is not a continuum and, thus, both Euclidean and topological dimensions are the same, $D_E = D_T = 0$. However, discrepancies between these dimensions appear when we take into account the line and other Figs. According to topology, the line has the dimension $D_T = 1$, regardless of the geometry of the line, it can be divided by non-continuous points. Similar to this, curves are required to split surfaces. Consequently, the surface's topological dimension is $D_T = 2$, and, in a similar way, the topological dimension of a space is $D_T = 3$, since to divide space, surfaces are necessary. A structure is said to be one-dimensional (1D) if it is embedded in a straight line, two-dimensional (2D) if it is embedded in a plane, and three-dimensional (3D) if it is embedded in space, according to the Euclidean definition. Only the straight line is considered one-dimensional by this definition, $D_E = 1$, since it does not occupy either the plane or the space. However, the complex curve in space is three dimensional while the curve line in the plane has the dimension DE=2, $D_E = 3$. Also, the flat surface is two dimensional, $D_E = 2$, but non-flat surface can be assumed as three dimensional [*Reljin'2002*], as shown in Fig. 2.19.

One way to quantify the features of man-made objects with consistent structural patterns is by using reference measures as benchmarks. For example, weight can be determined by comparing it to the standard weight of 1 kilogram, and length can be calculated by comparing it to 1 meter. To measure characteristics like curve length or surface area, analytical methods such as line or surface integrals can be employed, while volume and weight can be calculated using suitable volume integrals. For many years, Euclidean geometry served as the fundamental principle behind the design, construction, and description of all man-made items.

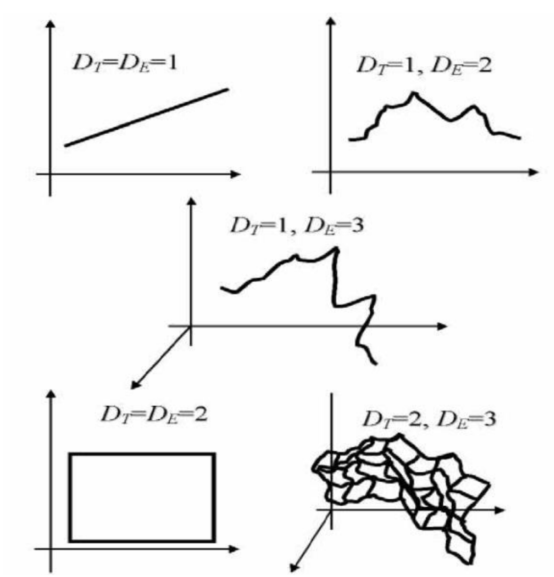


Fig 3.25: Examples describing differences between topological and Euclidean dimension

Today, measuring of length, area and volume is very easy. But, it is not the case when mapping complex and irregular objects such as a coastline. Mandelbrot (1967) published a paper named "How long is the coast of Britain? Statistical self-similarity and fractional dimension" [*Peitgen'1992*], and demonstrated that measurement of Britain's coastline and its accuracy will depend on the scale of observation.

So far we have seen that measuring, describing and comparing different objects happen with the use of dimensions. But, how do we measure fractals?A number of ways have been discovered of measuring fractional dimensions, and therefore, non-Euclidean. These methods comprises of the correlation dimension, the capacity dimension, the information dimension, and others, all the rest that are related mathematically. Here the "fractal" or "Hausdorff–Besicovitch" dimension is discussed.

Hausdorff dimension was introduced in 1919 by Felix Hausdorff (1869–1942) as the principal definition of fractal dimension.It is found difficult to be estimated by computational means ,even when it is defined for the mathematical set [*Falconer'2003*]. We call the dimension 'fractal' because it is a fraction , not a whole number and we call it dimension as it provides a measure of how completely space is filled by an object [*Jelinek'1998*].

Fractal Dimension can be defined as the fundamental parameter of a fractal set. The dimension can be expressed by the following relation:

$$a = \frac{1}{s^D} \qquad (2.1)$$

where*a* denotes the number of self-similar "pieces", *s* denotes the linear scaling factor of the individual pieces to the whole, and lastly *D* denotes the dimension to be calculated. *D* can be calculated as:

$$D = -\frac{(\log a)}{(\log s)} \qquad (2.2)$$

By definition, D is not an integer for fractals. D expresses the power law that connects the self-similar components to the total and gauges the set's complexity. For instance, the fractal dimension of a fractal curve will range from 1 (the Euclidean dimension for a line) to 2. (the Euclidean dimension for a plane). The dimension will be closer to two the more complicated the curve is. A fractal curve can theoretically have a maximum dimension of 2, at which point it becomes so complicated that it fills the plane. A fractal object's dimension contains crucial details about the nature of the phenomenon. The type of nonlinear process that produced the pattern can also be determined by the fractal dimension [Brown'2003]. Let's examine a couple of classic examples of fractals to see what these ideas mean in practice.

First let us evaluate the fractal dimension of the Cantor set. We can calculate it easily using Eq. (2.2), relating the size *s* to the fractal dimension *D* and number *a* of the pieces. During each iteration, there is scaling down of line segments by 1/3 (the variable *s* in Eqs.) and hence yield two new pieces (the variable *a*in [Eq. (2.1) and (2.2)]). So,

$$D = -\frac{\log 2}{\log \frac{1}{3}} = 0.6309$$

For the Koch Curve the fractal dimension is $D = -\frac{\log 4}{\log 1/3} = 1.262$ since *a* = 4 and *s* = 1/3. Instead of the straight-line (initiator), having $D_E = 1$, the successive structures partially occupy a space, so, the dimension is greater than unity. Similarly, for the Sierpinski Carpet the dimension is$D = -\frac{\log\log 8}{\log 1/3} = 1.893$.

The fractal type is defined by the ranges in the value of the fractal dimension. Fractal dust is a structure with a fractal dimension between 0 and 1, fractal signal (fractal line) is a structure with a fractal dimension between 1 and 2, fractal surface (fractal image) is a structure with a fractal dimension between 2 and 3, and fractal volume is a structure with a fractal dimension between 3 and 4 [Reljin'2002].

As opposed to deterministic fractals, natural fractals do not have a regular structure. For instance, a shoreline's magnified portion will roughly mirror the entire coastline. There is statistical self-similarity in this structure. The similarity dimension provided by Eq. (2.1) is inappropriate for such structures because there is no precise production rule. Different methods for determining the fractal dimensions of such structures are derived [*Reljin'2002*].

Generally, two simple methods are used to determine fractal dimensions. In a case of fractals where there is a fixed size and having infinitely small details, the dimension of the objects can be determined by the scaling of the number of non-empty boxes having diminishing size. In this method of "box counting", The structure is divided into a grid with a mesh size of 1, and an occupied box or lattice unit is one that intersects with the fractal by more than zero. To study growing fractal structures, the mass scaling within a given region is examined. This method is an extension of the approach known as the "sand box method."[*Tél'1989*].

3.3.5 Application of Fractals and Multifractals:

Fractal geometry has helped many areas of

- **Science:** Geophysics, Mathematics, Statistics, Bio-Science, Astrophysics.
- **Engineering:**Image-processing, Bio-sensors, Biotechnology, Electronic waves and pulses, Impedance transformers, Power-pricing, Load-characterizing;
- **Social science:**Economics, Census;
- **Computer Graphics:**To name a few and has become one of the most important techniques in computer graphics.

3.4 References:

Abadi, M., et al. The 11th Iberoamerican Congress on Pattern Recognition **4225** 297 (2006)

Absil, P.A., et al. Physica A **272** 235 (1999)

Alessio, E., et al. European Physical Journal B **27** 197 (2002)

Alpigini, J.J. Inf. Vis. **3** 271 (2004)

Alvarez-Ramirez, J., et al. Physica A **354** 199 (2005)

Alvarez-Ramirez, J., et al. Physica A **361** 677 (2006)

Anderson, J., et al. Journal American College of Cardiology **30** 226 (1997)

Appleby, S., Geographical Analysis 28 147 (1996)

Arianos, S., et al. Physica A **382** 9 (2007)

Arneodo, A. et al., The science of disaster: climate disruptions, market crashes, and heart attacks Springer, Berlin (2002)

Arnéodo, A., et al. Physical Review Letters **74** 3293 (1995)

Arnéodo, A., et al. European Physical Journal B **1** 129 (1998)

Arnéodo, A., et al. European Physical Journal B **15** 567 (2000)

Ashkenazy, Y., et al. Fractals **7** 85 (1999)

Ashkenazy, Y., et al. Physical Review Letters **86** 1900 (2001)

Babbs, C.F.J. Clin. Exp. Cardiol **5** 2 (2014)

Bacry, E., Delour J., Muzy J.F., et al. Physical Review E **64** 026103 (2001)

Badii, R., et al. Physical Review Letters **52** 1661 (1984)

Badii, R., et al. Journal of Statistical Physics **40** 725 (1985)

Bahar, S., Europhysics Letters **56** 454 (2001)

Barabási, A.L., et al. Physica Review A **44** 2730 (1991)

Barnes, J.A., et al. Proc. IEEE **54** 176 (1996)

Bartsch, R., et al. Physica A **354** 415 (2005)

Bashan, A., et al. Physica A **387** 5080 (2008)

Bassingthwaighte, J., et al. Annals of the New York Academy of Science **591** 392 (1990)

Batty, M., et al. Academic Press: London, UK (1994)

Batty, M., et al. Discret. Dyn. Nat. Soc. **3** 109 (1999)

Batty, M., et al. Springer: Berlin, Germany, pp. 21–45 (2012)

Batty, M. The New Science of Cities; MIT Press: Cambridge, MA, USA (2013)

Beaulac, S., et al. Physics of Fluids **16** 2126 (2004)

Benbachir, S., et al. Int Research J of Finance and Economics **78** (2011)

Benguigui, L., et al. Environ. Plan. B **27** 507 (2000)

Billat, V.L., et al. Physica A **388** 3798 (2009)

Bisoi, A., et al. Pattern Recognition Letters **22** 631 (2001)

Biswas, M., et al. Pattern Recognition Letters **19** 309 (1998)

Blanton, R., et al. Psychiatry Research **107** 29 (2001)

Blesic, S., et al. Physica A **268** 275 (1999)

Boiangiu, C.A., 6th Int Conf Proceed on Applied Informatics and Computing Theory, Salerno, Italy (2015)

Box, G.E.P., et al. Prentice Hall, New Jersey (1994)

Bradley, E. Springer: Berlin, Germany (2003)

Bradley, E., et al. Chaos **25** 097610 (2015)

Brown Clifford, T., et al. Journal of Archaeological Science **30** 1619 (2003)

Buldyrev, S.V., et al. Physical Review E **51** 5084 (1995)

Buldyrev, S.V., et al. Physica A **249** 430 (1998)

Bullmore, E., et al. Psychological Medicine **24** 771 (1994)

Bunde, A., et al. Fractals in science, Springer, Berlin (1994)

Bunde, A., et al. Physical Review Letters **85** 3736 (2000)

Byng, J., et al. Physics in Medicine and Biology **41** 909 (1996)

Caldwell, C., et al. Physics in Medicine and Biology **35** 235 (1990)

Carbone, A., et al. Physica A **344** 267 (2004_a)

Carbone, A., et al. Physical Review E **69** 026105 (2004_b)

Carbone, A., Stanley H.E., et al. Physica A **340** 544 (2004_c)

Carbone, A., Physical Review E **76** 056703 (2007)

Carbone, A., Science and Technology for Humanity (TICSTH) IEEE **691** (2009)

Carpena, P., et al. Physical Review E **75** 032903 (2007)

Carter, P.H., et al. Materials Research Society, Pittsburgh, (1985)

Cartwright, T.J. J. Am. Plan. Assoc. 57 44 (1991)

Caruso, F., et al. Fractals **14** 179 (2006)

Caswell Schuckers, S. Computers in Cardiology **1998** (13–16) 265 (1998)

Chakraborty, S., et al. International Journal of Computational Cognition **9** (2011)

Chatfield, C. Taylor & Francis Ltd. (2003)

Chaudhuri, B., et al. IEEE Transactions on Pattern Analysis and Machine Intelligence **17** 72 (1995)

Chen Z., et al. Physical Review E **71** 011104 (2005)

Chen, C. Springer: London, UK (2006)

Chen, S., et al. IEEE Transactions on Pattern Analysis and Machine Intelligence **15** 1087 (1993)

Chen, W.D., et al. International Conference on Transportation Engineering 2007 (ICTE 2007)

Chen, W.L., et al. Microwave and Optical Technology Letters **49** 7 (2007)

Chen, Y., et al. Chaos Solitons Fractals **35** 85 (2008)

Chen, Z., et al. Physical Review E **65** 041107 (2002)

Chen,W.C. Chaos Solitons Fractals **36** 1305 (2008)

Chhabra, A., Jensen, R., Physical Review Letters **62** 1327 (1989)

Chianca, C.V., et al. Physica A **357** 447 (2005)

Choudhury, P.P., et al. arXiv:0909.2517 (2009)

Churchill, M., Keble Summer Essay: Introduction to Fractal Geometry Pg 1-24 (2004)

Cohen, N.L., Communications Quarterly, **5** 3 (1995)

Cohen, N.L., Communications Quarterly, **6** 3 (1996)

Conlon, T., et al. Physica A **388** 705 (2009)

Cook, M., et al. European Neurology **35** 327 (1995)

Costa, R., et al. Physica A **329** 231 (2003)

Cottet, A., et al. Physical Review Letters **92** 206801 (2004)

Cross, S., et al. Journal of Pathology **170** 479 (1993)

Cross, S., et al. Journal of Pathology **173** 115 (1994)

Das, A., et al. Fractals **14** 165 (2006)

Daubechies, I. Communications on Pure and Applied Mathematics **41** 909 (1988)

De Bartolo, S., etg al. Water Resources Research **40** W02201 (2004)

Decoster, N., et al. European Physical Journal B **15** 739 (2000)

Delignieresa, D., et al. Journal of Mathematical Psychology **50** 525 (2006)

DePenya, F.J., et al. Global Finance Journal **18** 84 (2007)

Dick, O.E., et al. Neurocomputing **82** 207 (2012_a)

Dick, O.E., et al. Human Physiology **38** 249 (2012_b)

Drożdż, S., et al. EPL (Europhysics Letters) **88** (2009)

Dubuc, B., et al. Physica Review A **39** 1500 (1989)

Dubuisson, M., et al. Pattern Recognition Letters **15** 419 (1994)

Enescu, B., et al. Annals of Disaster Prevention Research Institute, Kyoto University **47** B (2004)

Enescu, B., et al. Pure Applied Geophysics **162** 249 (2005)

Eom, G., et al. Physica A **383** 139 (2007)

Espinal F., et al. Proc. SPIE of Wavelet Applications **3391** 602 (1998)

Ezekiel, S., Proc. of the Applied Informatics **378** 220 (2003)

Falconer, K., John Wiley & Sons Ltd 2nd Edition (2003)

Feder, J., Fractals, Plenum Press, New York (1988)

Fighola, A., et al. Nonequilibrium Statistical Mechanics and Nonlinear Physics, **913** 190 (2007)

Free, S., et al. Cerebral Cortex **6** 830 (1996)

Ge, E., et al. Journal of Geographical Systems **15** 115 (2013)

Giese, E., et al. Erdkunde **61** 186 (2007)

Gilmore M., et al. Physics of Plasmas, **9** 1312 (2002)

Glass, L. Chaos **19** 028501 (2009)
Gleick, J., & Berry, M. (1987). Chaos-making a new science. *Nature, 330,* 293.

Glenny, R., et al. Journal of Applied Physiology **70** 1024 (1991)

Godano, C., et al. Geophysics Journal International **121** 385 (1995)

Goldbeter, A. Nature **420** 238 (2002)

Gorski, A.Z., et al. Journal of Anatomy **208** 353 (2006)

Goupillaud, P., et al. Geoexploration **23** 85 (1984)

Grassberger, P., Procaccia, I., et al. Physical Review Letters **50** 346 (1983)

Grassberger, P., et al. Journal of Statistical Physics **51** 135 (1988)

Grau-Carles, P., Physica A **287** 396 (2000)

Grau-Carles, P., Physica A **299** 521 (2001)

Grau-Carles, P., Physics A **360** 89 (2006)

Grech, D., Mazur Z.,et al. Acta Physica Polonica B **36** 2403 (2005)

Gu, G.F., Zhou W.X., et al. Physical Review E **74** 061104 (2006)

Gu, G.F., et al. European Physical Journal B **57** 81 (2007)

Guastello, S.J. Psychology Press: New York, USA (2013)

Guégan, D. Annu. Rev. Control **33** 89 (2009)

Guillemet, H. Ecole Nationale Supérieure des Télécommunications, Paris, France **171** (1996)

Guo, Q., et al. International Journal of Computer Assisted Radiology and Surgery **2** 336 (2007)

Gyuchang, L., et al. Physica A **386** 259 (2007)

Hajian, S., et al. Physica A **389** 4942 (2010)

Halsey, T.C., et al. Physica Review A **33** 1141 (1986)

Hamouche, M.B. Nexus Netw. J. 11 217 (2009)

Hastings, A., et al. Annu. Rev. Ecol. Syst. **24** 1 (1993)

Havlin, S., et al. Chaos, Solitons & Fractals **6** 171 (1995)

Havlin, S., et al. Physica A **273** 46 (1999)

Hayakawa, M., et al. Geophysics Research Letters **26** 2797 **(**1999)

Hayakawa, M., et al. Geophysics Research Letters **27** 1531 (2000)

Heneghan, C., et al. Physical Review E **62** 6103 (2000)

Holschneider, M. Journal of Statistical Physics **50** 953 (1988)

Hong, Z., et al. Proceed Int Conf on Computer Appl and Syst Modeling (ICCASM 2010), Taiyuan, China, October pp. 332–334 (2010)

Hoshi, R.A., et al. Auton. Neurosci. **177** 271 (2013)

Hsu, W.Y., et al. Journal of Neuroscience Methods **163** 145 (2007)

Hu, K., et al. Physical Review E **64** 011114 (2001)

Huang, Y., Yu S.et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3922-3925 (2007)

Hunt, G.A., Transactions of the American Mathematical Society **71** 38 (1951)

Hurst, H.E., et al. Constable and Co., Ltd, London (1965)

Hurst, H.E., Transactions of the American Society of Civil Engineering **116** 770 (1951)

Ida, T., et al. IEEE transactions on circuits and systems for video technology **8** 968 (1998)

Iftekharuddin, K., et al. Machine Vision and Applications **13** 352 (2003)

Iftekharuddin, K., et al. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society **4** 3064 (2000)

Imre, A.R., et al. Acta Biotheoretica **52** 41 (2004)

Innes, J.E., et al. Planning with Complexity; Routledge: London, UK (2010)

Ivanov, P.C., et al. Europhysics Letters **43** 363 (1998)

Ivanov, P.C., et al. Europhysics Letters **48** 594 (1999)

Ivanov, P.C., et al. Europhysics Letters **52** 40 (2000)

Ivanov, K., et al. European Physical Journal B **8** 665 (1999)

Iyengar, N., et al. The American Journal of Physiology **40** R1078 (1996)

Ilya, P., & Stengers, I. (1984). Order out of chaos: man’s new dialogue with nature. *New York*, *Bantam*.

Jafari, G.R., Pedram P., Hedayatifar L., et al. Journal of Statistical Mechanics P04012 (2007)

Jain, R., et al. Nature Reviews Cancer **2** 266 (2002)

Jánosi, I.M., et al. Physical Review E **71** 056126 (2005)

Jelinek Herbert, F., et al. Journal of Neuroscience Methods **81** 9 (1998)

Jiang, Z., et al. Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September (2005)

Jiang, Z.Q., et al. Physica A **381** 343 (2007)

Jin, X., et al. Pattern Recognition Letters 16 457 (1995)

Jizba, Petr., et al. Proceedings, 15th Applied Stochastic Models and Data Analysis (ASMDA 2013) International Conference, Mataró (Barcelona), Spain, June (2013)

John, Set al. MIT Press (Eds), London (1993)

Jun, et al., Physical Review E **73** 066128 (2006)

Jun, Y., et al. Proceedings of the 16th Annual International Conference of the IEEE Engineering in Medicine and Biology Society **1** 161 (1994)

Jung, W.S., et al. Physica A **361** 263 (2006)

Kalmanti E., et al. In Vivo **21** 641 (2007)

Kantelhardt, J.W., et al. Physica A **220** 219 (1995)

Kantelhardt, J.W., et al. Physica A **295** 441 (2001)

Kantelhardt, J.W., et al. Physica A **316** 87 (2002)

Kantelhardt, J.W. arXiv:0804.0747v1 [physics.data-an] (2008)

Kaplan, L. IEEE Transactions on Image Processing **8** 1572 (1999)

Katsuragi, H. Physica A 278 275 (2000)

Kedzia, A., et al. Medical Science Monitor **8** 46 (2002)

Keller, J., et al. Computer Vision Graphics and Image Processing **45** 150 (1989)

Kenkel, N., et al. Coenoses **1** 77 (1996)

Keough, K., et al. Journal of Microscopy **163** 95 (1991)

Kestener, P., et al. Physical Review Letters **91** 194501 (2003)

Kestener, P., et al. Physical Review Letters **93** 044501 (2004_a)

Kestener, P., et al. Image Analysis and Stereology **20** 169 (2004_b)

Kikuchi, A., et al. Early Human Development **81** 655 (2005)

Kimiagar, S., et al. Journal of Statistical Mechanics P03020 (2009)

Kiyono, K., et al. Physical Review Letters **95** 058101 (2005)

Koscielny-Bunde, E., et al. Physical Review Letters **81** 729 (1998)

Kravchenko, A.N., et al. Agronomy Journal **92** 1279 (2000)

Krenz, G., et al. Journal of Applied Physiology **72** 2225 (1992)

Kulish, V., et al. Computers in Biology and Medicine **36** 291 (2006)

Kurnaz,, M.L. Fractals **12** 365 (2004)

Landini, G., Rippin J.W., et al. Analytical & Quantitative Cytology & Histology **18** 167 (1996)

Lanyi, M. Springer-Verlag (Eds), Berlin, Heidelberg, New York 252 pp (1986)

Lapenna,V., et al. Geophysics **70** 11 (2005)

Layek, G.C. Springer: New Delhi, India (2015)

Lee, J.M., et al. Computers in Biology and Medicine **32** 3 (2002)

Lee, W., et al. Information Sciences **175** 177 (2005)

Lemmerling, P., et al. Advances in Experimental Medicine and Biology **510** 369 (2003)

Lévy-Véhel, J., et al. Technical report of INRIA-Rocquencourt, **1706** (1992)

Lévy-Véhel, J. Fractals **3** 755 (1995a)

Lévy-Véhel, J., et al. Technical report of INRIA-Rocquencourt, **2576** (1995b)

Li, H., et al. Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medecine and Biology Society **3** 1111 (1996)

Li, H., et al. Academic Radiology **14** 513 (2007)

Li, X., et al. Journal of Neural Engineering **2** 11 (2005)

Lim, G., et al. Physica A **386** 259 (2007)

Lippiello, E., et al. Physical Review Letters **100** 038501 (2008)

Litvin, V.A. Physica A **344** 178 (2004)

Liu, J., et al. Biophysical Journal **85** 4041 (2003)

Liu, Y., et al. Physical Review E **60** 1390 (1999)

Lopes, R., et al. International Journal of Computer Assisted Radiology and Surgery **3** 341 (2008)

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of atmospheric sciences*, *20*(2), 130- 141.

Maeda, J., et al. Proceedings of the 14th International Conference on Pattern Recognition **2** 991 (1998)

Makikallio, T., et al. American Journal of Cardiology 81 27 (1998)

Makris, G., et al. Proceed 5th Chaotic Model and Simul Int Conf, Athens, Greece, June pp. 309–318 (2012)

Mamishev, A.V., et al. IEEE Transactions on Power Systems, **11** 435 (1996)

Mandelbrot, B.B., et al. SIAM Review **10** 422 (1968)

Mandelbrot, B.B., et al. Water Resources Research **5** 321 (1969)

Mandelbrot, B.B. New York: W. H. Freeman and Company (1977)

Mandelbrot, B.B. The Fractal Geometry of Nature. Freeman (Eds), 468 pp (1983)

Mandelbrot, B.B. Scientific American **280** 70 (1999)

Mansury, Y., et al. Physica A **331** 219 (2004)

Mantegna, R.N., et al. CUP, Cambridge (2000)

Mantegna, R.N., et al. Nature **383** 587 (1996)

Mantegna, R.N., Stanley H.E., et al. Cambridge University Press, Cambridge (2004)

Martinez, P., et al. Radar **97** 135 (1997)

Masugi, M. IEEE Transactions on Circuits and Systems Part I, Regular Papers **53** 2318 (2006)

Matia, K., et al. Europhysics Letters **61** 422 (2003)

Matsushita, R., et al. Physics Letters A **368** 173 (2007)

Mavroforakis, M., et al. Artificial Intelligence in Medicine **37** 145 (2006)

May, R.M. Nature **261** 459 (1976)

Midha, P. 9th Biennial International Conference & Exposition on Petroleum Geophysiscs P-382 (2012)

Mielniczuk, J., et al. Computational Statistics & Data Analysis **51** 4510 (2007)

Mohammad, F., et al. Multifractal Structure in Indian Stock Market Indices 5 261 (2012)

Montanari, A., et al. Mathematical and Computer Modelling **29** 217 (1999)

Montrol, E.W., et al. Non-equilibrium phenomena ii from stochastics to hydrodynamics, Ed., J.L. Lebowitz, North-Holland, Amsterdam (1984)

Munoz, D.A., et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society **7** 6981 (2005)

Murali, S. M.Sc. dissertation, Nanyang Technological University, Singapore (2005)

Muzy, J.F., et al. Physical Review Letters **67** 3515 (1991)

Muzy, J.F., et al. International Journal of Bifurcation and Chaos in Applied Sciences and Engineering **4** 245 (1994)

Muzy, J.F., et al. Journal of Statistical Physics **70** 635 (1993_a)

Muzy, J.F., et al. Physical Review E **47** 875 (1993_b)

Nagarajan, R., et al. Physica A **354** 182 (2005)

Nagarajan, R., et al. Physica A **363** 226 (2006_a)

Nagarajan, R., et al. Physica A **366** 1 (2006_b)

Nayak, S.R., et al. J Adv Research Dyn Contr Sys **9** 76 (2017)

Nguyen, T., et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medecine and Biology Society **3** 3210 (2005)

Niu, M., et al. Chemical Engineering Journal **136** 364 (2008)

Normant, F., et al. Physical Review A **43** 6518 (1991)

Norouzzadeh, P., et al. Physica A **367** 328 (2006)

Novianto, S., et al. Pattern Recognition Letters **24** 365 (2003)

Oczeretko, E., et al. Folia Histochemica et Cytobiologica **39**(Suppl. 2) 75 (2001)

Ossadnik, S.M., et al. Biophysical Journal **67** 64 (1994)

Ostwald, M.J. Environ. Plan B **40** 644 (2013)

Oswiecimka, P., et al. Acta Physica Polonica B No 8 **36** (2005$_a$)

Oswiecimka, P., et al. Physica A **347** 626 (2005$_b$)

Oswiecimka, P., et al. Acta Physica Polonica B **37** 3083 (2006)

Oswiecimka, P., et al. Acta Physica Polonica A **114** 547 (2008)

Ott, E., et al. Physical Review Letters **64** 1196 (1990)

Owis, M., et al. IEEE Transactions on Biomedical Engineering **49** 733 (2002)

Oxley, L., et al. Environ. Model. Softw. **22** 580 (2007)

Packard, N.H., et al. Phys. Rev. Lett. **45** 712 (1980)

Pallikari, F., et al. Journal of Scientific Exploration **13** 25 (1999)

Pastén, D., et al. Physical Review E **84** 066123 (2011)

Patrzalek, E., General Introduction to Fractal Geometry, pp. 1–7, Eindhoven University of Technology (2006)

Pedram, P., et al. International Journal of Modern Physics C **19** 855 (2008)

Peitgen, H.O., et al. New York: Springer-Verlag (1992)

Peitgen, H.O., et al. Chaos and Fractals (Springer, Berlin, 2004)

Peng, C.K., et al. Nature **356** 168 (1992)

Peng, C.K., et al. Physical Review Letters **70** 1343 (1993)

Peng, C.K., et al. Physical Review E **49** 1685 (1994)

Peng, C.K., et al. Physica A **221** 180 (1995$_a$)

Peng, C.K., et al. Chaos **5** 82 (1995$_b$)

Penn, A., et al. Academic Radiology **6** 156 (1999)

Penzel, T., et al. IEEE Transactions on Biomedical Engineering **50** 1143 (2003)

Pereda, E., et al. Neuroscience Letters **250** 91 (1998)

Pereira, D., et al. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society **3** 1775 (2000)

Pereira-Pinto, F.H.I., et al. Chaos, Solitons & Fractals **22** 653 (2004)

Peter, E.E. John Wiley & Sons, New York (1994)

Phothisonothai, M., et al. Journal of Physiological Sciences **57** 217 (2007)

Pickover, C., et al. Computer Graphics **1** 51 (1986)

Pikkujamsa, S.M., et al. Circulation **100** 393 (1999)

Podobnik, B., et al. Physical Review Letters **100** 084102 (2008)

Podobnik, B., et al. European Physical Journal B **71** 243 (2009_a)

Podobnik, B., et al. Proceedings of the National Academy of Sciences of the United States of America **106** 22079 (2009_b)

Podobnik, B., et al. Physical Review E **84** 066118 (2011)

Prigarin, S., et al. Numerical Analysis and Applications **1** 163 (2008)

Pruess, S. Fractals in the Earth Sciences, C.C. Barton and P.R. La Pointe, Plenum Press (Eds), New-York **3** 65 (2007)

Puu, T. Springer Science & Business Media: New York, USA (2013)

Qianli, M, et al. Annual International Conference of the IEEE Engineering in Medicine and Biology Society **5** 4526 (2005)

Rak, R., et al. Acta Physica Polonica A **114** (2008)

Rangayyan, R., Nguyen, T.,et al. Proceedings of Computer Assisted radiology and Surgery (CARS) **1281** 1041 (2005)

Reljin, I.S., et al. Archive of Oncology **10** 283 (2002)

Richards, D. Chaos Theory in the Social Sciences, University of Michigan Press: Ann Arbor, MI, USA, pp. 89–116 (1996)

Rickles, D., et al. J. Epidemiol. Commun. Health **61** 933 (2007)

Rodriguez, E., et al. Physica A **375** 699 (2007)

Rosenow, B., et al. Physica A **324** 241 (2003)

Rosser, J.B. Univ of Michigan Press: Ann Arbor, MI, USA, pp. 199–213 (1996)

Roux, S.G., et al. European Physical Journal B **15** 765 (2000)

Roy, P.N.S., et al. Journal of Earth System Science **121** 1033 (2012)

Russel, D., et al. Physical Review Letters 45 1175 (1980)

Ruttiman, U., et al. Oral Pathology **74** 98 (1992)

Rybaczuk, M., et al. Folia Morphologica **55** 434 (1996)

Salinas, A., et al. Progress in Electromagnetics Research Symposium Proceedings, Marrakesh, Morocco, March **1171** 20 (2011)

Sanderson, B., et al. Tellus **42A** 550 (1990)

Santhanam, M.S., et al. Physical Review E **73** 015201 (2006)

Sato, K., et al. Proceedings of IEEE Transactions on Nuclear Science **43** 3230 (1996)

Scafetta, N., et al. Physica A **328** 561 (2003)

Schmitt, F. Europhysics Letters **34** 195 (1996)

Scrivener, J. Proceedings of Bridges: Mathematical Connections in Art, Music, and Science ed. Reza Sarhangi, pp. 185–92. Winfield, Kan.: Southwestern College (2000)

Serletis, A., et al. Physica A **380** 325 (2007)

Serletis, D. Chaos, Solitons & Fractals **38** 921 (2008)

Serletis, A., et al. Chaos, Solitons & Fractals **40** 2007 (2009)

Shadkhoo, S., et al. European Physical Journal B **72** 679 (2009)

Shan, Z., et al. Magnetic Resonance Imaging **24** 1015 (2006)

Shen, G. Int. J. Geogr. Inf. Sci. **16** 419 (2002)

Shen, J., et al. Europhysics Letters **86** 48005 (2009)

Sheng, Hu., et al. Proceedings of the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference IDETC/CIE Washington DC, USA, August (2011)

Singh, M., et al. Nuclear Tracks and Radiation Measurements **19** 417 (1991)

Singh, S.L. et al. Commun. Nonlinear Sci. Numer. Simul. **17** 521 (2012)

Sisodiya,, S., et al. Brain **120** 271 (1997)

Siwy, Z., et al. Physical Review E **65** 031907 (2002)

Small, M., et al. Chaos, Solitons & Fractals **13** 1755 (2002)

Smith, T., et al. The Journal of Comparative Neurology **331** 402 (1993)

Smith, T., et al. Brain Research **634** 181 (1994)

Smrcka, P., et al. Measurement Science Review **3** 13 (2003)

Soltys, Z., et al. Journal of Neuroscience Research **63** 90 (2001)

Stanley, H.E., et al. Physica A **299** (2001)

Staudacher, M., et al. Physica A **349** 582 (2005)

Stavroyiannis, S., et al. International Review of Financial Analysis **19** 19-24 (2010)

Stojic, T., et al. Physica A **367** 494 (2006)

Stosic, T., et al, IEEE Transactions on Medical Imaging **25** 1101 (2006)

Su, Z.Y., et al. Physica A **380** 418 (2007)

Su, Z.Y., et al. Physica D **221** 188 (2006)

Suetani, H., et al. Phys. Rev. E **86** 036209 (2012)

Sun, X., et al. Physica A. **291** 553 (2001)

Suri, J., et al. Springer (Eds) New-York 668 (2002)

Tabar, L., et al. Cancer **72** (suppl. 4) 1437 (1993)

Takahashi, T., et al. NeuroImage **32** 1158 (2006)

Talkner, P., et al. Physical Review E **62** 150 (2000)

Tamás, T., et al. Physica A **159** 155 (1989)

Tanki, N., et al. **26** 207 (2006)

Taqqu, M.S., et al. Fractals **3** 785 (1995)

Taylor, P., et al. British Journal of Radiology **67** 456 (1994)

Telesca, L., et al. Chaos, Solitons & Fractals **19** 1 (2004$_{a}$)

Telesca, L., et al. Journal of Asian Earth Sciences **54** 72 (2012)

Telesca, L., et al. Natural Hazards and Earth System Sciences, **5** 673 (2005)

Telesca, L., et al. Physics and Chemistry of the Earth **29** 289 (2004a)

Telesca, L., et al. Physics and Chemistry of the Earth **29** 289 (2004$_{b}$)

Telesca, L., et al. Physics Letters A **332** 398 (2004$_{c}$)

Telser, S., et al. Journal of Biological Physics **33** 19 (2007)

Teotia, S.S., et al. Indian Journal of Marine Sciences **36** 122 (2007)

Thakor, N., et al. IEEE Transactions on Biomedical Engineering **37** 837 (1990)

Thompson, P., et al. Journal of Neuroscience **16** 4261 (1996)

Tokinaga, S., et al. Electronics and Communications in Japan, Part 3 **80**(8) (1997)

Toweill, D., et al. Crit. Care Med. **28** 2051 (2000)

Tsui, A.K., et al. Mathematics and Computers in Simulation **48** 503 (1999)

Tulppo, M., et al. American Journal of Physiology - Heart and Circulatory Physiology **80** H1081 (2001)

Türk, C., et al. Physical Review E **81** 026706 (2010)

Vahabi, M., et al. Physica A **388** 3859 (2009)

Van De Ville, D., et al. Neuroscience PNAS. **107** 18179 (2010)

Vandewalle, N., et al. Physical Review E **58** 6832 (1998_a)

Vandewalle, N., et al. The European Physical Journal B **4** 257(1998_b)

Varotsos, P.A., et al. Physical Review E **66** 011902 (2002)

Varotsos, P.A., et al. Physical Review E **67** 021109 (2003)

Varotsos, P.A., et al. Physical Review E **71** 032102 (2005)

Veldkamp, W., et al. Medical Physics **27** 2600 (2000)

Vicsek, T. Physica A 168 490 (1990)

Viswanathan, G.M., et al. Physical Review E **55** 845 (1997)

Vyushin, D., et al. Geophysical Research Letters **31** L10206 (2004)

Wang, G., et al. Journal of Zhejiang University - Science A **8** 910 (2006)

Wang, G., et al. Medical Engineering & Physics **29** 375 (2007)

Wang, Yudong., et al. Physica A **389** 5759 (2010)

Wax, A., et al. Cancer Research **63** 3556 (2003)

Website of http://www.math.nus.edu.sg/aslaksen/gem-projects/maa/World of Fractal.pdf (accessed on 17 July 2015)

Werner, D.H., et al. Frontiers in Electromagnetics, IEEE Press Series on Microwave Technology and RF (1999)

Weron, A., et al. Chaos, Solitons & Fractals **11** 289 (2000)

Weron, R. Physica A **312** 285 (2002)

Wilcox, D., et al. Physica A **344** 294 (2004)

Woyshville, M., et al. Biological Psychology **35** 291 (1994)

Xia, Y., et al. IEEE Transactions on Image Processing **15** 614 (2006)

Xiong Zheng-feng. Estimating the Fractal Dimension of Financial Time Series by Wavelet, Systems Engineering-theory & Practice **12** 48-53 122 (2002)

Xu, L., et al. Physical Review E **71** 051101 (2005)

Xu, N., et al. Nonlinear Dynamics **61** 207 (2010)

Yu, C.H., Wu C.C.,et al. International Review of Economics & Finance **10** 19 (2001)

Yuan, J., et al. Performance Evaluation **61** 163 (2005)

Yuan, Y., et al. Physica A **388** 2189 (2009)

Yum, M.K., et al. Journal of Cardiovascular Electrophysiology **13** 788 (2002)

Zamani, A., et al. IJST A1 Iranian Journal of Science & Technology 39-51 (2011)

Zebendea, G.F., et al. Physica A **388** 4863 (2009)

Zeleke, T.B., et al. Agronomy Journal **96** 1082 (2004)

Zhang, H., et al. International Journal of Bifurcation and Chaos **12** 2293 (2002)

Zhang, L., et al. Neurobiology of Aging **28** 1543 (2006)

Zhang, X.S., et al. IEEE Transactions on Biomedical Engineering **46** 548 (1999)

Zhao, X.J., et al. Physica A **390** 3670 (2011)

Zhou, W.X. Physical Review E **77** 066211 (2008)

Zhou, W.X. EPL (Europhysics Letters) **88** (2009)

Zhuang, X., et al. Artificial Intelligence in Medicine **32** 29 (2004)

Zlatintsi, A., et al. Musical Instruments Signal Analysis and Recognition Using Fractal Features, 19th European Signal Processing Conference (EUSIPCO) (2011)

Zlatintsi, A., Maragos P., et al. IEEE Transactions on Audio, Speech and Language Processing, 21 737 (2013)

Zook, J., et al. Magnetic Resonance Imaging **23** 671 (2005)

Zorick, T., Mandelkern Mark, A., et al. PLOS ONE **e68360** 8 (2013)

Chapter 4
Previous Work

“Order is needed by the ignorant but it takes a genius to master chaos.”

— Albert Einstein

4.1 Emotion and visual perception

To illustrate the effect of emotion even in the most mundane of visual perception, let's look at the study by Reiner et al (2011). Participants influenced by negative/sad mood reported a slant steeper than those with positive/happy mood. This goes to show emotion not only changes one's interpretations of social events, but can also change the perceptions of the scale of the world. In fact, emotions routinely affect how and what our visual senses decide to see. In this section, we shall gloss over the effects emotion has on our visual perception. For detailed accounts, it is advised to study works such as Zadra & Clore (2011) and Niedenthal & Wood (2019).

As far back as 1943, research efforts based on Gestalt psychology argued that emotions attached during experiencing an object fundamentally altered perceptual representations of it (Schafer & Murphy, 1943). In more recent works, Niedenthal et al. (2000), exploring the exogenous levels of visual perception, argued that the perceiver's current emotional state affects and his efficiency of processing visual cues involving emotional stimuli. In a similar vein, Siegel et al. (2018) shows that visual percepts are infused with affective feelings, indicating the inseparability of affect from cognition and perception. Using CFS (Continuous Flash Suppression) paradigm, Gayet et al. (2016) provides evidence that fear-induced stimulus potentiates associated visual percepts. Now, not only emotional arousal guides attention to influence perceptual processing, but it also can influence pre-attentive processes. As demonstrated by Phelps et al. (2006), contrast sensitivity (process of discriminating between emotion-induced and neutral stimuli) increases following visuals of fearful faces. Again, while investigating the influence of any top-down motivational process, one important issue is to separate between perceptual and post-perceptual (or judgemental) responses. In such an attempt with ambiguous color stimulus, the results revealed that even low-level processing of basic perceptual features can be open to motivational top-down influences (Voss et al., 2008). In other words, the superordinate states (goals, tasks, actions, motives, emotional states, beliefs, expectations etc.) can have a wide-ranging influence on many aspects of information processing.

These studies indicate that emotions not only influence our experiences, all the way down to perception, but in fact these influences are quite frequent and possibly, multi-modal.

4.2 Emotion and auditory perception

It is well established that sounds evoke emotions and can provide affective information, perhaps more effectively than many other forms of information channels (Juslin & Västfjäll, 2008). Auditory percepts often help elicit emotional reactions in our everyday world - startled by the sudden sound of a door slamming, annoyed by the noise of horns honking in the street, pleased by the sound of a water stream in the forest etc (Tajadura-Jiménez & Västfjäll, 2008). Although humans are exposed to sounds continuously, researches on how humans respond to affective auditory stimulus is still underreported. Frequently, emotional experience has been defined as either discrete feeling states or states that can be placed along dimensions of experience (Levenson, 1999). This approach, following the 'basic emotion theory', assumes that there exist universal fundamental emotions, which are spontaneous and uncontrollable, and other emotions are derived from their complex combinations. Other approach characterise emotions in a dimensional model and emotional responses can be placed in affective space (Osgood et al., 1957).

Most researches on affective response to auditory stimuli is centred around its physical determinants (Tajadura-Jiménez & Västfjäll, 2008), i.e., focused on the affective state of *annoyance*, quantified in decibel level, or in loudness, sharpness etc (Guski, 1999). It has also been argued that intensity of sound and arousal might be analogous, since increasing loudness results in an increase in the orienting response. This assumption holds until a level where the intensity of the sound becomes highly aversive (85-90 dB) (Lang et al., 1990).

Physical properties of sound are no doubt an important factor in their affective appearances, but it is the psychological attributes that moderates the subjective interpretations. Many studies attempted to characterize natural acoustic stimuli on the basis of their affective quality (Bjork, 1985; Bradley & Lang, 2000). In these works, Physiological changes showed to be highly correlated with self-reported emotional reactions in terms of valence, arousal and dominance, indicating that acoustic cues activate the appetitive and defensive motivational circuits underlying emotional expression in ways similar to visual stimulus. In human social interaction, vocal cues are as important as visual cues, and human speech contains many features (melody, rate, pauses, intonation, etc.) which inform us about the speaker's affective state. Hietanen et al. (1998) explored how tendencies to approach or withdraw varied in response to vocal affective expressions. Results suggested that emotional expressions may be contained in vocal cues. Also, music and its ability to both express and produce emotions is an important field of study in auditory perception domain. A number of studies over the years have investigated and provided evidence of music's importance in eliciting affective responses (musical emotions are innate and pre-attentive perceptual processes in most cases) (Juslin & Sloboda, 2001; Ghosh et al., 2018).

4.3 Emotion and cross-modal perception:

As we have seen in the previous sections, emotion is significantly interrelated in affecting both the visual and auditory perception and subsequent cognition, separately. Usually, the studies on emotion have traditionally focused on restricted sensory aspects such as visual, auditory, tactile etc (Krishna, 2012). In real world, a wide variety of emotional cues reach different sensory channels simultaneously and interactions between different sensory modalities are usually nonlinear, i.e., the 'whole' is not a simple algebraic sum of its components (Bresciani et al., 2005; Seigneuric et al., 2010; Shimojo & Shams, 2001; Driver & Noesselt, 2008). Although neurobiological studies have shown that emotional signals delivered via different sensory modalities interact at multiple processing levels in the brain, influence each other, and form holistic percepts, involving a variety of brain structures from unisensory cortices to high-level association areas (Klasen et al., 2014), it is still not clear how multisensory input interacts with emotion and affects behaviour. In this section, we review briefly on the present state of research on emotional responses due to multisensory stimuli (interested readers should go through Schreuder et al. (2016) for a detailed review).

In a multisensory environment, each modality affects the other modalities, which can lead to the sensory cues to be multiplied, inhibited or even produce some novel effect as well (Schreuder et al., 2016). When Emotional stimuli across modalities are congruent, then the perceptions are enhanced and positively facilitated (De Gelder et al., 2005), whereas incongruent stimuli increase activation in regions involved in cognitive control and generates surprise (Ludden et al., 2009). The amygdala is activated when the stimuli is arousing, and the activity is significantly attenuated when a neutral stimulus is paired with an emotional one compared to conditions where emotional stimuli were present in both channels (Muller et al., 2012). Also, emotional information from one modality can automatically and unconsciously influence emotion processing in another. This is why sad (happy) faces are perceived sadder (happier) in combination with music that evokes a sad (happy) emotion. Interestingly, fear recognition in the voice is modulated by unconsciously recognized facial expressions but not by unconsciously recognized affective pictures, indicating that processing of facial expressions is more exogenous than pictures (De Gelder, 2002). In addition, this study suggests that negative or fearful stimuli are more likely to bias the perception than positive or happy stimuli (since the former is evolutionarily relevant to immediate survival).

In audio-visual context, it is seen that congruency among the modalities increase positive appraisal and requires less cognitive effort to accept the environment compared to incongruent stimuli (Russell, 2002; Baumgartner et al., 2006). Furthermore, when presented together, it is the visual cue that dominates the appraisal over auditory cues (Kuwano et al., 2001). The reverse is also argued by some (Vines et al., 2006). In our recent study, we showed how structural complexity of the auditory stimulus is consistent with visual and emotional correspondence related to it (Roy et al., 2020). Hence, it can be said that which modality would contribution majorly or influence the other that depends on the task parameters and related contexts. Altogether, knowledge on emotion and multi-sensory stimulus remains considerably limited since studies on this topic are still scarce and haphazard. Any holistic framework seems difficult to achieve given the variations in experimental conditions or methodological diversities.

To summarise, the growing interest in the neurobiology and psychology of emotion parallels a wider recognition of its importance to human experience. Intertwined with cognition, emotion determines our holistic view towards the environment surrounding us and our decisions regarding every aspect of it. Complex human behaviour, also, emerges from dynamic interactions between multiple processes and brain networks. Hence, emotion remains a guiding factor in navigating through the complex sea of perception and information in our everyday world.

4.4 COLOR, MUSIC, RASAS

Color and music form the very core of human sensory experiences. Although being two separate sensory perceptions, the awareness of the relationship between color and music has existed since ancient times. Aristotle wrote – "It is possible that colors may stand in relationship to each other in the same manner as concords in music." (Von Goethe, 2006). In eighteenth century, Sir Isaac Newton (1952, originally published in 1704) argued whether the harmony and discord of colors arise from the vibrational proportions propagated through optic nerves into the brain, much like sound arising from the vibrations of the air. This idea was furthered by Jesuits like Athanasius Kircher and Pere Louis Bertrand Castel in the next century - the latter even built a color-clavichord (ocular harpsichord) that linked music with color (Franssen, 1991). It was an attempt, albeit not well-accepted, to make the deaf experience the beauty of music by means of color. In the next century the German literary giant Goethe gave a rich analysis of colors in his seminal book 'Theory of colors'. He differed from the mathematical approach of Newton and his students and talked about the association of colors with moods, attitudes and emotional states. He believed that color and music, though not comparable with one another, stems from the same 'higher law' (Von Goethe, 2006).

The exploration of the interrelation between color and music blossomed in the twentieth century through some of the synaesthetic artists, musicians and architects like Alexander Scriabin (1872-1915) – creator of a color keyboard named *Tastiera per luce* (Ballard & Bengtson, 2017), Wassily Kandinsky (1866-1944) – wrote at length about the emotional qualities of colors and musical instruments that corresponds those emotions (Walz, 2013), Ira Belmont (1877-1964) – started the 'color-music expressionism' in painting, Gyorgy Doczi (1909-1995) – argued about shared harmonies in colors and musical chords (Doczi, 1981), Olivier Messiaen (1908-1992) and Johannes Itten (1888-1967), among others (Beattie, 1998). Their theories and analytical deductions formed the core of later developed concepts of color-music association, consistent with modern psychological ideas. Swiss expressionist painter Johannes Itten (1970) designed and elaborated a basic course on color in his book 'The elements of color' using inspirations from basic practice of music scales. In this book he also gave a chart of seven basic VIBGYOR color hues and their corresponding wavelengths and frequencies. Something similar was done by Gyorgy Doczi. From their works, it was seen that the musical tone C-B# was compared to the color green. Such correspondences of wavelengths and frequencies between other tonal combinations and colors were reported by Itten and they, together, formed a 12-pointed color star (Itten 1970, p. 48). This worked as a guideline of creating colors from musical scores. Later, in the last two decades on the previous century, systematic visual-auditory synaesthesia studies were conducted by Polzella and Biers (1987; Polzella et al., 1982; Polzella & Hassen, 1997). They concluded that "..*the link between chromesthetic responses and music are mediated by attributes common to both visual and auditory experience*."

Modern psychology has proposed two possible explanations regarding such mediating attributes. First one is direct correspondence of the two perceptions (direct link hypothesis). For example, Caivano (1994) says that properties of the musical scale maps properties of color (luminosity = loudness, saturation = timbre and size = duration). In similar manner, Pridmore (1992) argued that due to the similarity in the cyclic nature of both the octave and hue cycles, amplitude connects loudness to brightness/lightness and wavelength connects musical tone to hue. Effect of audio pitch on perceived brightness is also documented in some studies (Collier & Hubbard, 2004; Ward et al., 2006). In contrast to such directness, the alternate explanation involves an indirect relation between color and music via emotional association (emotional mediation hypothesis). In this view, colors are associated with music based on shared emotional content. It is seen in various studies that happy/sad music has a strong correlation with happy/sad color when mediated with an emotional component, even in non-synesthetes (Bresin, 2005; Palmer et al., 2013, 2016; Lindborg & Freiberg, 2015). Between these two possibilities, evidence supporting the latter has been in abundance (Isbilen & Krumhansl, 2016; Whiteford et al., 2018; Roy et al., 2020), that is to say, the color-music association is strongly influenced by emotional or affective mediation (as Whiteford et al., (2018) suggests, this doesn't negate the relevancy of the directness of music's perceptual properties in such association, since they carry information which helps determine the emotional character of the music).

The Western view of emotion (when perceived as mental states) is dominated by the basic emotion theory which includes: happiness, sadness, fear, anger, surprise, disgust (Ekman, 1992; Izard, 1992). However, there do exist concepts of some background and social emotion sets such as pain-pleasure, envy, empathy, guilt etc. (Tripathi et al., 2018). There are many arguments that have come up against the discreet states approach. Foremost of which is the psychological constructionist movement (see section 1.3) that says emotions are not fixed observable entities or natural kinds, rather products of various psychological processes interacting through neural mechanisms. Other arguments include lack of dynamism in considering emotional expression (which is crucial for certain emotional states), lack of functionalism (Campos et al., 1994), and lack of diversity in emotional taxonomy across cultures (Russell, 1991). Another glaring omission in dominant Western outlook of emotion is its experiential component, loosely termed as 'feeling'. The closest feature to it probably is 'Affect'. This constitutes the subjective experiential aspects of emotions as against the physiological changes and behavior accompanying emotions. The Indian traditional point of view towards emotion is, on the other hand, centred on this very idea and treats 'Affect' as the focal point (Ramaprasad, 2013). The major source that guides the Indian approach of emotion classification is the *Natyashastra* by Bharatha, written in the 2nd century AD (Kavi, 1934). This is probably the oldest surviving treatise on performing arts in the world and hosts a detailed compendium on the theory of emotions in a manner quite different than the Western view: it articulates the *Rasa* theory in light of the performer's pragmatic goal of conveying emotional states to the audience. *Natyashastra* discusses the practical means for creating a distinct mood through the performance, which evokes a certain 'sentiment' or 'Rasa', the aesthetic equivalent of an emotional tone, in the viewer. It is evident that this certainly corresponds to the experiential aspect of emotion in a direct manner, akin to Immanuel Kant's cognitive 'free play of imagination and understanding' or David Hume's generic aesthetic 'sentiment' (Higgins, 1907). *Rasa* is a conjunction of three components: (1) permanent dominant emotional states or *sthayibhava*: 8 in number (Erotic Love/*Rati*, Mirth/*Hasya*, Sorrow/*Soka*, Anger/*Krodha*, Enthusiasm/*Utsaha*, Fear/*Bhaya*, Disgust/*Jugupsa*, Astonishment/*Vismaya*), (2) transitory emotional states or *vyabhicaribhava*: 33 in number, feeds the dominant emotions but incapable of existing independently and (3) temperamental states or *sattvikabhava*: 8 in number, basically are the involuntary and spontaneous physiological changes while experiencing the emotion. Each of the *sthayibhava* serves as a basic affective tone to produce one sentiment or *Rasa*, each. They are: *Sringara* (The erotic, comes from *Rati*), *Hasya*(The comic, from *Hasya*), *Karuna* (The pathetic, from *Soka*), *Raudra* (The furious, from *Krodha*), *Veera* (The heroic, from *Utsaha*), *Bhayanaka* (The terrible, from *Bhaya*), *Bibhatsa* (The odious, from *Jugupsa*) and *Adbhuta* (The marvellous, from *Vismaya*) (Higgins, 1907). Another Rasa, called *Santa* (The peace) was later added and together, these are known as *Navarasa* or the 'Nine sentiments'. This Rasa theory of emotions laid down by Bharatha is the strong foundation that provides a perennial vision of the rich and complex world of emotions in Indian aesthetics.

The western taxonomy of emotions is more familiar with the negative emotions depicted in *Natyashastra* than its positive ones. Anger, Fear, Sadness/Sorrow and Disgust are well-documented in Western approach but concepts of Enthusiasm, Erotic Love, Astonishment or Peace are not (Hejmadi et al., 2000). Additionally, *Natyashastra* puts huge emphasis on the gestures and expressions unlike the western theories. It contains rich descriptions of how the emotions are to be expressed. Schechner (2003) considered the expressive treatments of *Natyashastra* to be comparable to the facial expression photographs from Ekman et al (1987). The main advantage that the Rasa theory enjoys over the Western ideas is the incorporation of conscious experience, which promises therapeutic implications.

Although mainly a discourse on dramaturgy, the emotional theory described in *Natyashastra* has expanded into the music and color perceptions as a guiding light, especially in Indian aesthetic perspective. Rasa, perceived as a sentiment, could also be described as an aesthetic experience, focused on two very basic characteristic: firstly, the disinterestedness or the feeling of exclusion, i.e., the experience makes the viewer/listener gradually grow unconscious of his/her existence. And secondly, the conscious realisations of joy of the experience, even painful events are represented through it. As Wieczorkowska et al. (2010) puts it – 'the Eastern approach to emotional aesthetics and intelligence treats rasa as a multi-dimensional principle that explains thoroughly the relation between a sentiment, a mood, the creative process and its transpersonal qualities'.Indian musicological treatment, mainly based on affective cues in *Natyashastra,* says that even individual notes bear the potential of producing emotional effects.In north Indian classical vocal music (also known as Hindusthani vocal music) *Raga* forms the musical basis. Ragas are congregations of various notes and musical properties (scale type, transilience, tessitura, characteristic motion etc.), and they elicit some specific emotions described in Rasa theory, although the same Raga could express more than one rasa (Kaufmann, 1965). There is a long tradition in assigning Ragas for evoking emotions in Hindustani and Carnatic systems (for example, Subhapantuvarali is said to evoke penitential emotions). And since Indian music is far less strict on structures, mostly not even having written scores, the characteristic phrases that identify the Raga can be elaborated multiple times, often with different ornamentations. Ragas are also assigned to a particular time of the day and particular season. Such associative elements, along with the complex relation between the composition, tempo, rhythm, and improvisational ornamentation correspond to a richly textured music with one (or more) deep emotional experiences. That is why various performers and scholars have agreed that the essence of Raga, that is the emotion it conveys, is not entirely reducible into these structural features. It is rather knowable only through the immersive experience of listening/performing. Clayton (2001) has categorised the following features of Rasa theory in regard to musical meaning:

It highlights the role of the perceiving subject and the importance of empathy.

● As a successor to the above point, this theory asserts on experience and affect; a piece of art is evaluated by its ability to invoke emotion among the perceivers.

● Rasa, literally standing for juice or essence, expresses the affective experience as a fluid and dynamic entity unlike Western static approach.

● Dissociates affect with the stimulus structure (structure is important, but not absolute).

● And of course, the emphasis on a holistic 'tasting', resisting reductionism.

He concludes, saying, that perhaps it is the nature of unwrittenness and abstraction of the pure auditory experience that "theorists allowed the affective power of music to remain within the irreducible domain of sound – something from which Western musicology could certainly learn."

Color perception and the emotional responses attached to it have strong psychological and physiological attributes - something which was incorporated in the Rasa theory efficiently, that too even long before the advent of any of the above as a serious scientific discipline. Generally, the emotional experience of color is elicited through association. The superficial association of a certain color with a certain deeper lying memory explains the affective responses (Cheriyan, 2017). The *Natyashastra* contains extremely detailed descriptions of garments and ornaments and their color combinations. According to Bharatha, *bhavanukarana* (or the 'imitation of the emotional states') becomes clear by the impact of colors. He also assigned a color corresponding to each Rasa, as given in Table below.

Rasa	**Color**
Shringara (Erotic)	Green
Hasya (Comic)	White
Karuna (Pathetic)	Dove-colored Grey
Raudra (Furious)	Red
Veera (Heroic)	Wheat Brown/ Pale Orange
Bhayanaka (Terrible)	Black
Bibhatsa (Odious)	Blue
Adbhuta (Wondrous)	Yellow

Table 1. Rasas and their corresponding colors, described in Chapter 21 of *Natyashastra* **(**Kavi, 1934)

The *Natyashastra* explains each color and the rationale behind choosing it to associate with said emotional state. For a brief review one should refer to Cheriyan (2017). Later studies on various aspects and properties of color and related psychological attributes have corroborated some of these ancient ideas. For example, studies on color and their association with mood-tones show that red is associated with 'exciting' and 'stimulating', both of which imply pleasure and high arousal. For Blue it is 'secure/comfortable' and 'tender/soothing', which imply pleasure and low arousal. On the other hand, Orange, associated with 'disturbing/distressed/upset', implies displeasure and high arousal and Black was associated with 'powerful/strong/masterful', implying high dominance (Wexner, 1954). Lakoff & Johnson (1999) proposed the conceptual metaphor theory of color where he argues that we think about abstract concepts like color in terms of metaphors to help understand and connect them with perceptual experiences. Hence, anger, which entails reddening of the face, is metaphorically described as 'seeing red'. Such metaphors drive moral judgements and stereotyping as well (White = pure and Black = evil). In his book (1991), Davidoff not only acknowledges the effect of warm or cool colors on physiological or emotional states, but believes that they affect the endocrine system directly via the pituitary gland. In another work with short wavelength lights, blue light in particular, is reported to activate the melanopsin photoreceptor system which, in turn, activates the brain structures involved in sub-cortical arousal and higher-order attentional processing (Cajochen et al., 2005). Also, psychological studies on combat fliers indicate that bodily reactions to anxiety and fear (pounding of the heart, tenseness of muscles, dryness of mouth, sickness in the stomach etc.) are quite similar to the ones described by Bharatha (Shaffer, 1947; Rachman, 1983). The treatise in *Natyashastra* is not only well founded in affective responses to colors, but it also described the primary colors as red , blue and yellow and the rest of the colors as derived compounds from the primary ones. According to Bharatha, appropriately painted body along with appropriately colored costumes are essentials in propagating the affective experience.

To summarise, investigating color and music perceptions and their association posit several challenges in both the fields of psychology and neurobiology. So does the abstractness of emotional experience. Despite that, one thing could be said with certainty - that to find connections between different perceptual events, it is emotions that are forming the cognitive bridges. Emotions are so much innate to our lives that they are central not only to how we interpret incoming information, but also to how we respond to them. Although the question remains on the best possible approach to explore emotions – Western stoicism vs. Eastern dynamism – but given the myriad connections from perceptions to emotions and from emotions to actions, it seems quite natural that emotions emerge so strongly, and perhaps, unconsciously.

4.5 A Summary on Studies Regarding Color Perception

Humans encounter the world primarily through color. Color is perceived on essentially every object that we view in daily life. A person with normal color vision experiences a vast and rich chromatic palette, i.e., up to 2.3 million discernible colors (Linhares et al., 2008). Considerations about color or color combinations emerge regularly in our everyday decision making and conversations, from the color of clothes to wear, or the color for a new car, to passing judgements on the color of someone's skin, hair, or makeup. Popular opinions abound on the nature of color associations and on presumed influences of color on our feelings, aesthetic judgments, and beyond.

Empirical research on color perception has a long history (Elliot & Maier, 2014; Elliot, 2019). Goethe, back in 1810, gave observation-based accounts of color perception and its association with emotional states (or 'feelings') in his book *Theory of colors* (Von Goethe, 2006). Some colors were assigned to induce positive feelings and some induced negative ones. According to him, Red is associated with both gravity and lightness, Blue with coldness and negativity, Green with calmness, Yellow with warmth and Orange with energy and power. Later in the same century, psychologist and writers like Wilhelm Wundt and Grant Allen addressed this issue in a similar manner and associated color with emotions based on experience and observation. They shared similar ideas such as: White is linked to positive emotions (pleasant, stimulating, cheerful), Black to negative emotions (unpleasant, gravity), Yellow and Red are exciting and arousing, Blue is depressing/relaxing, and Green is linked to tranquillity and calmness (Wundt, 1874; Allen, 1877). Subsequent quantitative researches from Charles Féré (1887) and Hugo Münsterberg et al. (1894), involving color stimulus and physiological signatures – pulse rate, respiratory pattern, head and eye movement – demonstrated that Red (and Yellow, in the latter) had a comparatively higher arousal and attention capturing effect whereas Blue (and Green, to some degrees) is calming/relaxing. Also, in some color preference studies, Blue was reported to be the most preferred color, followed by Red (Cohn, 1894; Jastrow, 1897).

These early empirical works, for obvious reasons, show various methodological weaknesses, such as: not maintaining participant naiveté and confidentiality (they, often, knew hypotheses beforehand and were individually identifiable), participants' color vision deficiency was not assessed, sample sizes were small, color stimuli and background color (also ambient illumination) were not precisely specified etc.

In the next century, color perception studies blossomed thanks to the advancement of science and gradual understanding of the underlying mechanism of light and vision. With that, the focus shifted towards the change in behavioral or psychological manifestation with changing color wavelengths (Nakshian, 1964). But even after studies spanning a good part of the century, the results are not always conclusive. For example, a study by Hill and Barton (2005) suggests that the color Red can be associated with dominance and aggression in both human and non-humans. Another one associates similar responses in human with Black, in competitive sports' perspective (Frank & Gilovich, 1988). Numerous studies on color and its association with different psychological attributes show that the longer wavelength colors like Red have an enhanced effect on such attributes. For example: viewing Red and feeling excited or stimulated (Goldstein, 1942; Ou et al., 2004; Buechner & Maier, 2016), wearing Red and exhibiting increased strength during combat sports (Hill & Burton, 2005; Dreiskaemper et al., 2013), enhanced attraction towards opposite sex when they wear Red (Elliot & Niesta, 2008) etc. On the other hand, shorter wavelength color such as Blue is reported to have increased effect on alertness (Vandewalle et al., 2007). Blue has also been found to elevate perception of trustworthiness in marketing research (Lee & Rao, 2010). When compared during cognitive task performances, it was seen that Red encourages avoidance motivation and analytical execution. Contrarily, Blue exhibit approach motivation and encourages creative performance (Mehta & Zhu, 2009). Majority of studies compare effects of colors Red and Blue because their wavelength differences put them on the opposite end of the spectrum. Few studies have ventured into other colors and linked Green with calmness (Suk & Irtel, 2010) and Orange/Yellow to excitement (AL-Ayash et al., 2016) but other studies disagreed (Ainsworth et al., 1993; Briki & Hue, 2016; Wilms & Oberfeld, 2018). The general trend in the literature available shows that the association between Red and excitement is the most reported scenario. The association of calmness/relaxation has been divided majorly between colors Blue and Green.

Another avenue of color perception research is studying the physiological response due to color stimulus exposure. Studies done in this area are mostly motivated by the hypothesis that long-wavelength colors (red/yellow) are more arousing than short-wavelength colors (blue/green). Although the fundamental question that remains unanswered in this field is whether the response is direct (i.e., stimulus evokes the response directly without cognitive intermediation) or indirect (cognition acts as an intermediary) (Kaiser, 1984). To measure physiological signals, varieties of parameters have been used – Galvanic Skin Resistance, Heart rate, respiration, blood-pressure etc. EEG remains the mostly used form of technique among them. Gerard (1958) used EEG to report high cortical arousal (the lower prominence of alpha waves) under the effect of Red color. Since then, brain activity during color exposure is studied by measuring the alpha waves. These EEG studies have given contradictory reports too: some argue that Red is associated with higher physiological arousal (Deutsch, 1937; Wilson, 1966; Ali, 1972), some disagree or remain unconvinced (Brown, 1966; Choi et al., 2011; Sakuragi & Sugiyama, 2011). During cognitive tasks, Blue light is reported to induce higher arousal and brain activity as well (Klimesch, 1999). Similar effects were attributed to Orange, Yellow and Violet (when compared to Green) by some (Erwin et al., 1961; Nourse & Welch, 1971; AL-Ayash et al., 2016).

The psychological investigations of color perception have relatively higher agreement in terms of generality than its physiological counterpart where the general outcome remains largely inconclusive. Also, majority of these studies explore the applicative side of the problem, i.e., establishing relationship between one particular color and one behavioural trait. The underlying neural mechanism is not addressed or explained. Evidently, the numbers of works on color induced EEG are in short supply; detailed studies on the physiological manifestations (especially that on the brain) is required to further our understanding about the problem. Taking this into account, an attempt was made in this thesis to investigate the brain response (via EEG) to color stimuli using novel nonlinear analysis techniques which are far more robust and efficient in detailing the underlying dynamics than any of the linear methods previously used. The obtained results not only report some unprecedented trends regarding color perception, but also analyses the existing ones, to a good degree of success, in the light of state-of-the-art nonlinear chaos-based tools and parameters.

4.6 Cross Modal Correspondence: An Overview

Human senses are separate entities designed to perform separate specific duties. By definition, they are not supposed to poke their noses (pun intended) into each other's responsibilities. For example, eyes don't go tasting food or skin doesn't try to visualise objects. Or so it was thought. Counter-intuitively, it is not the distinctness of the senses that shapes the human perceptual world, but it is their power of combining. More often than not one sensual modality crosses path with the other. Depending on whether such 'superposition's are constructive or destructive, human experiences about the external environment either thrive or thwart. At the outset, the cognitive neuroscience research on multisensory integration have examined the temporal and spatial aspects of multimodal perception, i.e., how closer the different stimuli (presented to different modalities) are on a time scale (Jones et al., 2006; Shore et al., 2006), or spatially in some cases (Frens et al., 1995; Slutsky & Recanzone, 2001). Based on the nature of the stimulus attributes, multisensory perception can be either semantically congruent (Chen & Spence, 2010; Grassi & Casco, 2010; Doehrmann & Naumer, 2008) - meaning the paired-up stimuli have different identity and meant to stimulate two different senses – or they can be synaesthetically congruent (Gallace & Spence, 2006; Evans & Treisman, 2010) – correspondences between basic stimulus features shared in different modalities – or, a bound effect of both of these together, known as the "unity effect" (Vatakis et al., 2008). There are a number of different ways in which sensory information can be associated. Due to the basic amodal redundant features of the stimulus, or seemingly unrelated modal features, or abstract features like pleasantness, user arousal potential or potential to change affective states like emotion etc. - reasonable evidences have supported the claim that crossmodal correspondences can occur from such low-level amodal properties to high level cognitive properties. For a detailed review on this topic, see Spence (2011). The initial researches on multimodal association involved sound symbolism – associating a sound (usually nonsense) with a shape. It was seen that subjects associate a specific phonetic with a specific shape (for example, in Sapir (1929),

“mal” and “mil” were linked to large and small rounded objects, respectively) (Köhler, 1929). In recent years, interest in this research has rekindled, due to the advances in neuropsychological studies and related investigations (Ramachandran & Hubbard, 2001, 2003; Ramachandran & Oberman, 2006; Nuckolls, 2003). The *bouba/kiki effect*, as it is called, shows that ‘bouba’ is associated with rounded edged star whereas kiki with sharp edged star. Curiously enough, this effect doesn’t hold in children with autism spectrum disorder, which is suggestive of high-level neural mechanisms behind such phonetic symbolism. Besides this stream of works, there are a lot of studies in semantic congruency which reported many non-arbitrary crossmodal correspondences between a variety of auditory and visual stimulus features. For instance, between brightness and loudness (Bond & Stevens, 1969), high-pitched tones with bright surfaces (Marks, 1974), loud sounds with high contrasting visuals (Wickers, 1968) and association of high pitch with high elevations (Roffler & Butler, 1968). Developmental researches showed that the perception and association between multiple senses is exhibited in children under 2 years of age: loudness and large objects (Smith & Sera, 1992), auditory pitch and visual elevation (Walker et al., 2010). Sensory integration is documented in other modalities as well, such as – vision and touch (Martino & Marks, 2000), flavours and auditory stimulus (Crisinel & Spence, 2009), colors and odour (Kemp & Gilbert, 1997), smells and shapes (Seo et al., 2010), and even shapes and flavours (Gal et al., 2007). From these studies, it appears likely that crossmodal correspondences exist between all possible pairings of sensory modalities.
The obvious question that follows is – whether the effect of simultaneous sensory stimulus can help or hinder sensory information integration in one certain modality. In their seminal paper, Bernstein and Edelstein (1971) showed that subjects respond more slowly to visual stimuli when their elevation happens to be inconsistent with the relative pitch of a task-irrelevant sound. The association between auditory pitch and visual elevation has turned out to be one of the most reported and replicated event in later researches. Since then, such speeded classification studies have been conducted involving various modal features, and it was seen that people find it harder (slower and less accurate) to classify the target stimuli presented in one sensory modality (e.g., vision) when the distractor stimuli presented in a task-irrelevant modality (e.g., audition) happen to vary incongruously with the target dimension (Marks, 2004). Later, Gallace & Spence (2006) reported similar findings in a visual size discrimination task. Additionally, their results indicated that such effects were more relative than absolute, dependent on experimental conditions and stimulus dimensions under consideration (Spence, 2011). Evans & Treisman (2010) suggested that bidirectional correspondence exist between auditory pitch and visual elevation, size and spatial frequency. Although their methodological treatment shows that these effects were fundamentally perceptual and not some form of response compatibility effect, despite that, most of the speeded classification studies fall under the disputed umbrella on whether the observed effects are decisional/response related or actually perceptive (Marks, 2004).

Among various models of cross-modal associations, one of the recent and most interesting involves the Bayesian integration theory (Ernst, 2006). This theory suggests that humans combine the sensory information in a statistically optimal manner by combining prior knowledge regarding them and weighting each of them by their relative reliabilities. Hence, the strength of crossmodal combination of two stimuli depends on the prior knowledge of our sensory system that those two can couple effectively: this knowledge is expressed using ‘coupling prior’, a representation of the expected joint distributions of the signals. According to such a Bayesian model, ‘the reliability of a person’s estimate regarding intersensory conflict is proportional to the strength of the coupling between the signals being integrated’ (Ernst et al., 2007). Meaning, stronger the coupling between the unimodal stimuli, better the chances that they would be blended together to form one multimodal percept. This effect can be interpreted in terms of differences in the strength (i.e., variance) of the coupling prior: for stimuli which are congruent in cross-modal aspect, the variance is small; and it is opposite in case of incongruent ones. Studies have reported that the strength of the crossmodal association can be modulated by meddling with or influencing the variance of the coupling prior (the knowledge about the modal stimuli) (Ernst, 2007; Helbig & Ernst, 2007). Also, a number of previous studies on multimodal correspondence can be explained using the Bayesian approach (Spence, 2011). That being said, it is possible that some of the reports result from the abnormal traits of the neural mechanisms responsible in integrating modal information.

When discussing about the neural mechanisms behind cross-modal correspondence, the first issue that is needed to be addressed is the representation of such effects in the neuroanatomical structure of the brain. Areas in the temporal cortex like superior temporal sulcus are shown to respond to cross-modal stimuli (Beauchamp et al., 2004a, 2004b). Also, damaged angular gyrus can interfere with a person's ability to match stimuli cross-modally (Ramachandran & Hubbard, 2003). Moving to the next concern, which is the change on a neurobiological level during new cross-modal associations, enhancement and suppression of activity in the task-relevant and task-irrelevant sensory systems (thalamic structures), respectively, were found when concurrently presented auditory and visual stimuli are paired by chance. But when information in the two modalities is reliably associated, activity is enhanced in both systems regardless of which modality is task-relevant (Baier et al., 2006). This indicates that when multisensory information is expected to integrate, the neural mechanism facilitates the process. And conversely, it suppresses the process when information is judged as a distraction. Another study also reported such implicit associations in Primary visual and auditory cortex using PET scan (Zangenehpour & Zatorre, 2010), something that was achieved within 45 minutes of exposure to congruent stimuli and lasted for more than 24 hours. Reports from these neuroimaging studies suggest that cross-modal connectivity is evident in the neurobiological level, which facilitate multimodal correspondence even in the presence of a unimodal component of a multisensory pair.

Another growing body of work had emerged in recent times where they dealt with cross-modal correspondence regarding complex auditory and visual stimuli, that is, music and color or painting (Barbiere et al., 2007; Palmer et al., 2013, 2016; Whiteford et al., 2018; Albertazzi et al., 2015). The main difference this stream of literature has from the main body of cross-modal studies is that their advocacy of the emotional mediation, typically illustrated by the participant's response to the stimulus on a number of semantic differential scales (Parrott, 1982). Spence (2019) has detailed a chronological review of this field. This review centres on a large number of studies, most of which used short classical music pieces (except Lindborg & Freiberg (2015) who used film music) and color patches and asked participants to associate the music with their choice of colors. The major findings in those works indicate that Grey is usually associated with sad music whereas lighter and saturated colors are associated with happier music. Also, Palmer et al. (2013) linked faster and slower music with saturated (and lighter) and unsaturated (and darker) colors. Isbilen & Krumhansl (2016) found color correspondence with various musical attributes like tempo, mode, pitch etc. Highly significant correlations were reported between colour–music matches and the similarity of the emotional content by Whiteford et al. (2018). Although the cross-modal correspondence results in these studies are interesting, but Spence questions whether emotional mediation is based on the emotion experienced in response to the music, or rather, on a more cognitive assessment of the emotion. With the definition regarding emotion not clearly addressed, it is often difficult to distinguish between perceptual and induced emotion. Hence, doubts remain on emotion and its affective correspondence during musical intervention (Marin & Bhattacharya, 2010).
Rapid growth in the multisensory research in the last few decades have demonstrated that cross-modal correspondence, in both perceptual and decisional levels, has influenced people's performance in a wide range of different paradigms, including direct cross-modal matching, speeded classification tasks, speeded simple detection tasks, perceptual discrimination tasks and the likes. Various classes of structural, statistical and semantic correspondences highlight their importance in human information processing and its perceptual view of the world around.

In light of this, we have attempted to address a relatively newer approach in the study of multimodality (Music and color associations, specifically) involving emotion as a mediator in this thesis. Our argument follows from the fact that both color and music have similar emotional qualities that inspire arousal in a similar manner, even from a young age (Cutietta & Haggerty, 1987). We hypothesise that the structural complexities of music and the basic components of compound color share a possible correspondence, and it is facilitated by the emotional cues shared by both of these stimuli. Applying latest fractal-based methodologies, well documented in scrutinizing the complex nonlinear nature of non-stationary signals, we seek to obtain a quantitative correlation between music, color and perceived emotion.

4.7 Nonlinear effects of music and color on human body

In spite of the undeniable importance of color vision to the development of human civilization, its neural basis continues to be a mystery. The electroencephalogram (EEG) is being used to investigate how the brain interprets various color inputs. A total of 16 people with normal color vision had electrodes placed in their temporal, frontal, and occipital lobes while they were shown images of seven VIBGYOR colors. In order to learn how the brain responds to various hues, EEG recordings were put through an analysis with two of the most recent non-linear algorithms (MFDFA and MFDXA) for complicated time series. According to research conducted by MFDFA, the EEG signal is at its most complex when the color blue is being viewed, followed by the colors red and green. When compared to the baseline grey, the MFDXA shows a lower inter and intra lobe correlation after viewing the VIBGYOR hues, which indicates that visual information is processed thereafter. This inquiry has the potential to create an indelible mark on the field of color perception thanks to the new approaches that were taken and the results that were drawn from it.

Since the beginning of time, people have been having experiences with color and forming opinions about how it should be seen. Color reshapes the complexity of visual information for a variety of purposes, ranging from survival and evolution, such as the selection of food and navigation, to aesthetics, such as the range of artistic expressions across time and space and emotional responses to different stimuli, to modern uses, such as corporate branding (Hanson 2012). Vision and visual processing have received more attention than any other sensory modality since seeing things and doing so visually has historically been our major means of engaging with the world around us (Hutmacher 2019; Pike et al. 2012). The usefulness of color is diminished due to the fact that it is both subjective and dependent on context (Lotto and Purves, 2002; Elliot and Maier, 2012).

Despite this, studying how the brain processes color vision is fascinating and important for a variety of reasons, including both practical and theoretical applications. The research that has been done on visual perception looks at both the psychological and physiological elements of the topic.

4.8 Approaches to Emotion Recognition Using Bio- signals

A significant amount of work has been conducted by Picard et al. at the MIT Laboratory showing that certain affective states may be recognized by using physiological data of heart rate, skin conductivity (SC), muscle activity, temperature as well as RSP velocity. A personalized imagery system was used to extract target emotions from a subject who had two years of experience in acting while achieving an overall 81% of recognition accuracy in eight emotions by using hybrid linear discriminant classification.

A study by Nasoz et al. involved the use of movie clips to extract specific emotions from 29 participants. They achieved an emotion classification accuracy rate of 83% using the Marquardt Backpropagation algorithm (MBP). In a separate study, a single participant was shown images from the International Affective Picture System (IAPS) photoset to elicit emotions with varying levels of arousal and valence. The participant's emotional responses were classified using a neural network, resulting in recognition accuracy rates of 96.6% for arousal and 89.9% for valence.

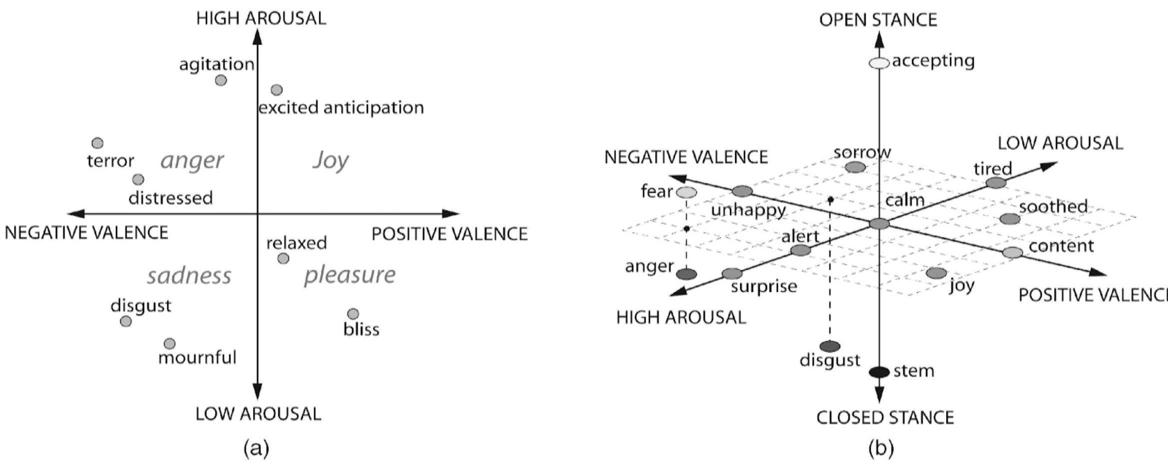


Fig 4.1. Emotion models. (a) a valence & arousal 2-dimensional model (b) 3-dimensional model including stance.

Kim and colleagues conducted a study on 175 children aged five to eight to explore how specific emotions (sadness, anger, stress, and surprise) could be evoked using a protocol based on multimodal stimuli. To achieve this, they developed a set of recording protocols and utilized pattern classifiers as support vector machines. The classification ratio achieved was 78.43 percent for three emotions (namely sadness, stress, and anger), and 61.76 percent for four particular emotions (sadness, stress, anger, and surprise). In contrast to previous studies that required longer signal lengths of about 2-6 minutes, the analysis steps were designed to handle relatively short input signals that were segmented into 50-second intervals.

The accuracy of valence differentiation is always lower than that of arousal discrimination: a finding that enabled the development of a classification scheme based on emotional characteristics. The calculation of a varied range of features in various analytical domains extracting valent features from ECG and RSP signals. However it is true that recognition rates are strongly dependent both on the used data sets on the context of application.

Participants were then instructed to emulate specific emotions while viewing selected photos or watching videos intended to evoke those emotions. However, individual differences in emotional states or mood were not taken into account, which could lead to inconsistencies in the resulting data sets. Another way inconsistencies can arise are due to the variations in how individuals label their emotional responses and situational variables affecting their respective ANS activities. Most of the previously mentioned engineering methods, however, suggest that the precision of identifying arousal is consistently higher than that of distinguishing valence. This could be attributed to the fact that the changes in arousal levels can be directly associated with the intensity of ANS activities, including sweat gland function and blood pressure, which are comparatively easier to evaluate. Conversely, distinguishing the valence of emotions requires a comprehensive analysis of ANS responses that are cross-correlated across multiple factors. Thus, this discovery pushed for the creation of a classification system specifically looking for emotional correlations, which involves the computation of a diverse range of features in multiple analytical domains to extract characteristics in the valence domain from RSP and ECG signals.

4.9 EEG Analysis during Music Perception

Musical emotion, cognition, syntax, and other brain functions are covered in the literature on EEG analysis in musical perception. We are to discuss musical style characteristics in this introduction to build EEG applications in music-brain interactions.

Music is everywhere in many styles. Musical perception incorporates syntactic processing, emotion, and sensation [1, 2, 3, 4]. The listener's age, cultural level, socioeconomic and cultural environment, musical experience and learning, familiarity with the sort of music heard, psychological condition, and preferences affect musical perception [5, 6, 7]. Nonetheless, the conflict between cognition and musical feeling has been extensively researched, leading to a continuum [8]. Reception of musical material includes understanding of structures and predictability, as well as feelings like happiness or melancholy. Concepts blend to create cognitive and sensitive perception.

Tonality (formerly modality), prevalent in Western academic and popular music since mediaeval times, is crucial to musical perception. Harmony underpins the tonal system. Intervallic relations can be harmonious, making humans feel good, or discordant, causing tension. Consonant chords relax, discordant chords tense. Intervallic relations are simplified because music theory, and harmony in particular, is a vast and complicated field that has been shaped by musical styles and history. Electroencephalography literature has examined many of these concepts.

Music recognition has relied heavily on cognition. Musical cognition involves perceptual and cerebral learning of the tonal hierarchical framework that dominates our culture [6]. Short-term memory affects how we hear Western music's tonal distributions [9]. Another extremely important topic that has been widely discussed is the predictability of the tonal system. Tonal music evolves briefly within certain tonal/spectral ranges with low uncertainty (entropy) bounds, making it predictable. McDermot's theory compares familiarity with society's tonal system to auditory neurobiology's attraction factor [10]. Bowling et al. study this element of neurobiology and conclude that without exposing the general public to the system or tonal structure, biological evidence shows that these concepts are tightly related [11].

Western academic music has rhythmic structures and tone. This means that when listening, we can notice temporary patterns that lead to a constant production of expectations and forecasts [12, 13, 14] and a certain capacity for anticipating [15]. Expectation, prediction, and anticipation affect music perception without our awareness. Two important kinds of musical expectancies are explicit knowledge of how a familiar piece of music will evolve and implicit knowledge of music rules while listening [16]. Each musical style, genre, and culture has rules, patterns, sound qualities, and time, which creates implicit expectations. An individual's emotional response depends on music instruction or societal and cultural influences [17].

Musical preferences may also depend on whether a pattern is fulfilled [18]. Regular listeners expect specific patterns of notes or phrases and forecast the musical event [12], which can be frustrating in contemporary/new music. Zatorre's review identifies auditory cortical circuits that code and store tonal patterns and discusses evidence that cortical loops between auditory and frontal cortices are important for maintaining musical information in working memory and recognising structural regularities in musical patterns that lead to expectations [19]. Prediction changes cause surprise in the tonal system. The spectrum of skin conductivity reactions to irregular or unexpected chord forms is proportional to surprise [20]. Hence, listening to tonal music generates musical emotions through expectancy, prediction, and anticipation.

From the last century, electroencephalographic analysis and techniques have been used to study the above musical perception elements. EEG frequency oscillations link diverse aspects and integrate them into a cohesive perception, which is important for music processing as a multifunctional stimulus [21]. Koelsch reviews the brain basis of musical perception using EEG-based signal and neuroimagen approaches [22].

4.9.1 EEG signals analysis during music perception

The first quantitative analyses of brain activity using EEG signals were done in the 1970s, after the fast Fourier transform was invented. This made it possible to show the spectral power of an EEG signal in different frequency bands. In particular, electrical brain activity has been used in brain music research using univariate procedures, which means analysing the individual activity of EEG/MEG (magneto-EEG)/ERP (event related potentials) signals extracted from certain cortical brain areas/channels. Multivariate methods have also been used to measure how two or more channels depend on each other, are linked, or work together (see Figure 1).

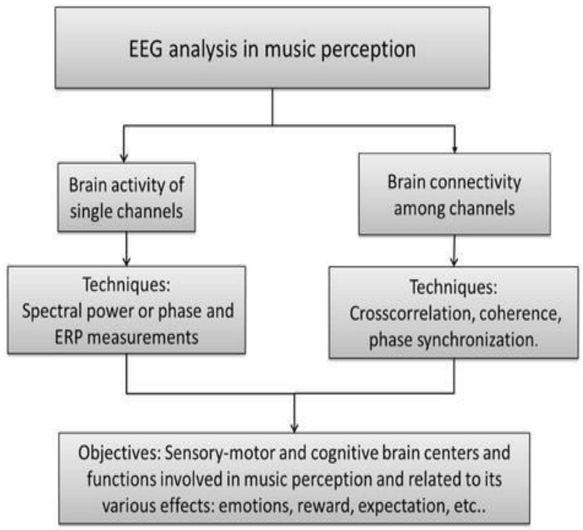


Figure 4.2.
Summary block diagram of the sections included in the EEG review.

4.9.1.1 Single channel analysis

4.9.1.1.1 General effects of listening music

Spectral power assessments from different cortical areas suggest that musical processing may involve local and/or distant neural networks whose communication may affect different EEG frequency bands [23], such as changes in alpha power in the parieto/occipital and fronto/temporal regions [24], beta power in the right parietal/temporal cortex [25], or gamma power [26]. Tonal music also alters EEG spectral power in distinct bands [27, 28] in bilateral cortical areas [29].

4.9.1.1.2 EEG and how we feel about music

Other studies have looked at how changes in spectral power in different EEG frequency bands in different parts of the brain show how emotions are processed by music. In a review of how music is processed by Koelsh, it is said that sounds are structured in time, space, and intensity, and that the way we perceive these structures has emotional effects that come from the music itself [20].

4.9.1.1.3 EEG and music styles and Experience

Music style and intra-musical factors affect EEG spectral power in different bands [27, 28]. Yet, evidence shows that musical experience affects brain functioning. Therefore, MEG showed that professional musicians had better phase blocking in gamma during discordant and minor chord auditions [48].

4.9.2. EEG channels interdependence measurements

Functional connectivity (FC) is the statistical interdependence between two neural signals (EEG or brain fMRI hemodynamic response signals) from anatomically different brain areas. This is a concept that was introduced by [62] and is also defined as the temporal statistical correlation between spatially distant neurophysiological events between groups and dispersed neuronal areas [63]. FC between different parts of the brain is important for brain processing because, in general, cognitive activity requires that different parts of the brain not only work together at the same time but also interact in a functional way [64].

4.9.2.1 EEG FC while music is being played

Authors have shown that hearing music requires different parts of the brain to work together [68]. Researchers have used connectivity analysis [69, 70, 71, 72] and network theory [73] to look at how different parts of the brain talk to each other while listening to music. In this vein, a study done on musicians shows that when musical expectations are broken, there is a synchronisation of phase changes in the alpha band between the right frontocentral cortical regions [74]. Also, different EEG studies [70, 74, 75, 76, 77] show that listening to music causes changes in EEG coherence/synchronization in different frequency bands. It has been thought to be interesting to study the configuration of the connectivity networks between different brain areas using modern graph theory, which we will look at in the next section. Music-induced EEG neural correlations at different frequencies on the prefrontal cortex and a set of functional connectivity patterns, defined by measures of coherence between channels, that are significantly different between the groups of emotional responses to music [78]. Recent research shows that different cortical areas must work together for us to understand music and feel emotions [79], and that the magnitude of the cross-correlation values was much higher when we listened to unfamiliar and coded music than when we listened to music we already knew. These results back up the idea that people react more strongly to music they don't know than to music they do know [80]. Also, when EEG and fMRI spectral coherence measurements were done together, a left cortical network was found to be involved in the pleasant feelings that come from music [70]. People have said that these aspects of music make situations that are unexpected or confusing or when expectations aren't met cause more sensory complexity and a higher level of arousal [81].

4.9.2.2 Functional Connections in the Expertise of Musicians

In point of fact, it is recognised that the brain of a musician has certain functions and structures that make it unique [82, 83, 84]. A lot of research has been done on this topic using signal analysis techniques (like EEG and EMG), but most of it has been done using BOLD neuroimagen fMRI signals. So, the size of the intranuclear length of the precentral gyrus seems to be inversely related to how old a keyboard player is when they start learning music [85]. Also, when doing a task, areas of the brain related to executive functions, like the pre-supplementary motor area and the supplementary motor area, are more active in children who have learned music [86]. When it comes to FC in neuroimagen, there is a lot of research done on expert musicians when they are at rest. So, it has been said that musicians have stronger functional connectivity (FC) between the primary auditory cortex, the primary motor cortex [87, 88], and the right ventral premotor cortex. This has to do with how the motor and auditory areas work together, and it changes based on how much you practise music [88]. Also, musicians have been shown to have a much higher density of local functional connections between different parts of the brain [89], as well as more connections between the brain's islands [90] and opercula [91]. In the musical interpretation task, there is activity in the auditory areas that is functionally linked to activity in the dorsal motor and pre-motor areas. This connectivity is linked to good performance in the musical interpretation task [92]. So, the musical experience seems to change how well some cortical areas work together (as measured by EEG). In fact, listening to excerpts of tonal music changed the spectral coherence of the EEG in the alpha and beta bands of expert musicians compared to non-musicians [93, 75]. It also changed the phase synchronisation of the gamma band, especially in the left hemisphere. Also, the phase synchronisation of expert musicians was better than that of non-musicians listening to the same piece of music [76]. In another study, the EEG activity of the posterior cortical theta and gamma bands decreased when non-musicians, amateur musicians, and professional musicians listened to major and minor compositions [94]. In this vein, a study based on the analysis of cortical images extracted from the ERPs and the responses of the subjects to the closure of complex musical stimuli (syntactic musical violations, which we talked about in the univariate approach) found big differences between groups, which were caused by their different musical experiences [95].

4.9.2.3 Graph metric for EEG FC

In the context of graph theory, EEG channels are taken to be the nodes of the graph and the connectivity values between them are taken to be the edges. It has been said that this metric could be useful for studying changes in the topological structure of neural networks in the brain. There are two ways to describe how a neural network is set up: the clustering coefficient (C), which looks at the groups of nodes, and the length of the characteristic path (L), which looks at how long the path between nodes is. For a given node, C measures how likely it is to link to neighbouring nodes, which shows how big the local domain is. L, on the other hand, is linked to the ability to integrate global information and, by extension, the brain's readiness to communicate [110, 111]. Different levels of topological organisation of a cortical brain network are defined by how big C and L are in comparison to each other. So, a network is called "regular" when its graph shows high values for C and L, and a network is called "random" when its graph shows low values for C and L. The small world (SW) type of network is defined by a graph that has a high C magnitude and a low L magnitude. So, SW neural networks are said to have a high level of local information distribution and a high efficiency for global information transfer, both of which are very important for the dynamics of how the brain processes complex information [110, 111]. For figuring out the SW level of a network NN, the C and L sizes are normalised with respect to the mean of a number (N = 100) of random networks with the same number of nodes, edges, and degree distributions as network NN [112]. A SW network is one in which L and C are about the same and C is bigger than in matched random networks (normalised L 1 and normalised C > 1). In the context of music perception, listening to Chinese music (Guquin music excerpts versus silence and noise) has been shown to increase functional connectivity (EEG phase coherence) in the alpha band, improve cortical network organisation of small world [73, 74], and also make the network more likely to be organised in a random way (when a phase delay index is used that shows a tendency to a more efficient but less random organisation). So, musical hearing changes the way brain networks are set up in some way.

Since computer algorithms for signal analysis were introduced in biomedicine, several cortical electrical signal analysis (EEG) methodologies have been employed to explore the brain multiple processes involved in musical perception. Uses include music recognition, brain processing, cognitive, and emotional consequences. Several brain centres and func tions—central and peripheral—intervene in this neuronal network. Over time, several EEG signal analysis and processing methods (including MEG and ERP cortical recordings) have studied the participation and relevance of some of these. The review highlights the most intriguing findings from the literature. They investigate musical grammar (its similarities to language), consonances and dissonances, musical expectation, and the emotions (including rewards) music evokes. The review found that cortical electrical signal analysis (EEG, MEG, ERP) is effective for studying numerous music-brain interaction concerns due to its high temporal resolution.

The extensive study on the previous works clearly indicates that the nonlinear approach is absent in all attempted works. It is now the common consensus that the method MF-DFA has the highest precision in the scaling analysis as the results obtained by the method turns out to be more reliable compared to other methods such as Wavelet Analysis, Discrete (WT) Approach, WTMM, DMA, BMA, MDFA, CDFA, Fourier DFA, EMD, SVD etc to name a few. In particular, the MF-DFA has slight advantages for negative q values and short series. The main advantage of the MF-DFA method lies in the simplicity of the method. It is a very rigorous and robust tool for assessment of correlation in non-linear time series. MF-DFA does not require the modulus maxima procedure, and hence does not involve more effort in programming than the conventional DFA. Some authors have shown MF-DFA to perform better than other multifractal analyses methods [*Kantelhardt'2002, Oswiecimka'2006, Serrano and Figliola' 2009, Huang' 2011*]. The advantages of MF-DFA over many techniques are the fact that it permits the detection of the multifractality behavior in stationary as well as non-stationary time series. This MFDFA technique has been used in recent research on non-classical correlation between Brain and Consciousness.

4.10 References:

Ashkenazy, Y., Baker, D. R., Gildor, H., & Havlin, S. (2003). Nonlinearity and multifractality of climate change in the past 420,000 years. *Geophysical research letters*, *30*(22).

Ausloos, M., & Ivanova, K. (2001). Power-law correlations in the southern-oscillation-index fluctuations characterizing El Ni ñ o. *Physical Review E*, *63*(4), 047201.

Banerjee, A., Sanyal, S., Patranabis, A., Banerjee, K., Guhathakurta, T., Sengupta, R., ... & Ghose, P. (2016). Study on brain dynamics by non linear analysis of music induced EEG signals. *Physica A: Statistical Mechanics and its Applications*, *444*, 110-120.

Beltran, L. (2021). Quantum Bose–Einstein Statistics for Indistinguishable Concepts in Human Language. *Foundations of Science*, 1-13.

Berument, H., Ceylan, N. B., & Dogan, N. (2010). The impact of oil price shocks on the economic growth of selected MENA countries. *Energy Journal*, *31*(1), 149.

Bigerelle, M., & Iost, A. (2000). Fractal dimension and classification of music. *Chaos, Solitons & Fractals*, *11*(14), 2179-2192.

Bizopoulos, P. A., Al-Ani, T., Tsalikakis, D. G., Tzallas, A. T., Koutsouris, D. D., & Fotiadis, D. I. (2013, July). An automatic electroencephalography blinking artefact detection and removal method based on template matching and ensemble empirical mode decomposition. In *2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)* (pp. 5853- 5856). IEEE.

Blank, A., & Solomon, S. (2000). Power laws in cities population, financial markets and internet sites (scaling in systems with a variable number of components). *Physica A: Statistical Mechanics and its Applications*, *287*(1-2), 279-288.

Borrelli, A. (2009). Bose—einstein statistics. In *Compendium of Quantum Physics* (pp. 74-78). Springer, Berlin, Heidelberg.

Chang, M. C., Yang, A. C. C., Stanley, H. E., & Peng, C. K. (2017). Measuring information-based energy and temperature of literary texts. *Physica A: Statistical Mechanics and its Applications*, *468*, 783-789.

Clauset, A., Young, M., & Gleditsch, K. S. (2007). On the frequency of severe terrorist events. *Journal of Conflict Resolution*, *51*(1), 58-87.

De Campos, H., & Tolman, J. M. (1982). The informational temperature of the text. *Poetics Today*, *3*(3), 177-187.

Di Lorenzo, P. (2003, December). Chaos hidden in recorded monodic music: what is the role of timbre. In *Proccedings of" 2nd International Conference" Understanding and creating music", Caserta* (pp. 11-15).

Ebel, H., Mielsch, L. I., & Bornholdt, S. (2002). Scale-free topology of e-mail networks. *Physical review E*, *66*(3), 035103.

Feder, J. (2013). *Fractals*. Springer Science & Business Media.

Figliola, A., Serrano, E., Rostas, J. A. P., Hunter, M., & Rosso, O. A. (2007, May). Study of EEG brain maturation signals with multifractal detrended fluctuation analysis. In *AIP Conference Proceedings* (Vol. 913, No. 1, pp. 190-195). AIP.

Figueira, F. C., Moura Jr, N. J., & Ribeiro, M. B. (2011). The gompertz–pareto income distribution. *Physica A: Statistical Mechanics and its Applications*, *390*(4), 689-698.

Gabaix, X., Gopikrishnan, P., Plerou, V., & Stanley, H. E. (2003). A theory of power-law distributions in financial market fluctuations. *Nature*, *423*(6937), 267-270.

Gao, J., Cao, Y., Tung, W. W., & Hu, J. (2007). *Multiscale analysis of complex time series: integration of chaos and random fractal theory, and beyond*. John Wiley & Sons.

Gao, J., Hu, J., Mao, X., & Perc, M. (2012). Culturomics meets random fractal theory: insights into long-range correlations of social and natural phenomena over the past two centuries. *Journal of The Royal Society Interface*, *9*(73), 1956-1964.

Gao, T. T., Wu, D., Huang, Y. L., & Yao, D. Z. (2007). Detrended fluctuation analysis of the human EEG during listening to emotional music. *Journal of Electronic Science and Technology*, *5*(3), 272- 277.

Ghosh, D., Dutta, S., & Chakraborty, S. (2014). Multifractal detrended cross-correlation analysis for epileptic patient in seizure and seizure free status. *Chaos, Solitons & Fractals*, *67*, 1-10.

Hardstone, R., Poil, S. S., Schiavone, G., Jansen, R., Nikulin, V. V., Mansvelder, H. D., & Linkenkaer-Hansen, K. (2012). Detrended fluctuation analysis: a scale-free view on neuronal oscillations. *Frontiers in physiology*, *3*, 450.

He, L. Y., & Chen, S. P. (2011). Multifractal detrended cross-correlation analysis of agricultural futures markets. *Chaos, Solitons & Fractals*, *44*(6), 355-361.

Hsü, K. J., & Hsü, A. J. (1990). Fractal geometry of music. *Proceedings of the National Academy of Sciences*, *87*(3), 938-941.

Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., ... & Liu, H. H. (1998). The

empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences*, *454*(1971), 903-995.

Jiang, Z. Q., & Zhou, W. X. (2011). Multifractal detrending moving-average cross-correlation analysis. *Physical Review E*, *84*(1), 016106.

Johnston, D. (1999). Cool edit 2000. *Syntrillium Software Corporation, Phoenix, Arizona, EEUU*.

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance*, *51*(2), 463-491

Jung CY, Saikiran SS (2016). A review on EEG artifacts and its different removal technique. *Asia- Pacific J Converg Res Interchang 2*(4):43–60

Kaniadakis, G. (2009). Maximum entropy principle and power-law tailed distributions. *The European Physical Journal B*, *70*(1), 3-13.

Kannathal, N., Acharya, U. R., Lim, C. M., & Sadasivan, P. K. (2005). Characterization of EEG—a comparative study. *Computer methods and Programs in Biomedicine*, *80*(1), 17-23.

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and its Applications*, *316*(1-4), 87-114.

Kantz, H., & Schreiber, T. (2004). *Nonlinear time series analysis* (Vol. 7). Cambridge university press.

Karkare, S., Saha, G., & Bhattacharya, J. (2009). Investigating long-range correlation properties in EEG during complex cognitive tasks. *Chaos, Solitons & Fractals*, *42*(4), 2067-2073.

Kasahara, K. (1981). *Earthquake mechanics* (Vol. 248). Cambridge: Cambridge university press.

Klonowski, W. (2009). Everything you wanted to ask about EEG but were afraid to get the right answer. *Nonlinear biomedical physics*, *3*(1), 1-5.

Kosmidis, K., Kalampokis, A., & Argyrakis, P. (2006). Statistical mechanical approach to human language. *Physica A: Statistical Mechanics and its Applications*, *366*, 495-502.

Lemoine, M., & Sigl, G. (Eds.). (2001). *Physics and astrophysics of ultra high energy cosmic rays* (Vol. 576). Springer Science & Business Media.

Lestrade, S. (2017). Unzipping Zipf's law. *PloS one*, *12*(8), e0181987.

Linkenkaer-Hansen, K., Nikouline, V. V., Palva, J. M., & Ilmoniemi, R. J. (2001). Long-range temporal correlations and scaling behavior in human brain oscillations. *Journal of Neuroscience*, *21*(4), 1370-1377.

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of atmospheric sciences*, *20*(2), 130- 141.

Mandelbrot, B. B., & Mandelbrot, B. B. (1982). *The fractal geometry of nature* (Vol. 1). New York: WH freeman.

Mantegna, R. N., & Stanley, H. E. (1999). *Introduction to econophysics: correlations and complexity in finance*. Cambridge university press.

Miyazima, S., & Yamamoto, K. (2008). Measuring the temperature of texts. *Fractals*, *16*(01), 25-32.

Movahed, M. S., & Hermanis, E. (2008). Fractal analysis of river flow fluctuations. *Physica A: Statistical Mechanics and its Applications*, *387*(4), 915-932

Nacher, J. C., & Ochiai, T. (2008). Power-law distribution of gene expression fluctuations. *Physics Letters A*, *372*(40), 6202-6206.

Newman, M. E. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary physics*, *46*(5), 323-351.

Pauli, W. (1940). The connection between spin and statistics. *Physical Review*, *58*(8), 716.

Peng, C. K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Physical review e*, *49*(2), 1685.

Peng, C. K., Yang, A. C. C., & Goldberger, A. L. (2007). Statistical physics approach to categorize biologic signals: from heart rate dynamics to DNA sequences. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *17*(1), 015115.

Podobnik, B., & Stanley, H. E. (2008). Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series. *Physical review letters*, *100*(8), 084102.

Podobnik, B., Grosse, I., Horvatić, D., Ilic, S., Ivanov, P. C., & Stanley, H. E. (2009). Quantifying cross-correlations using local and global detrending approaches. *The European Physical Journal B*, *71*(2), 243-250.

Podobnik, B., Horvatic, D., Ng, A. L., Stanley, H. E., & Ivanov, P. C. (2008). Modeling long-range cross-correlations in two-component ARFIMA and FIARCH processes. *Physica A: Statistical Mechanics and its Applications*, *387*(15), 3954-3959.

Podobnik, B., Jiang, Z. Q., Zhou, W. X., & Stanley, H. E. (2011). Statistical tests for power-law cross-correlated processes. *Physical Review E*, *84*(6), 066118

Reˆgo, H. H. A., Braunstein, L. A., D′ Agostino, G., Stanley, H. E., & Miyazima, S. (2014). When a text is translated does the complexity of its vocabulary change? Translations and target

readerships. *PloS one*, *9*(10), e110213.

Reboredo, J. C., Rivera-Castro, M. A., & Zebende, G. F. (2014). Oil and US dollar exchange rate dependence: A detrended cross-correlation approach. *Energy Economics*, *42*, 132-139

Redner, S. (1998). How popular is your paper? An empirical study of the citation distribution. *The European Physical Journal B-Condensed Matter and Complex Systems*, *4*(2), 131-134.

Rovenchak, A. (2014). Trends in language evolution found from the frequency structure of texts mapped against the Bose-distribution. *Journal of Quantitative Linguistics*, *21*(3), 281-294.

Rovenchak, A., & Buk, S. (2011). Application of a quantum ensemble model to linguistic analysis. *Physica A: Statistical Mechanics and its Applications*, *390*(7), 1326-1331.

Roy, S., Banerjee, A., Sanyal, S., Ghosh, D., & Sengupta, R. (2019). Categorization of Indian Classical Music Using MB-BE Distributions. *Journal of Software Engineering Tools & Technology Trends*. *6*(3), 9–15.

Roy, S., Banerjee, A., Sanyal, S., Ghosh, D., & Sengupta, R. (2021, April). A study on Raga characterization in Indian classical music in the light of MB and BE distribution. In *Journal of Physics: Conference Series* (Vol. 1896, No. 1, p. 012007). IOP Publishing.

Sengupta, R., Dey, N., Datta, A. K., & Ghosh, D. (2005). Assessment of musical quality of tanpura by fractal-dimensional analysis. *Fractals*, *13*(03), 245-252.

Shlesinger, M. F., Zaslavsky, G. M., & Klafter, J. (1993). Strange kinetics. *Nature*, *363*(6424), 31-37.

Sjölander, K., & Beskow, J. (2000). Wavesurfer-an open source speech tool. In *Sixth International Conference on Spoken Language Processing*.

Stanley, H. E., & Meakin, P. (1988). Multifractal phenomena in physics and chemistry. *Nature*, *335*(6189), 405-409.

Walton, D. B., & Rafelski, J. (2000). Equilibrium distribution of heavy quarks in Fokker-Planck dynamics. *Physical review letters*, *84*(1), 31.

Wang, F., Liao, G. P., Zhou, X. Y., & Shi, W. (2013). Multifractal detrended cross-correlation analysis for power markets. *Nonlinear Dynamics*, *72*(1), 353-363.

Xu, N., Shang, P., & Kamae, S. (2010). Modeling traffic flow correlation using DFA and DCCA. *Nonlinear Dynamics*, *61*(1), 207-216.

Zhou, W. X. (2008). Multifractal detrended cross-correlation analysis for two nonstationary signals.

Zipf, G. K. (2016). *Human behavior and the principle of least effort: An introduction to human ecology*. Ravenio Books.

CHAPTER 5

METHODOLOGY

"Methodology must be flexible. Companies often don't adopt the materials & methods they were trained on because they aren't flexible enough".
Brian Lawley

5.1 Introduction

The chapter discusses chaos based nonlinear techniques for analyzing music and EEG signals. Tools for analyzing the complex data are discussed here. Quite a few of which have been used later in a number of different studies:

i) Empirical mode decomposition (EMD)

ii) Detrended fluctuation analysis (DFA).

iii) Multifractal detrended fluctuation analysis (MFDFA)

iv) Multifractal cross-correlation analysis (MFDXA)

Four of these techniques (i-iv) use the multi-fractal spectral width (which is the result of the MFDFA approach) or the Fractal Dimension (FD) as an essential determinant for measuring the emotional responses caused by certain visual or auditory cognitive tasks acivities.. For dynamic and nonlinear signals like EEG, EMD is a good decomposition method. Detrended Fluctuation Analysis (DFA) is employed to examine the long-range temporal correlations (LRTC) of the signal's observed fluctuations. Advancing from DFA, MFDFA is a fractal analysis technique which is highly scale-dependent. Here, signal components of different scaling ratios are analysed together in the form of spectral dimension which indicates the signal's degree of complexity. Lastly, During higher-order cognitive tasks, MFDXA can be used to objectively evaluate cross-correlation degree of two EEG signals that are nonlinear in nature and originate from distinct brain regions. This is an important tool. Because of this, we are in a position to conduct a quantitative analysis of the manner in which the various lobes of the brain are cross-correlated in the course of higher-order thinking activities and the perception of environmental stimuli. A higher value of the cross-correlation coeffient would indicate a similarity between the signals in some aspects. Further can be utilised to obtain a cue for the informational connectivity the human brain displays while processing real-world stimuli.

The rest of the two methods discussed here (v-vi) rely on the fact that the distribution of basic units among the complex signal under observation follows power law distribution pattern. Analogies of the complex acoustic signal with ensembles of distinguished (for MB) and indistinguished (for BE) gas particles in a container enables us to use the physical properties of MB and BE distributions in describing their dynamics. This approach is novel in the field of acoustic stimuli, especially in the Indian Classical Music scenario. The emergent parameters could prove to be of great importance in the categorization and classification of structured data regarding acoustic and biosignals.

5.2 Preview of Related Works

Research in the human neurophysiological and cognitive domains have gone through a technological revolution in the last few decades. Biological signals, one of the major gateways to the treasure hunt that is human physiology, exhibit both ordered as well as disordered behaviour. They are complex, often irregular and devoid of discernible patterns to the general observation. Not only bio-signals, such chaos can be found everywhere in nature – from music to visual arts to natural phenomena like weather patterns to even finance (Mantegna & Stanley, 1999) and culture (Gao et al., 2012). Edward Lorentz, in a seminal paper in 1963, first introduced deterministic chaos and explored the possibility of weather prediction (Lorentz, 1963). He saw that the nonperiodic solutions to the nonlinear differential equations designed to represent dissipative nature of a complex system are highly unstable and even the slightest change in initial conditions could result in considerably different outcomes. Thus, the Chaos theory was born. It closely observed the mechanism which is followed by deterministic, simple and straightforward systems which can also show very complex and random long-term behavior at times. Soon, Chaos theory was found to be ubiquitous across the fields like turbulent water flows, DNA sequence, faults in bone, weather changes, financial time series, earthquake etc. and it led the researches on the mechanisms describing such complex unpredictable systems. But, to call an observed system chaotic, some strict criteria need to be met. These include the criteria of determinism, stationarity and exponential divergence (Kantz & Schreiber, 2004; Gao et al., 2007). Also, the signal needs to be relatively noise-free. Such conditions make application of Chaos theory in experimental bio-signals complicated because often such signals tend to be noisy and non-stationary. As a result, the countertheory that began to emerge is: random fractal theory, championed by Benoit Mandelbrot (1982). This theory presupposes that the signal has intrinsic randomness - unlike Chaos theory which deals with irregular behaviours generated by nonlinear deterministic interactions with only a few degrees of freedom but excludes noise or randomness majorly. The epicentre of random fractal theory is, of course, the fractals (and fractal dimension). Mandelbrot defined fractal as: "a rough or fragmented geometric shape that can be subdivided in parts, each of which is (at least approximately) a reduced/size copy of the whole" (Mandelbrot & Mandelbrot, 1982). Fractal dimensions, which correspond in a unique way to the shape being studied and are often not integers, could be used to categorise complex structures quantitatively (Stanley & Meakin, 1988). Using fractal dimension has led to a huge number of new studies that look at the complicated dynamics of a wide range of natural tasks. This chapter is mostly a clear explanation of the algorithms that are used in different parts of this thesis. First, we look at how traditional Fourier decomposition methods compare to non-linear methods. Next, we explore particular non-linear analysis methods that were used on different EEG and music signal data.

Fourier decomposition is used often in EEG analysis; a method whose main purpose is to decompose the original signal from time domain to frequency domain. But those Fourier decomposition methods are linear, which means that the Fourier transform of a set of functions is the sum of their Fourier transforms. But EEG signals (and most of the signals occurring in nature) are essentially complex and rarely linear. The neurons under the scalp are plethric in number and they give rise to the EEG series by interacting with the neighboring neurons and also with the remote neurons through electrical pulses. In such a complex neuronal network, nonlinearity stems from the cellular level, because threshold, integration and saturation phenomena control the dynamics of every individual neuron.

Moreover, the hypothesis of brain is an extremely stochastic and non deterministic system and its hypothesis can be turned down because of its ability to perform higher order cognitive jobs (Kannathal et al., 2005). Hence, emerging dynamic patterns are should not be linear and stationary and so they can cause fluctuations which are not best explained by linear decomposition. To analyse these signals, it would be more suitable to use techniques that are robust against inherent non-stationarities. Primitive methods of signal analysis, although function well on stationary waves, are extremely limited in dealing with bio-signals in an adequate manner. Fast Fourier Transform (FFT), Wavelet Transform (WT), Matching Pursuit (MP) are some of the examples. The results obtained could very well be misleading. For example, an observed signal having frequency of 12 Hz (with amplitude modulation of 1 Hz frequency) will decompose into two harmonic components having frequencies 11 and 13 Hz after Fourier decomposition, leading to complete disappearance of the original 12 Hz signal (Klonowski, 2009).

This highlights the need for an advanced solution and smart methods of analysis. Non-linear dynamical analysis has emerged as a novel method for the study of complex systems in the past few decades. The non-linear analysis method is effectively applied to electroencephalogram (EEG) data to study the dynamics of the complex underlying behaviour. The concept of 'fractal dimension's being a measure of the signal complexity introduces newer horizons which were unattainable using classical techniques. Calculated directly in the time domain using a moving window, the fractal analysis could be applied to signals that are nonstationary, noisy, stochastic or even deterministic. Principles of non-linear dynamics (also, elements of deterministic chaos) govern this approach and engages the characteristics of that particular system attractors along with its invariant parameters. For such reasons, EEG data seems to be the area for the application of nonlinear time-series testing techniques.

The signal's scaling exponent is evaluated by the nonlinear dynamics which indicates the presence or absence of fractal properties (self-similarity). The fractal dimension, or FD, of a waveform represents a powerful tool for transient detection. It is recognised that many systems with apparent random structure possess something called a scale symmetry, implying that the structures remain same under different scales of observation. However, in recent years, quite a number of natural phenomena has been studied which require multiple scaling exponents in describing them. In order to identify and differentiate the specific transitions of physiological functions of ECG & EEG, This feature has been extensively used. This fractal tool could be described as a mathematical-microscope that zooms in its own original way into the inherent complex patterns of the signal and helping to decipher complex scaling exponents from the so called random pattern. Many algorithms that are robust and methodological approaches are available to examine the fractality present in the signal such as - Box counting method , Correlation dimension, Lyapunov exponent, etc. These are extremely noise-sensitive and need stationary conditions when on the other hand, EEG signals are highly dynamic. To tackle the issue, a nonlinear method named Detrended-Fluctuation-Analysis (DFA), further extended by its advanced form Multifractal-Detrended-Fluctuation-Analysis (MFDFA) has been developed that has the capability to identify the scale varying nature of different naturally occurring time-series signals. To further explain how the internal dynamics of one signal impacts the other, i.e., to identify the degree of cross-correlation between the two, we will take the help of Multifractal Detrended Cross-Correlation analysis (MFDXA) which produces the cross-correlation coefficient as an indicator of correlation.

5.3 Fractals and Multifractals in Music

Even mathematical analysis of music is not a new term, still no standard method is there and different tools applied for different analysis. In this section nonlinear tool is applied to quantify some of the prevailing classifications in music.

Different types of what is referred to as fractional noise are used in a regularly used method of creating musical structure from the discipline of chaos theory. (also called fractal noise). The phrase refers to a variety of noise types that can be distinguished based on their spectral densities, which express how noise power is distributed with frequency. The most intriguing type of noise that facilitates the emergence of musical structures is pink noise, also known as 1/fnoise, whose behaviour falls between two extremes, namely, white noise, with a spectral density of 1/f0 (suggesting a stochastic process of uncorrelated random variables), and Brownian noise, with a spectral density of 1/f2 (implicating a deterministic process of random variables). (implying a stochastic process involving highly correlated random variables). The characteristics of pink noise produce a progression in pitch in a musical mapping (for example, on pitches).[*Choudhury'2009*]

The non-uniformity trait in the structures of melodic and rhythmic motions in music is confirmed by the observed fluctuations of the Hölder exponent along the musical sequences. The outcome implies that distinct musical genres can be identified by the width and form of multifractal spectra. Additionally, a distinctive curve is built by projecting the point sequences from a musical work's melody and rhythm onto a two-dimensional graph. Each piece of music has a distinctive characteristic curve of its own. The inherent structure of music is revealed by this characteristic curve, which also displays fractal characteristics [Su'2006]. Utilizing the Hurst exponent and Fourier spectrum studies, Su et al. quantified the characteristics of each musical composition. The findings demonstrate that a fractional Brownian motion's fractal features are similar to those of music. (fBm). That is, across decades of musical notes, music exhibits an anti-persistent trend in the tone changes (melody), and music sequences typically exhibit the 1/f -type spectrum (fractal characteristic), with ostensibly two different values in two separate temporal scales.

Zlatintsi et al. introduced a multiscale fractal approach to analyze the structure of musical instrument tones, which has been inspired by similar techniques used in speech recognition. The experimental findings and recognition evaluation provides strong evidence that MFDs can effectively highlight the structure of musical instruments and it's properties. The results demonstrate that MFDs can provide insights into various characteristic notes and instruments, and the recognition experiments show promising results in most cases, if not all. [*Zlatintsi'2011*].

Das et al. investigated the fractal dimension (D) of musical pieces played by various instruments, including Western and Eastern ones. The musical pieces were converted into time series data and their fractal dimension was calculated. The authors observed that instrumental music sounds tend to have higher D values compared to vocal performances of different types of Indian songs. They also attempted spectral analysis of the selected clips to identify fundamental and harmonic peaks in the frequency domain.[*Das'2006*].

Scrivener used fractal analysis to study the player piano works of composer Conlon Nancarrow, particularly focusing on the canons that explore mathematical relationships. These canons ranged from simple two-voice relationships to complex twelve-voice proportional relationships. The acceleration canons, which used controlled rates of acceleration and deceleration among the voices, were particularly interesting for studying fractal properties. [*Scrivener'2000*].

Chakraborty et al. found that the melodic structure of the raga Malkauns depicts a fractal nature that increases better with the increase with fractional dimension(D) taking the mean value 2.454 and standard deviation 0.111[*Chakraborty'2011*].

Zlatintsi et al. employed fractal dimension measurements and proposed the use of a multiscale fractal feature for structure analysis of musical instrument tones motivated from similar successful ideas used for speech recognition tasks. Their main goal is to gain insight about the instruments' characteristics and achieve better discrimination in tasks such as instrument classification. Based on the experimental hypothesis and recognition evaluation, there is strong evidence that musical instruments have structure and properties that could be emphasized by the use of multiscale fractal methods as an analysis tool of their characteristics [*Zlatintsi'2013*].

In the subsequent chapters we will discuss about the different methodologies used to detect the multi fractality of human brain waves in response to color and music stimuli.

5.4 Fractal & Multifractal Time Series

5.4.1 Fractality, Self-Affinity and Scaling:

We often try to measure the values of the considered observable in homogeneous time intervals as most time series are one dimensional. Hence, until there are missing values, the fractal dimension of the support is D (0) = 1. There are extremely rare cases where most of the values of a time series are very small or even zero, resulting in a dimension D (0) < 1 of the series. In such situations, selecting appropriate analysis techniques has to be done very carefully since many of the methods are not accurate for such data. While the notion of self-affinity is described one keeps in mind that the axises of time and that of the measured values $x(t)$, are not equivalent. Therefore a rescaling of time t by a factor a possibly calls for rescaling of the series values $x(t)$ by another factor a^H in order to get a statistically comparable/similar (i.e., self-similar) picture. In this case the scaling relation

$$x(t) \rightarrow a^H x(at) \qquad 5.1$$

holds for an arbitrary factor a, which describes the data as self-affine [*Kantelhardt'2008*]. The Hurst exponent H named after the water engineer H.E. Hurst [*Hurst'1951*] characterizes the type of self affinity.

The scaling behavior of the data, that are self-affine, can also be examined by studying at their mean-square displacement. Since the mean-square displacement of a random walker increases linearly in time, $\langle x^2(t)\rangle \sim t$, deviations from this postulate will show the presence of self-affine scaling [*Kantelhardt'2008*].

5.4.1.1 Persistence, Long- and Short-term Correlations:

When a large value is followed by a large value and so is a small one, the data set is called to be persistent. Studies show that Self-affine data are such in nature.

For the trajectory of a random walk, persistence on all time scales is straightforward, as a later point is only a previous position plus a random increment. The persistence stands true for all time scales for which the self-affinity relation given by Equation (2.4) holds. Moreover, the degree of persistence might vary across different time scales. On longer time scales, persistence is much more difficult to observe. While the weather tomorrow or in one week will likely be similar to the weather today (owing to a stable general weather state), persistence is much more difficult to observe on shorter time scales.

Considering the increments $\Delta x_i = x_i - x_{i-1}$ of a self-affine series, $(x_i), i = 1, \dots \dots \dots, N$, where N is the total no of values taken and they are collected equidistant in time. It is found that the Δx_i can either be persistent and independent or even anti-persistent. Persistent and anti-persistent increments, in which a positive increment is most likely to be followed by another positive or negative increment respectively, also leads to persistent integrated series. $x_i = \sum_{j=1}^{i} \Delta x_j$.

If we consider stationary data with constant mean and standard deviation, the auto-covariance function of the increments is obtained as

$$C(s) = \langle \Delta x_i \Delta x_{i+s} \rangle = \frac{1}{(N-s)} \sum_{i=1}^{N-s} \Delta x_i \Delta x_{i+s} \qquad 5.2$$

This is used to determine the degree of persistence of any wave. If $we\ devide\ C(s)$ by the variance $\langle(\Delta x_i)^2\rangle$, we get the auto-correlation function. Both are obtained identical if the data are normalised with unit variance. If Δx_i are uncorrelated (as for the random walk), $C(s)$ is zero for s > 0. Short-range correlations of the increments Δx_i are usually described by $C(s)$ declining exponentially,

$$C(s) \sim \exp\left(-\frac{s}{t_x}\right) \qquad 5.3$$

with a characteristic decay time t_x . Increments that are generated by an Auto-Regressive (AR) process, exhibit such behavior.

$$\Delta x_i = c\Delta x_{i-1} + \varepsilon_i \qquad 5.4$$

with random uncorrelated offsets ε_i and $c \sim \exp\left(-\frac{1}{t_x}\right)$.

For correlations over long ranges, $\int_0^\infty C(s)ds$ diverges itself in the limit of infinitely long series ($N \to \infty$). It indicates that t_x is undefined as it increases with increasing *N*. For example, $C(s)$ declines as a power-law

$$C(s) \propto s^{-\gamma} \qquad 5.5$$

with an exponent $0 < \gamma < 1$[*Kantelhardt'2008*].

5.4.1.2 Crossovers and Non-stationarities in Time Series:

A crossover is caused due to the short-term correlated increments Δx_i which is characterized by a finite characteristic correlation decay time t_x in the scaling behaviour of the integrated series $x_i = \sum_{j=1}^{i} \Delta x_j$. As the location of the crossover can be numerically dissimilar from t_x it is denoted by s_x . Crossovers in time series make them not self-affine, and there is no single Hurst exponent H that describes them. For small time scales (indicating correlations in the increments) the value of Hurst component H, is often greater than 0.5, and this indicates the asymptotic behaviour (for large time scales $s \gg t_x$ and $\gg s_x$) since all correlations have decayed by that time. In addition to scaling long-term correlations, many naturally recorded time series also have short-term correlations. For example, there are short-term correlations in temperature data and heartbeat data due to the effects of breathing. Different control mechanisms on fast and slow time scales can also lead to crossovers in the scaling behaviour of complex time series. For example, changes in river runoff behave differently on scales of less than a year and more than a year.

If non-stationarities aren't addressed the right way, they can also induce crossovers in how data scales. Non-stationarities are basically changes in the mean, standard deviation, or distribution of data values that go against weak stationarities (violating strong stationarities). Non-stationarities like monotonous, periodic, or step-like trends are often caused by things outside of the system. For example, the greenhouse effect and seasonal changes in temperature, varying levels of activity in long-term physiological parameters, or unsteady light sources in photon correlation spectroscopy are all instances of things that can cause non-stationarities. Another example of data that is not stationary is a record that has parts with big changes and parts with small changes. This kind of behaviour causes a crossover in scaling at the time scale that corresponds to how long the homogeneous segments usually last. Different ways of controlling things at different times, like how the heartbeat changes at different stages of sleep at night, can also cause crossovers. These are also called non-stationarities. So, if there are crossovers in how data scales, more in-depth studies are needed to figure out why there are crossovers [Kantelhardt, 2008].

5.4.2 Multifractal Time Series:

This section takes the fractal analysis one step further. It has already been mentioned that fractals are characterized by a 'roughness' at all scales. This roughness comes from the scaling properties of fractals. The term *scaling* is used to combine all the terms such as *self-similarity* and *self-affinity*. Scaling sets are distributed in the same way (deterministically or statistically) at smaller scales as they are at larger scales.

Many records don't show simple monofractal behaviour that can be explained by a single scaling exponent [*Kantelhardt'2001, Hu'2001*]. Different scaling exponents are required for different parts of the series [*Chen'2002*]. So in general, a multifractal analysis of the data should be performed. A multifractal analysis of time series also reveals higher order correlation. If the small scale and large scale fluctuations exhibit different scaling behavior, Multifractal scaling is also observed.

Multifractals are characterized by a sequence of fractal dimensions, rather than just one fractal dimension. They also have an associated multifractal spectrum. This spectrum contains no more information than the dimensions.

5.4.2.1 Methods for Stationary Fractal Time Series Analysis:

In this section we will discuss four traditional methods for fractal analysis of time series

5.4.2.1.1 Autocorrelation Function Analysis:

First a record (x_i) of $i = 1 \ldots \ldots N$ equidistant measurements is considered where index i corresponds to the time of the measurements in most of the applications. The correlation of the values of x_i and x_{i+s} for different time lags, i. e. correlations over different time scales s is studied. In order to remove a constant offset in the data, the mean $\langle x \rangle = \frac{1}{N}\sum_{i=1}^{N} x_i$ is usually subtracted $\tilde{x}_i \equiv x_i - \langle x \rangle$. Quantitatively the auto-covariance function $C(s) = \langle \tilde{x}_i \tilde{x}_{i+s} \rangle$ or the auto-correlation function $\frac{C(s)}{\langle \tilde{x}_i^2 \rangle}$ define the correlations between $\tilde{x}$ values separated by s steps.

As already mentioned in Section 2.7.1.2 that $\tilde{x}_i$ are short term correlated if $C(s)$ declines exponentially, $C(s) \sim \exp\left(-\frac{s}{t_x}\right)$ and long-term correlated if $C(s)$ declines as a power law. $C(s) \propto s^{-\gamma}$ with a correlation exponent $0 < \gamma < 1$. A direct calculation of C(s) is not appropriate due to noise superimposed on the data $\tilde{x}_i$ and due to underlying non-stationarities of unknown origin. Further, $C(s)$ fluctuates around zero on large scales s, thus making it impossible to find the potential scaling behaviour Eq. (2.8). Thus the correlation exponent γ has to be determined indirectly [*Kantelhardt'2008*].

5.4.2.1.2 Spectral Analysis:

For stationary time series, standard spectral analysis techniques (Fourier transform) can be applied and the power spectrum $S(f)$ of the time series $\tilde{x}_i$ as a function of the frequency f to obtain self-affine scaling behaviour can be calculated [*Hunt'1951*]. For long-term correlated data characterized by the correlation exponent γ,

$$S(f) \sim f^{-\beta} \quad with \quad \beta = 1 - \gamma \qquad 5.6$$

By fitting a power-law to a double logarithmic plot of the power spectrum $S(f)$, $t$he spectral exponent β and the correlation exponent γ can be derived. If instead of $\tilde{x}_i = \Delta x_i$ the integrated run off time series is Fourier transformed, i.e., $\tilde{x}_i = x_i \sum_{j=1}^{i} \Delta x_j$ the resulting power spectrum scales as $S(f) \sim f^{-2-\beta}$.

Spectral analysis, does not yield more reliable results than autocorrelation analysis unless a logarithmic binning procedure is applied to the double logarithmic plot of $S(f)$ [*Taqqu'1995*], the average of log $S(f)$ is calculated in successive, logarithmically wide bands from $a^n f_o$ to $a^{n+1} f_0$, where f_0 is the minimum frequency, $a > 1$ is a factor (e. g., $a = 1.1$), and the index n is counting the bins. Spectral analysis also requires stationarities of the data.

5.4.2.1.3 Hurst's Rescaled-Range Analysis:

Based on random walk theory, water construction engineer Harold Edwin Hurst came up with the first way to look at long-term persistence in time series. He did this while working in Egypt. The rescaled range analysis (R/S analysis) was made to figure out how complex systems behave when they are scaled. This method lets us look at how time series depend on each other. The Hurst exponent shows how much scaling is going on, which can be estimated by measuring the data series at different times. In Rescaled Range Analysis (R/S analysis) [*Hurst'1951,1965, Mandelbrot'1968,1969,1999, Feder'1988*] first the time series ($\tilde{x}_i$) is divided into v no of non-overlapping segments of size (time scale) s which yields $N_s = int\left(\frac{N}{s}\right)$ segments altogether. In the second step for each segment $\nu = 0, \dots \dots, N_s - 1$, the profile (integrated data) is calculated

$$(j) = \sum_{i=1}^{j} (\tilde{x}_{\nu s+i} - \langle \tilde{x}_{\nu s+i} \rangle_s) = \sum_{i=1}^{j} \tilde{x}_{\nu s+i} - \frac{j}{s} \sum_{i=1}^{s} \tilde{x}_{\nu s+i} \qquad 5.7$$

By subtracting the local averages, piecewise constant trends in the data are eliminated. In the third step, the differences between minimum and maximum value (ranges) $R_\nu(s)$ and the standard deviations $S_\nu(s)$ in each segment are calculated,

$$R_\nu(s) = max_{j=1}^{s} Y_\nu(j) - min_{j=1}^{s} Y_\nu(j), \quad S_\nu(s) = \sqrt{\frac{1}{s \sum_{j=1}^{s} Y_\nu^2(j)}} \qquad 5.8$$

Finally, the rescaled range is averaged over all segments to obtain the fluctuation function *F(s)*,

$$F_{RS}(s) = \frac{1}{N_s} \sum_{\nu=0}^{N_s-1} R_\nu(s) \,/ S_\nu(s) \sim s^H \quad for\ s \gg 1 \qquad 5.9$$

where H is the Hurst exponent. It can be shown [*Hunt'1951, Mandelbrot'1968*] that the relation between H, β and γ is given by 2H ≈ 1+ β = 2 - γ Eq. (2.9).for 0 < γ < 1, it is understandable that the right part of the equation holds iff 1> H > 0. This relationship does not hold in general for multifractal data. It can also be seen that H actually characterizes the self-affinity of the profile function Eq. (2.10), while β and γ refer to the original data.

Hurst's rescaled range analysis show that H is limited to 0 < H < 2. Rescaled range analysis for stationary data can help to calculate H as it can be increased or decreased by 1 if the data is integrated $\tilde{x}_j \rightarrow \sum_{i=1}^{j} \tilde{x}_i$ or differentiated $\tilde{x}_i \rightarrow \tilde{x}_i - \tilde{x}_{i-1}$, respectively. Long-term anti-correlated behaviour of the data $\tilde{x}_i$, is shown by values of H less than 1/2. Positively correlated behaviour is shown by values of H greater than 1/2. For power-law correlations that break down faster than 1/s, H = 1/2 for large s values, like when the data are not correlated.

Hurst's rescaled range analysis shows smoother curves with less computational effort and also stands for data with piecewise constant trends in comparison to spectral analysis[*Kantelhardt'2008*].

Salinas et al. applied *R/S* method to Extremely Low Frequency-band (512 Hz sample frequency) electromagnetic noise, measured in Antarctica during January and February 2008. The Hurst exponent obtained showed the persistent behaviour of the process. The number of samples where the transition occurred seemed to be related to the lightning rate in the atmosphere, as was shown in a numerical simulation [*Salinas'2011*]. Gilmore et al. [*Gilmore'2002*] applied R/S method to search for long-time correlations (via the Hurst exponent, H) in plasma turbulence. They found that the method can be deployed to accurately calculate *H*, provided a long enough data record is used, and that *H* is an index of persistence in the data. Additionally, subtleties of the correct application of both methods are discussed, and potential advantages of structure functions are also pointed out.

Pallikari et al. applied this method on sets of random numbers to demonstrate its potential in studying various types of biases and the presence of periodical features. They showed that the method provides an alternative source of information for tracing biases and investigating periodical features within the data [*Pallikari'1999*].

5.4.2.1.4 Fluctuation Analysis (FA):

The standard Fluctuation Analysis (FA) [*Peng'1992, Bunde'1994*] is also based on random walk theory.

For a time series $\tilde{x}_i,\ i = 1, \ldots\ldots, N$, with zero mean, the global profile, i.e., the cumulative sum is defined as

$$Y(j) = \sum_{i=1}^{j} \tilde{x}_i \,, j = 0, 1, 2, \ldots\ldots, N \qquad 5.10$$

The profile $Y(j)$ is considered as the position of a random walker on a linear chain after *n* steps. The random walker starts at the origin and performs, in the *i*th step, a jump of length $\tilde{x}_i$ to the right, if $\tilde{x}_i$ is positive, and to the left, if $\tilde{x}_i$ is negative.

To find how the square-fluctuations of the profile scale with *s*, first each record of N elements is divided into $N_s = int\left(\frac{N}{s}\right)$ non-overlapping segments of sizes s starting from the beginning and N_s non-overlapping segments of size *s* starting from the end of the considered series. The fluctuations in each segment ν is then determined.

The two endpoint values of each segment $\nu = 0, \dots \dots, N_s - 1$, indicate the amount of fluctualtions in FA,

$$F_{FA}^2(\nu, s) = [\, Y\,(\nu s) - \mathrm{Y}\big((\nu+1)s\big)]^2 \qquad 5.11$$

and analogous for $\nu = N_s, \dots \dots, 2N_s - 1$,

$$F_{FA}^2(\nu, s) = [\, Y(N - (\nu - \mathrm{N_s})s) - \mathrm{Y}(\mathrm{N} - (\nu + 1 - \mathrm{N_s})s]^2 \qquad 5.12$$

Then the average of $F_{FA}^2(\nu, s)$ is calculated over all subsequence's to obtain the mean fluctuation $F_2\,(s)$,

$$F_2\,(s) = [\frac{1}{2\mathrm{N_s}} \sum_{\nu=0}^{2\mathrm{N_s}-1} F_{FA}^2(\nu, s)]^{\frac{1}{2}} \sim s^{\alpha} \qquad 5.13$$

By definition, $F_2\,(s)$ is the root-mean-square displacement of the random walker on the chain, after *s* steps. For uncorrelated x_i values, Fick's diffusion law is $F_2\,(s) \sim s^{1/2}$. For the long-term correlations, where $C(s)$ follows the power-law behaviour of the Eq. (2.8), $F_2\,(s)$ increases by a power law,

$$F_2\,(s) \sim s^{\alpha} \quad with\ \alpha \approx H, \qquad 5.14$$

For mono-fractal data, the fluctuation exponent α is identical with the Hurst exponent H and related to γ and β by

$$2\alpha = 1 + \beta = 2 - \gamma \qquad 5.15$$

The range of the α values that can be studied by standard FA is limited to $0 < \alpha < 1$. The results of FA become statistically unreliable for scales *s* larger than one tenth of the length of the data, i.e. the analysis is limited by $s < N/10$.

5.4.3 Methods for Non-Stationary Fractal Time Series Analysis:

5.4.3.1 Wavelet Analysis:

Signal theory elaborately discusses the frequency decompositions of time series and Wavelet Analysis originates from there [*Goupillaud'1984*, *Daubechies'1988*]. Wavelet transform of a signal $x(t)$ is a convolution integral which is replaced by a summation for a discrete time series $\tilde{x}_i$, *i=1*,....., *N*, like Fourier transform.

$$(\tau, s) = 1/s \int_{-\infty}^{\infty} x(t)\ \Psi\left[\frac{t-\tau}{s}\right] dt = 1/s \sum_{i=1}^{N} \widetilde{x}_i\ \Psi\left[\frac{i-\tau}{s}\right] \qquad 5.16$$

Here $\Psi(t)$ is the mother wavelet from which all daughter wavelets $\Psi_{\tau,s}(t) = \Psi(t-\tau)/s$ is obtained by shifting and stretching of the time axis. The wavelet coefficients $L_{\Psi}(\tau, s)$ depend on both, time position τ and scale s. Hence, the local frequency decomposition of the signal is described with a time resolution appropriate for the considered frequency $f = 1/s$. The mean value for all wavelets $\Psi(t)$ must have zero. The wavelets are picked up in such a way that they are orthogonal to polynomial trends, so that the analysis method is not sensitive to probable trends in the data.

5.4.3.2 Discrete Wavelet Transform (WT) Approach:

A detrending fractal analysis of time series can be easily implemented by considering Haar wavelet coefficients of the profile $Y(j)$, Eq.(2.13) [*Koscielny-Bunde'1998, Kantelhardt'2005*]. In this case the convolution Eq. (2.19) relates to the addition and subtraction of mean values of $Y(j)$ within segments of size s. Hence, defining $\bar{Y}_{\nu}(s) = \frac{1}{s}\sum_{j=1}^{s} Y(\nu s + j)$, the coefficients can be written as

$$F_{WTO}(\nu, s) \equiv L_{\psi_{Haar}^{(0)}}(\nu s, s) = \bar{Y}_{\nu}(s) - \bar{Y}_{\nu+1}(s) \qquad 5.17$$

$$F_{WT1}(\nu, s) \equiv L_{\psi_{Haar}^{(1)}}(\nu s, s) = \bar{Y}_{\nu}(s) - 2\bar{Y}_{\nu+1}(s) + \bar{Y}_{\nu+2}(s) \qquad 5.18$$

$$F_{WT2}(\nu, s) \equiv L_{\psi_{Haar}^{(2)}}(\nu s, s) = \bar{Y}_{\nu}(s) - 3\bar{Y}_{\nu+1}(s) + 3\bar{Y}_{\nu+2}(s) - \bar{Y}_{\nu+3}(s) \quad 5.19$$

for quadratic, constant & linear detrending, respectively. The simplification for higher orders of detrending is obvious. The resulting mean-square fluctuations $F_{WTn}^2(\nu, s)$ are averaged over all ν to get the mean fluctuation $F_2(s)$, see Eq. (2.16). Fig. 5 shows typical results for WT analysis of long-term correlated, short-term correlated and uncorrelated data.

Wavelet transform WT0 corresponds to standard FA as far as trend elimination is considered and only the constant trends in the profile are eliminated. WT1 is closely related to Hurst's rescaled range analysis: linear trends in the profile and constant trends in the data are eliminated, and the range of the fluctuation exponent $\alpha \approx H$ is up to 2. In general, WTn determines the fluctuations from the nth derivative, this way eliminating trends described by (n-1) st-order polynomials in the data. The results become statistically unreliable for scales s larger than one tenth of the length of the data, just as for FA.

5.4.3.3 Detrended Fluctuation Analysis (DFA)

Detrended Fluctuation Analysis (DFA), originally introduced by Peng et al. [*Peng'1994*], has been established as an important method to reliably detect long-range auto-correlations in non-stationary time series. The method is based on random walk theory and basically represents a linear detrending version of FA. DFA was later generalized for higher order detrending [*Bunde'2000*], separate analysis of sign and magnitude series [*Ashkenazy'2001*], multifractal analysis [*Kantelhardt'2002*] and data with more than one dimension [*Gu'2006*]. Its features have been studied in many articles [*Kantelhardt'2001, Hu'2001, Chen'2002,2005, Grau-Carles'2006, Nagarajan'2006a*]. apart from this, many comparisons of DFA with other exixting methods for stationary and non-stationary time-series analysis have been discussed, e.g., [*Taqqu'1995, Heneghan'2000, Weron'2002, Mielniczuk'2007*] and in particular [*Delignieresa'2006*], where a comparison between DFA & other established methods for short data sets have been discussed in details, and [*Bashan'2008*] discusses the comparison between DFA and other recently suggested improved methods. In most cases positive auto-correlations are reported leaving only a few exceptions with anti-correlations, e. g., [*Bahar'2001, Bartsch'2005, Santhanam'2006*].

Like the FA method, here also first the global profile or the cumulative sum is calculated and then is divided into $N_s = int\left(\frac{N}{s}\right)$ segments that are of size s and strictly non-overlapping. DFA deals with monotonous trends in a detrending procedure. This is accomplished by estimating a polynomial trend $y_{\nu,s}^{m}(j)$ within each segment ν by least-square fitting and subtracting the trend from the original profile,

$$\bar{Y}_s(j) = Y(j) - y_{\nu,s}^{m}(j) \qquad 5.20$$

The degree of the polynomial can be varied in order to eliminate constant (m = 0), linear (m = 1), quadratic (m = 2) or higher order trends of the profile function [*Bunde'2000*]. Conventionally the DFA is named after the order of the fitting polynomial (DFA0, DFA1, DFA2, ...). In DFA *m*, trends of order m in the profile $Y(j)$ and of order m-1 in the original record $\tilde{x}_i$ are eliminated. The variance of the detrended profile $\bar{Y}_s(j)$ in each segment ν yields the mean-square fluctuations,

$$F_{DFAm}^{2}(\nu, s) = \frac{1}{s}\sum_{j=1}^{s}\bar{Y}_s^2(j) \qquad 5.21$$

Like FA the $F_{DFAm}^{2}(\nu, s)$ are averaged over all segments ν to obtain the mean fluctuations $F_2(s)$, [Eq. (5.21)]. Calculating $F_2(s)$ for many *s*, the fluctuation scaling exponent α can be determined just like FA.

If $F_2(s)$ increases for increasing s by $F_2(s) \sim s^{\alpha}$ with $0.5 < \alpha < 1$, it is found that the scaling exponent $\alpha \approx H$ is related to the correlation exponent γ by $\alpha = 1 - \gamma/2$ [Eq. (2.18)]. Value of $\alpha = 0.5$ indicates that there is no (or only short-range) correlations. If $\alpha > 0.5$ for all scales *s*, the data are long-term correlated. The higher the α, the stronger is the correlations in the signal. $\alpha > 1$ indicates a non-stationary local average of the data; but in this case, FA fails and yields only $\alpha = 1$. The case $\alpha < 0.5$ corresponds to long-term anti-correlations, meaning that large values are most likely to be followed by small values and vice versa. α values below 0 are not possible. Since the maximum value for α in DFA*m* is *m+1*, higher detrending orders is used for non-stationary data with large α. Like in FA and Hurst's analysis, α will decrease or increase by one upon additional differentiation or integration of the data, respectively.

Small deviations from the scaling law [Eq. (2.17)] occur for small scales *s*, particularly for DFA*m* with large detrending order m. These deviations are intrinsic to the usual DFA method, since the scaling behaviour is asymptotic. The deviations limit the capability of DFA to determine the correct correlation behaviour in very short records and for small *s*. An approach for correction of this systematic artefact in DFA is described in [*Kantelhardt'2001*].

The number of independent segments of length *s* is larger in DFA than in WT, and the fluctuations in FA are larger than in DFA. Hence, the analysis has to be based on *s* values lower than s_{max} = N/4 for DFA compared with s_{max} = N/10 for FA and WT. The accuracy of scaling exponents α determined by DFA is recently studied as a function of the length N of the data [*Bashan'2008*].

DFA has wide range of application in diverse fields e.g. Geology, DNA sequences, neuron spiking, and heart rate dynamics, economic time series, weather related and earthquake signals, computer science, bio-dynamics, bioinformatics, and meteorology [*Peng'1993,1994,1995, Ossadnik'1994, Buldyrev'1995,1998, Havlin'1999, Iyengar'1996, Ivanov'1998,1999,2000, Ho'1997, Viswanathan'1997, Blesic'1999, Liu'1999, Pikkujamsa'1999, Stanley'1999, Ashkenazy'1999,2001 Makikallio'1999, Absil'1999, Toweill'2000, Bunde'2000, Laitio'2000, Talkner'2000, Heneghan'2000, Siwy'2002, Santhanam'2006, Masugi'2006, Carpena' 2007*].

Kurnaz [*Kurnaz'2004*] used DFA to investigate correlations between the monthly averages of the maximum daily temperatures for different locations in the continental US and the different climates these locations have. The study suggested that different climates can be readily distinguished using the DFA method on the fluctuations of the maximum daily temperatures. DFA is also used to study the roughness features of texture images [*Alvarez-Ramirez'2006*].

A study conducted on a small group of patients suffering from heart rate variability, suggests that the DFA scaling exponents allow the discrimination of normal neonates from neonates having experienced an apparent life threatening event (ALTE), which are considered to be at increased risk for sudden infant death syndrome (SIDS) [*Lemmerling'2003*]. The DFA scaling exponents are also reported to be dependent on a number of confounding factors such as age, gender, body position, physical activity level (rest vs. exercise) [*Tulppo'2001*], sleep stages [*Penzel'2003*] etc.

Jiang et al. applied the DFA method, to explore the characteristics of multichannel EEG, recorded from many subjects performing different mental tasks. The results show that mental EEG exhibits long-range power-law correlations by calculating its scaling exponents (α), which can reflect the kinds of mental tasks. The scaling exponent of Letter-composing is different from that of Multiplication especially at positions C3 and C4, and at positions O1 and O2 the scaling exponent of Rotation is also different distinctively from that of Multiplication. The value of α at O1 is distinctively less than the value at the other channels during each mental task. The authors also observed that DFA is robust against noises [*Jiang'2005*].

Some researchers like Lee applied DFA to analyze EEG signals in sleep and observed that scaling exponents α become greater significantly as sleep stage goes to deep sleep [*Lee'2002*]. As we known, sleep stage determines the complexity of EEG which indexes the extent of random, and the complexity of EEG is high during waken and light sleep stage but reduce during deep sleep. Not only the physiological function but also the psychological activities like thinking affect EEG complexity. So it can be explained with complexity that α changes corresponding to mental tasks.

A major advantage of the DFA technique is the systematic elimination of polynomial trends of different order [*Bunde'2000, Chen'2002,2005*], though an additive composition of fluctuations and trends is assumed. The technique can thus assist in gaining insight into the scaling behaviour of the natural variability as well as into the kind of trends of the considered time series [*Giese'2007*].

However, the DFA method is insufficient to characterize time series having multi-fractal properties. This method assumes that both stationary and non-stationary time series are mono-fractal revealed by a single scaling exponent. Nevertheless, some time series contain many interwoven fractal subsets exhibiting multi-fractal scaling property. In practice, the property of multifractality can be detected by measuring the series of different moments. Advanced fractal methods are thus required for the identification of long-range correlation and multifractal properties of such time series [*Ge'2013*].

If it is not clear whether a given time series is long-term correlated or short-term correlated with a fairly large correlation time scale, results of DFA should be compared with other methods. Wavelet methods can be employed. Removing short-term correlations by considering averaged series is another option. For a time series with daily observations and possible short-term correlations up to two years, the series of two-year averages might be considered and DFA as well as FA, Hurst's Analysis, binned power spectra analysis, and/or wavelet analysis can be applied. Only if at least two independent methods consistently indicate long-term correlations, one can be sure that the data are long-term correlated [*Bashan'2008*].

Several modifications of the DFA method have been suggested with many different techniques for the elimination of monotonous and periodic trends. These methods are

- Detrended Moving Average technique [*Alessio'2002, Carbone'2004$_a$,2004$_b$*], which is denoted by DMA,
- Backward Moving Average (BMA) technique [*Alvarez-Ramirez'2005*],
- Centered Moving Average (CMA) method [*Alvarez-Ramirez'2005*], an essentially improved version of BMA,
- Modified Detrended Fluctuation Analysis (MDFA) [*Kiyono'2005*], which is essentially a mixture of old FA and DFA,

- Continuous DFA (CDFA) technique [*Staudacher'2005, Telser'2007*], which is particularly intended for the detection of transitions,
- Fourier DFA [*Chianca'2005*],
- Variant of DFA based on empirical mode decomposition (EMD) [*Jánosi'2005*],
- Variant of DFA based on singular value decomposition (SVD) [*Nagarajan'2005,2006$_b$*] and
- Variant of DFA based on high-pass filtering [*Rodriguez'2007*].

5.4.4 A Detailed overview of DFA, MFDFA & MFDXA

In recent years, the Detrended Fluctuation Analysis (DFA) [Peng'1994, Ossadnik'1994] has become a widely used method for determining (mono-) fractal scaling properties and finding long-range correlations in noisy, non-stationary time series [Taqqu'1995, Hu'2001, Kantelhardt'2001, Chen'2002]. In the last chapter, we talked about different ways to use the DFA method. One reason to use the DFA method is to avoid finding false correlations that are caused by the fact that the time series is not stationary.

Many records don't follow a simple scaling pattern that can be explained by a single scaling exponent. In some cases, there are crossover (times-) scales s_x that separate regimes with different scaling exponents [Kantelhardt 2001, Hu 2001], such as long-range correlations on small scales s«s_x and a different type of correlation or uncorrelated behavior on larger scales s » s_x. In other cases, scaling behavior is more complicated, and different scaling exponents are needed for different parts of the series [Chen, 2002]. This happens, for example, when the way the scaling works in the first half of the series is different from how it works in the second half. In even more complicated situations, you can see this kind of different scaling behavior for many different fractal subsets of the time series that are all connected to each other. In this case, a full description of how scaling works needs a lot of scaling exponents, and a multifractal analysis must be used. Kantelhardt et al. proposed the Multifractal Detrended Fluctuation Analysis (MF-DFA) [Kantelhardt'2002] to investigate multifractality of time series.

5.4.4.1 Multifractal Detrended Fluctuation Analysis (MFDFA)

The Multifractal Detrended Fluctuation Analysis (MF-DFA) developed by Kantelhardt et al. [Kantelhardt'2002] provides an approach to characterize long-range correlation and multi-fractal property of time series. Since its creation, this method has been used to find long-range dependencies and multifractality in fields like hydrology [Kantelhardt 2003], earthquakes [Telesca 2005a, Telesca and Lapenna 2006], economics [Du and Ning 2008], magnetic field data [Anh 2007], and sunspot activity [Movahed 2006].

The generalized multifractal DFA (MF-DFA) procedure consists of five steps. The first three steps are identical to the conventional DFA procedure.

Step 1. Let us suppose $x(i)$ for $i = 1 \ldots\ldots\ldots\ldots N$, be a series of length N and the series be of compact support. The mean of the above series is given by

$$x_{ave} = \frac{1}{N}\sum_{i=1}^{N} x(i) \qquad 5.22$$

If $x(i)$ are assumed to be increments of a random walk process around the average, the trajectory can be obtained by integration of the signal.

$$Y(i) = k = \sum_{k=1}^{i} \sum_{k=1}^{i} [x(k) - x_{ave}] \qquad 5.23$$

The integration also reduces the level of measurement noise present in experimental records and finite data.

Step 2. The integrated time series is then divided into $N_s = int(N/s)$ non-overlapping segments, of equal length s. Since N is not a multiple of s, a short part of the series is left at the end. To include this part of the series the entire process is repeated starting from the opposite end, thus leaving a short part at the beginning. Thus $2N_s$ segments are obtained altogether.

Step 3. The local trend for each of the $2N_s$ segments is calculated by a least-square fit of the series and then the variance is determined.

$$F^2(s, \nu) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(\nu - 1)s + i] - y_{\nu}(i)\}^2 \qquad 5.24$$

for each segment ν, $\nu = 1, \dots \dots . N_s$ and

$$F^2(s, \nu) = \frac{1}{s}\sum_{i=1}^{s}\{Y\,[\,N - (\nu - N_s)s + i\,\,] - y_{\nu}(i)\}^2 \qquad 5.25$$

for each segment $\nu = N_s + 1, \dots \dots ,2N_s$. Here $y_{\nu}(i)$is the fitting polynomial in segment ν. Linear, quadratic, cubic, or higher order polynomials can be used in the fitting procedure (conventionally called DFA 1,DFA 2, DFA3,......) [*Peng'1994, Ossadnik'1994, Bunde'2000*]. Since the detrending of the time series is done by subtraction of the polynomial fits from the profile, different order DFA differ in their capability of eliminating trends in the series. In (MF-)DFAm [m^{th} order (MF-)DFA] trends of order m in the profile (or, equivalently, of order $m - 1$ in the original series) are eliminated. Thus a comparison of the results for different orders of DFA can help to estimate the type of polynomial trend in the time series [*Kantelhardt'2001, Hu'2001*].

Step 4. The q^{th} order fluctuation function $F_q(s)$ is obtained after averaging over $2N_s$ segments

$$F_q(s) = \{1/2N_s \sum_{\nu=1}^{2N_s} [\,F^2\left(s, \nu\right)^{\frac{q}{2}}\Big)]\}^{1/q} \qquad 5.26$$

where q is an index that can take all possible values except zero, because in that case the factor $1/q$ is infinite. For $q = 2$ the standard DFA procedure is retrieved. To see how the generalized q dependent fluctuation functions

$F_q(s)$depend on the time scale s for different values of q steps 2 to 4 is repeated for several time scales s.$F_q(s)$depends on the DFA order m. By construction, $F_q(s)$is only defined for $s \geq m+2$.

Step 5. The scaling behaviour of the fluctuation functions is determined by analyzing log-log plots $F_q(s)$versus s for each value of q.If the series is long range power correlated, then $F_q(s)$ increases for large values of s, as a power-law,

$$F_q(s) \propto s^{h(q)} \qquad 5.27$$

For very large scales, $s > N/4$, $F_q(s)$becomes statistically unreliable because the number of segments N_s for the averaging procedure in step 4 becomes very small. Thus, scales $s > N/4$ should be excluded from the fitting procedure determining $h(q)$. Besides that, systematic deviations from the scaling behaviour in Eq. (3.6), which can be corrected, occur for small scales $s \approx 10$. Generally the exponent $h(q)$ in Eq. (3.6), may depend on q. For stationary time series, $h(2)$ is identical to the well-known Hurst Exponent H. Thus the function $h(q)$ is called generalized Hurst exponent which can be used to characterize the scaling behaviour of time series.

The value of $h(0)$, which corresponds to the limit$h(q)$ for $q \rightarrow 0$, cannot be determined directly using the averaging procedure in Eq. (3.5) because of the diverging exponent. Instead, a logarithmic averaging procedure has to be employed,

$$F_0(s) \equiv \exp\{1/4N_s \sum_{\nu=1}^{2N_s} ln[\,F^2(s,\nu)]\} \;\sim\; s^{h(0)} \qquad 5.28$$

$h(0)$ cannot be defined for time series with fractal support, where $h(q)$ diverges for $q \rightarrow 0$.

For mono-fractal time series with compact support, $h(q)$ is independent of q, since the scaling behaviour of the variances $F^2(s,\nu)$is identical for all segments ν, and the averaging procedure in Eq. (3.5) will give just this identical scaling behaviour for all values of q. Only if small and large fluctuations scale differently, there will be a significant dependence of $h(q)$ on q. If positive values of q are considered, the segments $\nu$with large variance $F^2(s,\nu)$ (i.e. large deviations from the corresponding fit) will dominate the average$F_q(s)$. Thus, for positive values of q, $h(q)$ describes the scaling behaviour of the segments with large fluctuations. On the contrary, for negative values of q, the segments ν with small variance $F^2(s,\nu)$will dominate the average $F_q(s)$. Hence, for negative values of q, $h(q)$ describes the scaling behaviour of the segments with small fluctuations.

Usually the large fluctuations are characterised by a smaller scaling exponent $h(q)$ for multifractal series than the small fluctuations. This can be understood from the following arguments: For the maximum scale $s = N$ the fluctuation function $F_q(s)$is independent of q, since the sum in Eq. (3.5) runs over only two identical segments ($N_s \equiv \left[\frac{N}{s}\right] = 1$).For smaller scales $s \ll N$ the averaging procedure runs over several segments, and the average value $F_q(s)$will be dominated by the $F^2(s,\nu)$from the segments with small (large) fluctuations if $q < 0$ ($q > 0$).Thus for

$s \ll N$, $F_q(s)$with $q < 0$ will be smaller than $F_q(s)$with $q > 0$, while both become equal for $s = N$. Hence, if a homogeneous scaling behaviour of $F_q(s)$following Eq. (3.6), is assumed the slope $h(q)$ in a log-log plot of $F_q(s)$with $q < 0$ versus s must be larger than the corresponding slope for $F_q(s)$with $q > 0$. Thus, $h(q)$ for $q < 0$will usually be larger than $h(q)$ for $q > 0$. A typical plot of $h(q)$ versus q is shown in Fig. 3.1

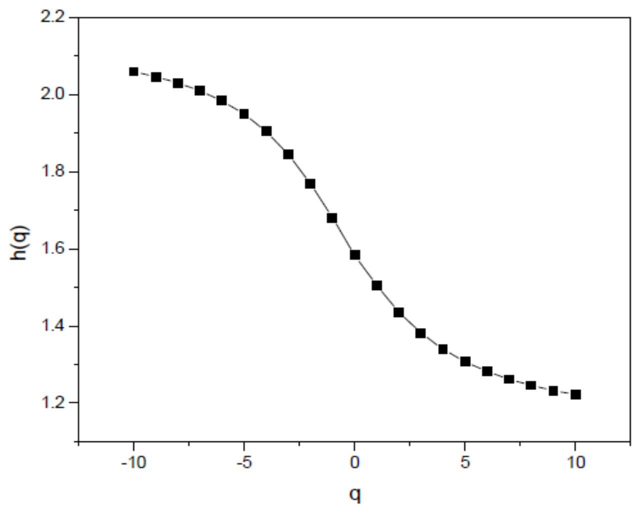


Fig. 5. 1: Plot of h(q) vs. q

A monofractal time series is characterized by unique $h(q)$ for all values of q. If small and large fluctuations scale differently, then $h(q)$ will depend on q, or in other words the time series is multifractal. Kantelhardt et al. [*Kantelhardt'2003*] have explained that the values of $h(q)$ for $q < 0$ will be larger than that for $q > 0$.

The generalized Hurst exponent $h(q)$ of MF-DFA is related to the classical scaling exponent $\tau(q)$ by the relation,

$$\tau(q) = qh(q) - 1 \qquad 5.29$$

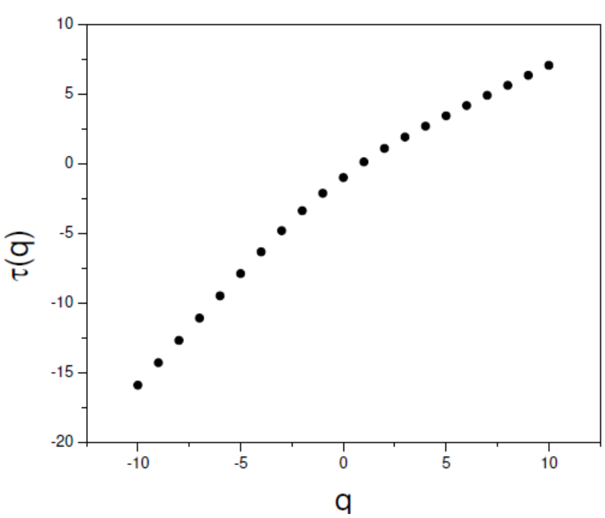


Fig. 5.2: Plot of $\tau(q)$ vs. q

A monofractal series with long range correlation is characterized by linearly dependent q - order exponent $\tau(q)$ with a single Hurst exponent H. Multifractal signals have multiple Hursts exponent and $\tau(q)$ depends nonlinearly on q[*Ashkenazy'2003$_a$*]. Fig. 3.2 depicts the non-linear dependence of $\tau(q)$ on q. The singularity spectrum $f(\alpha)$ is related to $\tau(q)$ by Legender transform [*Parisi'1985*]

$$\alpha = \frac{d\tau}{d\alpha} \qquad 5.30$$

$$f(\alpha) = q\alpha - \tau(q) \qquad 5.31$$

where α is the singularity strength or Hölder exponent and $f(\alpha)$ specifies the dimension of subset series that is characterized by α. Using Eq. (3.8), α and $f(\alpha)$ can be written in terms of $h(q)$,

$$\alpha = h(q) + qh'(q) \; 3.11$$

$$f(\alpha) = q[\alpha - h(q)] + 1 \qquad 5.32$$

The singularity spectrum, in general, quantifies the long range correlation property of a time series [*Ashkenazy'2002*]. The multifractal spectrum is capable of providing information about relative importance of various fractal exponents in the series e.g. the width of the spectrum denotes range of exponents. A quantitative characterization of the spectra can be made by least square fitting it to a quadratic function [*Shimizu'2002*] around the position of maximum α_0.

$$f(\alpha) = A(\alpha - \alpha_0)^2 + B(\alpha - \alpha_0) + C \qquad 5.33$$

Where C is a additive constant, $C = f(\alpha_0) = 1$; B indicates the asymmetry of the spectrum, and zero for a symmetric spectrum. The width of the spectrum can be obtained by extrapolating the fitted curve to zero. Width W is defined as $W = \alpha_1 - \alpha_2$ with $(\alpha_1) = f(\alpha_2) = 0$. A typical plot of the spectrum is shown in the following Fig. 3.3. It has been proposed by some workers [*Ashkenazy'2003$_b$*] that the width of the multifractal spectrum is a measure of the degree of multifractality.

Singularity strength or Hölder exponent α and the dimension of subset series $f(\alpha)$ can be obtained from Eq. (3.11) & (3.12). For a monofractal series, $h(q)$ is independent of q. Hence from the Eq. (3.11) & (3.12) it is evident that there will be a unique value of α and $f(\alpha)$, the value of α being the generalized Hurst exponent H and the value of $f(\alpha)$ being 1. Hence the width of the spectrum will be zero for a monofractal series. The more the width, the more multifractal is the spectrum.

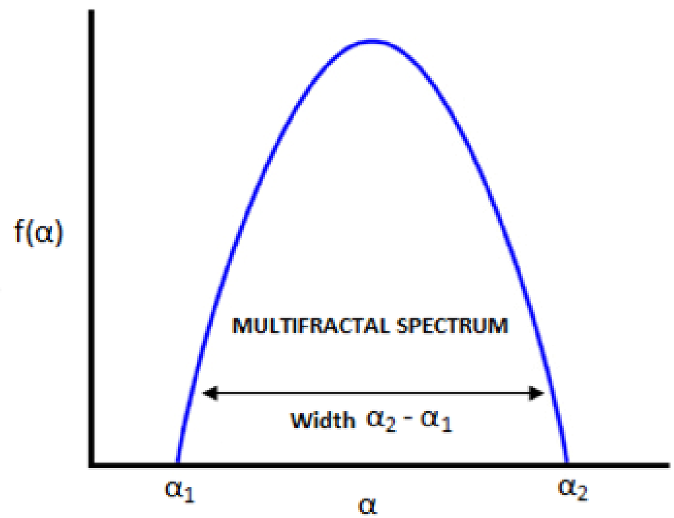


Fig. 5.3: Plot of $f(\alpha)$ vs. α

One can also ascertain the origin of multifractality. Two different types of multifractality may be present in a time series: Both of them require a multitude of scaling exponents for small and large fluctuations:

(i) Multifractality of a time series can be due to a broad probability density function for the values of the time series, and

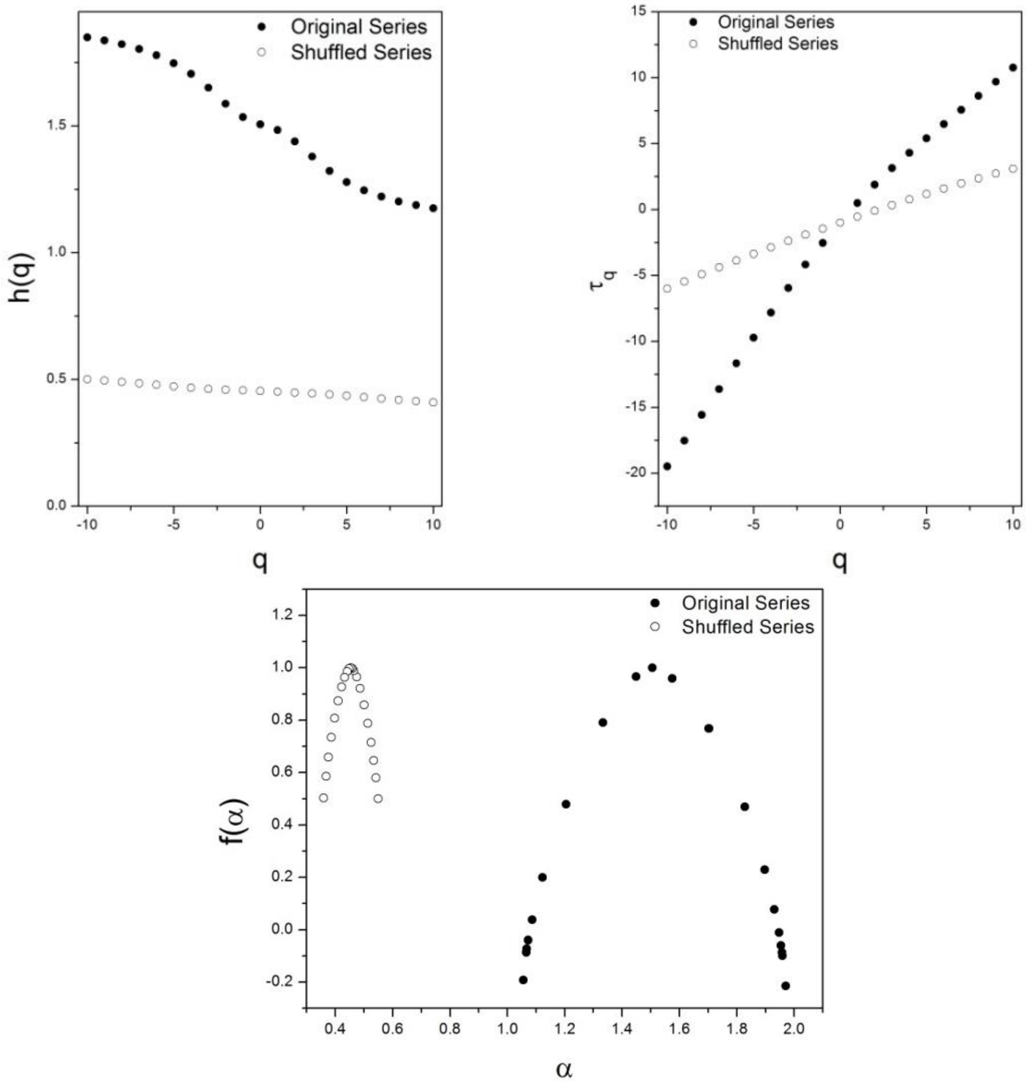
(ii) Multifractality can also be due to different long-range correlations for small and large fluctuations.

The easiest way to distinguish between the two is to analyze the corresponding randomly shuffled series. In the shuffling procedure the values are put in random order, and hence all correlations are destroyed. Hence if the multifractality is due to long range correlations, then the shuffled series will exhibit non-multifractal scaling. On the other hand, if the multifractality is due to broad probability density, then the original $h(q)$ dependence is not changed, $h(q) = h_{shuff}(q)$. However, if both kinds of multifractility are present in a given series, the shuffled series will show weaker multifractality than the original one. Fig. 3.4(a-c) pictorially depicts weaker multifractality of the shuffled series. The auto-correlation exponent γ can be estimated from the relation given below [*Kantelhardt'2001, Movahed'2008*]

$$\gamma = 2 - 2h(q = 2) \qquad 5.34$$

For uncorrelated or short range correlated data, $h(2)$ is expected to have a value 0.5 while a value greater than 0.5 is expected for long range correlation. Therefore for uncorrelated data, γ has a value 1 and the lower the value of γ more correlated is the data.

(a) (b)



(c)

Fig 5.4: (a) Plot of h(q) vs. q, (b) τ(q) vs. q, (c) f(α) vs. α for original and shuffled series

The MF-DFA method can only determine positive generalised Hurst exponents $h(q)$, and it becomes inaccurate for strongly anti-correlated signals when $h(q)$ is close to zero. In such cases, a modified (MF-) DFA technique has to be used. The simplest way to analyze such data is to integrate the time series before the MF-DFA procedure. Hence the single summation in Eq. (3.2) is replaced by a double summation.

$$\widetilde{Y}(i) \equiv \sum_{k=1}^{i}[Y(k) - \langle Y \rangle \qquad 5.35$$

Following the MF-DFA procedure as described above, a generalised fluctuation function is obtained $\tilde{F}_q(s)$described by a scaling law with $\tilde{h}(q) = h(q) + 1$.

$$\tilde{F}_q(s) \sim s^{h(q)} = s^{h(q)+1} \qquad 5.36$$

The scaling behaviour can thus be accurately determined even for $h(q)$ which are smaller than zero (but larger than -1) for some values of q. $\tilde{F}_q(s)/s$ corresponds to $F_q(s)$in Eq. (3.6). If the average value in each step of the summation in Eq. (3.15) is not subtracted, the summation leads to quadratic trends in the profile $\tilde{Y}(i)$. In this case the second order MF-DFA must be employed to eliminate the artificial trends.

There are many situations that several variables are simultaneously recorded that exhibit long-range dependence or multifractal nature.To investigate the long-range cross-correlations between two non-stationary time series, Detrended Cross-Correlation Analysis (DXA) was proposed and later to reveal the multifractal features of these cross-correlated signals Multifractal Detrended Cross-Correlation Analysis (MF-DXA) [*Zhou'2008*] was proposed.

5.4.4.2 Multifractal Detrended Cross-Correlation Analysis (MFDXA):

In 2008, Zhou [*Zhou'2008*], extended the DXA method to Multifractal Detrended Cross-Correlation Analysis (MF-DXA), an advanced version of the DXA method to investigate multifractal behaviour between two time series in one or higher dimensions, that are recorded simultaneously. The MF-DXA method is a combination of multifractal analysis and detrended cross-correlation analysis and is based on the q^{th} order detrended covariance [*Campillo'2003, Cottet'2004, Podobnik'2009$_b$*]. Just same as the MF-DFA method, MF-DXA consists of the 4 steps.

Step 1. Let us suppose $x(i)$ and $y(i)$ for for $i = 1 \dots \dots . N$ be a two non-stationary time series of length N. The means of the above series' are given by

$$x_{avg} = 1/N \sum_{i=1}^{N} x(i) \& \quad y_{avg} = 1/N \sum_{i=1}^{N} y(i) \qquad 5.37$$

Then the profiles of the underlying data series $x(i)$ and $y(i)$ are computed as

$$X(i) \equiv \sum_{k=1}^{i}[x_k - x_{avg}],$$

$$Y(i) \equiv \sum_{k=1}^{i}[y_k - y_{avg}] \qquad 5.38$$

the subtraction of mean is not compulsory. Since two different time series are to be compared, data sets are constructed with zero mean and unit variance using initial ones.

Step 2. The integration also reduces the level of measurement noise present in experimental records and finite data. The integrated time series is then divided into $N_s = int(N/s)$ non-overlapping segments, of equal length s. Since N is not a multiple of s, a short part of the series is left at the end. To include this part of the series the entire process is repeated starting from the opposite end, thus leaving a short part at the beginning. Thus $2N_s$ segments are obtained altogether. For each segment, least-square linear fit is performed and the fluctuation function is obtained:

$$F(s,\nu) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(\nu-1)s+i] - y_\nu(i)\} \times \{X[(\nu-1)s+i] - x_\nu(i)\} \qquad 5.39$$

for each segment ν, $\nu = 1, \dots, N_s$ and:

$$F(s,\nu) = \frac{1}{s}\sum_{i=1}^{s}\{Y[N-(\nu-N_s)s+i] - y_\nu(i)\} \times \{X[N-(\nu-N_s)s+i] - x_\nu(i)\} \qquad 5.40$$

for $\nu = N_s + 1, \dots, 2N_s$, where $x_\nu(i)$and $y_\nu(i)$are fitting polynomial in segment ν. Usually, a linear function is selected for fitting the function. If there is no trend in the data, a zeroth-order fitting function is used.

Step 3. Next the q^{th} order detrended covariance $F_q(s)$is obtained after averaging over $2N_s$ segments

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{\nu=1}^{2N_s}[F(s,\nu)]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \qquad 5.41$$

where q is an index which can take all possible values except zero because in that case the factor $1/q$ blows up. The procedure can be repeated by varying the value of s. $F_q(s)$ increases with increase in value of s.

Step 4. If the series is long range power correlated, then $F_q(s)$ shows power law behaviour

$$F_q(s) \sim s^{\lambda(q)} \qquad 5.42$$

If such a scaling exists $lnF_q(s)$ depends linearly on $ln\, s$, with $\lambda(q)$ as the slope. Scaling exponent $\lambda(q)$represents the degree of the cross-correlation between the two time series. In general the exponent $\lambda(q)$depends on q. The value of $\lambda(0)$ cannot be obtained directly because F_q blows up at $q = 0$. F_q cannot be obtained by the normal averaging procedure; instead a logarithmic averaging procedure is applied

$$F_0(s) \equiv exp\left(\frac{1}{4N_s}\sum_{\nu=1}^{2N_s}\ln F(s,\nu)\right) \sim s^{\lambda(0)} \qquad 5.43$$

For $q = 2$ the method reduces to standard DXA.

$F(s, \nu)$may obtain negative values in general. To eliminate the problem in evaluation of fluctuation functions which may be complex valued for different values of q we have taken the modulus of $F(s, \nu)$to eliminate the negative values. However there is a very recent work by Oswiecimka et al. [*Oswiecimka'2014*] in which the authors have suggested an alternative more rigorous method Multifractal Cross-Correlation Analysis (MFCCA) to take care of the negative values in cross covariances. The authors suggest that the proposed method is a more natural generalization of DXA compared to MF-DXA. It prohibits losing information that is stored in the negative cross-covariance. The method is yet to be tested in various systems.

If scaling exponent $\lambda(q)$ is independent of q, the cross-correlations between two time series are monofractal. If scaling exponent $\lambda(q)$ is dependent on q, the cross-correlations between two time series are multifractal. Further, for positive q, $\lambda(q)$ describes the scaling behaviour of the segments with large fluctuations and for negative q, $\lambda(q)$ describes the scaling behaviour of the segments with small fluctuations. Scaling exponent $\lambda(q)$represents the degree of the cross-correlation between the two time series $x(i)$and $y(i)$. The value $\lambda = 0.5$ denotes the absence of cross-correlation. $\lambda > 0.5$ indicates persistent long range cross-correlations where a large value in one variable is likely to be followed by a large value in another variable, while the value $\lambda < 0.5$ indicates anti-persistent cross-correlations where a large value in one variable is likely to be followed by a small value in another variable, and vice versa [*Movahed'2008*].

Zhou found that for two time series constructed by binomial measure from p-model, there exits the following relationship [*Zhou'2008*]:

$$\lambda(q = 2) \approx \frac{h_{xx}(q = 2) + h_{yy}(q = 2)}{2} \qquad 5.44$$

Podobnik and Stanley have studied this relation when $q = 2$ for monofractal Autoregressive Fractional Moving Average (ARFIMA) signals and EEG time series [*Podobnik'2008*]. Zhou has shown that the above relation holds for any q for Multifractal Random Walks (MRW) and binomial measures generated from the p model [*Mars'1983, Shadkhoo'2009*]. However there are also examples in which the above relation does not exist for all values of q, such as daily price changes for DJIA and NASDAQ indices [*Zhou'2008*, *Shadkhoo'2009*], but for q = 2 it is still correct [*Podobnik'2008*, *Shadkhoo'2009*]. The other example is the case of two time series generated by using two uncoupled ARFIMA processes, each of both is auto-correlated, but there is no power-law cross correlation with a specific exponent [*Podobnik'2008, Shadkhoo'2009*].

According to auto-correlation function given by:

$$C(\tau) = \langle [x(i+\tau) - \langle x \rangle][x(i) - \langle x \rangle] \rangle \sim \tau^{-\gamma} \qquad 5.45$$

Hajijan et al. [*Hajijan'2010*] introduced the cross-correlation function as

$$C_x(\tau) = \langle [x(i+\tau) - \langle x \rangle][y(i) - \langle y \rangle] \rangle \sim \tau^{-\gamma_x} \qquad 5.47$$

where γ and γ_x are the auto-correlation and cross-correlation exponents, respectively. Due to the non-stationarities and trends superimposed on the collected data direct calculation of these exponents are usually not recommended rather the reliable method to calculate auto-correlation exponent is the DFA method, namely $\gamma = 2 - 2h(q = 2)$ [*Kantelhardt'2001*, *Movahed'2008*]. Recently Podobnik et al. have demonstrated the relation between cross-correlation exponent, γ_x and scaling exponent derived by Eq. (3.22) according to $\gamma_x = 2 - 2\lambda(q = 2)$ [*Podobnik'2008*]. For uncorrelated data, γ_x has a value 1 and the lower the value of γ_x more correlated is the data.

In general, $\lambda(q)$ depends on q, indicating the presence of multifractality. In other words, we want to point out how two series are cross-correlated in various time scales. To clarify this correlation, we generalize the singularity spectrum, $f(\alpha)$, concept to two cross-correlated series. This generalized concept gives useful information about the distribution of the degree of cross-correlation in different time scales. The way to characterize multifractality of cross-correlation between two series is to relate via a $\lambda(q)$ Legendre transform, as in the case of one series [*Feder'1988*, *Peitgen'1992*].

$$\alpha = \lambda(q) + q\lambda'(q) \qquad 5.48$$

$$f(\alpha) = q[\alpha - \lambda(q)] + 1 \qquad 5.49$$

Here, α is the singularity strength or Hölder exponent, while $f(\alpha)$ denotes the dimension of the subset of the series that is characterized by α. Unique Hölder exponent denotes monofractality, while in the multifractal case, the different parts of the structure are characterized by different values of α, leading to the existence of the spectrum $f(\alpha)$. The width of the spectrum can be obtained by extrapolating the fitted curve to zero. Width W is defined as

$$W = \alpha_1 - \alpha_2 \qquad 5.50$$

with $f(\alpha_1) = f(\alpha_2) = 0.$ The growth of the width of $f(\alpha)$ shows the increase in the degree of multifractality of two coupled signals.

Since we know that two different types of multifractality may be present in a time series, the series is randomly shuffled and analyzed. In the shuffling procedure, the values are put into random order and hence all correlations are destroyed. Hence, if the multifractality is due to long range correlation, then, the shuffled series will exhibit non-multifractal scaling. On the other hand, if the multifractality is due to broad probability density, then, the original $\lambda(q)$ dependence is not changed, $\lambda(q) = \lambda_{shuff}(q)$. If both kinds of multifractality are present in a given series, the shuffled series shows weaker multifractality than the original one.

5.5 Superiority of MFDFA over other methods:

It is now the common consensus that the method MF-DFA has the highest precision in the scaling analysis as the results obtained by the method turns out to be more reliable compared to other methods such as Wavelet Analysis, Discrete (WT) Approach, WTMM, DMA, BMA, MDFA, CDFA, Fourier DFA, EMD, SVD etc to name a few. In particular, the MF-DFA has slight advantages for negative q values and short series. The main advantage of the MF-DFA method lies in the simplicity of the method. It is a very rigorous and robust tool for assessment of correlation in non-linear time series. MF-DFA does not require the modulus maxima procedure, and hence does not involve more effort in programming than the conventional DFA. Some authors have shown MF-DFA to perform better than other multifractal analyses methods [*Kantelhardt'2002, Oswiecimka'2006, Serrano and Figliola' 2009, Huang' 2011*]. The advantages of MF-DFA over many techniques are the fact that it permits the detection of the multifractality behaviour in stationary as well as non-stationary time series.

5.6 Music, Cognition and Brain Imaging Studies

The brain's various processes are better coordinated while music is playing. This argues that music cognition should be compared to other highly developed cognitive capacities. It is impossible to fully explain the profound effect that music has on both the brain and the emotions. The effects of music on the brain are not fully known at this time. The term "cognitive science" refers to a broad field of study that encompasses disciplines such as cognitive psychology, cognitive musicology, cognitive linguistics, neuroscience, neurolinguistics, cognitive anthropology, and more. At the beginning of the 1950s, the first generation of neuroscientists were defining some memory function mechanics, discovering more brain locations for specific functions, learning how experience could change brain anatomy (for example, string musicians have larger hand cortices than nonmusicians), and identifying the physical sources of cognition (Kandel & Squire, 2000). These neuroscientists came to the conclusion in 1970 that changes in the anatomical makeup of the brain are the root cause of memory. At the close of the 1970s, PET scans gained the ability to photograph brain activity. In 1990, images obtained using fMRI revealed dynamic neural activities. With all of these new technological advancements, mind-blowing images, and scientific and medical breakthroughs, neuroscience has taken the spotlight.

Cognitive Music study, conceived of by Seifert and Leman, to create a combination of brain research and artificial intelligence for the purpose of gaining a deeper understanding of music. The ambitious Blue Brain Project and the silicon retina (Chow et al., 2004) both have the same overarching goal: to transform computers by replacing their circuits with neocortical column models. Research in auditory neuroscience pertaining to music is quickly catching up to research in visual neuroscience. According to Shamma (2001), the visual and auditory processing in the brain are essentially the same. Smith and Lewicki disassembled musical signals into gammatone functions resembling the basilar membrane impulse response in feline brains.

(Drevets & Raichle, 1998) Current research has shown that neural regions involved in cognition and emotion share connections with one another. This runs counter to the traditional model of how the brain functions (Wager & Feldmann Barrett, 2004). Several people in the academic world are of the opinion that emotion came before cognition because it is the driving force behind cognitive and behavioral processes such as making decisions and being active. According to certain views on the origin of the brain, emotion came before intellect. Core affect is an argument that the structure-functional difference cannot cleanly separate cognition and emotion. It was proposed by Russell and Barrett in 1999 and explains the fundamental affective experience that takes place whenever a self-relevant event takes place. Brain imaging has been used to research the influence of music on emotional reactions as well as individual variances in these responses. Many research investigated the activation of different parts of the brain as participants listened to music with varying emotional valences, tones, and structural qualities that lead to emotional processing. In Recent times, participants have seen images that were designed to elicit standardized emotional responses while listening to music. Numerous studies have analysed how various musical training have the power to influence brain responses to different musical feelings.

5.6 References

Abadi, M., et al. The 11th Iberoamerican Congress on Pattern Recognition 4225 297 (2006)

Absil, P.A., et al. Physica A 272 235 (1999)

Alessio, E., et al. European Physical Journal B 27 197 (2002)

Alpigini, J.J. Inf. Vis. 3 271 (2004)

Alvarez-Ramirez, J., et al. Physica A 354 199 (2005)

Alvarez-Ramirez, J., et al. Physica A 361 677 (2006)

Anderson, J., et al. Journal American College of Cardiology 30 226 (1997)

Appleby, S., Geographical Analysis 28 147 (1996)

Arianos, S., et al. Physica A 382 9 (2007)

Arneodo, A. et al., The science of disaster: climate disruptions, market crashes, and heart attacks Springer, Berlin (2002)

Arnéodo, A., et al. Physical Review Letters 74 3293 (1995)

Arnéodo, A., et al. European Physical Journal B 1 129 (1998)

Arnéodo, A., et al. European Physical Journal B 15 567 (2000)

Ashkenazy, Y., et al. Fractals 7 85 (1999)

Ashkenazy, Y., et al. Physical Review Letters 86 1900 (2001)

Babbs, C.F.J. Clin. Exp. Cardiol 5 2 (2014)

Bacry, E., Delour J., Muzy J.F., et al. Physical Review E 64 026103 (2001)

Badii, R., et al. Physical Review Letters 52 1661 (1984)

Badii, R., et al. Journal of Statistical Physics 40 725 (1985)

Bahar, S., Europhysics Letters 56 454 (2001)

Barabási, A.L., et al. Physica Review A 44 2730 (1991)

Barnes, J.A., et al. Proc. IEEE 54 176 (1996)

Bartsch, R., et al. Physica A 354 415 (2005)

Bashan, A., et al. Physica A 387 5080 (2008)

Bassingthwaighte, J., et al. Annals of the New York Academy of Science 591 392 (1990)

Batty, M., et al. Academic Press: London, UK (1994)

Batty, M., et al. Discret. Dyn. Nat. Soc. 3 109 (1999)

Batty, M., et al. Springer: Berlin, Germany, pp. 21–45 (2012)

Batty, M. The New Science of Cities; MIT Press: Cambridge, MA, USA (2013)

Beaulac, S., et al. Physics of Fluids 16 2126 (2004)

Benbachir, S., et al. Int Research J of Finance and Economics 78 (2011)

Benguigui, L., et al. Environ. Plan. B 27 507 (2000)

Billat, V.L., et al. Physica A 388 3798 (2009)

Bisoi, A., et al. Pattern Recognition Letters 22 631 (2001)

Biswas, M., et al. Pattern Recognition Letters 19 309 (1998)

Blanton, R., et al. Psychiatry Research 107 29 (2001)

Blesic, S., et al. Physica A 268 275 (1999)

Boiangiu, C.A., 6th Int Conf Proceed on Applied Informatics and Computing Theory, Salerno, Italy (2015)

Box, G.E.P., et al. Prentice Hall, New Jersey (1994)

Bradley, E. Springer: Berlin, Germany (2003)

Bradley, E., et al. Chaos 25 097610 (2015)

Brown Clifford, T., et al. Journal of Archaeological Science 30 1619 (2003)

Buldyrev, S.V., et al. Physical Review E 51 5084 (1995)

Buldyrev, S.V., et al. Physica A 249 430 (1998)

Bullmore, E., et al. Psychological Medicine 24 771 (1994)

Bunde, A., et al. Fractals in science, Springer, Berlin (1994)

Bunde, A., et al. Physical Review Letters 85 3736 (2000)

Byng, J., et al. Physics in Medicine and Biology 41 909 (1996)

Caldwell, C., et al. Physics in Medicine and Biology 35 235 (1990)

Carbone, A., et al. Physica A 344 267 (2004_a)

Carbone, A., et al. Physical Review E 69 026105 (2004_b)

Carbone, A., Stanley H.E., et al. Physica A 340 544 (2004_c)

Carbone, A., Physical Review E 76 056703 (2007)

Carbone, A., Science and Technology for Humanity (TICSTH) IEEE 691 (2009)

Carpena, P., et al. Physical Review E 75 032903 (2007)

Carter, P.H., et al. Materials Research Society, Pittsburgh, (1985)

Cartwright, T.J. J. Am. Plan. Assoc. 57 44 (1991)

Caruso, F., et al. Fractals 14 179 (2006)

Caswell Schuckers, S. Computers in Cardiology 1998 (13–16) 265 (1998)

Chakraborty, S., et al. International Journal of Computational Cognition 9 (2011)

Chatfield, C. Taylor & Francis Ltd. (2003)

Chaudhuri, B., et al. IEEE Transactions on Pattern Analysis and Machine Intelligence 17 72 (1995)

Chen Z., et al. Physical Review E 71 011104 (2005)

Chen, C. Springer: London, UK (2006)

Chen, S., et al. IEEE Transactions on Pattern Analysis and Machine Intelligence 15 1087 (1993)

Chen, W.D., et al. International Conference on Transportation Engineering 2007 (ICTE 2007)

Chen, W.L., et al. Microwave and Optical Technology Letters 49 7 (2007)

Chen, Y., et al. Chaos Solitons Fractals 35 85 (2008)

Chen, Z., et al. Physical Review E 65 041107 (2002)

Chen,W.C. Chaos Solitons Fractals 36 1305 (2008)

Chhabra, A., Jensen, R., Physical Review Letters 62 1327 (1989)

Chianca, C.V., et al. Physica A 357 447 (2005)

Choudhury, P.P., et al. arXiv:0909.2517 (2009)

Churchill, M., Keble Summer Essay: Introduction to Fractal Geometry Pg 1-24 (2004)

Cohen, N.L., Communications Quarterly, 5 3 (1995)

Cohen, N.L., Communications Quarterly, 6 3 (1996)

Conlon, T., et al. Physica A 388 705 (2009)

Cook, M., et al. European Neurology 35 327 (1995)

Costa, R., et al. Physica A 329 231 (2003)

Cottet, A., et al. Physical Review Letters 92 206801 (2004)

Cross, S., et al. Journal of Pathology 170 479 (1993)

Cross, S., et al. Journal of Pathology 173 115 (1994)

Das, A., et al. Fractals 14 165 (2006)

Daubechies, I. Communications on Pure and Applied Mathematics 41 909 (1988)

De Bartolo, S., etg al. Water Resources Research 40 W02201 (2004)

Decoster, N., et al. European Physical Journal B 15 739 (2000)

Delignieresa, D., et al. Journal of Mathematical Psychology 50 525 (2006)

DePenya, F.J., et al. Global Finance Journal 18 84 (2007)

Dick, O.E., et al. Neurocomputing 82 207 (2012_a)

Dick, O.E., et al. Human Physiology 38 249 (2012_b)

Drożdż, S., et al. EPL (Europhysics Letters) 88 (2009)

Dubuc, B., et al. Physica Review A 39 1500 (1989)

Dubuisson, M., et al. Pattern Recognition Letters 15 419 (1994)

Enescu, B., et al. Annals of Disaster Prevention Research Institute, Kyoto University 47 B (2004)

Enescu, B., et al. Pure Applied Geophysics 162 249 (2005)

Eom, G., et al. Physica A 383 139 (2007)

Espinal F., et al. Proc. SPIE of Wavelet Applications 3391 602 (1998)

Ezekiel, S., Proc. of the Applied Informatics 378 220 (2003)

Falconer, K., John Wiley & Sons Ltd 2nd Edition (2003)

Feder, J., Fractals, Plenum Press, New York (1988)

Fighola, A., et al. Nonequilibrium Statistical Mechanics and Nonlinear Physics, 913 190 (2007)

Free, S., et al. Cerebral Cortex 6 830 (1996)

Ge, E., et al. Journal of Geographical Systems 15 115 (2013)

Giese, E., et al. Erdkunde 61 186 (2007)

Gilmore M., et al. Physics of Plasmas, 9 1312 (2002)

Glass, L. Chaos 19 028501 (2009)

Glenny, R., et al. Journal of Applied Physiology 70 1024 (1991)

Godano, C., et al. Geophysics Journal International 121 385 (1995)

Goldbeter, A. Nature 420 238 (2002)

Gorski, A.Z., et al. Journal of Anatomy 208 353 (2006)

Goupillaud, P., et al. Geoexploration 23 85 (1984)

Grassberger, P., Procaccia, I., et al. Physical Review Letters 50 346 (1983)

Grassberger, P., et al. Journal of Statistical Physics 51 135 (1988)

Grau-Carles, P., Physica A 287 396 (2000)

Grau-Carles, P., Physica A 299 521 (2001)

Grau-Carles, P., Physics A 360 89 (2006)

Grech, D., Mazur Z.,et al. Acta Physica Polonica B 36 2403 (2005)

Gu, G.F., Zhou W.X., et al. Physical Review E 74 061104 (2006)

Gu, G.F., et al. European Physical Journal B 57 81 (2007)

Guastello, S.J. Psychology Press: New York, USA (2013)

Guégan, D. Annu. Rev. Control 33 89 (2009)

Guillemet, H. Ecole Nationale Supérieure des Télécommunications, Paris, France 171 (1996)

Guo, Q., et al. International Journal of Computer Assisted Radiology and Surgery 2 336 (2007)

Gyuchang, L., et al. Physica A 386 259 (2007)

Hajian, S., et al. Physica A 389 4942 (2010)

Halsey, T.C., et al. Physica Review A 33 1141 (1986)

Hamouche, M.B. Nexus Netw. J. 11 217 (2009)

Hastings, A., et al. Annu. Rev. Ecol. Syst. 24 1 (1993)

Havlin, S., et al. Chaos, Solitons & Fractals 6 171 (1995)

Havlin, S., et al. Physica A 273 46 (1999)

Hayakawa, M., et al. Geophysics Research Letters 26 2797 (1999)

Hayakawa, M., et al. Geophysics Research Letters 27 1531 (2000)

Heneghan, C., et al. Physical Review E 62 6103 (2000)

Holschneider, M. Journal of Statistical Physics 50 953 (1988)

Hong, Z., et al. Proceed Int Conf on Computer Appl and Syst Modeling (ICCASM 2010), Taiyuan, China, October pp. 332–334 (2010)

Hoshi, R.A., et al. Auton. Neurosci. 177 271 (2013)

Hsu, W.Y., et al. Journal of Neuroscience Methods 163 145 (2007)

Hu, K., et al. Physical Review E 64 011114 (2001)

Huang, Y., Yu S.et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3922-3925 (2007)

Hunt, G.A., Transactions of the American Mathematical Society 71 38 (1951)

Hurst, H.E., et al. Constable and Co., Ltd, London (1965)

Hurst, H.E., Transactions of the American Society of Civil Engineering 116 770 (1951)

Ida, T., et al. IEEE transactions on circuits and systems for video technology 8 968 (1998)

Iftekharuddin, K., et al. Machine Vision and Applications 13 352 (2003)

Iftekharuddin, K., et al. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society 4 3064 (2000)

Imre, A.R., et al. Acta Biotheoretica 52 41 (2004)

Innes, J.E., et al. Planning with Complexity; Routledge: London, UK (2010)

Ivanov, P.C., et al. Europhysics Letters 43 363 (1998)

Ivanov, P.C., et al. Europhysics Letters 48 594 (1999)

Ivanov, P.C., et al. Europhysics Letters 52 40 (2000)

Ivanov, K., et al. European Physical Journal B 8 665 (1999)

Iyengar, N., et al. The American Journal of Physiology 40 R1078 (1996)

Jafari, G.R., Pedram P., Hedayatifar L., et al. Journal of Statistical Mechanics P04012 (2007)

Jain, R., et al. Nature Reviews Cancer 2 266 (2002)

Jánosi, I.M., et al. Physical Review E 71 056126 (2005)

Jelinek Herbert, F., et al. Journal of Neuroscience Methods 81 9 (1998)

Jiang, Z., et al. Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September (2005)

Jiang, Z.Q., et al. Physica A 381 343 (2007)

Jin, X., et al. Pattern Recognition Letters 16 457 (1995)

Jizba, Petr., et al. Proceedings, 15th Applied Stochastic Models and Data Analysis (ASMDA 2013) International Conference, Mataró (Barcelona), Spain, June (2013)

John, Set al. MIT Press (Eds), London (1993)

Jun, et al., Physical Review E 73 066128 (2006)

Jun, Y., et al. Proceedings of the 16th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 1 161 (1994)

Jung, W.S., et al. Physica A 361 263 (2006)

Kalmanti E., et al. In Vivo 21 641 (2007)

Kantelhardt, J.W., et al. Physica A 220 219 (1995)

Kantelhardt, J.W., et al. Physica A 295 441 (2001)

Kantelhardt, J.W., et al. Physica A 316 87 (2002)

Kantelhardt, J.W. arXiv:0804.0747v1 [physics.data-an] (2008)

Kaplan, L. IEEE Transactions on Image Processing 8 1572 (1999)

Katsuragi, H. Physica A 278 275 (2000)

Kedzia, A., et al. Medical Science Monitor 8 46 (2002)

Keller, J., et al. Computer Vision Graphics and Image Processing 45 150 (1989)

Kenkel, N., et al. Coenoses 1 77 (1996)

Keough, K., et al. Journal of Microscopy 163 95 (1991)

Kestener, P., et al. Physical Review Letters 91 194501 (2003)

Kestener, P., et al. Physical Review Letters 93 044501 (2004_a)

Kestener, P., et al. Image Analysis and Stereology 20 169 (2004_b)

Kikuchi, A., et al. Early Human Development 81 655 (2005)

Kimiagar, S., et al. Journal of Statistical Mechanics P03020 (2009)

Kiyono, K., et al. Physical Review Letters 95 058101 (2005)

Koscielny-Bunde, E., et al. Physical Review Letters 81 729 (1998)

Kravchenko, A.N., et al. Agronomy Journal 92 1279 (2000)

Krenz, G., et al. Journal of Applied Physiology 72 2225 (1992)

Kulish, V., et al. Computers in Biology and Medicine 36 291 (2006)

Kurnaz,, M.L. Fractals 12 365 (2004)

Landini, G., Rippin J.W., et al. Analytical & Quantitative Cytology & Histology 18 167 (1996)

Lanyi, M. Springer-Verlag (Eds), Berlin, Heidelberg, New York 252 pp (1986)

Lapenna,V., et al. Geophysics 70 11 (2005)

Layek, G.C. Springer: New Delhi, India (2015)

Lee, J.M., et al. Computers in Biology and Medicine 32 3 (2002)

Lee, W., et al. Information Sciences 175 177 (2005)

Lemmerling, P., et al. Advances in Experimental Medicine and Biology 510 369 (2003)

Lévy-Véhel, J., et al. Technical report of INRIA-Rocquencourt, 1706 (1992)

Lévy-Véhel, J. Fractals 3 755 (1995a)

Lévy-Véhel, J., et al. Technical report of INRIA-Rocquencourt, 2576 (1995b)

Li, H., et al. Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medecine and Biology Society 3 1111 (1996)

Li, H., et al. Academic Radiology 14 513 (2007)

Li, X., et al. Journal of Neural Engineering 2 11 (2005)

Lim, G., et al. Physica A 386 259 (2007)

Lippiello, E., et al. Physical Review Letters 100 038501 (2008)

Litvin, V.A. Physica A 344 178 (2004)

Liu, J., et al. Biophysical Journal 85 4041 (2003)

Liu, Y., et al. Physical Review E 60 1390 (1999)

Lopes, R., et al. International Journal of Computer Assisted Radiology and Surgery 3 341 (2008)

Lorenz, E.N. J. Atmos. Sci. 20 130 (1963)

Maeda, J., et al. Proceedings of the 14th International Conference on Pattern Recognition 2 991 (1998)

Makikallio, T., et al. American Journal of Cardiology 81 27 (1998)

Makris, G., et al. Proceed 5th Chaotic Model and Simul Int Conf, Athens, Greece, June pp. 309–318 (2012)

Mamishev, A.V., et al. IEEE Transactions on Power Systems, 11 435 (1996)

Mandelbrot, B.B., et al. SIAM Review 10 422 (1968)

Mandelbrot, B.B., et al. Water Resources Research 5 321 (1969)

Mandelbrot, B.B. New York: W. H. Freeman and Company (1977)

Mandelbrot, B.B. The Fractal Geometry of Nature. Freeman (Eds), 468 pp (1983)

Mandelbrot, B.B. Scientific American 280 70 (1999)

Mansury, Y., et al. Physica A 331 219 (2004)

Mantegna, R.N., et al. CUP, Cambridge (2000)

Mantegna, R.N., et al. Nature 383 587 (1996)

Mantegna, R.N., Stanley H.E., et al. Cambridge University Press, Cambridge (2004)

Martinez, P., et al. Radar 97 135 (1997)

Masugi, M. IEEE Transactions on Circuits and Systems Part I, Regular Papers 53 2318 (2006)

Matia, K., et al. Europhysics Letters 61 422 (2003)

Matsushita, R., et al. Physics Letters A 368 173 (2007)

Mavroforakis, M., et al. Artificial Intelligence in Medicine 37 145 (2006)

May, R.M. Nature 261 459 (1976)

Midha, P. 9th Biennial International Conference & Exposition on Petroleum Geophysiscs P-382 (2012)

Mielniczuk, J., et al. Computational Statistics & Data Analysis 51 4510 (2007)

Mohammad, F., et al. Multifractal Structure in Indian Stock Market Indices 5 261 (2012)

Montanari, A., et al. Mathematical and Computer Modelling 29 217 (1999)

Montrol, E.W., et al. Non-equilibrium phenomena ii from stochastics to hydrodynamics, Ed., J.L. Lebowitz, North-Holland, Amsterdam (1984)

Munoz, D.A., et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 7 6981 (2005)

Murali, S. M.Sc. dissertation, Nanyang Technological University, Singapore (2005)

Muzy, J.F., et al. Physical Review Letters 67 3515 (1991)

Muzy, J.F., et al. International Journal of Bifurcation and Chaos in Applied Sciences and Engineering 4 245 (1994)

Muzy, J.F., et al. Journal of Statistical Physics 70 635 (1993_a)

Muzy, J.F., et al. Physical Review E 47 875 (1993_b)

Nagarajan, R., et al. Physica A 354 182 (2005)

Nagarajan, R., et al. Physica A 363 226 (2006_a)

Nagarajan, R., et al. Physica A 366 1 (2006_b)

Nayak, S.R., et al. J Adv Research Dyn Contr Sys 9 76 (2017)

Nguyen, T., et al. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medecine and Biology Society 3 3210 (2005)

Niu, M., et al. Chemical Engineering Journal 136 364 (2008)

Normant, F., et al. Physical Review A 43 6518 (1991)

Norouzzadeh, P., et al. Physica A 367 328 (2006)

Novianto, S., et al. Pattern Recognition Letters 24 365 (2003)

Oczeretko, E., et al. Folia Histochemica et Cytobiologica 39(Suppl. 2) 75 (2001)

Ossadnik, S.M., et al. Biophysical Journal 67 64 (1994)

Ostwald, M.J. Environ. Plan B 40 644 (2013)

Oswiecimka, P., et al. Acta Physica Polonica B No 8 36 (2005_a)

Oswiecimka, P., et al. Physica A 347 626 (2005_b)

Oswiecimka, P., et al. Acta Physica Polonica B 37 3083 (2006)

Oswiecimka, P., et al. Acta Physica Polonica A 114 547 (2008)

Ott, E., et al. Physical Review Letters 64 1196 (1990)

Owis, M., et al. IEEE Transactions on Biomedical Engineering 49 733 (2002)

Oxley, L., et al. Environ. Model. Softw. 22 580 (2007)

Packard, N.H., et al. Phys. Rev. Lett. 45 712 (1980)

Pallikari, F., et al. Journal of Scientific Exploration 13 25 (1999)

Pastén, D., et al. Physical Review E 84 066123 (2011)

Patrzalek, E., General Introduction to Fractal Geometry, pp. 1–7, Eindhoven University of Technology (2006)

Pedram, P., et al. International Journal of Modern Physics C 19 855 (2008)

Peitgen, H.O., et al. New York: Springer-Verlag (1992)

Peitgen, H.O., et al. Chaos and Fractals (Springer, Berlin, 2004)

Peng, C.K., et al. Nature 356 168 (1992)

Peng, C.K., et al. Physical Review Letters 70 1343 (1993)

Peng, C.K., et al. Physical Review E 49 1685 (1994)

Peng, C.K., et al. Physica A 221 180 (1995_a)

Peng, C.K., et al. Chaos 5 82 (1995_b)

Penn, A., et al. Academic Radiology 6 156 (1999)

Penzel, T., et al. IEEE Transactions on Biomedical Engineering 50 1143 (2003)

Pereda, E., et al. Neuroscience Letters 250 91 (1998)

Pereira, D., et al. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society 3 1775 (2000)

Pereira-Pinto, F.H.I., et al. Chaos, Solitons & Fractals 22 653 (2004)

Peter, E.E. John Wiley & Sons, New York (1994)

Phothisonothai, M., et al. Journal of Physiological Sciences 57 217 (2007)

Pickover, C., et al. Computer Graphics 1 51 (1986)

Pikkujamsa, S.M., et al. Circulation 100 393 (1999)

Podobnik, B., et al. Physical Review Letters 100 084102 (2008)

Podobnik, B., et al. European Physical Journal B 71 243 (2009_a)

Podobnik, B., et al. Proceedings of the National Academy of Sciences of the United States of America 106 22079 (2009_b)

Podobnik, B., et al. Physical Review E 84 066118 (2011)

Prigarin, S., et al. Numerical Analysis and Applications 1 163 (2008)

Pruess, S. Fractals in the Earth Sciences, C.C. Barton and P.R. La Pointe, Plenum Press (Eds), New-York 3 65 (2007)

Puu, T. Springer Science & Business Media: New York, USA (2013)

Qianli, M, et al. Annual International Conference of the IEEE Engineering in Medicine and Biology Society 5 4526 (2005)

Rak, R., et al. Acta Physica Polonica A 114 (2008)

Rangayyan, R., Nguyen, T.,et al. Proceedings of Computer Assisted radiology and Surgery (CARS) 1281 1041 (2005)

Reljin, I.S., et al. Archive of Oncology 10 283 (2002)

Richards, D. Chaos Theory in the Social Sciences, University of Michigan Press: Ann Arbor, MI, USA, pp. 89–116 (1996)

Rickles, D., et al. J. Epidemiol. Commun. Health 61 933 (2007)

Rodriguez, E., et al. Physica A 375 699 (2007)

Rosenow, B., et al. Physica A 324 241 (2003)

Rosser, J.B. Univ of Michigan Press: Ann Arbor, MI, USA, pp. 199–213 (1996)

Roux, S.G., et al. European Physical Journal B 15 765 (2000)

Roy, P.N.S., et al. Journal of Earth System Science 121 1033 (2012)

Russel, D., et al. Physical Review Letters 45 1175 (1980)

Ruttiman, U., et al. Oral Pathology 74 98 (1992)

Rybaczuk, M., et al. Folia Morphologica 55 434 (1996)

Salinas, A., et al. Progress in Electromagnetics Research Symposium Proceedings, Marrakesh, Morocco, March 1171 20 (2011)

Sanderson, B., et al. Tellus 42A 550 (1990)

Santhanam, M.S., et al. Physical Review E 73 015201 (2006)

Sato, K., et al. Proceedings of IEEE Transactions on Nuclear Science 43 3230 (1996)

Scafetta, N., et al. Physica A 328 561 (2003)

Schmitt, F. Europhysics Letters 34 195 (1996)

Scrivener, J. Proceedings of Bridges: Mathematical Connections in Art, Music, and Science ed. Reza Sarhangi, pp. 185–92. Winfield, Kan.: Southwestern College (2000)

Serletis, A., et al. Physica A 380 325 (2007)

Serletis, D. Chaos, Solitons & Fractals 38 921 (2008)

Serletis, A., et al. Chaos, Solitons & Fractals 40 2007 (2009)

Shadkhoo, S., et al. European Physical Journal B 72 679 (2009)

Shan, Z., et al. Magnetic Resonance Imaging 24 1015 (2006)

Shen, G. Int. J. Geogr. Inf. Sci. 16 419 (2002)

Shen, J., et al. Europhysics Letters 86 48005 (2009)

Sheng, Hu., et al. Proceedings of the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference IDETC/CIE Washington DC, USA, August (2011)

Singh, M., et al. Nuclear Tracks and Radiation Measurements 19 417 (1991)

Singh, S.L. et al. Commun. Nonlinear Sci. Numer. Simul. 17 521 (2012)

Sisodiya,, S., et al. Brain 120 271 (1997)

Siwy, Z., et al. Physical Review E 65 031907 (2002)

Small, M., et al. Chaos, Solitons & Fractals 13 1755 (2002)

Smith, T., et al. The Journal of Comparative Neurology 331 402 (1993)

Smith, T., et al. Brain Research 634 181 (1994)

Smrcka, P., et al. Measurement Science Review 3 13 (2003)

Soltys, Z., et al. Journal of Neuroscience Research 63 90 (2001)

Stanley, H.E., et al. Physica A 299 (2001)

Staudacher, M., et al. Physica A 349 582 (2005)

Stavroyiannis, S., et al. International Review of Financial Analysis 19 19-24 (2010)

Stojic, T., et al. Physica A 367 494 (2006)

Stosic, T., et al, IEEE Transactions on Medical Imaging 25 1101 (2006)

Su, Z.Y., et al. Physica A 380 418 (2007)

Su, Z.Y., et al. Physica D 221 188 (2006)

Suetani, H., et al. Phys. Rev. E 86 036209 (2012)

Sun, X., et al. Physica A. 291 553 (2001)

Suri, J., et al. Springer (Eds) New-York 668 (2002)

Tabar, L., et al. Cancer 72 (suppl. 4) 1437 (1993)

Takahashi, T., et al. NeuroImage 32 1158 (2006)

Talkner, P., et al. Physical Review E 62 150 (2000)

Tamás, T., et al. Physica A 159 155 (1989)

Tanki, N., et al. 26 207 (2006)

Taqqu, M.S., et al. Fractals 3 785 (1995)

Taylor, P., et al. British Journal of Radiology 67 456 (1994)

Telesca, L., et al. Chaos, Solitons & Fractals 19 1 (2004$_a$)

Telesca, L., et al. Journal of Asian Earth Sciences 54 72 (2012)

Telesca, L., et al. Natural Hazards and Earth System Sciences, 5 673 (2005)

Telesca, L., et al. Physics and Chemistry of the Earth 29 289 (2004a)

Telesca, L., et al. Physics and Chemistry of the Earth 29 289 (2004$_b$)

Telesca, L., et al. Physics Letters A 332 398 (2004$_c$)

Telser, S., et al. Journal of Biological Physics 33 19 (2007)

Teotia, S.S., et al. Indian Journal of Marine Sciences 36 122 (2007)

Thakor, N., et al. IEEE Transactions on Biomedical Engineering 37 837 (1990)

Thompson, P., et al. Journal of Neuroscience 16 4261 (1996)

Tokinaga, S., et al. Electronics and Communications in Japan, Part 3 80(8) (1997)

Toweill, D., et al. Crit. Care Med. 28 2051 (2000)

Tsui, A.K., et al. Mathematics and Computers in Simulation 48 503 (1999)

Tulppo, M., et al. American Journal of Physiology - Heart and Circulatory Physiology 80 H1081 (2001)

Türk, C., et al. Physical Review E 81 026706 (2010)

Vahabi, M., et al. Physica A 388 3859 (2009)

Van De Ville, D., et al. Neuroscience PNAS. 107 18179 (2010)

Vandewalle, N., et al. Physical Review E 58 6832 (1998$_a$)

Vandewalle, N., et al. The European Physical Journal B 4 257(1998$_b$)

Varotsos, P.A., et al. Physical Review E 66 011902 (2002)

Varotsos, P.A., et al. Physical Review E 67 021109 (2003)

Varotsos, P.A., et al. Physical Review E 71 032102 (2005)

Veldkamp, W., et al. Medical Physics 27 2600 (2000)

Vicsek, T. Physica A 168 490 (1990)

Viswanathan, G.M., et al. Physical Review E 55 845 (1997)

Vyushin, D., et al. Geophysical Research Letters 31 L10206 (2004)

Wang, G., et al. Journal of Zhejiang University - Science A 8 910 (2006)

Wang, G., et al. Medical Engineering & Physics 29 375 (2007)

Wang, Yudong., et al. Physica A 389 5759 (2010)

Wax, A., et al. Cancer Research 63 3556 (2003)

Website of http://www.math.nus.edu.sg/aslaksen/gem-projects/maa/World of Fractal.pdf (accessed on 17 July 2015)

Werner, D.H., et al. Frontiers in Electromagnetics, IEEE Press Series on Microwave Technology and RF (1999)

Weron, A., et al. Chaos, Solitons & Fractals 11 289 (2000)

Weron, R. Physica A 312 285 (2002)

Wilcox, D., et al. Physica A 344 294 (2004)

Woyshville, M., et al. Biological Psychology 35 291 (1994)

Xia, Y., et al. IEEE Transactions on Image Processing 15 614 (2006)

Xiong Zheng-feng. Estimating the Fractal Dimension of Financial Time Series by Wavelet, Systems Engineering-theory & Practice 12 48-53 122 (2002)

Xu, L., et al. Physical Review E 71 051101 (2005)

Xu, N., et al. Nonlinear Dynamics 61 207 (2010)

Yu, C.H., Wu C.C.,et al. International Review of Economics & Finance 10 19 (2001)

Yuan, J., et al. Performance Evaluation 61 163 (2005)

Yuan, Y., et al. Physica A 388 2189 (2009)

Yum, M.K., et al. Journal of Cardiovascular Electrophysiology 13 788 (2002)

Zamani, A., et al. IJST A1 Iranian Journal of Science & Technology 39-51 (2011)

Zebendea, G.F., et al. Physica A 388 4863 (2009)

Zeleke, T.B., et al. Agronomy Journal 96 1082 (2004)

Zhang, H., et al. International Journal of Bifurcation and Chaos 12 2293 (2002)

Zhang, L., et al. Neurobiology of Aging 28 1543 (2006)

Zhang, X.S., et al. IEEE Transactions on Biomedical Engineering 46 548 (1999)

Zhao, X.J., et al. Physica A 390 3670 (2011)

Zhou, W.X. Physical Review E 77 066211 (2008)

Zhou, W.X. EPL (Europhysics Letters) 88 (2009)

Zhuang, X., et al. Artificial Intelligence in Medicine 32 29 (2004)

Zlatintsi, A., et al. Musical Instruments Signal Analysis and Recognition Using Fractal Features, 19th European Signal Processing Conference (EUSIPCO) (2011)

Zlatintsi, A., Maragos P., et al. IEEE Transactions on Audio, Speech and Language Processing, 21 737 (2013)

Zook, J., et al. Magnetic Resonance Imaging 23 671 (2005)

Zorick, T., Mandelkern Mark, A., et al. PLOS ONE e68360 8 (2013)

CHAPTER 6

NEURO-COGNITIVE NONLINEAR STUDY FOR CATEGORIZATION & QUANTIFICATION OF EFFECT OF COLORS & RAGAS ON HUMAN BRAIN

“It is known from ages which notes make up which raga, the time has come for music researchers to decipher the underlying process of emotions being elicited by a particular raga"

Rabindranath Tagore

Abstract

This work elaborates on a neuro-cognitive research on brain responses to various color stimuli. Red, Green, Blue: three primary colors utilizing the signals of electro-encephalograms and nonlinear multifractal approaches to establish the magnitude of complexity using a quantitative parameter. Color stimuli were imposed to subjects and the EEG readings from the corresponding lobes were taken note of and analyzed. Along with this, two ragas namely Chhayanat and Darbari, were used to study the effect on human brain using exactly the same methodology adopted in case of the colors. Along with this we also explored to correlate whether colors are also associated with Ragas of Indian Classical Music. The experiment reveals new data of extreme interest in color-raga-emotion scenario.

6.1 INTRODUCTION

The association between the brain, emotion, color, and music has been desperately sought by researchers worldwide. Although the subject is still in its infancy, few literatures, described in the book, illustrate the kind of research that has been done so far with apparently different purposes but deep down in coherence, they all link to the extended spectrum of the subject. [1] Explored cerebral plasticity. Auditory-cognitive training strategies are either ineffective or unproven. Our inadequate understanding of how interventions improve cognitive and perceptual abilities and how various activities and experience positively modify brain systems underlies such abilities limits the benefits of such regimens. Music training improves auditory function biologically and long-term [2] researchers did a great job.

Researchers from all over the world have been trying hard to find out what links the human brain, emotions, colors, and music. Even though the subject is still young, the text mentions a few literatures that show the kinds of research that have been done so far. These researches have had different goals, but they all fit into the larger scope of the subject. In [1], an attempt was made to understand how big and wide brain plasticity is. Training programs that aim to help or improve auditory-cognitive skills have had mixed results or have yet to be fully validated. The limited benefits of these kinds of routines are mostly due to the fact that we don't know enough about how interventions improve cognitive and perceptual abilities in the most stable and long-lasting ways, and how the neural mechanisms that support these kinds of abilities can be positively changed by certain activities and experience. Recent studies show that learning to play music has strong, long-lasting biological benefits for hearing. The researchers in [2] have done a great job of testing how different emotional stimuli affect the two sides of the brain in the band range of gamma (30–90 Hz). The subjects were exposed to slides with content of different emotions. The frontal electrodes were used to record how the right and left sides of the brain responded when their emotions were stirred up, and the responses were compared. The wide spread of specific gamma band range activities could potentially indicate assemblies of cells with members in frontal, temporal and limbic neocortical structures that are spread out in different ways specific to the form of processing of emotion. [3] shows a multimodal data set for analyzing how people feel. The electro-encephalogram (EEG) and a number of other bodily indicators were documented from 32 individuals while they were exposed to 40 one-minute music video clips. The participants rated each video based on its level of valence, arousal, likeability, familiarity and dominance. A frontal facial video was also captured for 22 out of the 32 participants. Another thorough search in [4] shows that different versions of the MFDFA technique are used to look into different time series. It was inferred from the analysis that the singularity spectra obtained was extremely order sensitive with respect to the MFDFA detrending polynomial method. There is a clear link between the multifractal spectral width and the polynomial order of the one used to calculate it. Also, this relationship-type is dependent on the analyzed signal type. Such an analysis can tell us more about how the time series being studied are related to each other. In reference [5], the EEG was done on 10 people with a standard acoustic stimulus, a tanpura drone. Multifractal Detrended Fluctuation Analysis (MFDFA) was used on the extracted time series data of theta and alpha from the EEG time series to study how their complexity changed over time. It was found that the alpha and theta frequencies get more complicated in all of the frontal electrodes. This is clear from the fact that the width of the multifractal spectrum also grows. This study was done very recent and provides an interesting information about how the alpha and theta brain rhythms are activated by simple acoustic stimuli. This study is important in the sense of using the width of multifractal spectrum as a parameter to measure emotion and in the field of cognitive music therapy.

This work is based on a neuro-cognitive study of how the brain reacts to different color stimuli. Red, Green, and Blue are the three primary colors. Using the signals from electroencephalograms and the multi-fractal method, you can measure the level of complexity with the help of quantitative parameters. We chose two subjects—one is a musician and the other is not—and gave them color stimuli. EEG signals from different lobes were recorded and analyzed using MFDFA. The significant observations were summed up and examined in the results and discussion section.
An attempt was made to see if colors and ragas make the same kind of emotional response. To do this, two ragas called Chhayanat and Darbari, which are usually associated with very different emotions, were used to study the effect on the human brain, using the same method as was used for the colors. The primary data is encouraging for validating our method. Both colors and music can be labeled by how they make you feel based on how much they change. Since we've taken EEG data from eight electrodes, we need to do a thorough analysis that includes multifractal cross-correlation with more data. But this approach and these data are new, and they can be seen as a step toward understanding a very complicated thing about how people understand emotions in the context of music and colors.

6.2 EXPERIMENTAL DETAILS

The work was divided initially in two interest regiments to correlate the relational interface between color and music stimuli. Three primary colors: Red, Blue and Green were exposed for a defined time period with an interval expose of grey color and their EEG was recorded during that time period. In the next half, music clips of Chhayanat and Darbari were played as audio stimuli to seven subjects (including the two, chosen for color test) with a defined protocol.

The color stimuli were three fundamental colors viz. red, Blue and Green. They were displayed for duration of 10 second to both the subjects with an interspacing of grey color of duration around 1 minute. The audio stimuli had seven counterparts. Initially the subject was exposed to no music phase for a defined interval. The next phase had a sound of drone from a tanpura which was noise free. The first music clip, Chhayanat, was played in the third segment. Fourth half was a sound of a drone again which was immediately followed by the other raga, Darbari, the raga of wide apart emotional arousal from Chhayanat. The sixth and seventh sessions were both no music parts of the predefined duration.

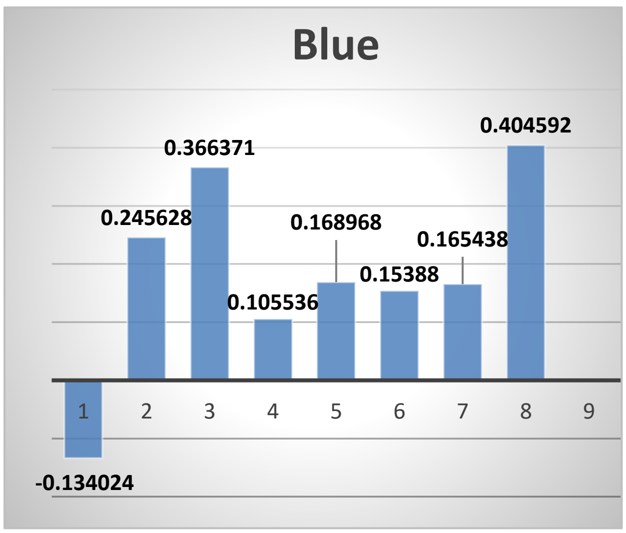
The collected EEG data was analysed with a tried-and-tested method by the name of MFDFA, with its establishment over chaos and fractals. Nature is essentially example of most of the complex phenomena, nonlinear in character - recent research has advocated the nonlinearity of manmade complex systems like music. EEG time series has been exhaustibly studied confirming the nonlinearity of brain functions. In view of above, we have opted the most vigorous approach proposed so far to analyse EEG time signal with music as well as color stimuli. The multifractal range reveals the digressions in the fractal configuration during time spans with significant and minor changes. Multifractals are inherently more intricate and depict time sequences characterized by exceedingly erratic dynamics, dotted with abrupt and strong surges of high-frequency variations [6]. The MFDFA methodology is in wide use across various sectors of work, from the stock market to disease prognosis in biomedical fields [7] [8].

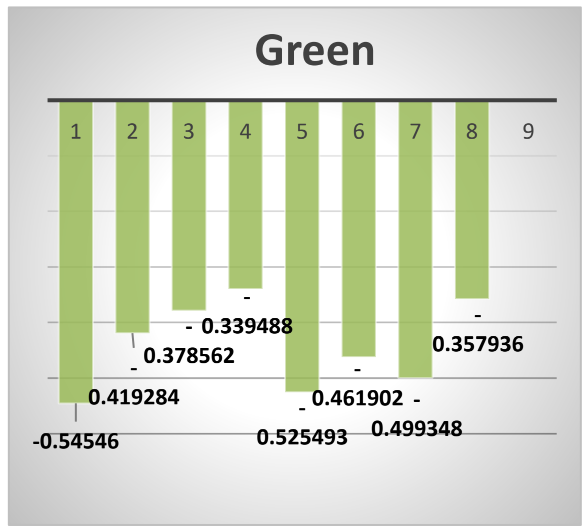
6.3 RESULTS AND DISCUSSION

The EEG of the subjects in phase of color testing underwent certain analysis from which the MFDFA was performed to obtain the spectral widths and the plot of the complexities with reference to all eight chosen electrodes are as follows. The complexity for the musician as shown in the table and the following plots. The errors are not shown in the figures as they are too small to appreciate.

TABLE 6. 1. THE MULTIFRACTAL SPECTRAL WIDTH FOR THE MUSICIAN FOR THREE PRIMARY COLORS IN ALL SELECTED ELECTRODES

Colors	P4	P3	O2	O1	F3	F4	F7	F8
Blue	-0.13402	0.245628	0.366371	0.404592	0.105536	0.168968	0.15388	0.165438
Green	-0.54546	-0.41928	-0.37856	-0.35794	-0.33949	-0.52549	-0.4619	-0.49935
Red	0.210326	-0.16914	0.043432	0.217274	0.054287	0.064133	-0.01061	0.007512





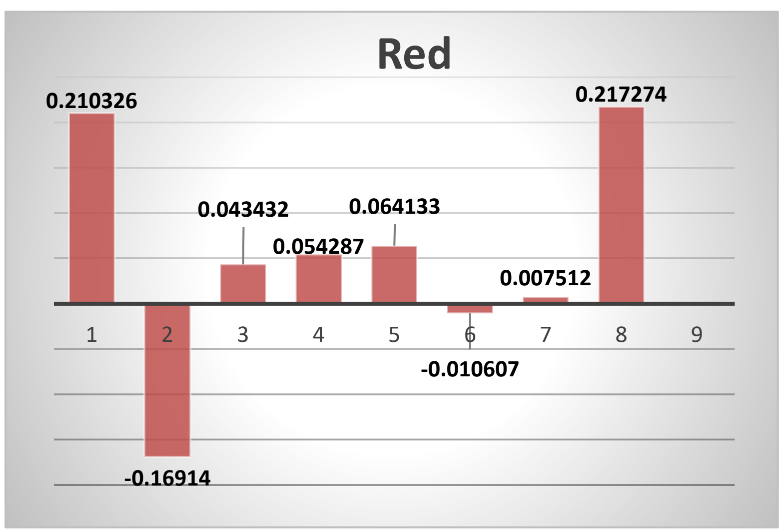


Figure 6.1. Variation of complexity for the musician in the selected electrodes (P4, P3, O2, O1, F3, F4, F7, F8) for the three primary colors

The same process was carried out to determine the complexity for the non-musician to obtain a comparable analysis of the results. The results are as follows:

Table 6.2. THE MULTIFRACTAL SPECTRAL WIDTH FOR THE NON-MUSICIAN FOR THREE PRIMARY COLORS IN ALL ELECTRODES.

Colors	P4	P3	O2	O1	F3	F4	F7	F8
Blue	-0.2889	-0.20126	-0.25267	-0.16572	-0.17568	-0.36631	-0.36615	-0.24935
Green	0.053849	-0.11921	-0.06182	0.15716	-0.10225	-0.10322	0.153174	-0.36035
Red	-0.25274	-0.31025	-0.14993	-0.05607	-0.15859	-0.01871	-0.15599	-0.20568

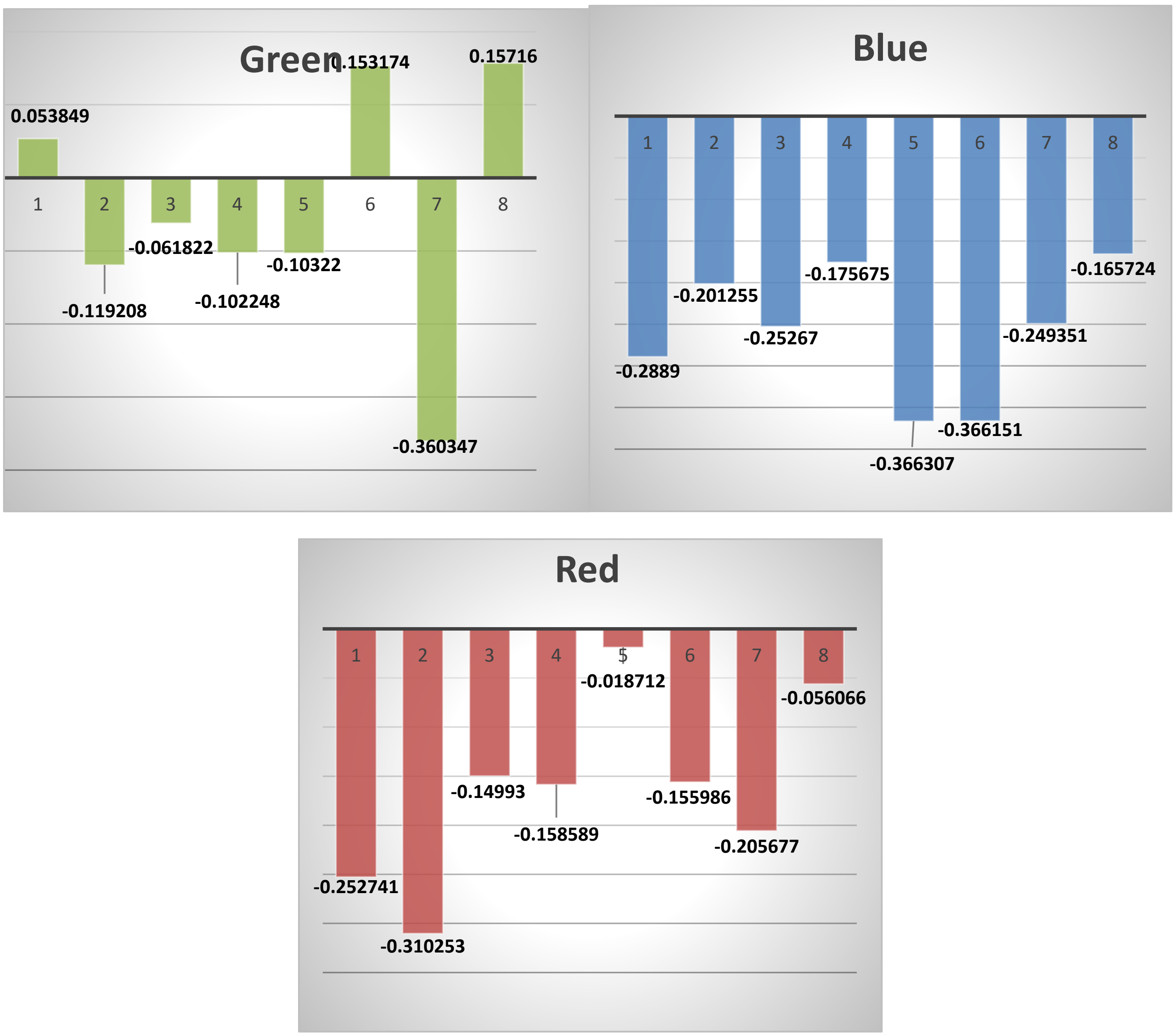


Figure 6.2. Variation of complexity for the non-musician in the selected electrodes (P4, P3, O2, O1,F3, F4, F7, F8)for the three primary colors

It was found that in case of the music practitioner, the degree of complexity in all the measured electrodes (O1, O2, P3, P4, F3, F4, F7, F8) is significantly low when he is exposed to GREEN color (HEX - #00FF00; R:0, G:255, B:0). In case of BLUE color (HEX - #0000FF; R: 0, G: 0, B: 255), only P4 electrode shows a little increase in complexity. For rest of the electrodes, the complexity is lower, though in a small amount. In P4, O2, O1, F3, F4, F8 electrodes, complexity increases in RED (HEX - #FF0000; R: 255, G: 0, B: 0) and decreases in P3 and F7 electrodes. Again, analysis of the non-musician subject shows a different trend. Here, the degree of complexity is significantly and consistently lower in all the electrodes in case of the blue color. Also exposed condition to Red color gives lower multi-fractal detrended fluctuation analysis values, whereas complexity is increased in P4, F7, O1 electrodes in cases of Green color and in the rest, it has lower and insignificant values.

In the experimental part for the music stimuli, the clips of Chhayanat and Darbari were played to seven different subjects preceded by a sound of drone in each case and process started and ended with no music session of predefined time frame. The nonlinear analysis using MFDFA was carried out on the emotional arousal in form of the EEG signal and the difference of the complexities with respect to the sound of the drone was calculated in each of the cases. The variations of the complexities in all selected electrodes for the seven subjects are shown below. The first table shows the difference in complexity in response to the clip of raga Chhayanat. And the next table depicts the same in reference to the clip of raga Darbari.

The averages of the spectral widths have been taken for each subject with regard to all the selected electrodes to infer further analysis in both the ragas and it is observed that both the ragas deliver positive as well as negative complexity values. The averages of the positive values as well as for the negative values are taken from the set of seven subjects. The results are as follows:

Table 6.3. DIFFERENCE OF COMPLEXITY IN SELECTED ELECTRODES FOR THE SUBJECTS IN RAGA CHHAYANAT

SUB	F3	F4	F7	F8	P3	P4	O1	O2
1	-0.11764	-0.19538	-0.02223	0.15545	0.040561	-0.01333	-0.08136	-0.0072
2	-0.11175	0.101016	-0.19497	-0.20265	0.058769	0.137888	-0.0483	0.099194
3	0.194118	0.034918	-0.0453	0.086613	0.236766	0.071304	0.036994	-0.09334
4	-0.00678	0.136008	-0.081	-0.18376	0.0066	0.441762	0.11616	-0.06371
5	-0.04007	0.115661	0.008872	0.041104	-0.09569	0.025076	-0.02448	0.186924
6	0.059554	0.052182	0.002922	-0.17516	-0.1578	0.002072	-0.04962	0.113642
7	-0.13292	0.037893	-0.05742	0.032044	-0.11842	-0.13719	-0.06003	-0.06761

Table 6.4. DIFFERENCE OF COMPLEXITY IN SELECTED ELECTRODES FOR THE SUBJECTS IN RAGA DARBARI

SUB	F3	F4	F7	F8	P3	P4	O1	O2
1	0.479994	-0.19221	-0.28564	0.081365	-0.01054	-0.09752	0.120307	0.013958
2	-0.16393	-0.00486	0.269524	-0.07948	-0.12779	-0.22387	-0.27031	-0.10561
3	0.01001	-0.19775	0.222891	-0.17127	0.070001	-0.05383	0.043424	0.133982

4	0.074835	-0.01327	0.046016	0.076165	-0.39446	-0.09155	-0.04842	-0.10371
5	0.008356	-0.20297	-0.19529	0.009554	-0.0091	-0.08467	-0.11218	-0.10117
6	-0.0328	0.107941	0.059712	0.219487	0.106503	-0.00941	0.282324	-0.11697
7	0.089985	0.139561	-0.23759	-0.22365	0.028115	-0.0126	0.287209	-0.01121

Table 6.5.

Choice of ragas	Positive average	Negative average
Chhayanat	0.046032	-0.03306
Darbari	0.026368	-0.07701

The beneath figures show the electrode wise variation of complexity in the seven subjects in case of raga Darbari and Chhayanat.

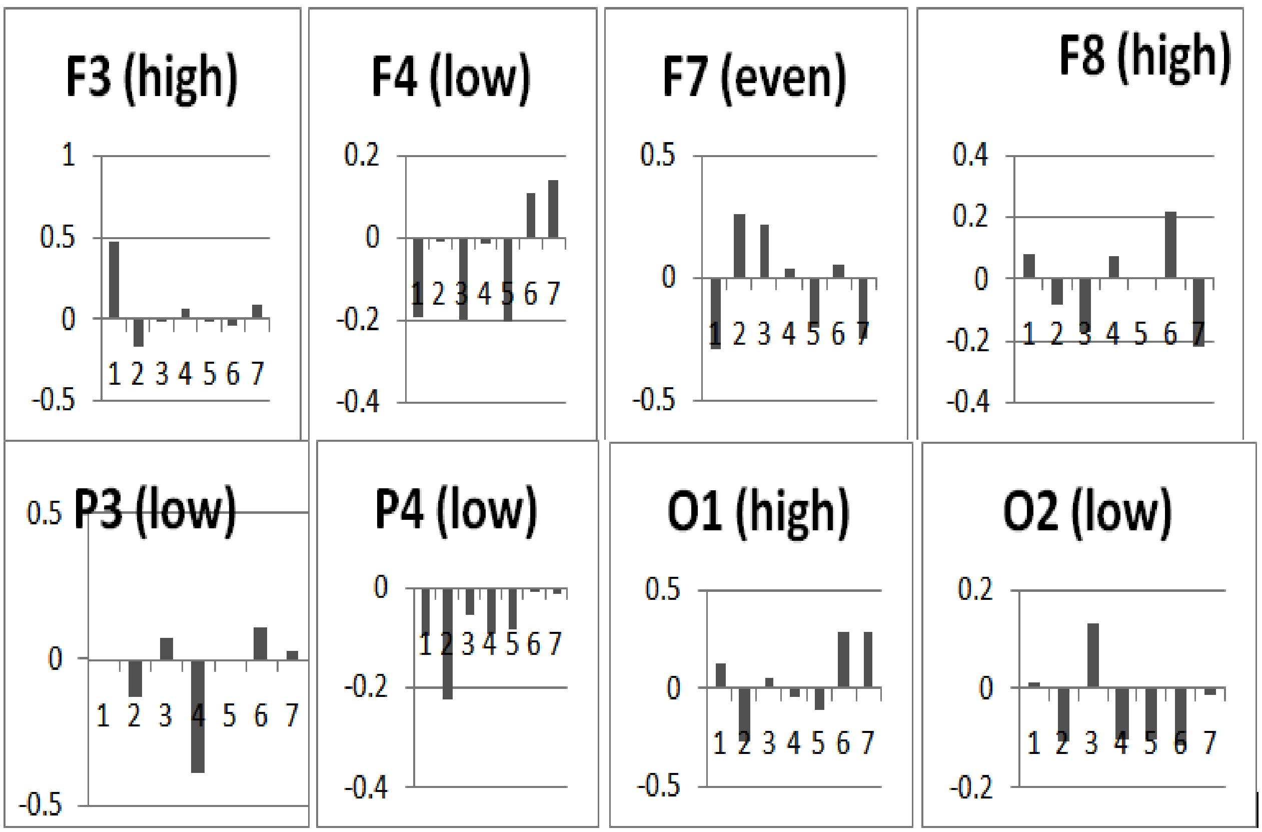


Figure 6.3. Electrode wise variation for Raga Darbari

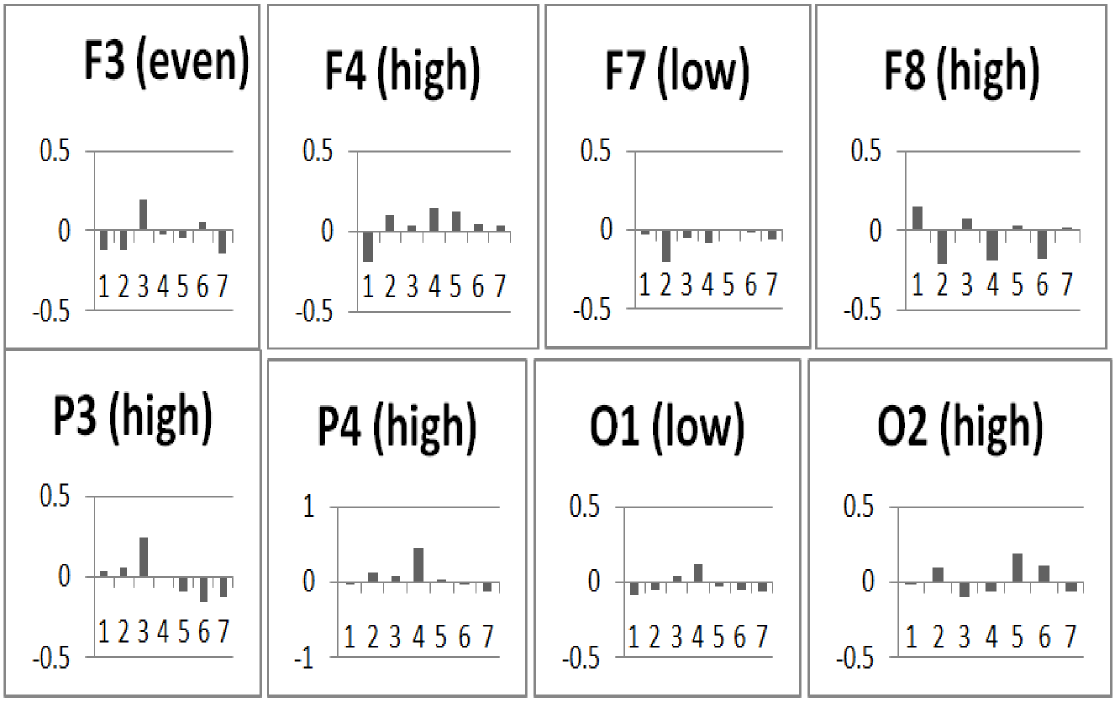


Figure 6.4. Electrode wise variation for Chhayanat

The average of the multifractal width of all the electrodes corresponding to the chosen three primary colors for both the subjects have been obtained and given in Table 5. The similar procedure was executed for achieving the same for the seven subjects of all electrodes with the audio stimuli of raga Chhayanat and Darbari and it yields to a set of averages incorporating both positive and negative values. Out of them, a mean was taken for the set of all positive values and the same for the negative values as well. These values are given in Table 6.6.

Table 6.6.normalised difference of complexity

Subject	**Red**	**Green**	**Blue**
Musician	0.06953	-0.5879	-0.2460
Non musician	-0.2178	-0.0638	-0.3440

6.4 CONCLUSION

The table 1 and 2 show that the multifractal width of the two subjects in all selected electrodes for three primary colors. Table 3 and 4 depict the variation of complexity for the different ragas in the electrodes for the chosen subjects. It is highly interesting to observe that –the change of degree of complexity in different lobes is different for both color and music stimuli.

Finally, this experiment manifests that:

(1) Non-linear MFDFA technique applied to EEG signal can indeed quantify effects of color on human brain and of course the effect of music.

(2) The effect of color is more pronounced than that of music.

This pilot study can initiate similar studies with more specified color and music samples of different known emotions. The result of this experiment will find application in many important domains like music therapy and/or color therapy and of course in neuro-marketing, where exhaustive research is imminent. Further, this pilot study is useful to extract more info about the dynamics of cross-modal participation of the brain.

ACKNOWLEDGEMENT

We are sincerely thankful to Ranjan Sengupta for his kind cooperation and guidance during the execution period of this work.

6.5 REFERENCES

[1] Sreeja, P. S., and G. S. Mahalakshmi. "Perc-an emotion recognition corpus for cognitive poems." *2019 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2019.
[2] Kang, Jin-Ae, Sookyeong Hong, and Glenn T. Hubbard. "The role of storytelling in advertising: Consumer emotion, narrative engagement level, and word-of-mouth intention." *Journal of Consumer Behaviour* 19.1 (2020): 47-56.
[3] Cummins, Fred. "The territory between speech and song: A joint speech perspective." *Music Perception* 37.4 (2020): 347-358.
[4] Johnson-Laird, Philip N., and Keith Oatley. "How poetry evokes emotions." *Acta Psychologica* 224 (2022): 103506.
[5] Freeman, Margaret H. *The poem as icon: A study in aesthetic cognition*. Oxford University Press, 2020.
[6] Farsi, Roghayeh. "Cognitive appraisal and coping in poetry." *Journal of Narrative and Language Studies* 9.18 (2021): 339-356.
[7] Cross, Emily S., et al. "A neurocognitive investigation of the impact of socializing with a robot on empathy for pain." *Philosophical Transactions of the Royal Society B* 374.1771 (2019): 20180034.
[8] Jaquess, Kyle J., et al. "Self-controlled practice to achieve neuro-cognitive engagement: Underlying brain processes to enhance cognitive-motor learning and performance." *Journal of Motor Behavior* 52.5 (2020): 544-557.
[9] Zmigrod, Leor. "A neurocognitive model of ideological thinking." *Politics and the Life Sciences* 40.2 (2021): 224-238.
[10] Russo, Frank A. "Motor system involvement in the perception of singing." *The Routledge companion to interdisciplinary studies in singing*. Routledge, 2020. 276-288.
[11] Howlin, Claire, Alison Stapleton, and Brendan Rooney. "Tune out pain: Agency and active engagement predict decreases in pain intensity after music listening." *PloS one* 17.8 (2022): e0271329.
[12] Casillo, Stephanie M., Diego D. Luy, and Ezequiel Goldschmidt. "A history of the lobes of the brain." *World Neurosurgery* 134 (2020): 353-360.
[13] Leblanc, Richard. "Pavlov, Penfield, and the physiology of the mind." *Neurology* 92.12 (2019): 575-578.
[14] Hu, Li, and Zhiguo Zhang, eds. *EEG signal processing and feature extraction*. Singapore: Springer Singapore, 2019.
[15] Martínez, Jorge Luis Morales, et al. "A modified multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation." *Physica A: Statistical Mechanics and its Applications* 565 (2021): 125611.
[16] Gorjão, Leonardo Rydin, et al. "MFDFA: Efficient multifractal detrended fluctuation analysis in python." *Computer Physics Communications* 273 (2022): 108254.
[17] David, Sergio Adriani, et al. "A combined measure to differentiate EEG signals using fractal dimension and MFDFA-Hurst." *Communications in Nonlinear Science and Numerical Simulation* 84 (2020): 105170.
[18] Sarkar, Uddalok, et al. "Language Independent Emotion Quantification using Non linear Modelling of Speech." *arXiv preprint arXiv:2102.06003* (2021).
[19] Avramidis, Kleanthis, et al. "Multiscale fractal analysis on EEG signals for music-induced emotion recognition." *2021 29th European Signal Processing Conference (EUSIPCO)*. IEEE, 2021.

[20] Banerjee, Archi, et al. "A novel study on perception–cognition scenario in music using deterministic and non-deterministic approach." *Physica A: Statistical Mechanics and its Applications* 567 (2021): 125682.

[21] Basu, Medha, et al. "Does musical training affect neuro-cognition of emotions? An EEG study with Indian Classical Instrumental Music." *Proceedings of Meetings on Acoustics 182ASA*. Vol. 46. No. 1. Acoustical Society of America, 2022.

[22] Scheuber, Sephra H. *Emotional and neurological responses to timbre*. University of Central Oklahoma, 2019.

[23] Zhang, Rui, Cairang Jia, and Jian Wang. "Text emotion classification system based on multifractal methods." *Chaos, Solitons & Fractals* 156 (2022): 111867.

[24] Basu, Medha, et al. "Neural Quantification of Timbre and Emotions from Indian Classical Music a Multifractal Exploration." *Available at SSRN 4374657*.

[25] Ahirwal, Mitul Kumar, and Mangesh Ramaji Kose. "Audio-visual stimulation based emotion classification by correlated EEG channels." *Health and Technology* 10.1 (2020): 7-23.

[26] Feradov, Firgan, Iosif Mporas, and Todor Ganchev. "Evaluation of features in detection of dislike responses to audio–visual stimuli from EEG signals." *Computers* 9.2 (2020): 33.

[27] DAŞDEMİR, YAŞAR, and RÜSTEM ÖZAKAR. "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning." *Turkish Journal of Electrical Engineering and Computer Sciences* 30.7 (2022): 2707-2724.

[28] Rodriguez-Larios, Julio, et al. "From thoughtless awareness to effortful cognition: alpha-theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic." *Scientific Reports* 10.1 (2020): 1-11.

[29] Lin, Sen, et al. "A flexible, robust, and gel-free electroencephalogram electrode for noninvasive brain-computer interfaces." *Nano letters* 19.10 (2019): 6853-6861.

[30] Yean, Choong Wen, et al. "Emotional states analyze from scaling properties of EEG signals using hurst exponent for stroke and normal groups." *Intelligent Manufacturing and Mechatronics: Proceedings of the 2nd Symposium on Intelligent Manufacturing and Mechatronics–SympoSIMM 2019, 8 July 2019, Melaka, Malaysia*. Springer Singapore, 2020.

[31] Guo, Fu, et al. "Research on color optimization of tricolor product considering color harmony and users' emotion." *Color Research & Application* 45.1 (2020): 156-171.

[32] Zeileis, Achim, et al. "colorspace: A toolbox for manipulating and assessing colors and palettes." *arXiv preprint arXiv:1903.06490* (2019).

[33] Shrestha, Badri, and Louese Dunn. "The declaration of Helsinki on medical research involving human subjects: a review of seventh revision." *Journal of Nepal Health Research Council* 17.4 (2019): 548-552.

[34] Farrens, Jaclyn L., et al. "Electroencephalogram (EEG) recording protocol for cognitive and affective human neuroscience research." (2021).

[35] Dilena, Robertino, et al. "Consensus protocol for EEG and amplitude-integrated EEG assessment and monitoring in neonates." *Clinical Neurophysiology* 132.4 (2021): 886-903.

[36] Moreno, S., & Bidelman, G. M. (2014). Examining neural plasticity and cognitive benefit through the unique lens of musical training. Hearing research,308, 84-97.

[37] Müller, Matthias M., et al. "Processing of affective pictures modulates right-hemispheric gamma band EEG activity." Clinical Neurophysiology 110.11 (1999): 1913-1920.

[38] Koelstra, Sander, et al. "Deap: A database for emotion analysis; using physiological signals." Affective Computing, IEEE Transactions on 3.1 (2012): 18-31.

[40] Oświęcimka, Paweł, et al. "Effect of detrending on multifractal characteristics."arXiv preprint arXiv:1212.0354 (2012).

[41] Maity, Akash Kumar, et al. "Multifractal Detrended Fluctuation Analysis of alpha and theta EEG rhythms with musical stimuli." Chaos, Solitons & Fractals81 (2015): 52-67.

[42] Ihlen EAF. Introduction to Multifractal Detrended Fluctuation Analysis in Matlab. Frontiers in Physiology. 2012;3:141. doi:10.3389/fphys.2012.00141.

[43] Shang, P., Lu, Y., & Kamae, S. (2008). Detecting long-range correlations of traffic time series with multifractal detrended fluctuation analysis. Chaos, Solitons & Fractals, 36(1), 82-90.

[44] Lan, Tong-Han, et al. "Detrended fluctuation analysis as a statistical method to study ion single channel signal." Cell biology international 32.2 (2008): 247-252.

CHAPTER 7

ACOUSTICAL & NEURO-COGNITIVE ANALYSIS OF RECITATION OF DIFFERENT TEXTS

7.1 Introduction

In the world of poetry, the power of language goes beyond simple communication while exploring the realms of emotion and thinking [1]. This research investigates the acoustical and neuro-cognitive aspects of recitations by three esteemed poets of Bengal: Rabindranath Tagore, Sankha Ghosh, and Joy Goswami. These poets, whose works span a century, have made a lasting impact on literature, captivating readers with their decorated verses. Our study covers a wide time span of 100 years to understand how different eras have shaped poetry how they affect the human psyche over time.

The main objective of this study is to examine the variations in cognitive engagement triggered by the recitation of different texts [2]. By analysing the influence of these recitations on human emotions and subsequent effects on said cognitive engagement, we aim to uncover the intricate relationship between poetry, emotions, and cognition [3-5]. To conduct this investigation, we collected a dataset of over 200 responses from human participants, by gathering data through an online interactive form where subjects listened to the stimuli and selected one of nine available emotions as options [6-8]. To ensure consistency and facilitate reliable analysis, we made sure the collected data was homogeneous. The human responses were then categorized according to the widely accepted western model of Russell's Emotional Circumplex [9-10], among which 9 major and specific emotions were mapped. Although Bharata's Natyashastra and Navaras [11-12] could also potentially be considered as models for baseline emotions in dealing with cognitive engagements as such, we opted for the former due to its greater acceptance, while the former also opening avenues for future research.

Our objective is to investigate the neuro-cognitive engagements observed with the emotions evoked by specific stimuli and establish a qualitative-to-quantitative parity between art forms and the cognitive engagements associated with them. We aim to measure the same from a physiological standpoint. By analysing the recorded human responses beforehand, our goal was to non-linearly measure and analyse the changes in different regions of the human brain caused by these stimuli [13-14]. To accomplish this, we utilized Electroencephalography (EEG) [15]. Our analysis focuses on four specific brain lobes: the frontal, temporal, occipital, and parietal lobes. The use of EEG allows us to study the response patterns associated with these cognitive engagements.

The analysis of EEG readings from the mentioned brain lobes follows a non-linear approach using the well-established technique of Multifractal Detrended Fluctuation Analysis (MFDFA). This algorithm, designed for the analysis of non-linear and highly complex systems, helps us examine the intricate complexities of the cognitive engagements to stimuli presented during the recitation of various poems [16-20]. Additionally, we aim to quantitatively evaluate the interrelationship between different recitation clips using Multifractal Detrended Cross-Correlation Analysis (MFDXA) [21-22]. By assessing the cross-correlation between each pair of unique clips associated with the same emotion, we can determine their level of correlation. A significantly low cross-correlation among these clips would indicate a stronger scientific association between them.

In this study, the Multifractal Width (w) of audio clips and recorded EEG brain waves is the main tool used to examine changes in cognitive engagements [23-24]. This parameter allows us to analyse and compare the multifractality of cognitive patterns. To ensure a thorough analysis, we aim to align qualitative assessments obtained from human responses to the stimuli with technical analysis. This simultaneous evaluation will help connect subjective human perception with objective scientific measurements, leading to a deeper understanding of the neuro-cognitive effects of art and literature.

7.2 Experimental Details:

7.2.1 Methodology

Understanding the human brain's response to different stimuli is fundamental to cognitive and neuroscience analysis and research. As discussed earlier, this paper aims to study the brain activity of subjects by exposing the individuals to various audio and visual stimuli while recording that data using Electroencephalography (EEG) [25-27]. EEG is a popular non-invasive technique that can measure and record the electrical activity of the brain. It can provide valuable information about cognitive processes and brain functioning by capturing brain wave patterns. During an EEG recording, there are multiple brain waves that can be observed. These brain waves represent different patterns of electrical activity in the brain and can be categorized based on their frequency ranges which are- Delta waves (0.5-4 Hz), Theta waves (4-7 Hz), Alpha waves (8-12 Hz), Beta waves (12-30 Hz) and Gamma waves (30-100 Hz) [28].

Alpha waves are associated with relaxed wakefulness and a calm state of mind. They are usually observed when individuals close their eyes or meditate. Additionally, Theta waves are prominent during periods of deep relaxation, meditation, and early stages of sleep. They are linked to creativity, memory formation, and deep emotional states.
Here, our focus is going to be analysing Alpha and Theta waves because these states comprise the brain activity during calm, non-aroused, and alert states of mind, and thus can provide insights into cognitive processes and emotional states.

To accomplish our goal, we have used a 19-10 electrode cap to record data, this cap is specifically designed for EEG purposes. It consists of 13 electrodes that are strategically placed on the different lobes of our brain [29].

1. Frontal Lobe: The frontal lobe plays a crucial role in decision-making, executive functions, problem-solving, and cognitive control. Electrodes placed on the frontal lobes will capture brain activity associated with these processes, thus allowing researchers to examine cognitive states during stimulus exposure. 4 electrodes were placed in this particular region namely- F3, F4, F7 and F8.

2. Parietal Lobe: The parietal lobe plays a pivotal role in various sensory integration processes, spatial awareness, attention, and perception. Electrodes placed on the parietal lobes enable the monitoring of brain activity associated with the attentional allocation and the integration of various visual and auditory stimuli. We placed 2 electrodes in this particular region namely- P3 and P4.

3. Occipital Lobe: The occipital lobe is mainly responsible for visual processing and perception. Electrodes placed on the occipital lobe capture brain activity associated with visual stimuli, allowing researchers to study visual perception and processing during stimulus exposure. 2 electrodes were placed in this particular region namely- O1 and O2.

4. Temporal Lobe: The temporal lobe plays a major role in auditory processing, language understanding, and memory functions. Electrodes placed on the temporal lobe enable the study of auditory perception, language-related processes, and memory formation during the presentation of audio stimuli. We placed 4 electrodes in this particular region namely- T3, T4, T5 and T6 [30].

The acquired EEG data of two separate frequencies (alpha and theta) from the subject are to be processed and analysed using a mathematical non-linear analysis technique called MFDFA (Multifractal Detrended Fluctuation Analysis) This method is specifically designed to understand the complex nature of EEG signals by evaluating their fractal properties(self-similarities) and long-range correlations.

The technique involves several steps- detrending: the data is detrended to remove any present patterns, fluctuation calculation: fluctuations in segments of varying lengths is calculated, scaling analysis: analysis of the fluctuations and lastly the exponent calculation: giving the degree of self-similarity. Using the fluctuation function obtained from the MFDFA algorithm, Hurst exponent (H) is also calculated. It helps to quantify the degree of self-similarity or self-affinity present in the given data. The value of H has different interpretations: H> 0.5 -indicates a persistent or positively correlated time series (having long term trends), H= 0.5- indicates uncorrelated time series (random or no trend) and H < 0.5- indicates an anti-persistent or negatively correlated time series (oscillatory trend).

Our next phase of work would be calculation of cross-correlation factor for the stimuli provided i.e. the audio clips [30]. Cross-correlation is a statistical technique to measure the similarity between two signals or data sets. In audio analysis, cross-correlation provides significant insights about the relationship between two audio clips. On the calculation of cross-correlation of two audio clips, we obtain a correlation function that helps us to quantify the similarity between the two signals at different time lags. Higher the correlation value indicates a strong similarity, while a low correlation value indicates a lack of similarity.

Cross-correlation can be best explained in graphical methods- q vs lambda q graph [31]: it describes the change in scaling properties along different statistical moments. This gives us a brief understanding into how the signals are distributed and how they behave at different scales. Another important comparison is drawn in q vs tau q graph: this explains the fluctuation properties change as we consider different statistical moments. This provides us insights into how the signals vary and whether they exhibit self-similarity or fractal-like patterns. Lastly, alpha vs F(alpha) graph: it is commonly used in multifractal analysis to understand the scaling properties of a signal or dataset. It provides insights into the distribution of scaling exponents and the multifractal nature of the data.

7.2.2 Stimuli Details:

We have carefully chosen nine poems by well-known poets who have made significant contributions to Bengali literature over the past 100 years as part of our research. These poems are a rich and diverse representation of the literary heritage of the Bengali language. Segments from each of these nine poems were extracted and used to create a controlled stimulus for our study, ensuring that each segment is approximately 30-35 seconds long. These meticulously curated snippets allow us to maintain consistency and precision in our experimental design while also capturing the essence and emotional depth of the original poems.

Here are brief descriptions of the poems that were used as stimuli:

Clip 1: ‘Rudra tomar darun dipti’: It is an excerpt taken from the Bengali poem ‘Suprabhat’. It is written by Ranbindranath Tagore and it is about the power of the divine force ‘Rudra’ and its ability to bring light and new beginnings. Kabyo Grontho of the poem is ‘Purabi’. It was written in the year of 1907 at Shantiniketan.

Clip 2: ‘Ogo ma rajar dulal’: This is also an endearing poem written by Rabindranath Tagore. It describes a mother's love for her son, who is about to leave home for the first time. Taken from the poem ‘Shubhokkhn’ having Kabyo Grontho ‘Kheya’ written in 1905.

Clip 3: ‘Keu j kare chini na ko’: A moving poem named ‘Achena’ having Kabyo Grontho ‘Khonika’. Written by Ranbindranath Tagore, about the power of love and the importance of being true to oneself. This poem encourages us to follow our dreams and to be full of hope. This was written in 1910.

Clip 4: ‘Dupure rukho gachhe patar’: A beautiful poem ‘Aarale’ written by Sankho Ghosh. It is describes at length the beauty of nature and the importance of taking some time to appreciate it. It was written in 1980.

Clip 5: ‘Ekre ojor mrityu elo’: Extracted from poem ‘Jamunabotee’ written by Sankho Ghosh. This poem explores the theme of death, its inevitability and the impact on loved ones. It was written in 1970.

Clip 6: ‘Se chhilo ekdin amader joubane kolkata’: Written by Sankho Ghosh in the year of 1975. The name of the poem is ‘Babu moshai’. The poet reflects on his nostalgic memories associated with Kolkata, the capital city of West Bengal, India, also known as the ‘City Of Joy’.

Clip 7: ‘Amra to alpe khusi’: This poem ‘Noon’ is written by Joy Goswami in the year 1997. He beautifully explains the mindset that appreciates the smaller joys and moments of happiness found in everyday life.

Clip 8: ‘Taranga jau, taranga fire aase’: Joy Goswami in this poem ‘Probaho’ splendidly explains the transient nature of life and draws a parallel between the waves in oceans and ups and downs in life. This was written in the year of 2010.

Clip 9: ‘Sabar sange bose chhilen’: This is a small part taken from the poem ‘Aaj Basanta’ written by Joy Goswami in 2005. He talks about the importance of friendship and community.

Henceforth the audio clips will be referred to as ‘Clip-‘ along with their respective number to maintain consistency and for easy understanding.

7.2.3 Participant Details:

A total of 10 individuals between the ages of 18 and 23 participated in this experiment to provide us with EEG recordings. Participants were reached out individually from personal contacts and word-of-mouth. All the participants were requested to provide their consent prior to the involvement in this study. To ensure the privacy and confidentiality of each of the participants, unique identification number were assigned to them, and their personal information was hidden and securely stored separately from the research data [30].

The participants consisted of young adults, comprising of both males and females. Each participant reported having right-handed dominance, indicating a right-handed preference. All participants had normal visual ability, with a vision of 6/6, indicating normal or optimal vision. Participants reported having proper hearing ability. Participants did not disclose any prevailing medical conditions that could potentially influence their responses or impact the validity of the study. It is worth mentioning that the participants were of sound body and mind, indicating that they were in good overall physical and mental health. This ensured that the data collected and later on the analysis was not disturbed by any underlying health issues that could influence the results.

To look after the safety and well-being of the participants, the experiments were conducted with proper precautions and following the ethical guidelines. All participants provided informed consent, indicating their voluntary involvement. Their consent was obtained prior to their engagement.

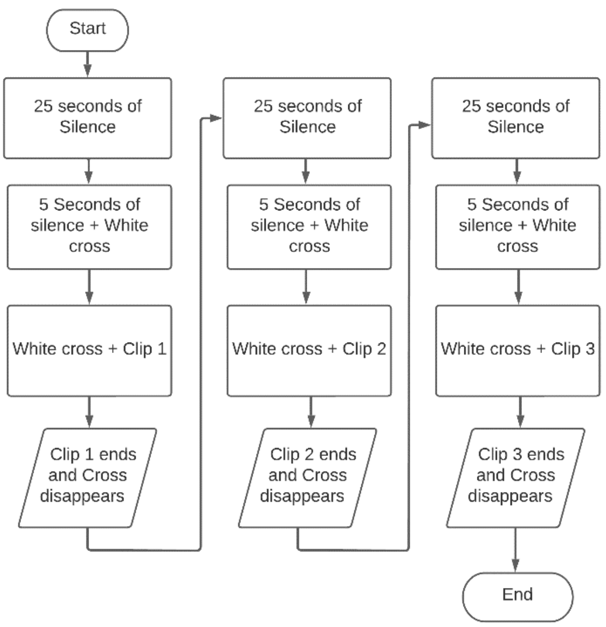
7.2.4 Protocol and Data Recording:

We began the process of capturing EEG recordings from the subjects following a standardized and uniform protocol while collecting human responses, to ensure consistency and reliability, each subject underwent the EEG procedure in the same way [32]. The aim of this approach was to establish a solid foundation for data analysis and interpretation. During the EEG sessions, electrodes were carefully placed in specific locations on the participants' scalps, following the international 10-20 system for electrode placement. This systematic approach ensured comprehensive data collection by allowing us to capture electrical activity from multiple regions of the brain simultaneously after the EEG recordings were obtained, the next step was to extract relevant data for further analysis. To extract meaningful insights from the collected EEG data, we used a computational technique known as Multifractal Detrended Fluctuation Analysis (MFDFA). This method enabled us to investigate the complex temporal patterns and fluctuations within the EEG signals.

The nine audio clips were arranged in a particular manner which is very important to the experiment. The nine audio clips has been categorized into three sets on the basis of the poet. First set comprising of clips 1 through 3, written by Rabindranath Tagore. Second set comprising of clips 4 through 6, written by Sankha Ghosh and the third set comprising of clips 7 to 9, written by Joy Goswami.

Each set follows the same protocol of the arrangement of the clips. Taking Set 1 as an example. As discussed set 1 has 3 clips, these clips need to be arranged in proper intervals of silence followed by audio. Beginning the clip with 25 seconds of complete silence, then there’s 5 seconds of silence but along with this silence a white cross is shown on screen to draw back the attention of the subject. After these 5 seconds, the first clip is played, while the clip is being played the white cross should stay on the screen till the end of the clip. As soon as the clip ends, the white cross also disappears. There is again silence of another 25seconds, followed by silence along with the white cross sign for 5 seconds. Then comes the 2nd clip which is again played along with the white cross and it cross disappears as soon as the clip ends. Lastly, another interval of silence for 25 seconds, 5 seconds of silence and cross followed by the 3rd audio clip and the cross. In the end, when the last audio clip finishes, the cross also disappears but another silence of 30s to be maintained so as to not disrupt or activate the brain activity unnecessarily. In Fig. 7.1, the protocol is explained in the form of a flowchart for one set, this entire set up is repeated for set 2 and set 3 without any interval.

This protocol is followed for all the sets of poems and this is maintained throughout to extract the EEG readings from all the subjects. This is done so as to maintain a uniformity in the procedure. The silence intervals are placed in such a way that the brain activity is maximum and focused during the interval of the audio clip.



Flowchart of the Protocol

It is very important to maintain a proper protocol along with creating an optimal environment for each participant to ensure that we get accurate and reliable results. The following guidelines were strictly followed to attain the best possible conditions for data collection:

1.) Sitting in a relaxed and comfortable position: The subjects were instructed to sit in a comfortable and relaxed position throughout the experiment to minimize physical discomfort or distractions that could potentially affect the emotional responses.

2.) Having no contact with the floor of the room: To prevent any grounding or interference from external sources, subjects were advised to keep their feet on a mat i.e avoid direct contact with the floor of the room.

3.) In a dark and cool environment: Subjects were taken in an environment with controlled lighting conditions. The room was kept in darkness to minimize visual distractions and to help focus attention on the experiment. Additionally, maintaining a cool temperature in the room to ensure the subjects' comfort and less distraction due to heat.

4.) In a noise-free zone: To create an environment for concentration and to minimize distractions, subjects were kept in a noise-free zone. Background noise, such as external conversations or environmental sounds, was tried to be blocked out to maintain a quiet and serene environment during the experiment.

5.) Focusing on the computer monitor only: Subjects were instructed to direct their attention on the computer monitor solely, where the stimuli were presented.

6.) Able to consume the video protocol files: Subjects were provided with the necessary equipment to effectively consume the video protocol files. This ensured that the audio-visual stimuli were presented to participants in a clear and accessible manner

By strictly adhering to these guidelines and maintaining a standardized protocol, we tried to create a controlled experimental environment for each subject. This helped to eliminate any possible errors that might have surfaced in the readings.

7.2.5 Human Response:

In the study of emotions, one of the widely accepted model is Russell's circumplex model. It is a psychological framework that helps represent emotions primarily on two dimensions: valence and arousal. The model provides a visual representation of all human emotions arranged in a circular pattern. Emotions closer to the centre of the circle have less intensity, while those towards the outer edge have higher intensity. Valence refers to the positive (happiness or joy) or negative (sadness or anger) quality of an emotion. It allows for the comparison between emotions, various emotional patterns, and different emotional states.

After all the audio clips were finalized, we went on to gather subjective responses from individuals to gauge their emotional interpretation of each clip. To do this, we used an online survey platform, specifically a Google Form. The form included all nine audio clips, with each clip accompanied by a list of nine emotions from which participants could choose their responses. The emotions provided were: Surprised, Happy, Calm, Angry, Disgusted, Anxious, Sad, Romantic, and Devotion [7].

Almost 200 people took part in this study by listening to the audio snippets and choosing the one emotion they felt most accurately captured the overall tone of each clip. It was made sure that these people were impartial, native Bengali speakers who were unaware of this project's intentions or objectives. This approach aimed to collect responses from participants with an unbiased mind-set, allowing for an authentic and reliable assessment of emotional interpretations.

This human response source, which was derived from the subjective interpretations of the participants, provides a valuable basis for our study. By collecting a wide range of emotional responses from individuals, we can analyse and compare their interpretations with mathematical measurements derived from the audio clips themselves. The depth and validity of our investigation into the emotional aspects of the selected poems are enhanced by this comprehensive approach.

7.2.6 Calculation of Parameters:

After the data collection phase, the next important phase was the analysis of the obtained data. The EEG recordings were properly extracted into .csv. The extracted EEG data was meticulously labelled and organized to prevent any inaccurate or redundant data.
These excel files helped to process the data efficiently and the data was further analyzed using appropriate algorithms and Multifractal Detrended Fluctuation Analysis (MFDFA) [16]. These computational methods helped us to quantify the complexity of the brain activity. By calculating the average multifractal width, we were able to obtain a measure of the complexity for each audio clip. This complexity metric served as a basis for comparing and contrasting the different audio stimuli utilized in the study. Also, we have tried to find out the cross-correlation between all the clips using the Multifractal Cross-Correlation analysis (MFDXA) tool. It provided us the idea of how closely are any two audio clips mathematically connected. The lower the cross-correlation coefficient the more resemblance the clips have for each other.

To get a comprehensive analysis, the data was needed to be arranged in a manner that helped us make visual representation such as bar and line graphs. Graphs were drawn to visually represent the findings and provide a clearer understanding of the patterns and relationships in the data. Firstly, we created an individual electrode-wise analysis, examining the contributions of each electrode. Furthermore, we performed lobe-wise analysis, focusing on the frontal, parietal, occipital, and temporal lobes. By examining the EEG data specific to these regions, we had observations into the activity of different brain areas during the processing of the stimuli. For both the alpha and theta frequency bands, graphs were plotted to visualize and explore the patterns, trends, and variations in brain wave activity.

From these graphs, we extracted key findings and results, which are presented in this research paper. These findings help us understand about the neural responses evoked by the stimuli and enable a deeper understanding of the emotional and cognitive processes associated with the audio clips.

The combination of human responses and EEG data analysis allowed us to establish a comprehensive study for investigating the relationship between the audio files and emotions. The utilization of multifractal analysis and graphical representations enhanced our ability to explain the intricacies of brain wave activity and derive meaningful insights from the collected data.

7.3 Results and Discussions:

Emotions Obtained Through Human Response Against Each Clip:

Clip	Invoked Emotion
1	Devotion
2	Anxiety
3	Happy

Clip	Invoked Emotion
4	Romantic
5	Angry
6	Happy

Clip	Invoked Emotion
7	Sad
8	Calm
9	Happy

Table 7.1: Emotions assigned to the clips

These Human responses are recorded through Google Forms where all the clips were present and each individual person were asked to choose an emotion from the 9 listed emotions after listening to each of the audio clips. The listed emotions are taken from the reference of the Russell's wheel of emotions. The readings are taken from individual, unbiased personal contacts.

As one might think that different people must have given various responses, so how did we get our results? Well, we plotted all the responses for each of the clips individually and we can see of all the 9 listed emotions only one emotion peeking for each of the clips. The peak emotion was considered for our study. The errors are not shown in the figures as they are too small to appreciate.

Acoustical Analysis:

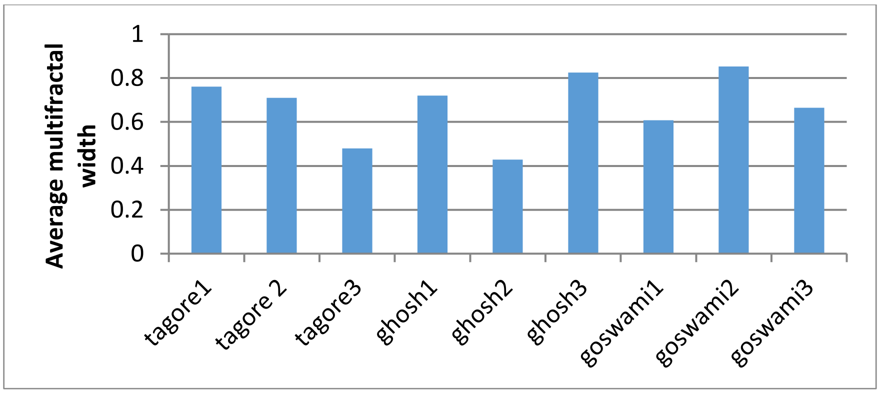


Fig 7.1: Average Multifractal width (w) of the clips

From Fig 7.1 we can see that apart from Tagore 3 and Ghosh 2, average value of w remains between 0.5 < w < 0.9. The graph shows that the highest w is of Ghosh 3 (0.825) and Goswami 2 (0.852). The lowest values of w are Tagore 3 (0.480) and Ghosh 2 (0.428) respectively. According to Russel's wheel of emotions both happy and anger are in the activated state.
The emotions invoked by both of the high and low w clips are happy (Tagore 3 and Ghosh 3). We can also see that Goswami 3 also invokes happiness in the minds of our subjects.
Now, let us consider the w changing patterns of the above 3, i.e., the multifractal width of 5 second intervals of the said clips, i.e., (Tagore 1,2,3; Ghosh 1,2,3 & Goswami 1,2,3).

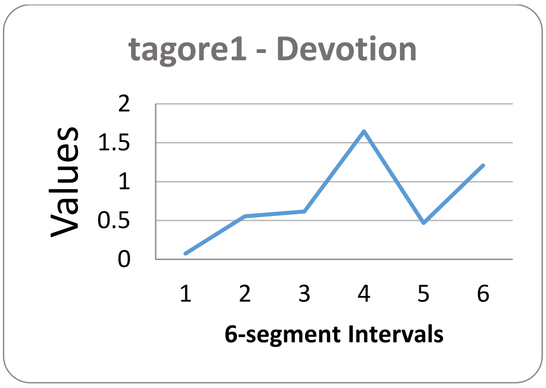


Fig 7.2: Tagore 1-showing Devotion

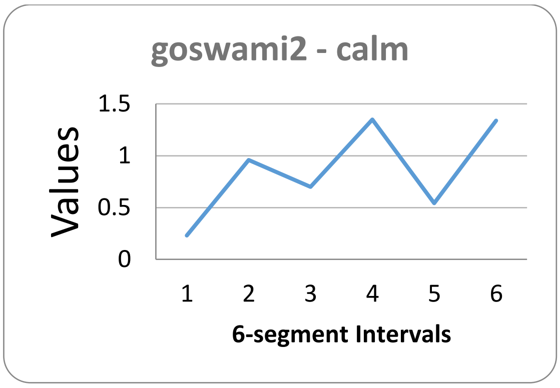


Fig 7.3: Goswami 2-showing Calmness

Figure 7.2 shows that this audio clip evokes feelings of devotion within the individuals. Figure 7.3 shows that this audio clip evokes feelings of calmness within the individuals.

Figure 7.2 (Devotion) and figure 7.3 (Calm) both shows emotions which are on the pleasant and deactivated quarter of the Russell's emotions wheels.

Hence, they show similar pattern of changes of multifractal width and this adds to the elicitation of emotions in the entire clip.

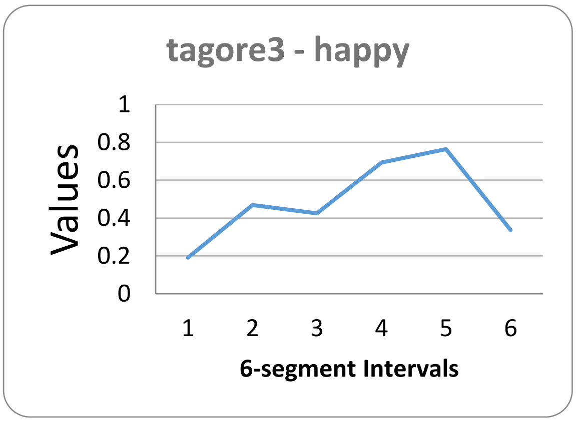


Fig 7.4: Tagore 3-showing Happiness

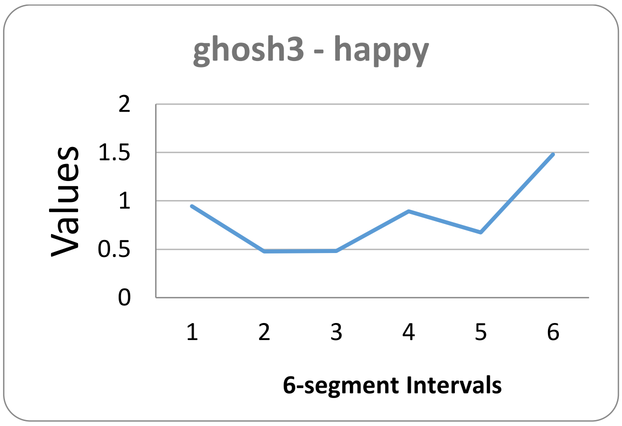


Fig 7.5: Ghosh 3-showing Happiness

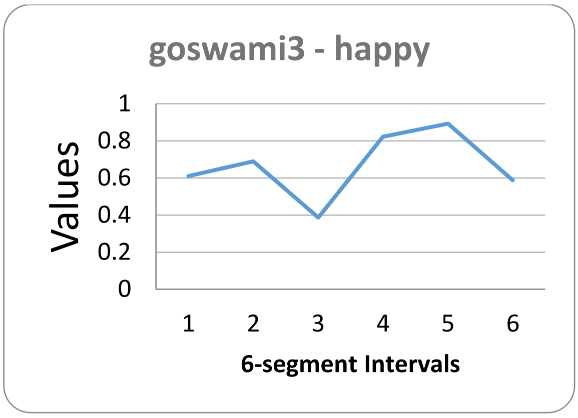
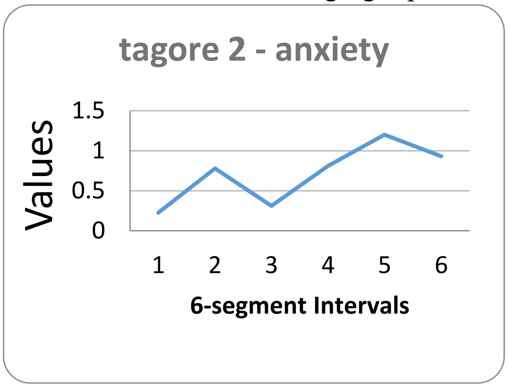


Fig 7.6: Goswami 3-showing Happiness

Figure 7.4 and figure 7.6 follow similar width changing pattern, whereas figure 7.5 does not. This could indicate that the changing pattern of multifractal width and changes in emotions.



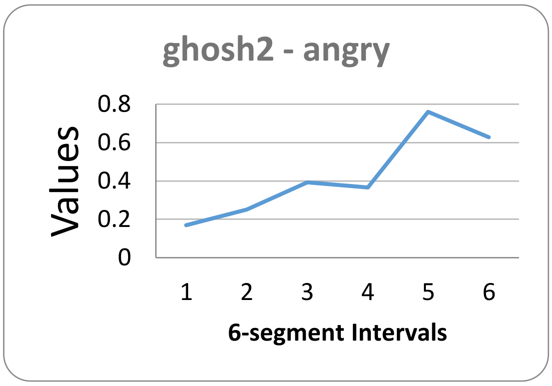
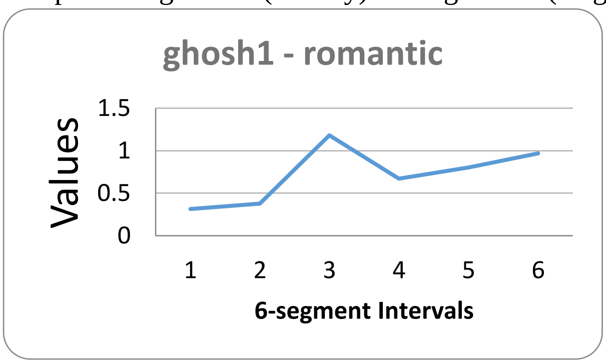


Fig 7.7: Tagore 2-showing Anxiety **Fig 7.8: Ghosh 2-showing Angry**

Changing pattern of multifractal width contributes to invoking emotions to the overall clip.
This is further substantiated when the patterns of 'negative' emotions like anxiety and anger are compared. Figure 7.7 (anxiety) and figure 7.8 (Anger) also display similar w changing patterns.



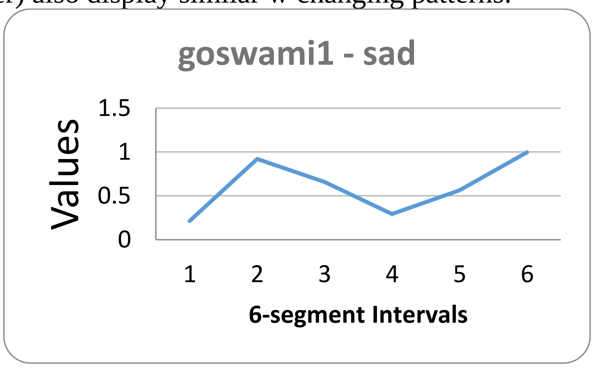


Fig 7.9: Ghosh 1-showing Romantic **Fig 7.10: Goswami 1-showing Sad**

Figure 7.9 shows that this audio clip evokes feelings of romance within the individuals. Figure 7.10 shows that this audio clip evokes feelings of Sadness within the individuals.

7.1. Electrode wise Graphs for Theta Values:

For the Frontal Lobes:

Now, in EEG we are using 4 electrodes from the frontal lobes which are denoted as electrodes F3, F4, F7 and F8 to evaluate the values of the Theta brain waves of our subjects.

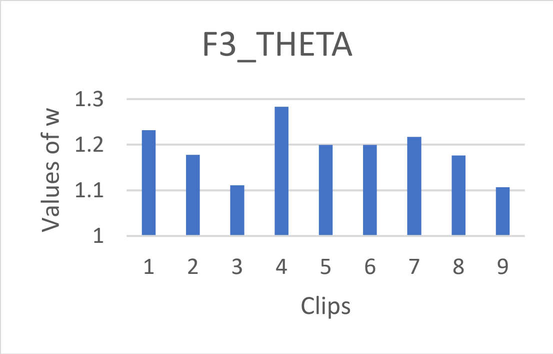


Fig 7.1.1: Theta Values for F3 electrode

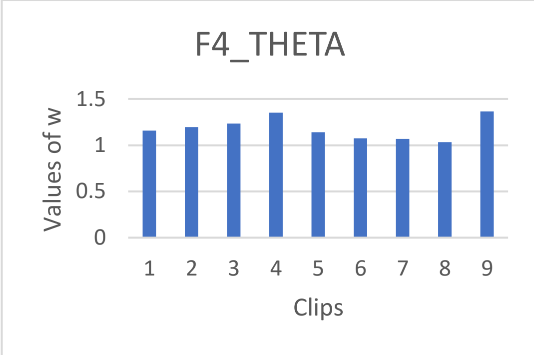


Fig 7.1.2: Theta Values for F4 electrode

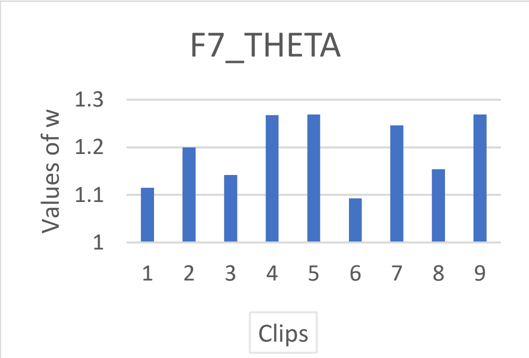


Fig 7.1.3: Theta Values for F7 electrode

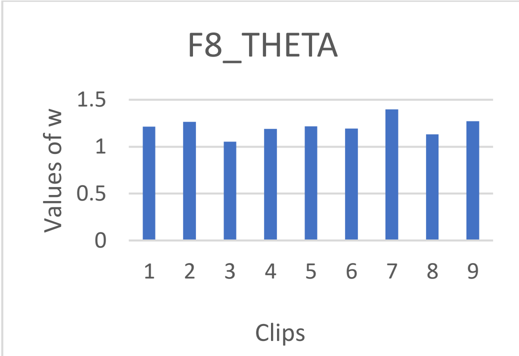


Fig 7.1.4: Theta Values for F8 electrode

From Fig 7.1.1 – 7.1.4:

Upon analysis of the electrodes, distinct patterns emerge. For F3, clip 4 has the highest w value, while clips 3 and 9 have the lowest, indicating positive emotions. Similarly, F4 shows higher w values for clips 4 and 9, and lower values for clips 7 and 8. F7 exhibits high w values for clips 4, 5, and 9, and the lowest value for clip 6. F8 displays the highest w peak in clip 7 and lowest values in clip 3, with sad emotions yielding higher w and happy emotions lower w. F4 and F8 show minimal variations, while F3 and F7 demonstrate notable variations across clips in w values.

For the Temporal Lobes:

Presently, in EEG, we are utilizing four electrodes positioned on the temporal lobes, specifically identified as T3, T4, T5, and T6, to assess the Theta brain wave values of our subjects.

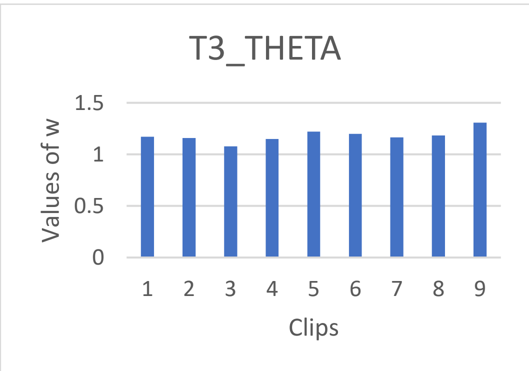


Fig 7.1.5: Theta Values for T3 electrode

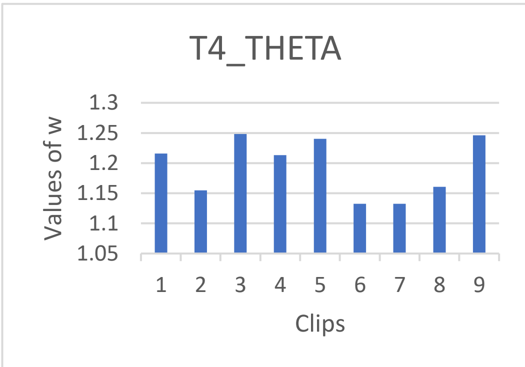
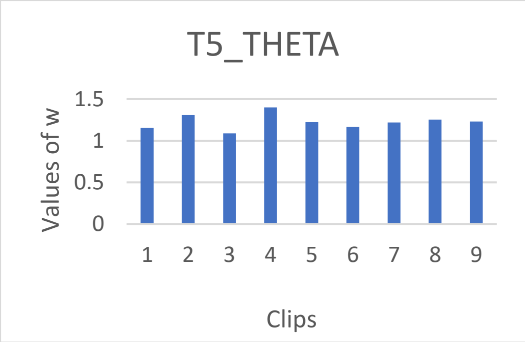


Fig 7.1.6: Theta Values for T4 electrode



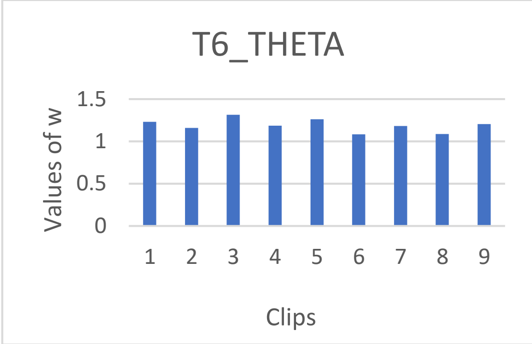


Fig 7.1.7: Theta Values for T5 electrode

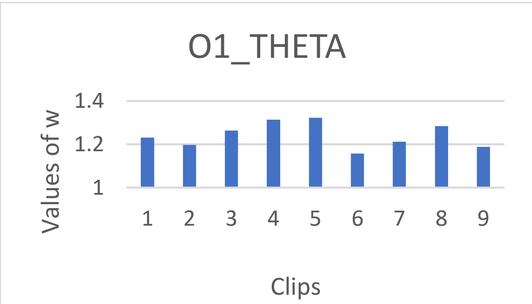
Fig 7.1.8: Theta Values for T6 electrode

From Fig 7.1.5 – 7.1.8: The electrodes T3, T5 and T6 shows very less variations in the readings as compared to T4 electrode which has the most fluctuations.

For electrode T4 clip 3, 5 and 9 shows the highest values whereas clip 6 and 7 shows the lowest values. This indicates that the emotions on the activated portion of the Russell's emotions wheel shows a higher value as compared to the emotions on the deactivated portion.

For the Occipital Lobes:

In EEG, we are using a pair of electrodes placed on the occipital lobes, specifically referred to as O1 and O2, to evaluate the Theta brain wave values of our subjects.



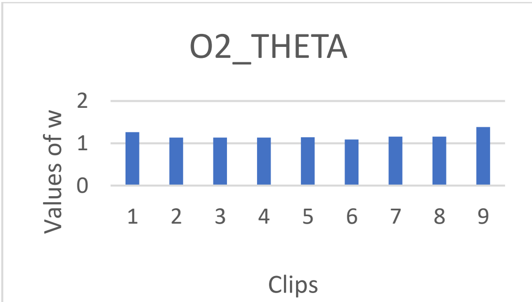


Fig 7.1.9: Theta Values for O1 electrode

Fig 7.1.10: Theta Values for O2 electrode

Upon analysis, the O1 graph shows greater fluctuations compared to O2, indicating varying processing of visual information in the occipital lobe. Specifically, O1 exhibits the highest value in clip 5 and the lowest in clip 6, suggesting distinct neural responses. In contrast, O2 demonstrates minimal variations across clips, with clip 9 showing the highest value and clip 6 the lowest. These findings highlight the role of O1 and O2 electrodes in processing visual stimuli, revealing different levels of neural engagement between specific clips.

For the Parietal Lobes:

In EEG, we are currently employing a pair of electrodes positioned on the parietal lobes, denoted as P3 and P4, to assess the Theta brain wave values of our subjects.

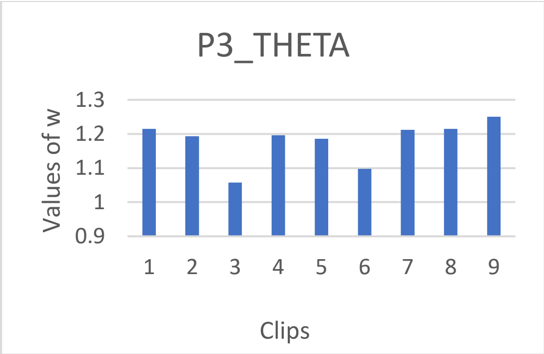


Fig 7.1.11: Theta Values for P3 electrode

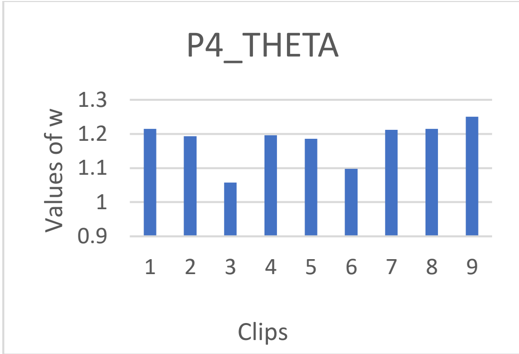


Fig 7.1.12: Theta Values for P4 electrode

The data acquired from the electrodes placed on the parietal lobes, specifically targeting P3 and P4, unveils a striking degree of consistency in the recorded readings, highlighting a notable alignment between the measurements obtained from these distinct locations on the brain's parietal regions.

Within both graphs, it is evident that clip 9 consistently exhibits the highest values, while clip 3 consistently demonstrates the lowest values, signifying a recurring pattern of extreme measurements across the depicted data.

7.2. Electrode wise Graphs for Alpha Values:

For the Frontal Lobes:

Now, in EEG we are using 4 electrodes from the frontal lobes which are denoted as electrodes F3, F4, F7 and F8 to evaluate the values of the Alpha brain waves of our subjects.

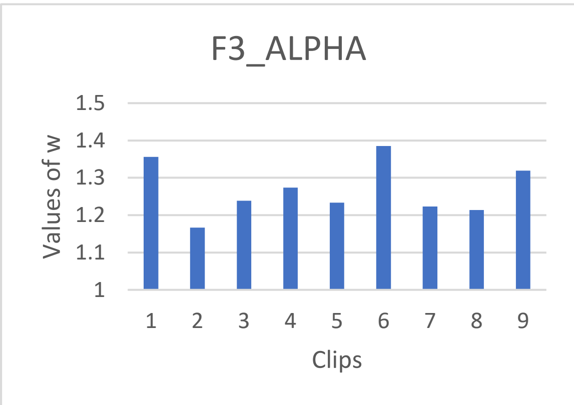


Fig 7.2.1: Alpha Values for F3 electrode

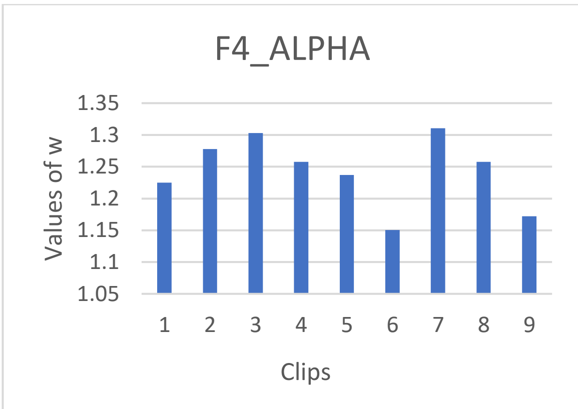


Fig 7.2.2: Alpha Values for F4 electrode

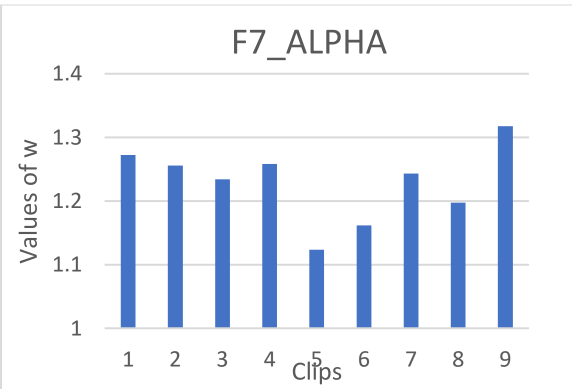


Fig 7.2.3: Alpha Values for F7 electrode

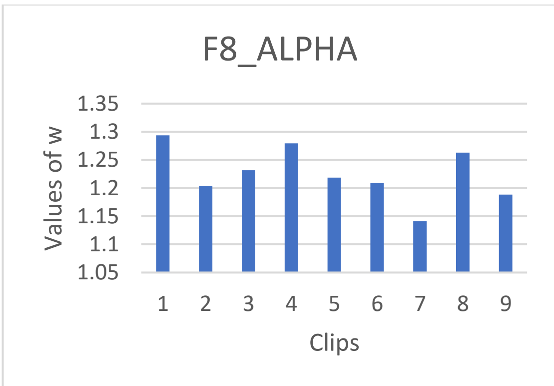


Fig 7.2.4: Alpha Values for F8 electrode

From Fig 7.2.1 – 7.2.4:

Upon observation, it becomes apparent that the graphs representing the alpha waves in the frontal lobes display a considerably greater degree of variability and fluctuations compared to the theta waves.

For F3 electrode the values of clip 6 shows the highest value whereas the values of clip 2 shows the lowest values

For F4 electrode the values of clip 3 and 7 are the highest and the values of clip 6 is the lowest

For F7 electrode the values of clip the values of clip 9 is the highest whereas the values of clip 5 is the lowest

For F8 electrode the values of clip 1 is the highest and the values of clip 7 are the lowest.

For the Temporal Lobes:

Presently, in EEG, we are utilizing four electrodes positioned on the temporal lobes, specifically identified as T3, T4, T5, and T6, to assess the Alpha brain wave values of our subjects.

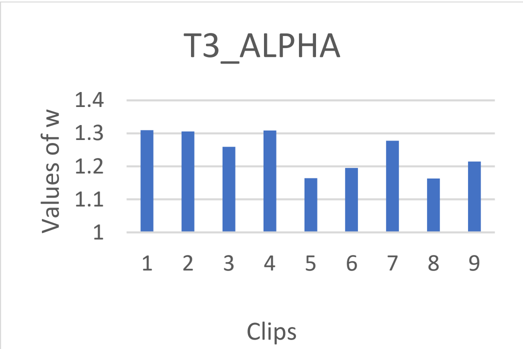


Fig 7.2.5: Alpha Values for T3 electrode

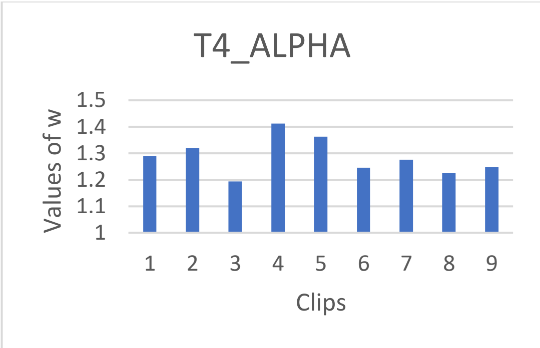


Fig 7.2.6: Alpha Values for T4 electrode

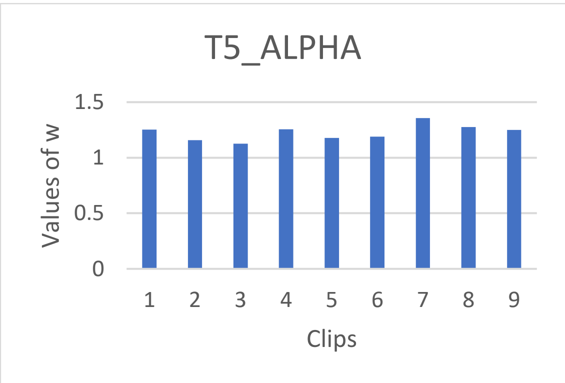


Fig 7.2.7: Alpha Values for T5 electrode

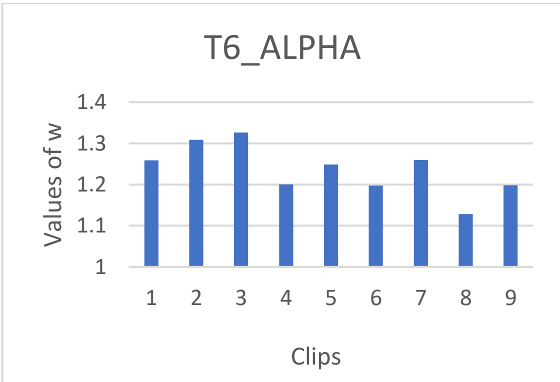


Fig 7.2.8: Alpha Values for T6 electrode

From Fig 7.2.5 – 7.2.8:

Upon observation, it becomes apparent that the graphs representing the alpha waves in the frontal lobes display a considerably greater degree of variability and fluctuations compared to the theta waves.

For T3 electrode the values of clip 1 and 4 shows the highest value whereas the values of clip 5 and 8 shows the lowest values. For F4 electrode the values of clip 3 and 7 are the highest and the values of clip 6 is the lowest. For F7 electrode the values of clip the values of clip 9 is the highest whereas the values of clip 5 is the lowest For F8 electrode the values of clip 1 is the highest and the values of clip 7 are the lowest.

For the Occipital Lobes:

In EEG, we are using a pair of electrodes placed on the occipital lobes, specifically referred to as O1 and O2, to evaluate the Alpha brain wave values of our subjects.

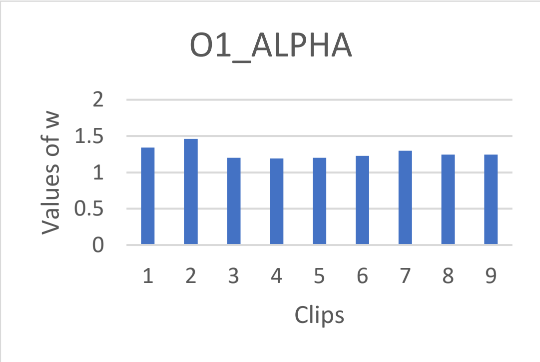


Fig 7.2.9: Alpha Values for O1 electrode

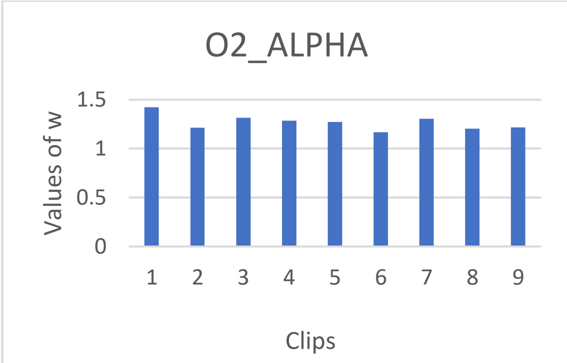


Fig 7.2.10: Alpha Values for O2 electrode

An observation can be made that the readings obtained from the electrodes positioned on both O1 and O2 exhibit a remarkable similarity.

No discernible fluctuations are apparent when comparing the two graphs, indicating a consistent and stable pattern or trend exhibited across both sets of data.

For the O1 electrode the highest value is of clip 2.

For the O2 electrode the highest value is of clip 1 and the lowest is of clip 2.

For the Parietal Lobes:

In EEG, we are currently employing a pair of electrodes positioned on the parietal lobes, denoted as P3 and P4, to assess the Alpha brain wave values of our subjects.

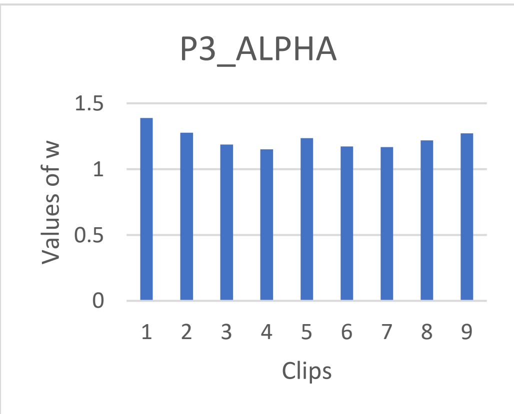


Fig 7.2.11: Alpha Values for P3 electrode

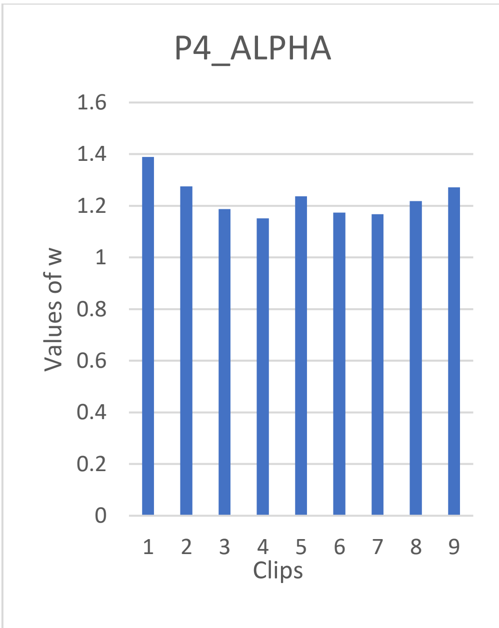


Fig 7.2.12: Alpha Values for P4 electrode

An observation can be made that the readings obtained from the electrodes positioned on both P3 and P4 exhibit a remarkable similarity. No discernible fluctuations are apparent when comparing the two graphs, indicating a consistent and stable pattern or trend exhibited across both sets of data.

In regard to the P3 and P4 electrodes, it is evident that clip 1 consistently displays the highest values, while clips 4 and 7 consistently exhibit the lowest values. This consistent pattern underscores the distinctive response characteristics associated with these electrode locations.

7.3. Lobe-wise Variations:

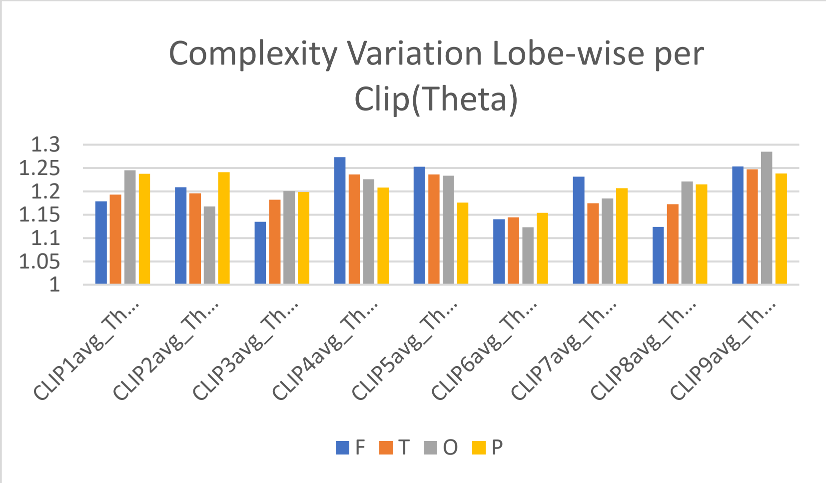


Fig 3.3.1: Lobe-wise variation for Theta Values

Figure 7.3.1 illustrates the lobe-wise variation of Alpha values for the 9 clips. Theta brain waves are associated with meditation, internal focus, and spiritual awareness. Clip 4 exhibits the highest value in the frontal lobe (1.27), while Clip 9 demonstrates the highest values in the temporal (1.25) and occipital (1.29) lobes. Additionally, Clips 2 and 4 both display the highest values in the parietal lobe (1.24). Conversely, Clip 8 has the lowest value in the frontal lobe (1.12), while Clip 6 has the lowest values in the temporal (1.14), occipital (1.12), and parietal lobes (1.15).

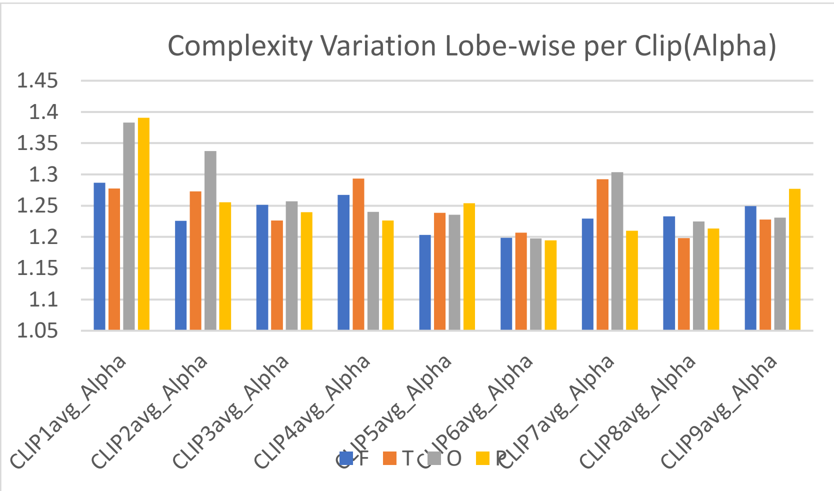


Fig 7.3.2: Lobe-wise variation for Alpha Values

In Figure 7.3.2, the Alpha values of the 9 clips are depicted, showcasing variations across the frontal, temporal, occipital, and parietal lobes. Alpha brain waves indicate increased activity and focus, promoting tranquillity, creative thinking, and learning. Notably, Clip 1 exhibits the highest values in the frontal (1.29), occipital (1.38), and parietal lobes (1.39), while Clip 7 demonstrates the highest value in the temporal lobe (1.29). Conversely, Clips 5 and 6 display the lowest values in the frontal lobe (1.20), Clip 6 and 8 have the lowest values in the temporal lobe (1.20), and Clip 6 shows the lowest values in the occipital (1.20) and parietal lobes (1.19).

3.4. Poet-wise Variations:

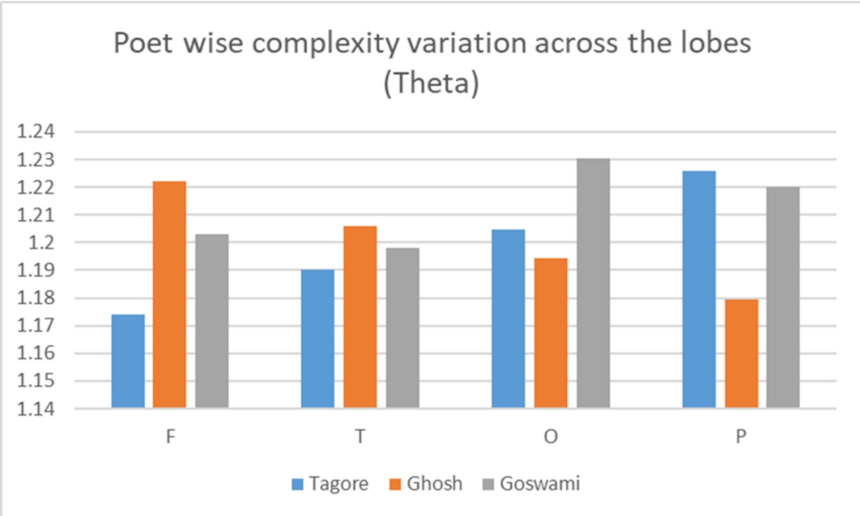


Fig 7.4.1: Poet-wise variation for Theta Values

In Figure 7.4.1 we can see that for the theta set of values we can see for the frontal lobes the values of Ghosh are the highest while Tagore are the lowest

For the temporal lobes the three poets have similar values whereas again in the occipital lobes we can see Goswami peeking and Ghosh is at the lowest. Again, in the parietal lobes Tagore is peeking whereas Ghosh is the lowest one. These figures show how the clips of each of the poets affect various sections of the brain showing different emotions.

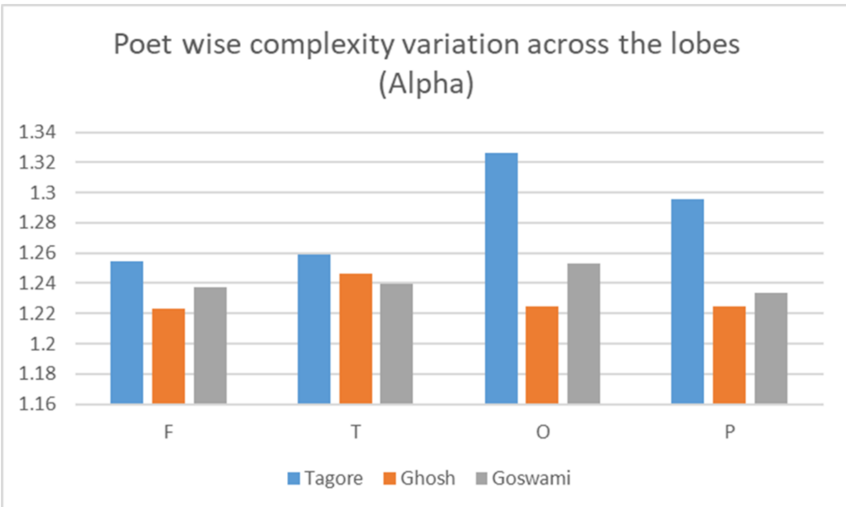


Fig 7.4.2: Poet-wise variation for Alpha Values

In Figure 7.4.2 we can see that for the theta set of values we can see for the frontal lobes and temporal lobes have similar values for all of the three poets.

However, in the occipital lobes we can see some striking difference that Tagore is peaking and Ghosh is at the lowest. Again, in the parietal lobes Tagore is peeking whereas Ghosh is the lowest one. These figures show how the clips of each of the poets affect various sections of the brain showing different emotions.

7.5. Cross-correlations:

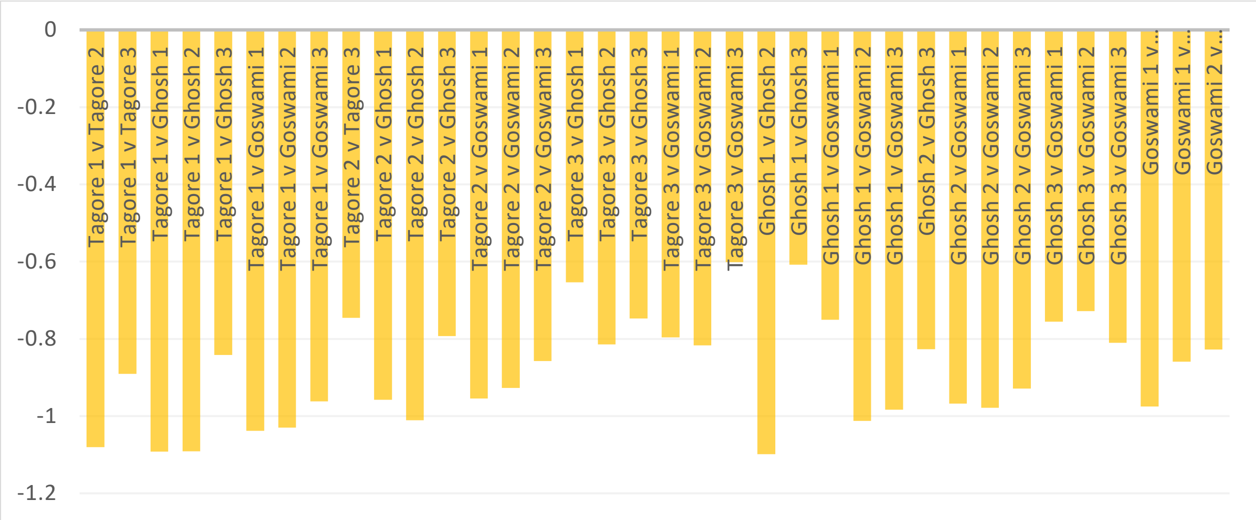


Fig 7.5: Cross-corelation among the 9 Clips

Cross-correlation measures similarity between two signals by comparing alignment and correspondence at different positions.

In our experiment we are finding the values of the cross-correlation for the 9 clips after comparing each of the clips with all other 8 clips to see how the values vary for each comparison and we can see some amazing results in the graph for each comparison of emotions.

Figure 7.5 illustrates the cross-correlation among the nine clips and the existence of long-range correlations.

The highest cross correlations were found in Tagore 1-Tagore 2, Ghosh1-Ghosh2, Tagore1-Ghosh1 and Tagore1-Ghosh2. Interestingly, 3 out of 4 of these correlations consist of clips that evoke contrasting emotions: Tagore 1-Tagore 2 (devotion-anxiety), Ghosh1-Ghosh2 (Romantic-Anger) and Tagore1-Ghosh2 (Devotion-Anger).

On the other hand, clips invoking similar 'positive' emotions found to have lower cross correlations: Tagore 3-Goswami 3 (Happy-happy), Ghosh 1-Ghosh 3 (Romantic-Happy) and Tagore 3-Ghosh 1 (Happy-Romantic).

Such cross correlations strengthen the idea that the complexity present in the signals does take part in influencing the invoked emotion and the cross-correlation coefficient γ could prove to be a useful parameter in this regard.

The graphs for lambda vs q for the various clips as well as the tau vs q and the f alpha vs alpha graphs are show below. The various explanations of the following graphs are shown in the methodology paper.

7.5.1. Lambda Graphs:

Tagore-Tagore

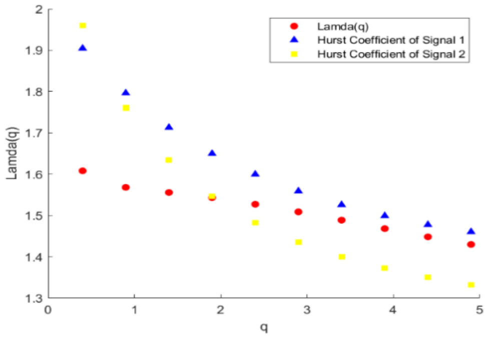


Fig 7.5.1.1 Tagore 1 vs Tagore 2

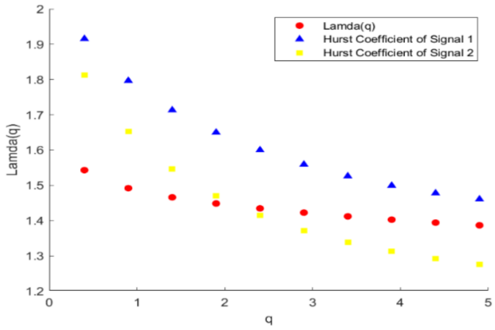


Fig 7.5.1.2 Tagore 1 vs Tagore 3

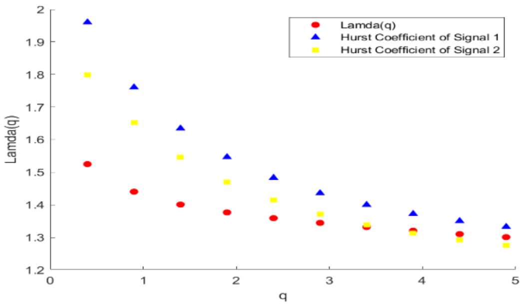


Fig 7.5.1.3 Tagore 2 vs Tagore 3

The figures display cross-correlations between three clips of Tagore. They compare the clips to each other, resulting in lambda(q) vs q graphs.

Tagore-Ghosh

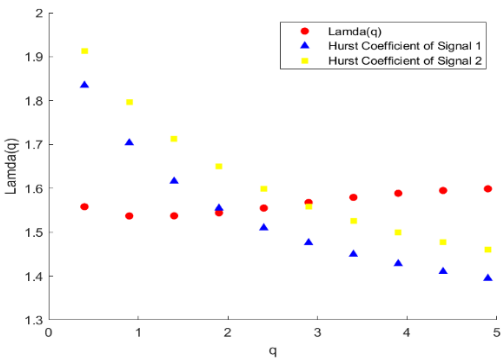


Fig 7.5.1.4 Ghosh 1 vs Tagore 1

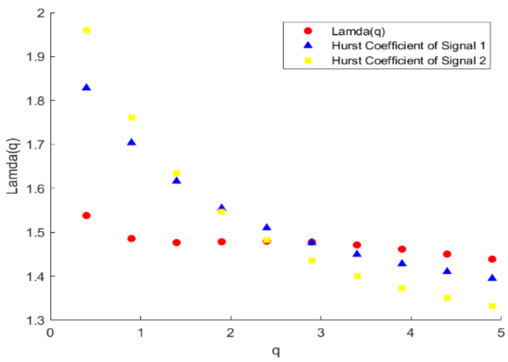


Fig 7.5.1.5 Ghosh 1 vs Tagore 2

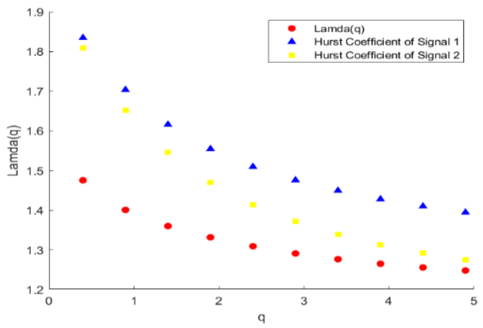


Fig 7.5.1.6 Ghosh 1 vs Tagore 3

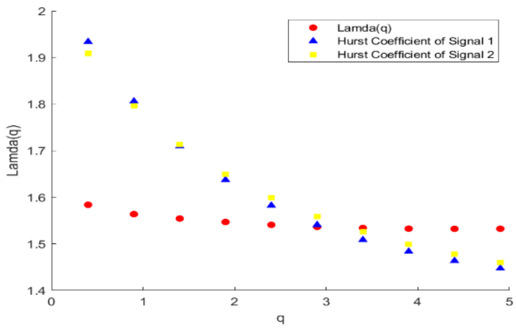


Fig 7.5.1.7 Ghosh 2 vs Tagore 1

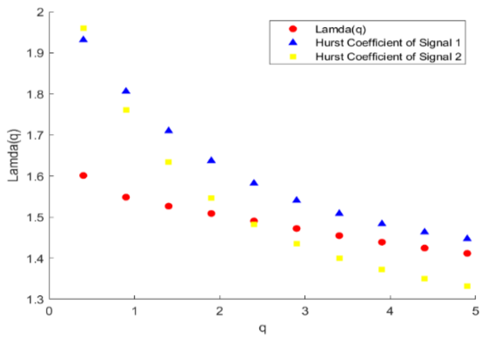


Fig 7.5.1.8 Ghosh 2 vs Tagore 2

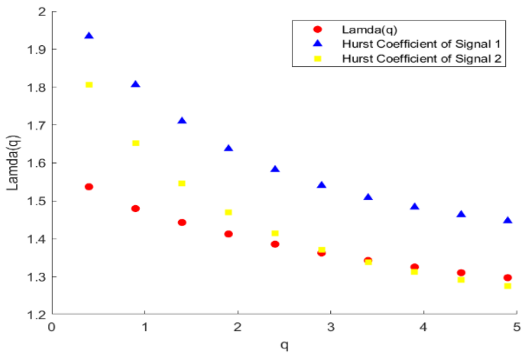


Fig 7.5.1.9 Ghosh 2 vs Tagore 3

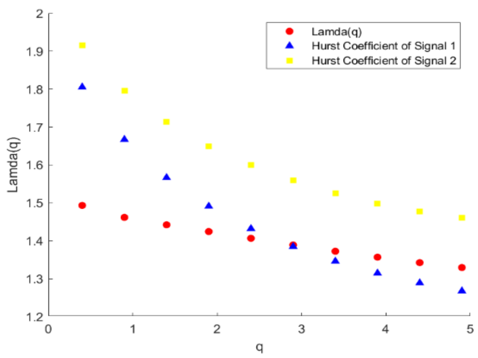


Fig 7.5.10 Ghosh 3 vs Tagore 1

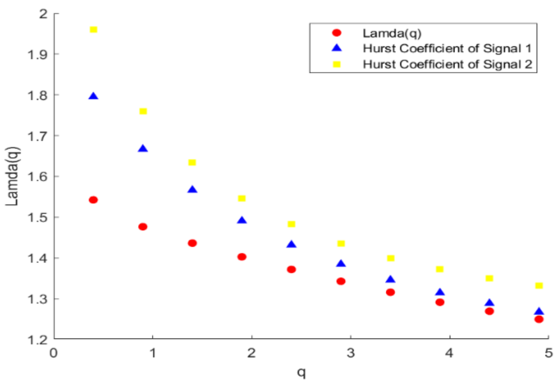


Fig 7.5.1.11 Ghosh 3 vs Tagore 2

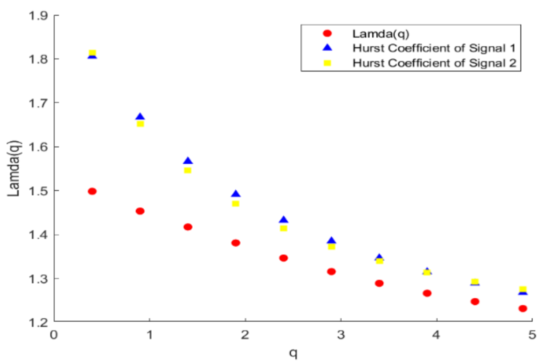


Fig 7.5.1.12 Ghosh 3 vs Tagore 3

The figures illustrate cross-correlations between three clips of Tagore and Ghosh resulting in lambda(q) vs q graphs. The red line represents lambda(q), while the blue and yellow lines indicate the Hurst coefficient of signals 1 and 2, respectively.

Tagore-Goswami

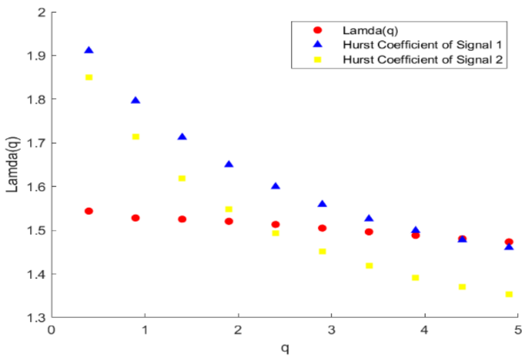


Fig 7.5.1.13 Goswami 1 vs Tagore 1

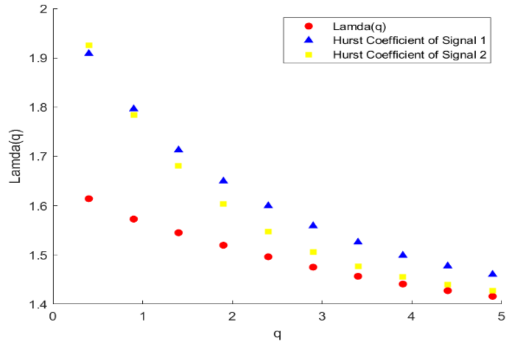


Fig 7.5.1.14 Goswami 2 vs Tagore 1

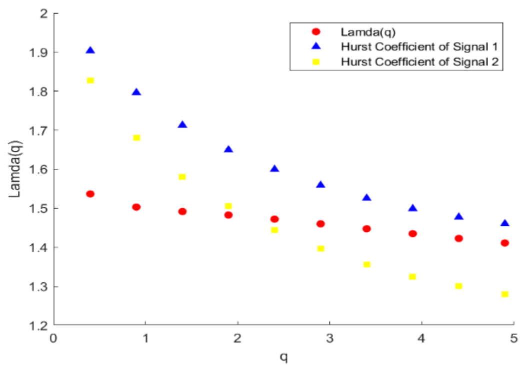


Fig 7.5.1.15 Goswami 3 vs Tagore 1

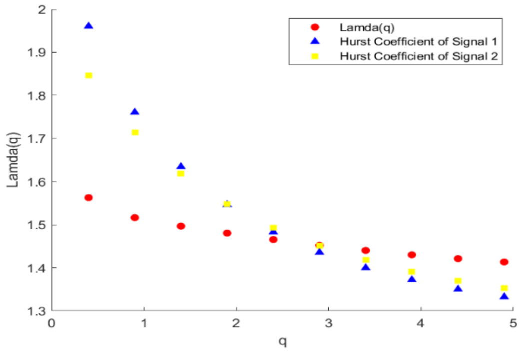


Fig 7.5.1.16 Goswami 1 vs Tagore 2

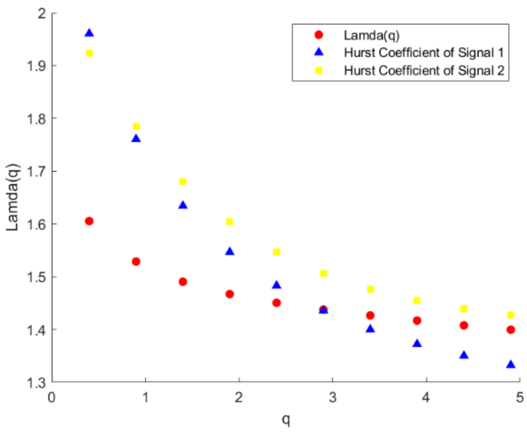


Fig 7.5.1.17 Goswami 2 vs Tagore 2

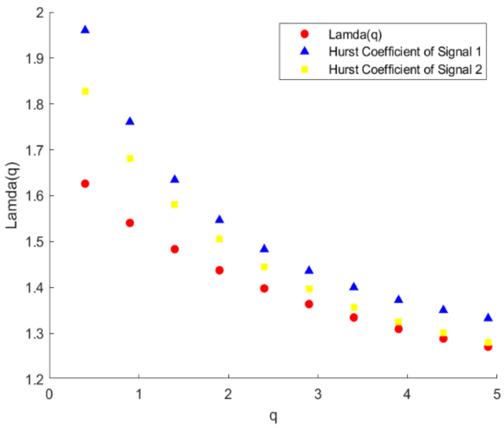
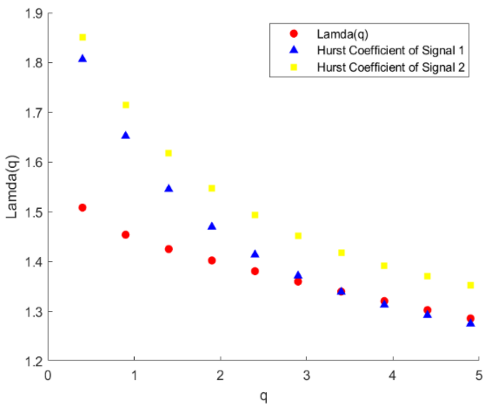


Fig 7.5.1.18 Goswami 3 vs Tagore 2



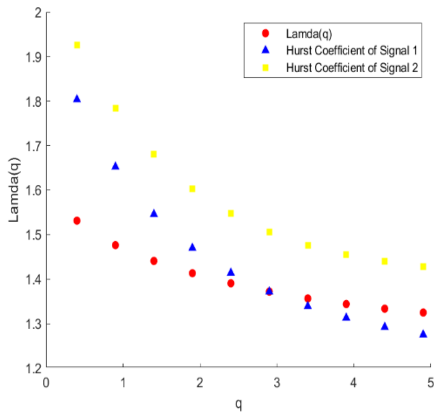


Fig 7.5.1.19 Goswami 1 vs Tagore 3 **Fig 7.5.1.20 Goswami 2 vs Tagore 3**

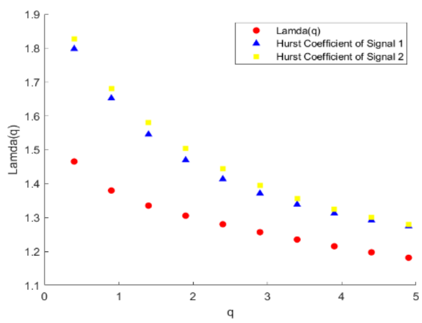
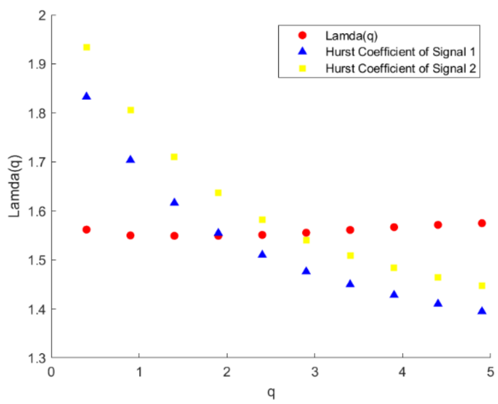


Fig 7.5.1.21 Goswami 3 vs Tagore 3

The figures depict cross-correlations between three clips of Tagore and Goswami showcasing lambda(q) vs q graphs. Lambda(q) is represented by the red line, while the blue and yellow lines correspond to the Hurst coefficient of signals 1 and 2, respectively.

Ghosh-Ghosh



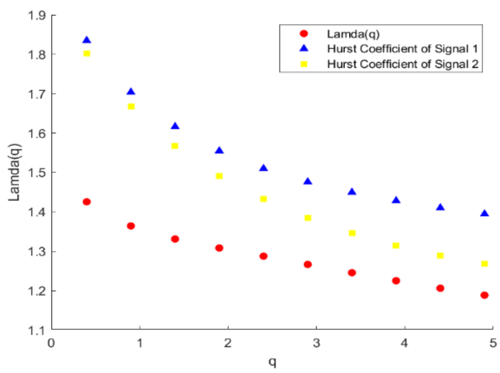


Fig 7.5.1.22 Ghosh 1 vs Ghosh 2 **Fig 7.5.1.23 Ghosh 1 vs Ghosh 3**

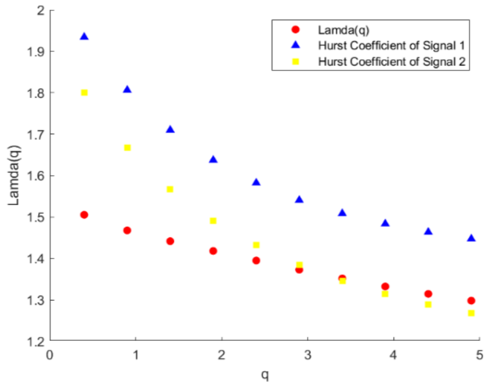


Fig 7.5.1.24 Ghosh 2 vs Ghosh 3

The figures display cross-correlations between three clips of Ghosh. They compare the clips to each other, resulting in lambda(q) vs q graphs.

Ghosh-Goswami

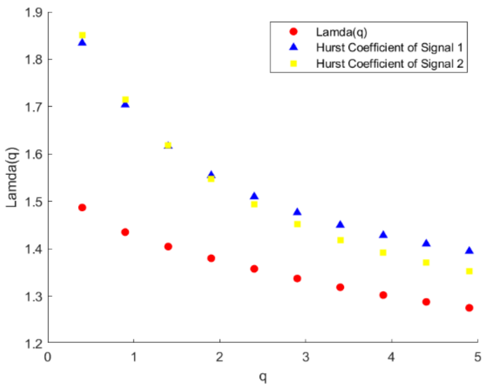


Fig 7.5.1.25 Ghosh 1 vs Goswami 1

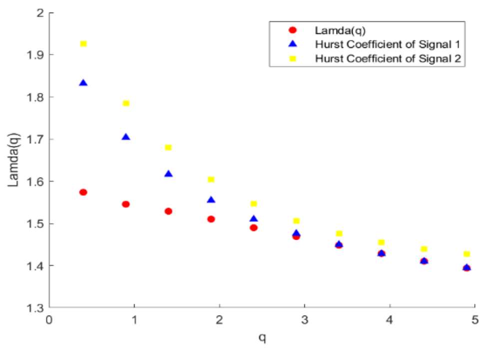


Fig 7.5.1.26 Ghosh 1 vs Goswami 2

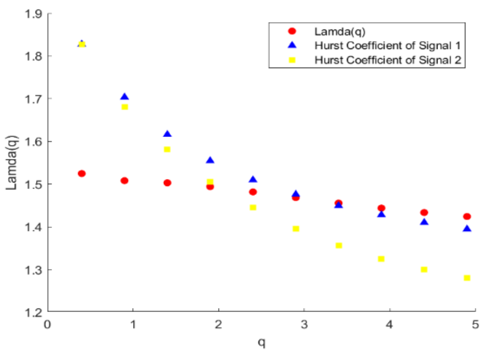


Fig 7.5.1.27 Ghosh 1 vs Goswami 3

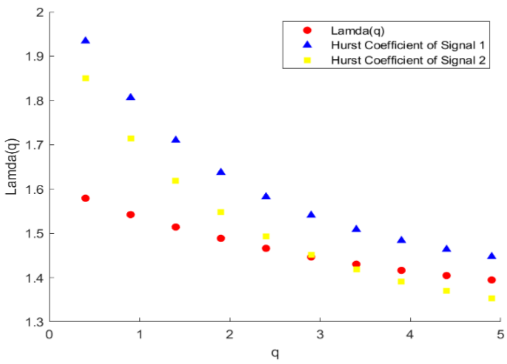
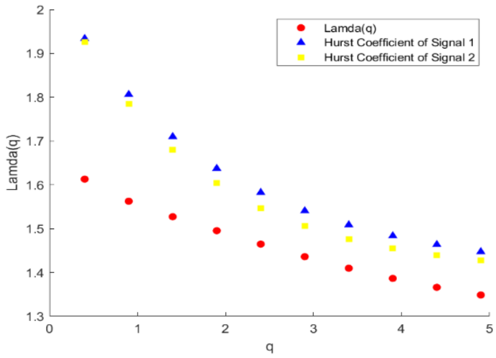


Fig 7.5.1.28 Ghosh 2 vs Goswami 1



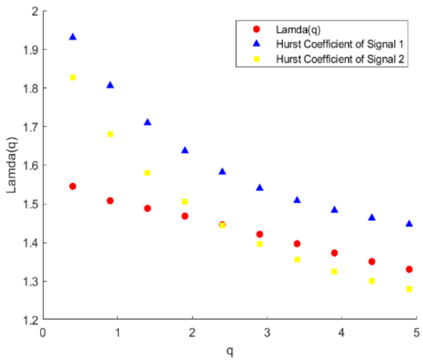
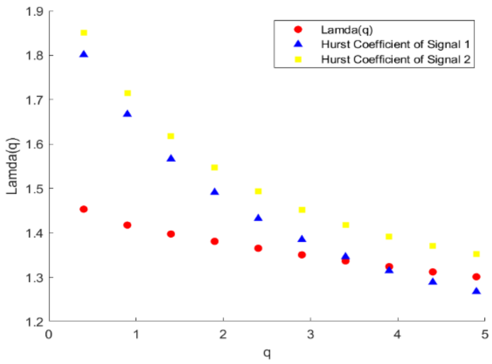


Fig 7.5.1.29 Ghosh 2 vs Goswami 2

Fig 7.5.1.30 Ghosh 2 vs Goswami 3



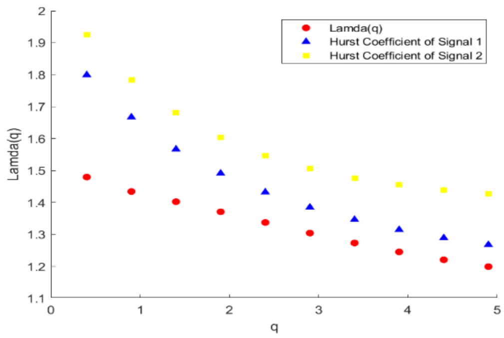


Fig 7.5.1.31 Ghosh 3 vs Goswami 1

Fig 7.5.1.32 Ghosh 3 vs Goswami 2

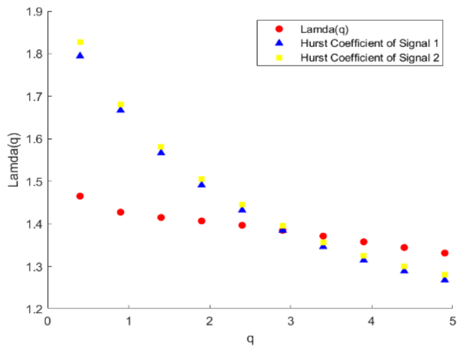


Fig 7.5.1.33 Ghosh 3 vs Goswami 3

The figures portray cross-correlations among three clips of Ghosh and Goswami, presenting lambda(q) vs q graphs. Lambda(q) is represented by the red line, while the blue and yellow lines depict the Hurst coefficient for signals 1 and 2, respectively.

Goswami-Goswami

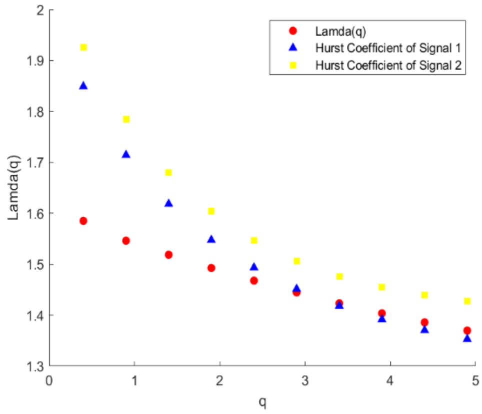


Fig 7.5.1.34 Goswami 1 vs Goswami 2

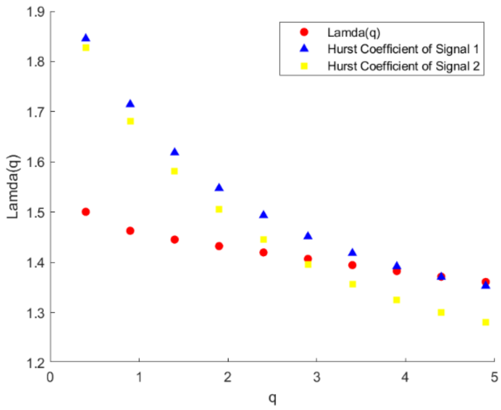


Fig 7.5.1.35 Goswami 1 vs Goswami 3

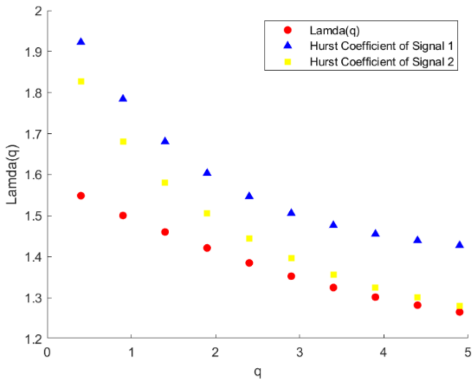


Fig 7.5.1.36 Goswami 2 vs Goswami 3

The figures display cross-correlations between three clips of Goswami. They compare the clips to each other, resulting in lambda(q) vs q graphs

7.5.2. Tau Graphs:

Tagore-Tagore

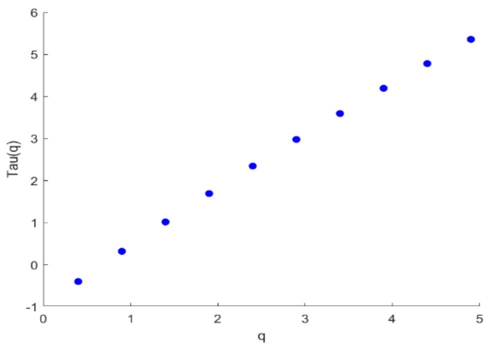


Fig 7.5.2.1 Tagore 1 vs Tagore 2

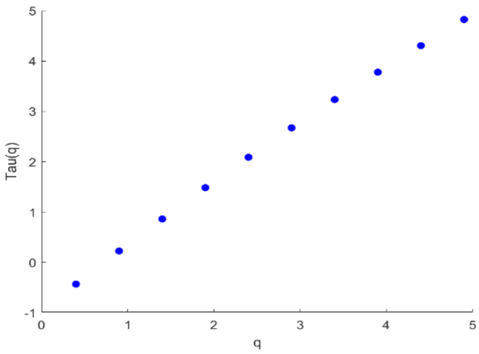


Fig 7.5.2.2 Tagore 1 vs Tagore 3

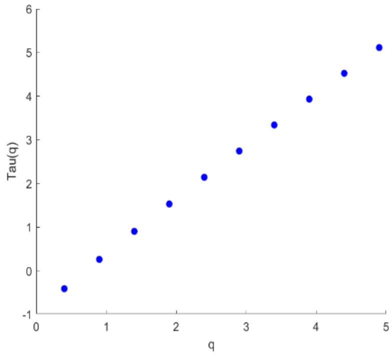


Fig 7.5.2.3 Tagore 2 vs Tagore 3

These figures show us the cross-corelations of the three clips of Tagore. They compare the clips to each other, resulting in tau(q) vs q graphs.

Tagore-Ghosh

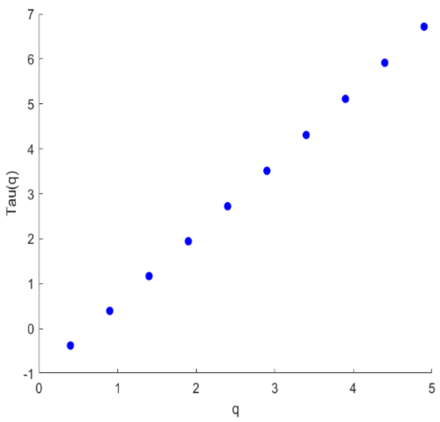


Fig 7.5.2.4 Tagore 1 vs Ghosh 1

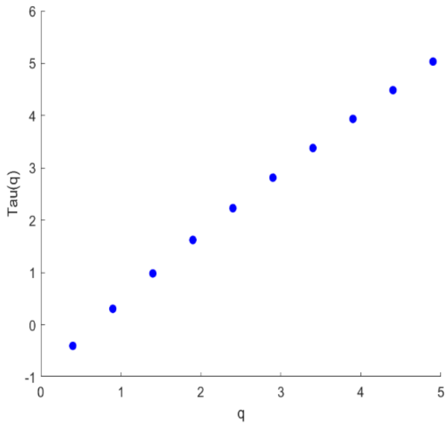


Fig 7.5.2.5 Tagore 1 vs Ghosh 2

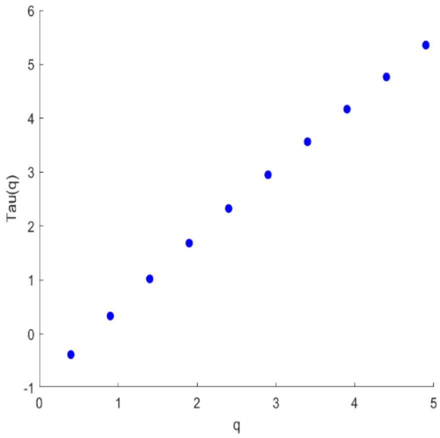


Fig 7.5.2.6 Tagore 1 vs Ghosh 3

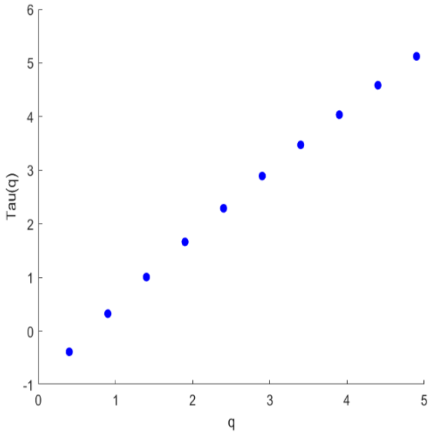


Fig 7.5.2.7 Tagore 2 vs Ghosh 1

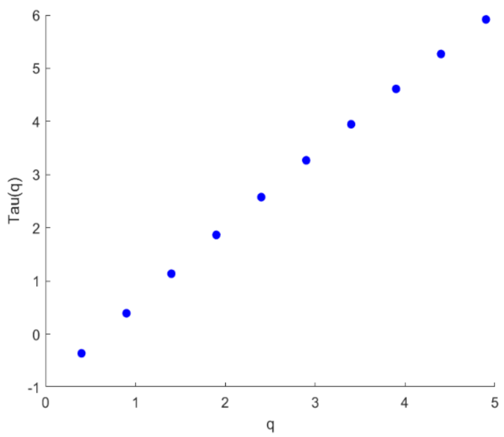


Fig 3.5.2.8 Tagore 2 vs Ghosh 2

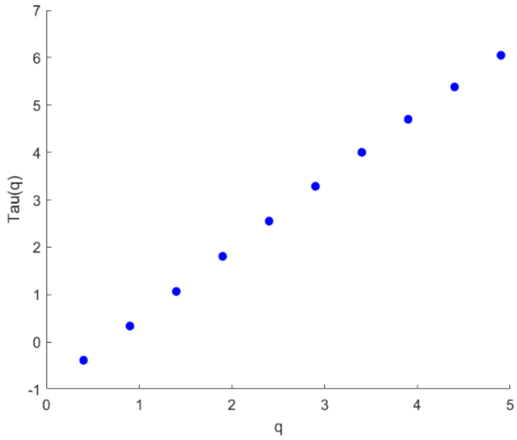


Fig 3.5.2.9 Tagore 2 vs Ghosh 3

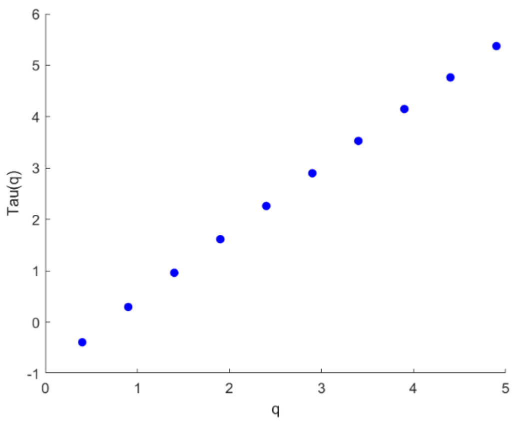


Fig 7.5.2.10 Tagore 3 vs Ghosh 1

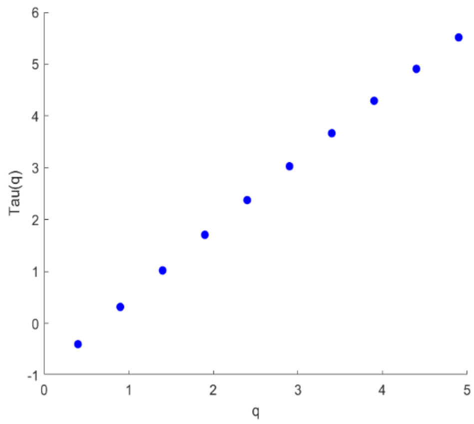


Fig 7.5.2.11 Tagore 3 vs Ghosh 2

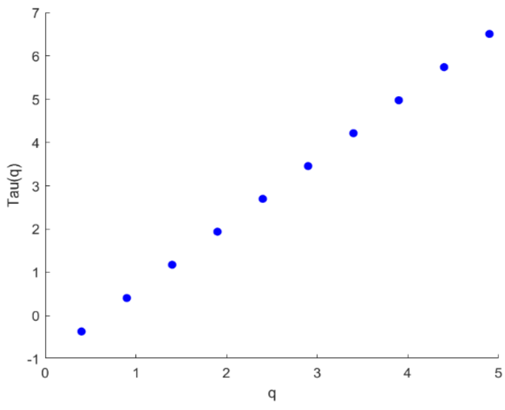


Fig 7.5.2.12 Tagore 3 vs Ghosh 3

These figures depict the cross-correlations between three clips of Tagore and Ghosh. The clips of Tagore are compared with the three clips of Ghosh, resulting in tau(q) vs q graphs displayed accordingly.

Tagore-Goswami

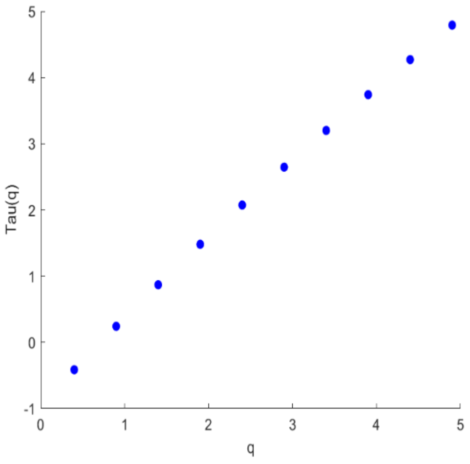


Fig 7.5.2.13 Tagore 1 vs Goswami 1

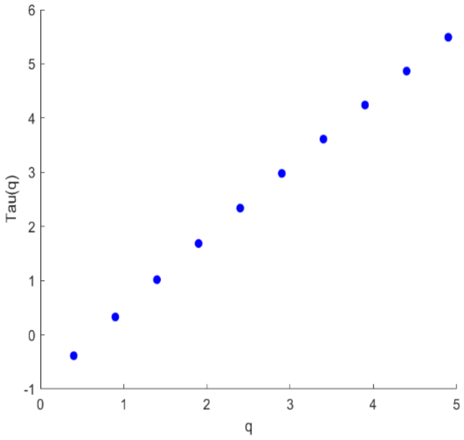


Fig 7.5.2.14 Tagore 1 vs Goswami 2

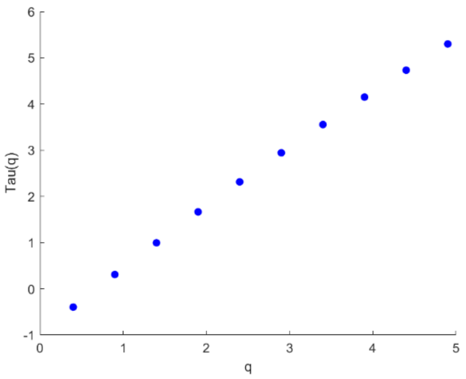


Fig 7.5.2.15 Tagore 1 vs Goswami 3

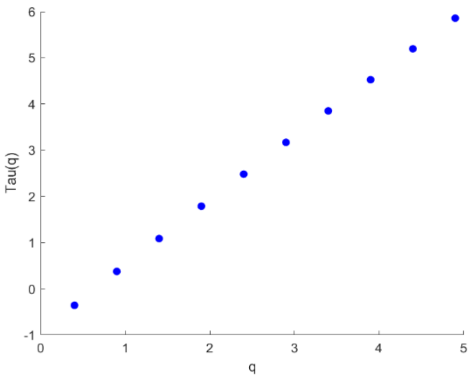


Fig 7.5.2.16 Tagore 2 vs Goswami 1

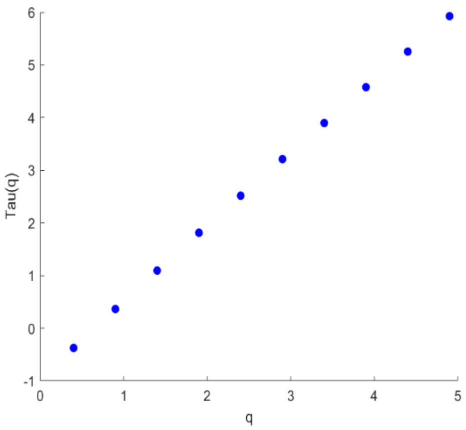


Fig 7.5.2.17 Tagore 2 vs Goswami 2

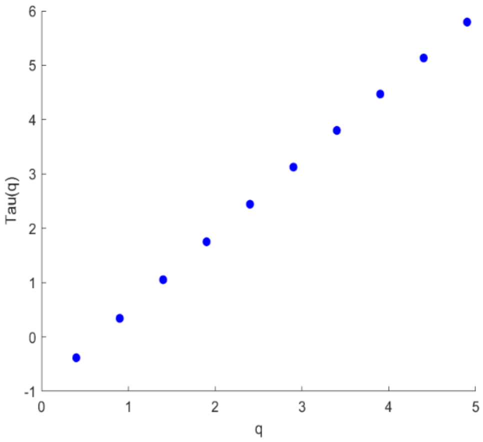


Fig 7.5.2.18 Tagore 2 vs Goswami 3

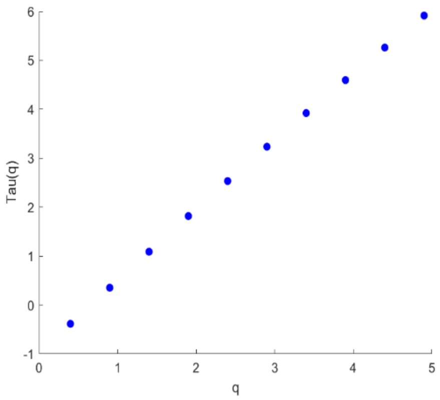


Fig 3.5.2.19 Tagore 3 vs Goswami 1

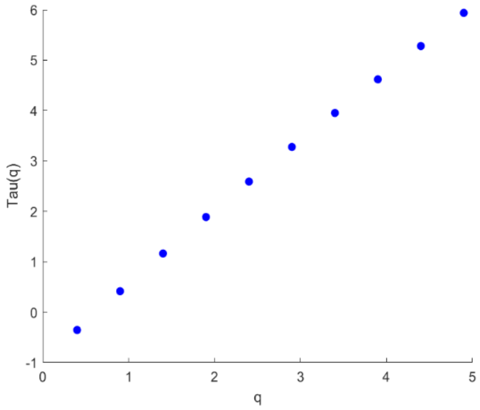


Fig 3.5.2.20 Tagore 3 vs Goswami 2

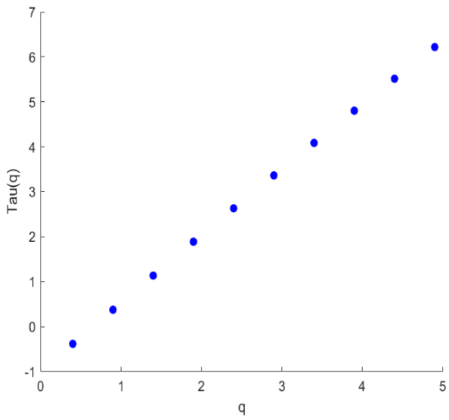


Fig 3.5.2.21 Tagore 3 vs Goswami 3

The figures present the cross-correlations between three clips of Tagore and Goswami. In this comparison, the Tagore clips are matched with the three clips of Ghosh, yielding tau(q) vs q graphs displayed accordingly.

Ghosh-Ghosh

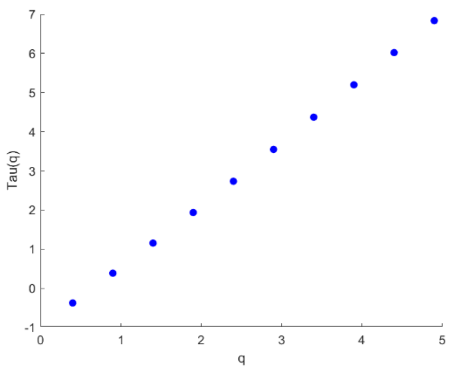


Fig 7.5.2.22 Ghosh 1 vs Ghosh 2

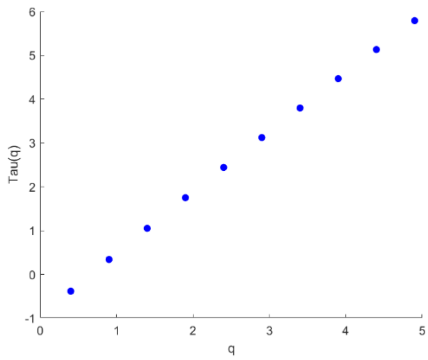


Fig 7.5.2.23 Ghosh 1 vs Ghosh 3

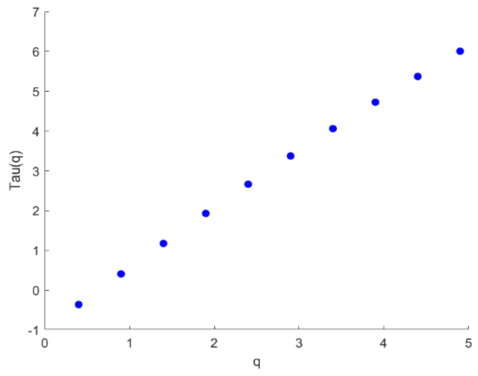


Fig 7.5.2.24 Ghosh 2 vs Ghosh 3

The figures display cross-correlations between three clips of Ghosh. They compare the clips to each other, resulting in tau(q) vs q graphs.

Ghosh-Goswami

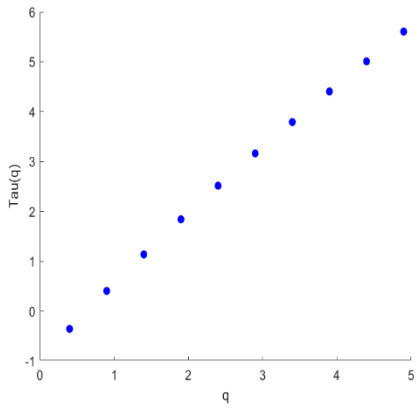


Fig 7.5.2.25 Ghosh 1 vs Goswami 1

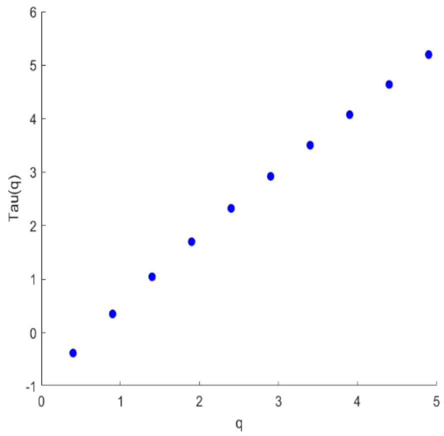


Fig 7.5.2.26 Ghosh 1 vs Goswami 2

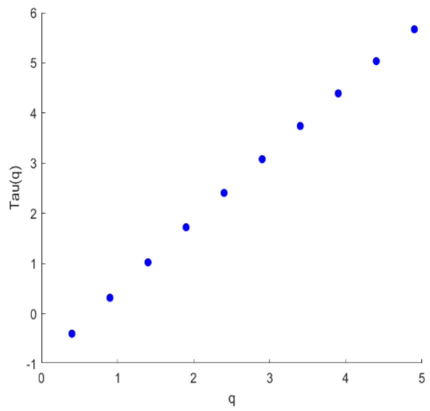


Fig 7.5.2.27 Ghosh 1 vs Goswami 3

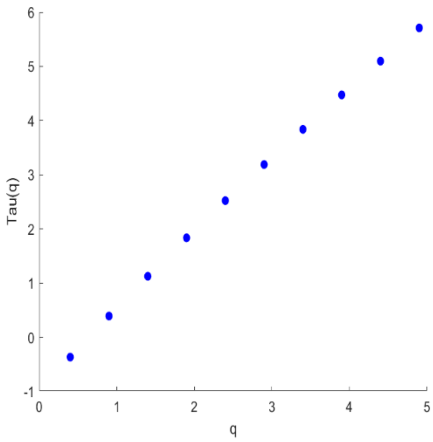
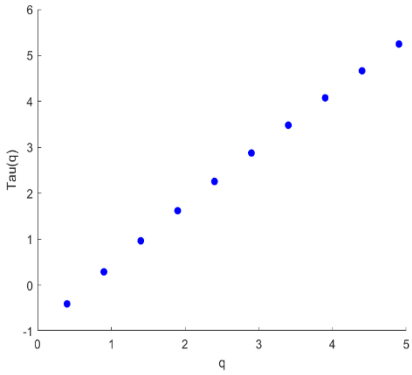


Fig 7.5.2.28 Ghosh 2 vs Goswami 1



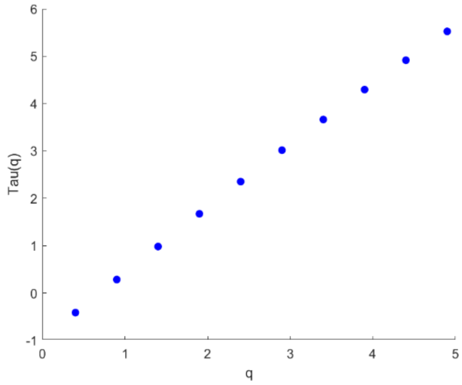
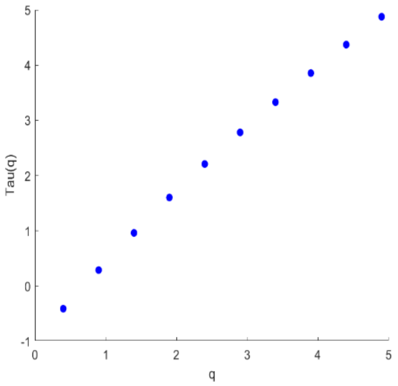


Fig 7.5.2.29 Ghosh 2 vs Goswami 2 **Fig 7.5.2.30 Ghosh 2 vs Goswami 3**



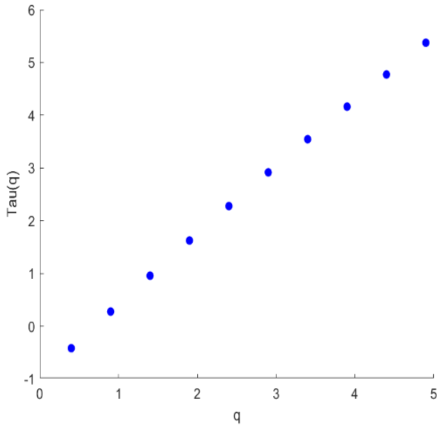


Fig 7.5.2.31 Ghosh 3 vs Goswami 1 **Fig 7.5.2.32 Ghosh 3 vs Goswami 2**

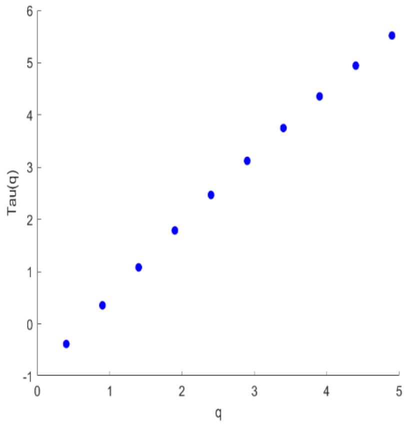


Fig 7.5.2.33 Ghosh 3 vs Goswami 3

The figures depict cross-correlations between Ghosh's three clips and Goswami's three clips, resulting in tau(q) vs q graphs.

Goswami-Goswami

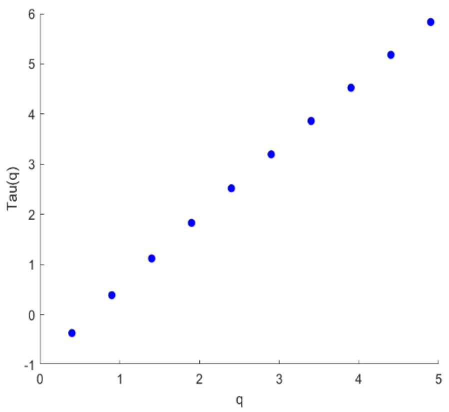


Fig 7.5.2.34 Goswami 1 vs Goswami 2

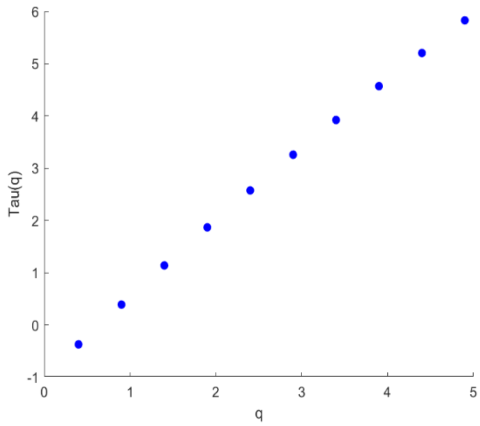


Fig 7.5.2.35 Goswami 1 vs Goswami 3

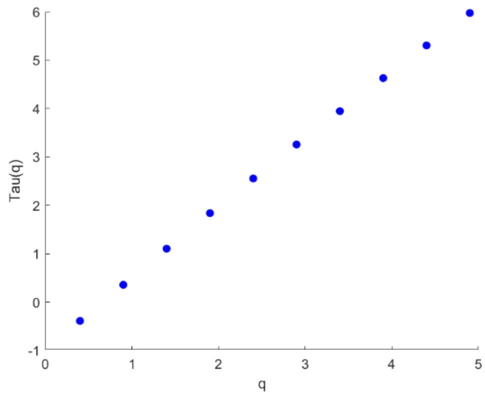


Fig 7.5.2.36 Goswami 2 vs Goswami 3

The figures depict cross-correlations of Goswami's three clips, resulting in tau(q) vs q graphs.

7.5.3. Spectrum Graphs:

Tagore-Tagore

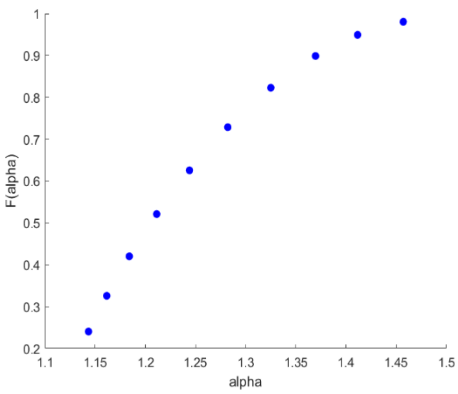


Fig 7.5.3.1 Tagore 1 vs Tagore 2

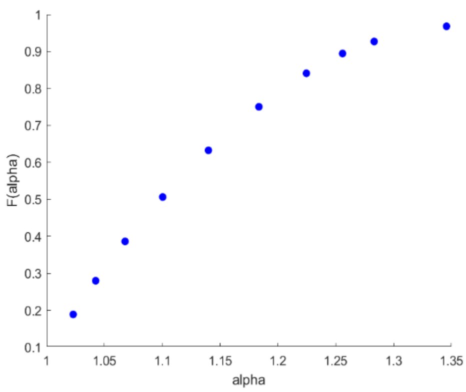


Fig 7.5.3.2 Tagore 1 vs Tagore 3

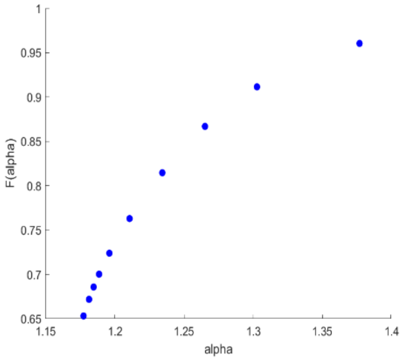
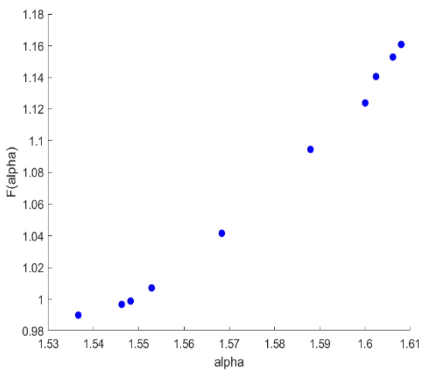


Fig 7.5.3.3 Tagore 2 vs Tagore 3

The figures display cross-correlations among three clips of Tagore. They compare the clips to each other, resulting in F(alpha) vs alpha graphs.

Tagore-Ghosh



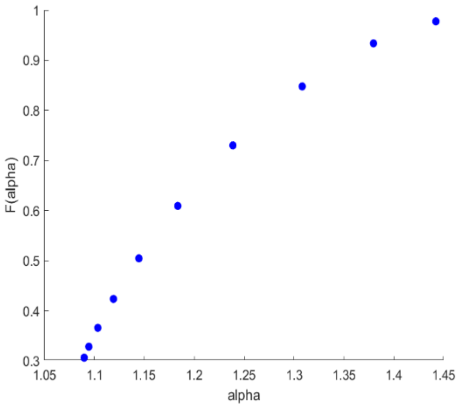
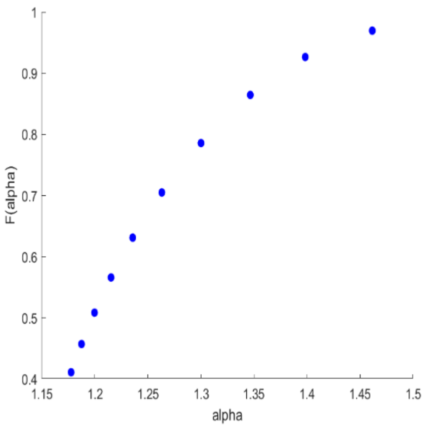


Fig 7.5.3.4 Tagore 1 vs Ghosh 1

Fig 7.5.3.5 Tagore 1 vs Ghosh 2



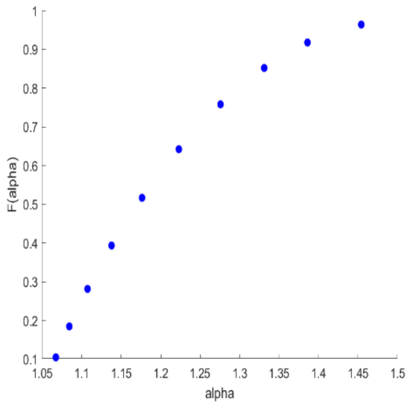


Fig 7.5.3.6 Tagore 1 vs Ghosh 3

Fig 7.5.3.7 Tagore 2 vs Ghosh 1

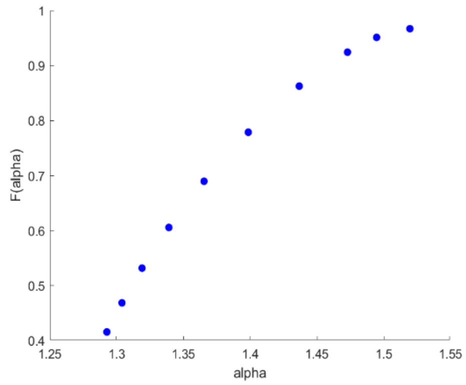


Fig 7.5.3.8 Tagore 2 vs Ghosh 2

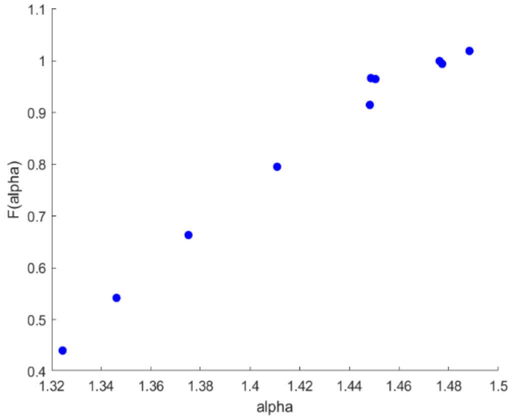


Fig 7.5.3.9 Tagore 2 vs Ghosh 3

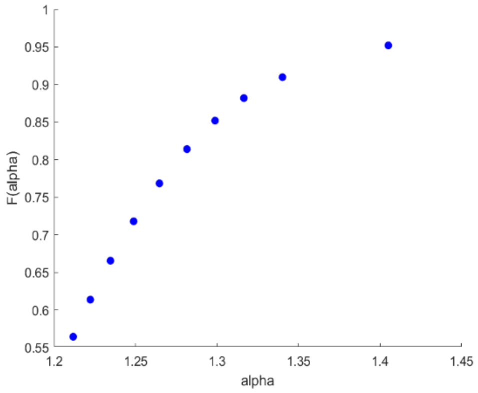


Fig 7.5.3.10 Tagore 3 vs Ghosh 1

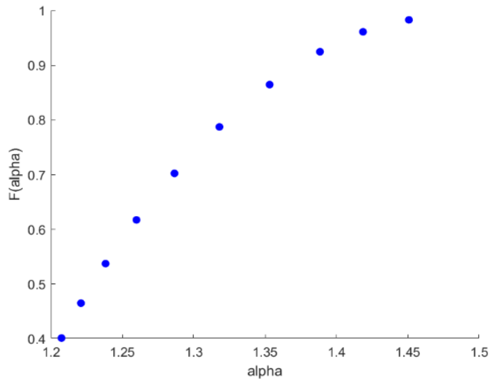


Fig 7.5.3.11 Tagore 3 vs Ghosh 2

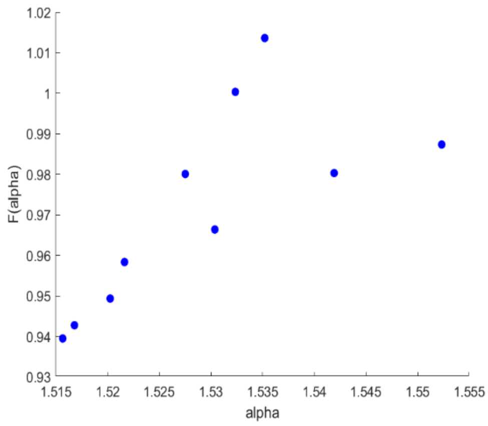


Fig 7.5.3.12 Tagore 3 vs Ghosh 3

The figures depict cross-correlations between the clips of Tagore and the three clips of Ghosh. They reveal F(alpha) vs alpha graphs, indicating their respective relationships.

Tagore-Goswami

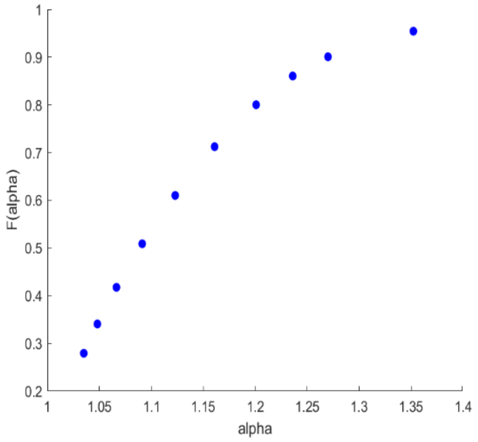


Fig 7.5.3.13 Tagore 1 vs Goswami 1

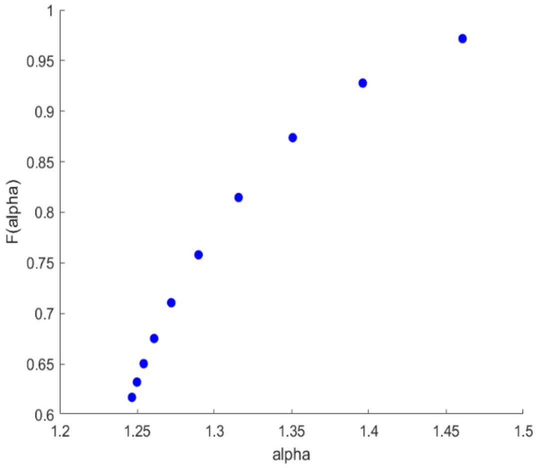


Fig 7.5.3.14 Tagore 1 vs Goswami 2

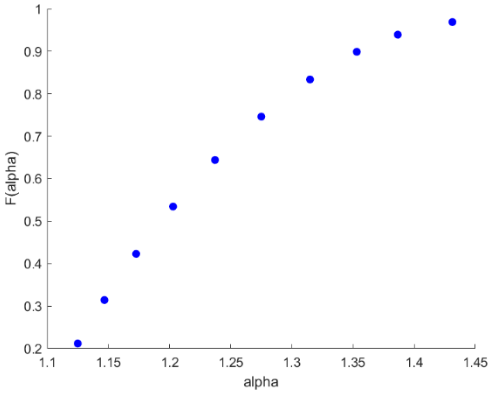


Fig 7.5.3.15 Tagore 1 vs Goswami 3

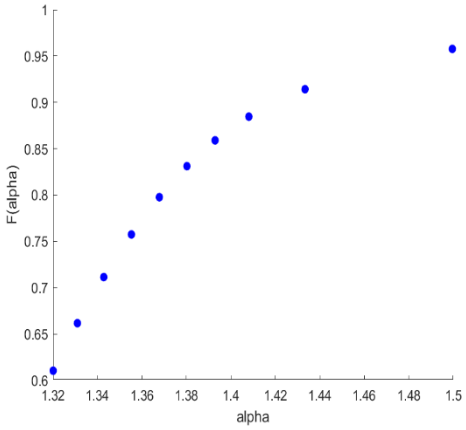


Fig 7.5.3.16 Tagore 2 vs Goswami 1

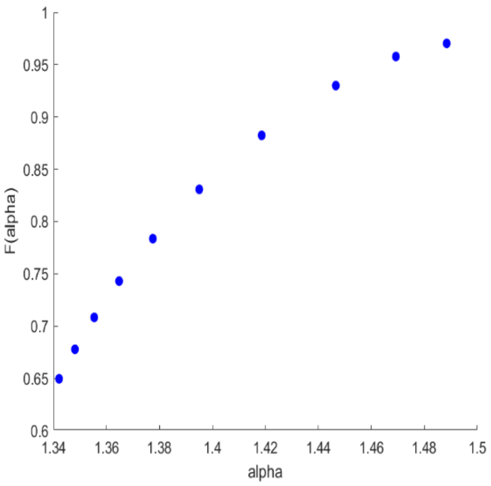


Fig 7.5.3.17 Tagore 2 vs Goswami 2

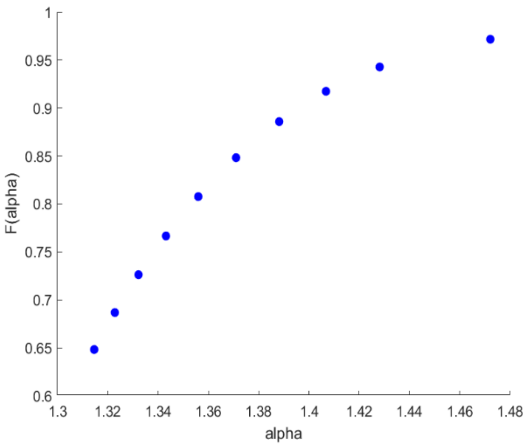
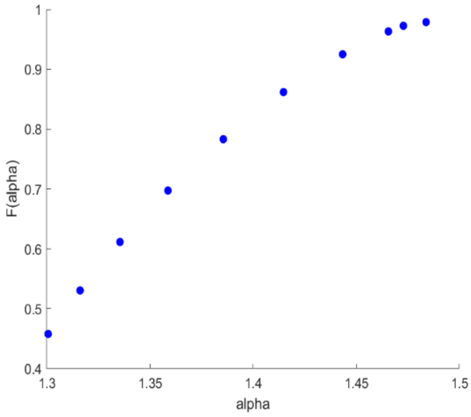


Fig 7.5.3.18 Tagore 2 vs Goswami 3



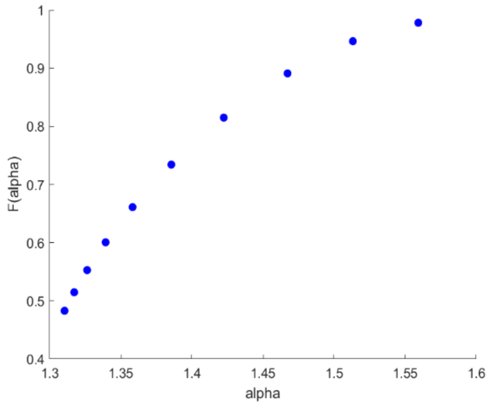


Fig 7.5.3.19 Tagore 3 vs Goswami 1

Fig 7.5.3.20 Tagore 3 vs Goswami 2

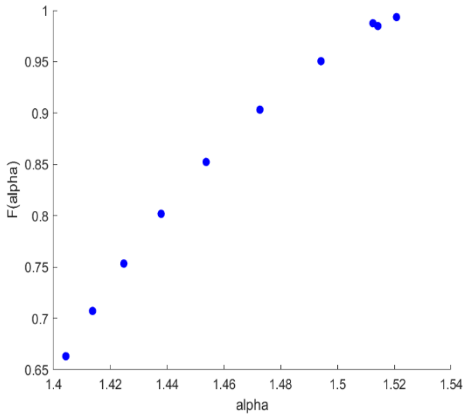
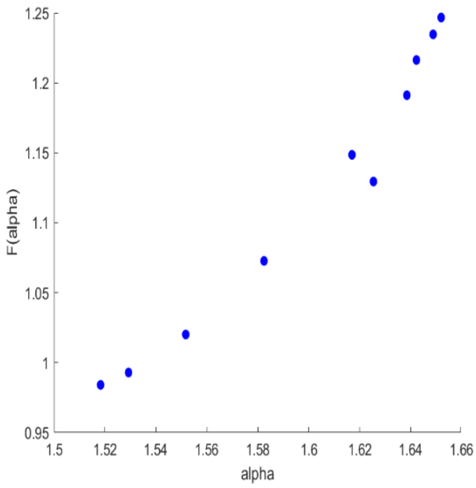


Fig 7.5.3.21 Tagore 3 vs Goswami 3

The figures illustrate cross-correlations between Tagore's clips and the three clips of Goswami. They showcase F(alpha) vs alpha graphs, revealing their relationships**.**

Ghosh-Ghosh



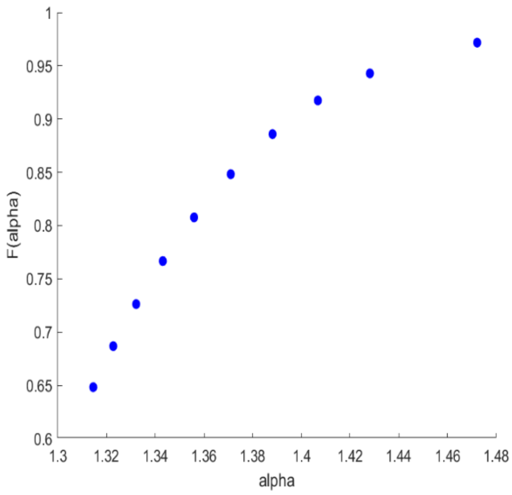


Fig 7.5.3.22 Ghosh 1 vs Ghosh 2

Fig 7.5.3.23 Ghosh 1 vs Ghosh 3

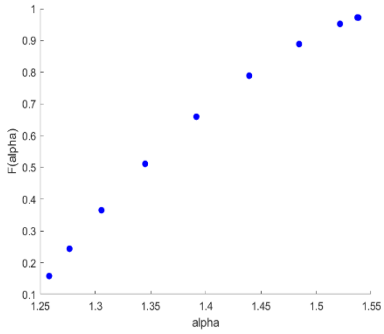


Fig 7.5.3.24 Ghosh 2 vs Ghosh 3

The figures display cross-correlations among three clips of Ghosh. They compare the clips to each other, resulting in F(alpha) vs alpha graphs.

Ghosh-Goswami

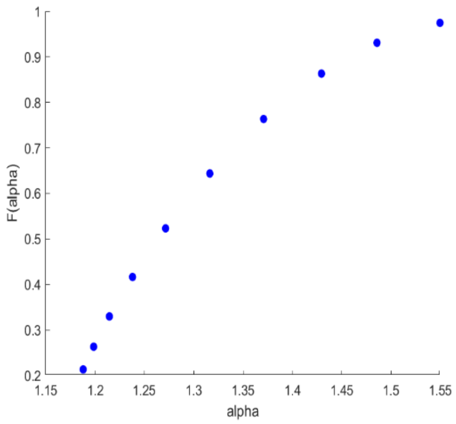


Fig 7.5.3.25 Ghosh 1 vs Goswami 1

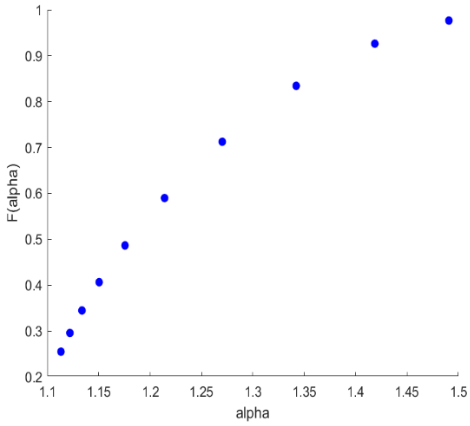


Fig 7.5.3.26 Ghosh 1 vs Goswami 2

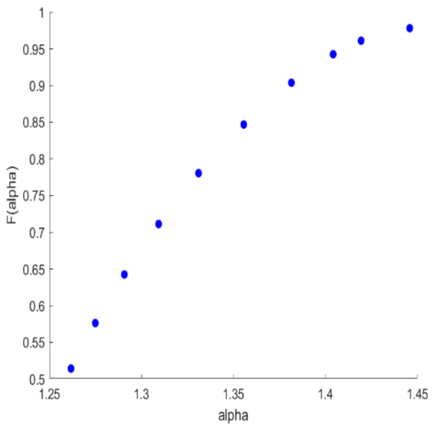


Fig 7.5.3.27 Ghosh 1 vs Goswami 3

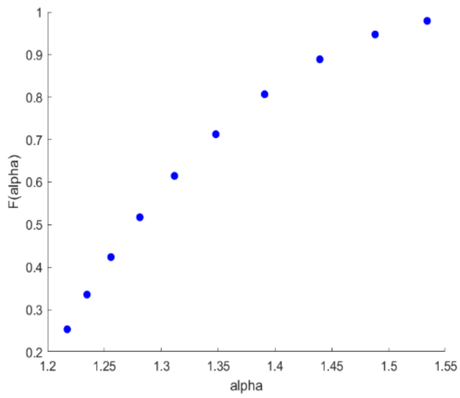


Fig 7.5.3.28 Ghosh 2 vs Goswami 1

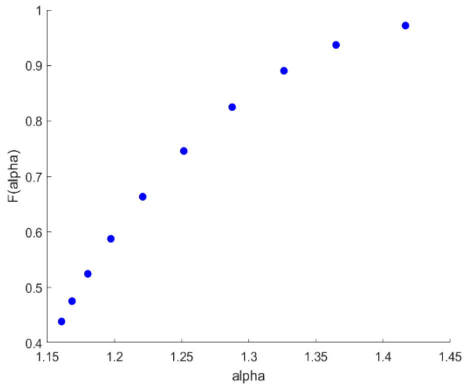


Fig 7.5.3.29 Ghosh 2 vs Goswami 2

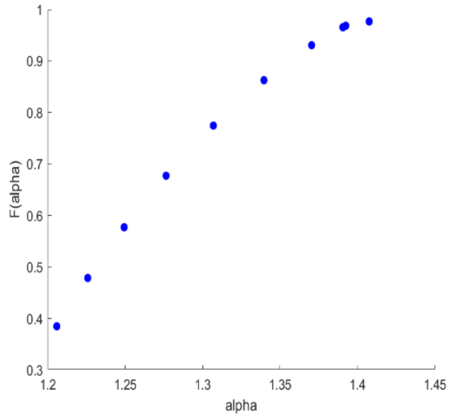


Fig 7.5.3.30 Ghosh 2 vs Goswami 3

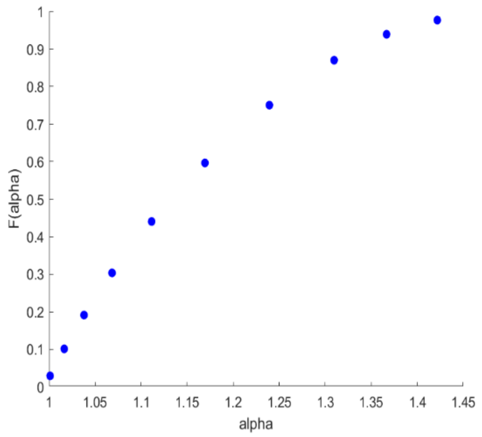


Fig 7.5.3.31 Ghosh 3 vs Goswami 1

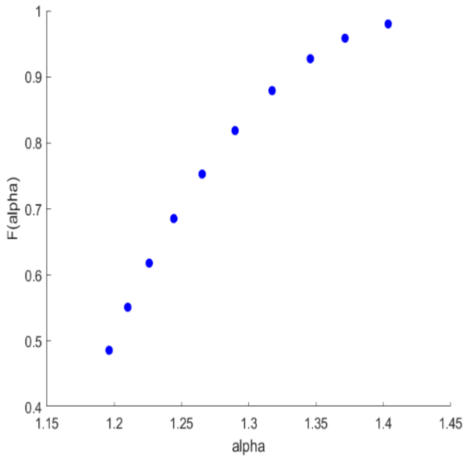


Fig 7.5.3.32 Ghosh 3 vs Goswami 2

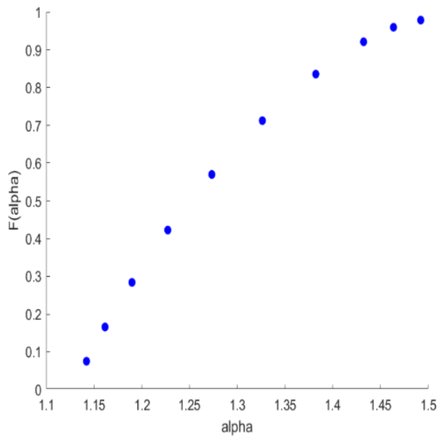


Fig 7.5.3.33 Ghosh 3 vs Goswami 3

The figures display cross-correlations between the clips of Ghosh and the three clips of Goswami. They present F(alpha) vs alpha graphs, showcasing their respective relationships.

Goswami-Goswami

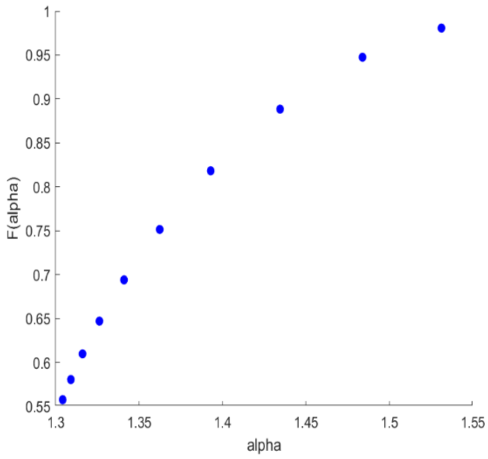


Fig 7.5.3.34 Goswami 1 vs Goswami 2

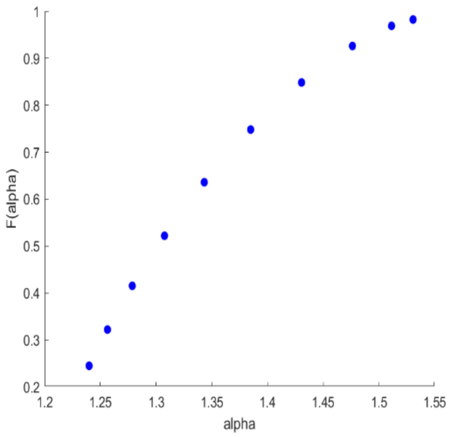


Fig 7.5.3.35 Goswami 1 vs Goswami 3

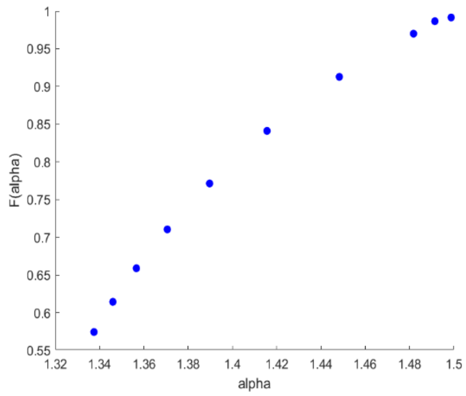


Fig 7.5.3.36 Goswami 2 vs Goswami 3

The figures display cross-correlations among three clips of Goswami. They compare the clips to each other, resulting in F(alpha) vs alpha graphs.

7.4 Conclusion:

In our comprehensive experiment, our primary aim was to understand the relationship between audio stimuli, specifically Bengali poems spread over 100 years, and their impact on brain activity as measured by EEG readings. To analyze the changes in brain activity, we utilized the scientific method known as Multifractal Detrended Fluctuation Analysis (MFDFA). The results from our research have provided valuable insights into the detailed connections between audio stimuli and the processing of emotions within the brain. We observed distinctive patterns of brain activity across different regions of the brain, indicating the influence of various emotional states. Additionally, we carried out a cross-correlation analysis of all the audio clips to quantitatively assess their self-similarity, helping us to determine if they convey the same emotions or not.

One of the first inference can be drawn from the electrode-wise readings, we shall be discussing about the results obtained in both alpha as well as theta frequency ranges. In theta range, w complexity was seen in all the lobes of the brain but not the entire lobe. In frontal lobe (F3 and F7), temporal lobe (T4), parietal lobe (P3 and P4) and in occipital lobe(O1) only the mentioned electrodes have shown some variation in the multifractal width. For alpha range, the frontal and temporal regions can be seen much activated but interestingly there has been very minor variation in the parietal as well as the occipital regions. Overall, it can be said that the during theta waves (meditative state) the activity of the brain has been relatively more as compared to during alpha waves(calm state) [25].

The poet-wise analysis gives us another interesting outlook towards the data. In theta range of frequencies, poems by Rabindranath Tagore has raised most activation in parietal region, poems by Sankho Ghosh is involved in activating the frontal region and poems by Joy Goswami has affected occipital as well as parietal region dominantly. As described in Russell's circumplex model emotions can be mapped under two axes- valence and activation [9]. It is seen that the emotions lying in the positive valence region (positive x-axis) like happy, anxiety are mostly involved in activation of the parietal lobe, emotions lying in the positive activation region (above x-axis) like anger, happy affect the frontal lobe the most and emotions having low activation like calm and sad activate the occipital and parietal lobes.

The calculation of cross-correlation has been very informative to explain us about the self-similarity properties that the clips hold. It has been seen through studies that a high cross-correlation value maps with the clips having the strongest similarities. Through all the lambda, tau and alpha graphs we can conclude the mentioned results. Clip 3 and clip 9 have the highest cross-correlation values, mathematically it means that both the clips are very similar, if we look into the human response for both of these clips we notice that both the audio clips denote the emotion 'happy'. Another instance that is seen is between clip 4 and clip 6, having high cross values and denoting emotions of romantic and happy respectively. Considering the clips with lowest value such as in clip 1 and clip 2, these clips depict the emotions: devotion and anxiety (completely opposite activation levels). Conclusively, it has been observed that the clips with highest cross-correlation values have signals almost coinciding in the graphs as well as have similar emotions and vice versa.

We have conducted a thorough quantitative analysis to evaluate the connection between audio stimuli and human emotions. The results have provided us with significant insights that can have a profound impact on various technological fields. By using the analysis done here and how audio cues influence emotional responses, we can develop advanced and personalized technological products. Creation of emotionally intelligent systems and devices such as personalized chat-bots and companions that can respond to users' needs and emotions, monitoring devices for mental health, and implementing emotion-based safety management systems for driving, among many other possibilities. The potential applications of this research are extensive and offer exciting opportunities for innovation and improvement.

7.5 References:

[1] Sarvinoz, Qosimova. "Emotional understanding of individuals the role of emotions." *ResearchJet Journal of Analysis and Inventions* 3.1 (2022): 1-7.

[2] Liu, Sannyuya, et al. "Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement." Computers & Education 181 (2022): 104461.

[3] Johnson-Laird, Philip N., and Keith Oatley. "How poetry evokes emotions." Acta Psychologica 224 (2022): 103506.

[4] Farsi, Roghayeh. "Cognitive appraisal and coping in poetry." Journal of Narrative and Language Studies 9.18 (2021): 339-356.

[5] Freeman, Margaret H. *The poem as icon: A study in aesthetic cognition*. Oxford University Press, 2020.

[6] Dzedzickis, Andrius, Artūras Kaklauskas, and Vytautas Bucinskas. "Human emotion recognition: Review of sensors and methods." Sensors 20.3 (2020): 592.

[7] Kosti, Ronak, et al. "Context based emotion recognition using emotic dataset." IEEE transactions on pattern analysis and machine intelligence 42.11 (2019): 2755-2766.

[8] Dewaele, Jean-Marc, and Chengchen Li. "Emotions in second language acquisition: A critical review and research agenda." Foreign Language World 196.1 (2020): 34-49.

[9] Zhong, Ke, Tianwei Qiao, and Liqun Zhang. "A study of emotional communication of emoticon based on Russell's circumplex model of affect." *Design, User Experience, and Usability. Design Philosophy and Theory: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part I 21*. Springer International Publishing, 2019.

[10] Patnaik, Suprava. "Speech emotion recognition by using complex MFCC and deep sequential model." Multimedia Tools and Applications 82.8 (2023): 11897-11922.

[11] Rai, Amod Kumar. "Bharatmuni's Natyasastra: A contemporary pertinence." An International Refereed Journal of English Language and Literature 8.2 (2022): 17.

[12] Pandey, Pankaj, et al. "Identifying Dominant Emotion in Positive and Negative Groups of Navarasa Using Functional Brain Connectivity Patterns." Neural Information Processing: 29th International Conference, ICONIP 2022, Virtual Event, November 22–26, 2022, Proceedings, Part II. Cham: Springer International Publishing, 2023.

[13] Casillo, Stephanie M., Diego D. Luy, and Ezequiel Goldschmidt. "A history of the lobes of the brain." World Neurosurgery 134 (2020): 353-360.

[14] Leblanc, Richard. "Pavlov, Penfield, and the physiology of the mind." Neurology 92.12 (2019): 575-578.

[15] Hu, Li, and Zhiguo Zhang, eds. EEG signal processing and feature extraction. Singapore: Springer Singapore, 2019.

[16] Gorjão, Leonardo Rydin, et al. "MFDFA: Efficient multifractal detrended fluctuation analysis in python." Computer Physics Communications 273 (2022): 108254.

[17] Martínez, Jorge Luis Morales, et al. "A modified multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation." Physica A: Statistical Mechanics and its Applications 565 (2021): 125611.

[18] David, Sergio Adriani, et al. "A combined measure to differentiate EEG signals using fractal dimension and MFDFA-Hurst." Communications in Nonlinear Science and Numerical Simulation 84 (2020): 105170

[19] Avramidis, Kleanthis, et al. "Multiscale fractal analysis on EEG signals for music-induced emotion recognition." 2021 29th European Signal Processing Conference (EUSIPCO). IEEE, 2021.

[20] Sarkar, Uddalok, et al. "Language Independent Emotion Quantification using Non linear Modelling of Speech." *arXiv preprint arXiv:2102.06003* (2021).

[21] Sanyal, Shankha, et al. "Music of brain and music on brain: a novel EEG sonification approach." *Cognitive neurodynamics* 13 (2019): 13-31.

[22] Banerjee, Archi, et al. "A Nonlinear Study on Time Evolution in Gharana Tradition of Indian Classical Music." (2019).

[23] Kunikullaya U, Kirthana, et al. "Electroencephalographic power spectrum and intersubject correlation on acoustic stimulation with modes of Indian music: a randomized controlled trial." *bioRxiv* (2022): 2022-12. [24] Banerjee, Archi, et al. "A Nonlinear Study on Time Evolution in Gharana Tradition of Indian Classical Music." (2019).

[24] Pino, Olimpia, and Graziana Romano. "Engagement and arousal effects in predicting the increase of cognitive functioning following a neuromodulation program." *Acta Bio Medica: Atenei Parmensis* 93.3 (2022).

[25] Ahirwal, Mitul Kumar, and Mangesh Ramaji Kose. "Audio-visual stimulation based emotion classification by correlated EEG channels." Health and Technology 10.1 (2020): 7-23.

[26] Feradov, Firgan, Iosif Mporas, and Todor Ganchev. "Evaluation of features in detection of dislike responses to audio–visual stimuli from EEG signals." Computers 9.2 (2020): 33.

[27] DAŞDEMİR, YAŞAR, and RÜSTEM ÖZAKAR. "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning." Turkish Journal of Electrical Engineering and Computer Sciences 30.7 (2022): 2707-2724.

[28] Rodriguez-Larios, Julio, et al. "From thoughtless awareness to effortful cognition: alpha-theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic." Scientific Reports 10.1 (2020): 1-11.

[29] Lin, Sen, et al. "A flexible, robust, and gel-free electroencephalogram electrode for noninvasive brain-computer interfaces." Nano letters 19.10 (2019): 6853-6861.

[30] Pan, Yafeng, et al. "Dual brain stimulation enhances interpersonal learning through spontaneous movement synchrony." *Social Cognitive and Affective Neuroscience* 16.1-2 (2021): 210-221.

[31] Cao, Jianing, Aijing Lin, and Guancen Lin. "Time series classification based on detrended partial cross-correlation." *Europhysics Letters* 134.5 (2021): 50006.

[32] Shrestha, Badri, and Louese Dunn. "The declaration of Helsinki on medical research involving human subjects: a review of seventh revision." *Journal of Nepal Health Research Council* 17.4 (2019): 548-552.

Chapter 8
Acoustical & Colour Based Neuro-Cognitive Analysis of Recitation of Different Texts

"The world speaks to me in colors, my soul answers in music."

Rabindranath Tagore

8.1 Introduction

In the domain of poetry, language holds a power that goes beyond mere communication, delving into the realms of emotion and thought [1]. This research paper focuses on exploring the acoustic and neuro-cognitive aspects of recitations by three extremely decorated poets from Bengal: Rabindranath Tagore, Sankha Ghosh, and Joy Goswami. Their work spanning a century, these poets have made a lasting impact on literature, captivating readers with their ornate verses. Our study covers a wide time span of 100 years to understand how different eras have influenced poetry and its effects on the human mind over time.

The primary aim of this research is to examine the diverse cognitive engagements invoked by the recitation of various texts [2], while associating them with matching and contrasting colours based on previous studies' colour mappings. By analysing the impact of these associations on human emotions and their subsequent influence on cognitive engagement, we seek to unravel the intricate relationship between poetry, emotions, colour, and cognition [3-5]. To conduct this inquiry, we collected a dataset of over 200 responses from human participants using an online form. The participants listened to the stimuli and selected one of nine available emotions as options [6-8]. To ensure consistency and make sure of a reliable analysis, we ensured a collected of homogenous data. The human responses were then categorized according to Russell's Emotional Circumplex model [9-10], a widely accepted framework that can be used to map emotions based on a plane of different emotions. While Bharata's Natyashastra and Navaras [11-12] could also be considered as models for baseline emotions in cognitive engagements, we chose the aforementioned one due to its broader acceptance and thus considering the latter as a potential for future research.

Our objective is to explore the neuro-cognitive engagements observed through the emotions elicited by specific stimuli and establish a qualitative-to-quantitative connection between art forms, colours, and the resulting cognitive engagements. We aim to measure these engagements from a physiological perspective [13-14]. To achieve this, we utilized Electroencephalography (EEG) [15] to analyse the recorded human responses. By analysing the EEG readings from the frontal, temporal, occipital, and parietal lobes, we can study the patterns of response associated with these cognitive engagements.

The analysis of EEG readings from these brain lobes follows an approach for non-linear systems using Multifractal Detrended Fluctuation Analysis (MFDFA), a well-established technique for examining non-linear and extremely complex systems, such as the human brain. This algorithm enables us to delve into the complexities of cognitive engagements incited by the recitation of various poems and their colour associations [16-20].

Incorporating colours as stimuli characteristics in this study allows us to associate human cognitive responses with colours that either match or contrast with the audio stimuli [21-22]. The EEG setup measures the resulting changes in cognitive engagement caused by these visual stimuli Through this approach, we aim to gain insights into the impact of colour on the neuro-cognitive processes associated with recitation.

This study considers the Multifractal Width (w) of audio clips and recorded EEG brain waves as the primary tool for examining changes in cognitive engagements. This parameter enables us to analyse and compare the multifractality of cognitive patterns [23-24]. To ensure a comprehensive analysis, we aim to align the qualitative assessments obtained from human responses to the stimuli with technical analysis. This simultaneous evaluation will bridge subjective human perception with objective scientific measurements, fostering a deeper understanding of the neuro-cognitive effects of art and literature.

8.2 Experimental Details:

8.2.1 Methodology

Understanding the human brain's response to different stimuli is fundamental to cognitive and neuroscience analysis and research. As discussed earlier, this paper aims to study the brain activity of subjects by exposing the individuals to various audio and visual stimuli while recording that data using Electroencephalography (EEG)[25-27]. EEG is a popular non-invasive technique that can measure and record the electrical activity of the brain. It can provide valuable information about cognitive processes and brain functioning by capturing brain wave patterns. During an EEG recording, there are multiple brain waves that can be observed. These brain waves represent different patterns of electrical activity in the brain and can be categorized based on their frequency ranges which are- Delta waves(0.5-4 Hz), Theta waves(4-7 Hz), Alpha waves(8-12 Hz), Beta waves(12-30 Hz) and Gamma waves(30-100 Hz)[28].

Alpha waves are associated with relaxed wakefulness and a calm state of mind. They are usually observed when individuals close their eyes or meditate. Additionally, Theta waves are prominent during periods of deep relaxation, meditation, and early stages of sleep. They are linked to creativity, memory formation, and deep emotional states.
Here, our focus is going to be analysing Alpha and Theta waves because these states comprise the brain activity during calm, non-aroused, and alert states of mind, and thus can provide insights into cognitive processes and emotional states.

To accomplish our goal, we have used a 19-10 electrode cap to record data, this cap is specifically designed for EEG purposes. It consists of 13 electrodes that are strategically placed on the different lobes of our brain [29].

1. Frontal Lobe: The frontal lobe plays a crucial role in decision-making, executive functions, problem-solving, and cognitive control. Electrodes placed on the frontal lobes will capture brain activity associated with these processes, thus allowing researchers to examine cognitive states during stimulus exposure. 4 electrodes were placed in this particular region namely- F3, F4, F7 and F8.

2. Parietal Lobe: The parietal lobe plays a pivotal role in various sensory integration processes, spatial awareness, attention, and perception. Electrodes placed on the parietal lobes enable the monitoring of brain activity associated with the attentional allocation and the integration of various visual and auditory stimuli. We placed 2 electrodes in this particular region namely- P3 and P4.

3. Occipital Lobe: The occipital lobe is mainly responsible for visual processing and perception. Electrodes placed on the occipital lobe capture brain activity associated with visual stimuli, allowing researchers to study visual perception and processing during stimulus exposure. 2 electrodes were placed in this particular region namely- O1 and O2.

4. Temporal Lobe: The temporal lobe plays a major role in auditory processing, language understanding, and memory functions. Electrodes placed on the temporal lobe enable the study of auditory perception, language-related processes, and memory formation during the presentation of audio stimuli. We placed 4 electrodes in this particular region namely- T3, T4, T5 and T6 [13].

The acquired EEG data of two separate frequencies (alpha and theta) from the subject are to be processed and analysed using a mathematical non-linear analysis technique called MFDFA (Multifractal Detrended Fluctuation Analysis). This method is specifically designed to understand the complex nature of EEG signals by evaluating their fractal properties (self-similarities) and long-range correlations.

The technique involves several steps- detrending: the data is detrended to remove any present patterns, fluctuation calculation: fluctuations in segments of varying lengths is calculated, scaling analysis: analysis of the fluctuations and lastly the exponent calculation: giving the degree of self-similarity. Using the fluctuation function obtained from the MFDFA algorithm, Hurst exponent (H) is also calculated. It helps to quantify the degree of self-similarity or self-affinity present in the given data. The value of H has different interpretations: H> 0.5 -indicates a persistent or positively correlated time series (having long term trends), H= 0.5- indicates uncorrelated time series (random or no trend) and H < 0.5- indicates an anti-persistent or negatively correlated time series (oscillatory trend) [30].

8.2.2 Stimuli Details:

We have carefully chosen nine poems by well-known poets who have made significant contributions to Bengali literature over the past 100 years as part of our research. These poems are a rich and diverse representation of the literary heritage of the Bengali language. Segments from each of these nine poems were extracted and used to create a controlled stimulus for our study, ensuring that each segment is approximately 30-35 seconds long. These meticulously curated snippets allow us to maintain consistency and precision in our experimental design while also capturing the essence and emotional depth of the original poems.

Here are brief descriptions of the pieces of the text that were used as stimuli:

Clip 1: ‘Rudra tomar darun dipti’: It is an excerpt taken from the Bengali poem ‘Suprabhat’. It is written by Ranbindranath Tagore and it is about the power of the divine force ‘Rudra’ and its ability to bring light and new beginnings. Kabyo Grontho of the poem is ‘Purabi’. It was written in the year of 1907 at Shantiniketan.

Clip 2: ‘Ogo ma rajar dulal’: This is also an endearing poem written by Rabindranath Tagore. It describes a mother's love for her son, who is about to leave home for the first time. Taken from the poem ‘Shubhokkhn’ having Kabyo Grontho ‘Kheya’ written in 1905.

Clip 3: ‘Keu j kare chini na ko’: A moving poem named ‘Achena’ having Kabyo Grontho ‘Khonika’. Written by Ranbindranath Tagore, about the power of love and the importance of being true to oneself. This poem encourages us to follow our dreams and to be full of hope. This was written in 1910.

Clip 4: ‘Dupure rukho gachhe patar’: A beautiful poem ‘Aarale’ written by Sankho Ghosh. It is describing at length the beauty of nature and the importance of taking some time to appreciate it. It was written in 1980.

Clip 5: ‘Ekre ojor mrityu elo’: Extracted from poem ‘Jamunabotee’ written by Sankho Ghosh. This poem explores the theme of death, its inevitability and the impact on loved ones. It was written in 1970.

Clip 6: ‘Se chhilo ekdin amader joubane kolkata’: Written by Sankho Ghosh in the year of 1975. The name of the poem is ‘Babu moshai’. The poet reflects on his nostalgic memories associated with Kolkata, the capital city of West Bengal, India, also known as the ‘City Of Joy’.

Clip 7: ‘Amra to alpe khusi’: This poem ‘Noon’ is written by Joy Goswami in the year 1997. He beautifully explains the mindset that appreciates the smaller joys and moments of happiness found in everyday life.

Clip 8: ‘Taranga jau, taranga fire aase’: Joy Goswami in this poem ‘Probaho’ splendidly explains the transient nature of life and draws a parallel between the waves in oceans and ups and downs in life. This was written in the year of 2010.

Clip 9: ‘Sabar sange bose chhilen’: This is a small part taken from the poem ‘Aaj Basanta’ written by Joy Goswami in 2005. He talks about the importance of friendship and community.

Henceforth the audio clips will be referred to as Clip along with their respective number to maintain consistency and for easy understanding.

Now we are introducing visual stimuli in this experiment. It has been found out through various studies that colors can invoke emotions as well. Specific colors are responsible for invoking specific emotions in human beings [22]. We have tried to implement this idea while preparing the stimuli. We have obtained a set of emotions corresponding to individual clips, using these emotions we have found out the color that is invoked by these emotions. These colors are in the standardized RGB format. Now two sets of color schemes are to be formulated. One being the Matching Colors and another being Contrasting Colors [31-32].

Matching Colors- In this scheme, during the 25 seconds of silence we are prompting a color on the screen. This is not just any color but the color which corresponds to the emotion that will be invoked by the following audio clip.

Contrasting Colors- In this scheme, like the previous one during the 25 seconds of silence we are prompting a color on the screen. This time this color is a contrasting color corresponding to the emotion that will be invoked by the following clip. We have found out the matching color and using other studies transformed the matching color into a contrasting one.

These colors are displayed before all the nine clips once for obtaining the results for the matching set and once for obtaining the results for the contrasting set.

Clip Number	Peaking Emotion	Matching Color	Contrasting Color
1	Devotion	G	R
2	Anxious	R	B
3	Happy	B	R
4	Romantic	G	R
5	Angry	R	G
6	Happy	B	R
7	Sad	G	R
8	Sad	G	R
9	Happy	B	G

Table 8.1: Color Distribution for clips

8.2.3 Participant Details:

A total of 10 individuals between the ages of 18 and 23 participated in this experiment to provide us with EEG recordings. Participants were reached out individually from personal contacts and word-of-mouth. All the participants were requested to provide their consent prior to the involvement in this study. To ensure the privacy and confidentiality of each of the participants, unique identification number were assigned to them, and their personal information was hidden and securely stored separately from the research data [33].

The participants consisted of young adults, comprising of both males and females. Each participant reported having right-handed dominance, indicating a right-handed preference. All participants had normal visual ability, with a vision of 6/6, indicating normal or optimal vision. Participants reported having proper hearing ability. Participants did not disclose any prevailing medical conditions that could potentially influence their responses or impact the validity of the study. It is worth mentioning that the participants were of sound body and mind, indicating that they were in good overall physical and mental health. This ensured that the data collected and later on the analysis was not disturbed by any underlying health issues that could influence the results.

To look after the safety and well-being of the participants, the experiments were conducted with proper precautions and following the ethical guidelines. All participants provided informed consent, indicating their voluntary involvement. Their consent was obtained prior to their engagement.

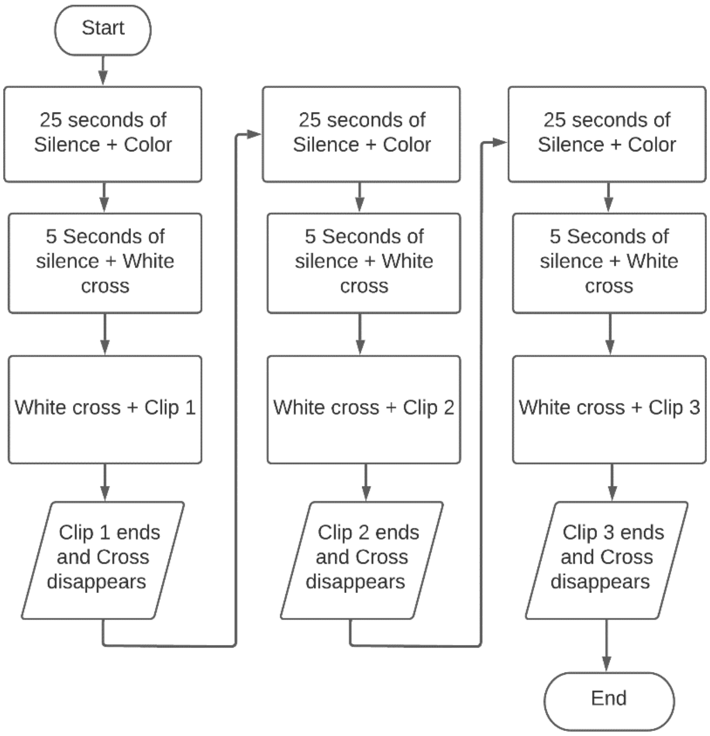
8.2.4 Protocol and Data Recording:

We began the process of capturing EEG recordings from the subjects following a standardized and uniform protocol, to ensure consistency and reliability, each subject underwent the EEG procedure in the same way. The aim of this approach was to establish a solid foundation for data analysis and interpretation. During the EEG sessions, electrodes were carefully placed in specific locations on the participants' scalps, following the international 10-20 system for electrode placement. This systematic approach ensured comprehensive data collection by allowing us to capture electrical activity from multiple regions of the brain simultaneously after the EEG recordings were obtained, the next step was to extract relevant data for further analysis. To extract meaningful insights from the collected EEG data, we used a computational technique known as Multifractal Detrended Fluctuation Analysis (MFDFA)[16]. This method enabled us to investigate the complex temporal patterns and fluctuations within the EEG signals.

The nine audio clips were arranged in a particular manner which is very important to the experiment. The nine audio clips has been categorized into three sets on the basis of the poet. First set comprising of clips 1 through 3, written by Rabindranath Tagore. Second set comprising of clips 4 through 6, written by Sankha Ghosh and the third set comprising of clips 7 to 9, written by Joy Goswami.

Each set follows the same protocol of the arrangement of the clips. Taking Set 1 as an example. As discussed set 1 has 3 clips, these clips need to be arranged in proper intervals of silence followed by audio. Beginning the clip with 25 seconds of complete silence along with the matching/contrasting color of clip1, then there’s 5 seconds of silence but along with this silence just a white cross is shown on screen to draw back the attention of the subject. After these 5 seconds, the first clip is played, while the clip is being played the white cross should stay on the screen till the end of the clip. As soon as the clip ends, the white cross also disappears. There is again silence of another 25 seconds with a color on the screen depending on the matching or contrasting set, followed by silence along with the white cross sign for 5 seconds. Then comes the 2nd clip which is again played along with the white cross and it cross disappears as soon as the clip ends. Lastly, another interval of silence for 25 seconds with color, 5 seconds of silence and cross followed by the 3rd audio clip and the cross. In the end, when the last audio clip finishes, the cross also disappears but another silence of 30 seconds to be maintained so as to not disrupt or activate the brain activity unnecessarily. In Fig. 2.1, the protocol is explained in the form of a flowchart for one set, this entire set up is repeated for set 2 and set 3 without any interval.

This protocol is followed for all the sets of poems and this is maintained throughout to extract the EEG readings from all the subjects. This is done so as to maintain a uniformity in the procedure. The silence intervals are placed in such a way that the brain activity is maximum and focused during the interval of the audio clip.



Flowchart of the Protocol

It is very important to maintain a proper protocol along with creating an optimal environment for each participant to ensure that we get accurate and reliable results [34-35]. The following guidelines were strictly followed to attain the best possible conditions for data collection:

1.) Sitting in a relaxed and comfortable position: The subjects were instructed to sit in a comfortable and relaxed position throughout the experiment to minimize physical discomfort or distractions that could potentially affect the emotional responses.

2.) Having no contact with the floor of the room: To prevent any grounding or interference from external sources, subjects were advised to keep their feet on a mat i.e avoid direct contact with the floor of the room.

3.) In a dark and cool environment: Subjects were taken in an environment with controlled lighting conditions. The room was kept in darkness to minimize visual distractions and to help focus attention on the experiment. Additionally, maintaining a cool temperature in the room to ensure the subjects' comfort and less distraction due to heat.

4.) In a noise-free zone: To create an environment for concentration and to minimize distractions, subjects were kept in a noise-free zone. Background noise, such as external conversations or environmental sounds, was tried to be blocked out to maintain a quiet and serene environment during the experiment.

5.) Focusing on the computer monitor only: Subjects were instructed to direct their attention on the computer monitor solely, where the stimuli were presented.

6.) Able to consume the video protocol files: Subjects were provided with the necessary equipment to effectively consume the video protocol files. This ensured that the audio-visual stimuli were presented to participants in a clear and accessible manner

By strictly adhering to these guidelines and maintaining a standardized protocol, we tried to create a controlled experimental environment for each subject. This helped to eliminate any possible errors that might have surfaced in the readings.

8.2.5 Human Response:

In the study of emotion, one of the widely accepted model is Russell's circumplex model. It is a psychological framework that helps represent emotions primarily on two dimensions: valence and arousal. The model provides a visual representation of all human emotions arranged in a circular pattern. Emotions closer to the centre of the circle have less intensity, while those towards the outer edge have higher intensity. Valence refers to the positive (happiness or joy) or negative (sadness or anger) quality of an emotion. It allows for the comparison between emotions, various emotional patterns, and different emotional states.

After all the audio clips were finalized, we went on to gather subjective responses from individuals to gauge their emotional interpretation of each clip. To do this, we used an online survey platform, specifically a Google Form. The form included all nine audio clips, with each clip accompanied by a list of nine emotions from which participants could choose their responses. The emotions provided were: Surprised, Happy, Calm, Angry, Disgusted, Anxious, Sad, Romantic, and Devotion [7].

Almost 200 people took part in this study by listening to the audio snippets and choosing the one emotion they felt most accurately captured the overall tone of each clip. It was made sure that these people were impartial, native Bengali speakers who were unaware of this project's intentions or objectives. This approach aimed to collect responses from participants with an unbiased mindset, allowing for an authentic and reliable assessment of emotional interpretations.

This human response source, which was derived from the subjective interpretations of the participants, provides a valuable basis for our study. By collecting a wide range of emotional responses from individuals, we can analyse and compare their interpretations with mathematical measurements derived from the audio clips themselves. The depth and validity of our investigation into the emotional aspects of the selected poems are enhanced by this comprehensive approach.

8.2.6 Calculation of Parameters

After the data collection phase, the next important phase was the analysis of the obtained data. The EEG recordings were properly extracted into .csv. The extracted EEG data was meticulously labelled and organized to prevent any inaccurate or redundant data.
These excel files helped to process the data efficiently and the data was further analyzed using appropriate algorithms and Multifractal Detrended Fluctuation Analysis (MFDFA) [16]. These computational methods helped us to quantify the complexity of the brain activity. By calculating the average multifractal width, we were able to obtain a measure of the complexity for each audio clip. This complexity metric served as a basis for comparing and contrasting the different audio stimuli utilized in the study.

To get a comprehensive analysis, the data was needed to be arranged in a manner that helped us make visual representation such as graphs. Graphs were drawn to visually represent the findings and provide a clearer understanding of the patterns and relationships in the data. Firstly, we created an individual electrode-wise analysis, examining the contributions of each electrode. Furthermore, we performed lobe-wise analysis, focusing on the frontal, parietal, occipital, and temporal lobes. By examining the EEG data specific to these regions, we had observations into the activity of different brain areas during the processing of the stimuli. For both the alpha and theta frequency bands, graphs were plotted to visualize and explore the patterns, trends, and variations in brain wave activity.

From these graphs, we extracted key findings and results, which are presented in this research paper. These findings help us understand about the neural responses evoked by the stimuli and enable a deeper understanding of the emotional and cognitive processes associated with the audio clips.

The combination of human responses and EEG data analysis allowed us to establish a comprehensive study for investigating the relationship between the audio files and emotions. The utilization of multifractal analysis and graphical representations enhanced our ability to explain the intricacies of brain wave activity and derive meaningful insights from the collected data.

8.3. Results and Discussions:

The human response taken for the individual 9 clips for over 200 participants has been evaluated and it is found out that each clip has a homogenous reaction towards one particular dominant emotion. It highlights the fact that the particular clip evokes the mentioned emotion in human beings. The peaking emotions along with the clip name have been clearly discussed.

Clip	Invoked Emotion
1	Devotion
2	Anxiety
3	Happy

Clip	Invoked Emotion
4	Romantic
5	Angry
6	Happy

Clip	Invoked Emotion
7	Sad
8	Calm
9	Happy

Table 8.2 Emotions assigned to the clips

Although these emotions have been pin-pointed by human interaction but we have also applied scientific and mathematical methods for the acoustal analysis, we calculated the complexity of these emotions. The multifractal width of the 9 audio clips that were used as stimuli has been obtained using the nonlinear technique MFDFA and here is a bar graph representation of the avg of segment-wise 'w' values. The complexity of the clips gives us a brief idea about the emotions. The errors are not shown in the figures as they are too small to appreciate.

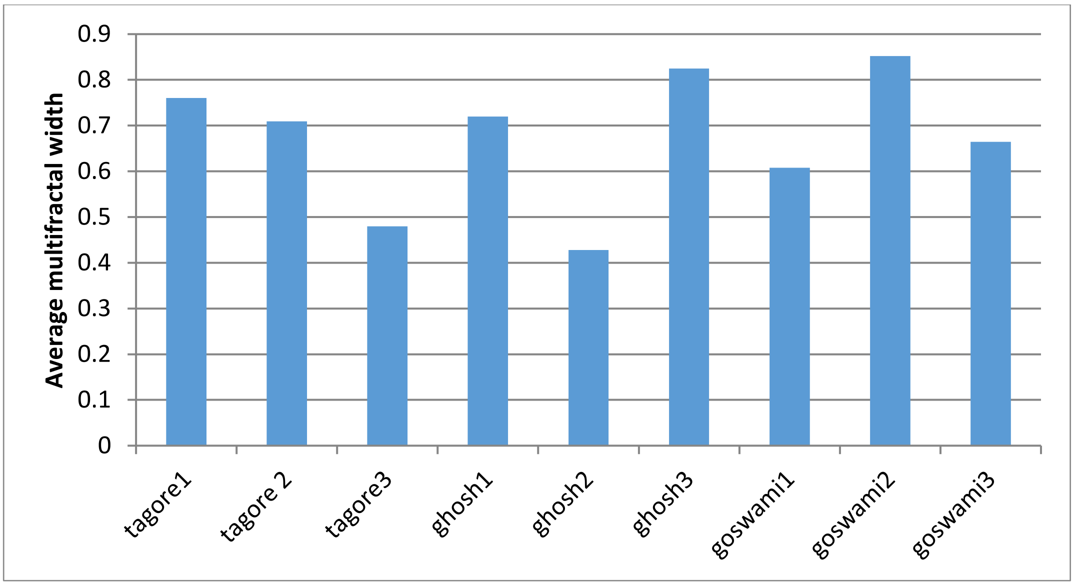


Fig 8.3.1. Average Multifractal width (w) of the clips

Analyzing the complexity of the clips, we have observed that higher the complexity value the emotions tend to fall in the first and second quadrant of the Russell's circumplex model which includes activation and more over pleasant emotions such as happy, calm, devotion. A detailed discussion has been done over the individual complexities in the previous chapter.

We now move our focus to the impact of color on our emotions. As discussed above, the stimuli has been crafted in a way which projects two types of color in each set of 9 clips. Set-1 highlights matching colors to the emotions invoked in the following clip while Set-2 highlights a contradictory color as that of the invoking emotion in the clip played. The observations have been divided into two parts for the sake of simplicity, Set-1: Matching Colors and Set-2: Contrasting Colors.

8.3.1. Set-1: Matching Colors:

Firstly, we are going to analyze each electrode individually and draw our observations.

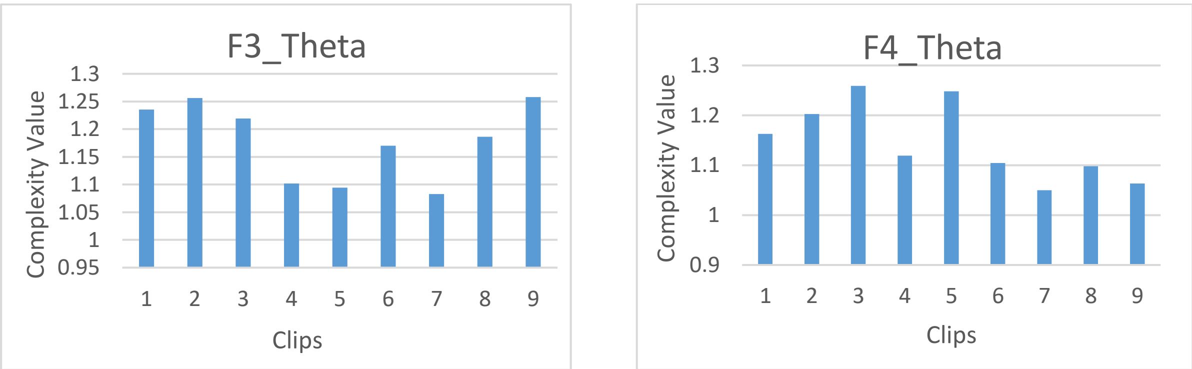


Figure 8.3.1.1: Complexity Variation in Frontal Electrodes Clip-wise

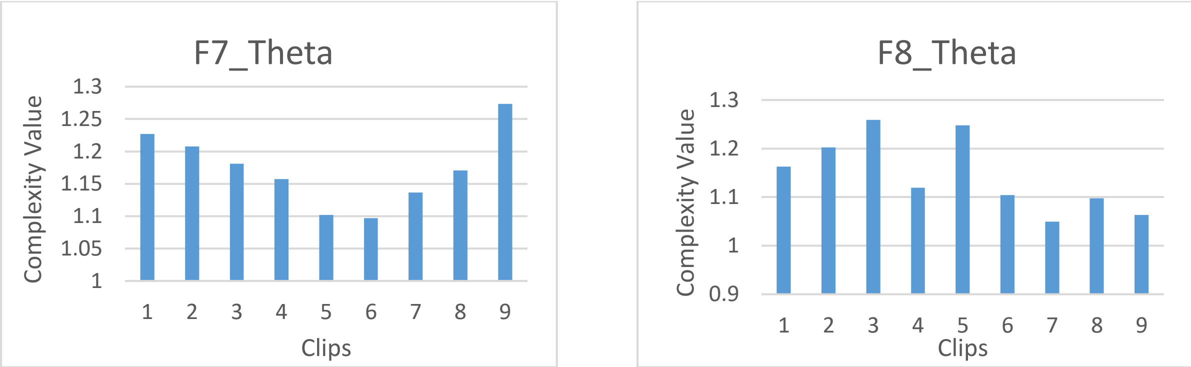


Figure 8.3.1.1: Complexity Variation in Frontal Electrodes Clip-wise

Considering the frontal electrodes for all the 9 clips. Let us discuss in details taking each electrode:

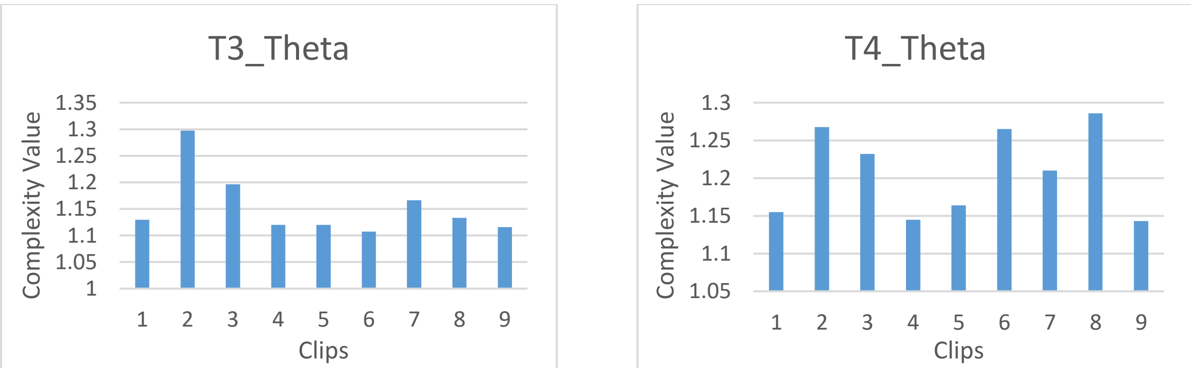
For F3, clip 5 has the lowest average w with a value of 1.0941 while the highest being for clip 9 with a value of 1.2578. Fluctuation can be seen in clips 4 through 8, while clip 1, 2, 3 and 9 have somewhat similar complexities (denoting similar emotions of happy and calm). Clip 4, 5 and 7 have relatively smaller complexity values showing emotions of angry and sad. Overall, the value of w lies between 1.083 and 1.258.

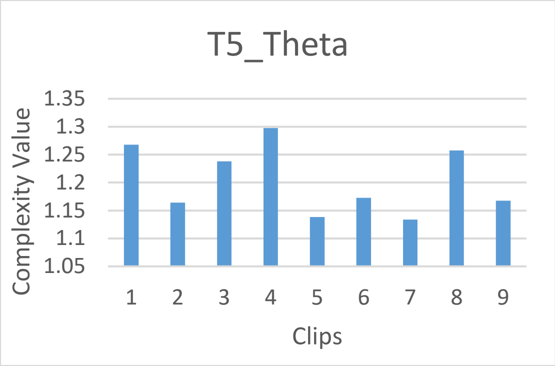
In F4, clip 7 is exhibiting the lowest complexity value i.e. 1.049 while the highest being for clip 3 with a value of 1.259. Similar complexity patterns are seen in clips 1, 2, 3 and 5 which are mostly exhibiting positive emotions. Clips 4 and 8 have almost similar complexity values are depicting emotions of romantic and calm, which puts into perspective that love and affection gives us a sense of calmness and tranquility.

In F7, clip 9 is dominates the entire graph with a value of 1.273, followed by clips 1,2 and 3 with almost similar values and depicting similar emotions in the pleasant half of the circumplex model. The lowest multifractal width value can be seen for clip 6 with a value of 1.097. Overall the fluctuation can be seen in a normal pattern.

In F8, clip 3 and 5 are having similar complexities with clip 3 being the highest with a value of 1.259 and clip 5 with a value of 1.248. These two clips are invoking emotions of happiness and anger, although both the emotions are different but it is to be noted that both the emotions are in the high activation region (upper half of the circumplex model). Clip 7 with a complexity of 1.049 is the lowest and hence denotes emotion of low activation as well as unpleasant.

Next, we are going to consider the temporal electrodes for the 9 clips and discuss them in details.





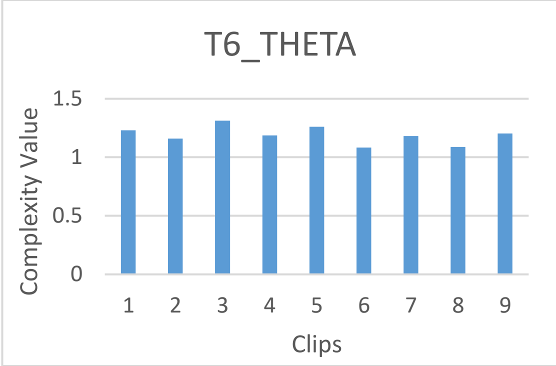


Figure 8.3.1.2: Complexity Variation in Temporal Electrodes Clip-wise

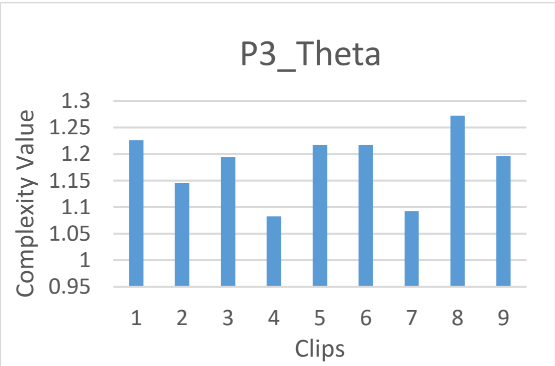
In T3, we can observe that almost in all the clips the complexity is pretty low differing between 1.107 and 1.166, with clip 2 with a large value of 1.297 which invokes anxiety according to human response.

In T4, we have multiple clips having a high w value as well as a few clips showing low w values. Clip 8 having the highest value of 1.287 which resembles emotions of calmness and clip 9 having the lowest value of 1.142 resembling positive emotion.

In T5, we can observe varying values of the complexity. Clip 4 being the highest with 1.297 and clip 7 with the lowest value of 1.133. Here the highest value denotes emotions of romance, basically emotions with low but pleasant activation whereas the lowest value denoting a negative emotion.

In T6, interestingly all the clips show almost similar values of complexity. The value of w lies between 1.082 and 1.313. Since there are not much differences in each clip for this particular electrode, we cannot obtain a definite result.

Next, we are going to consider the parietal electrodes for the all the clips and discuss.



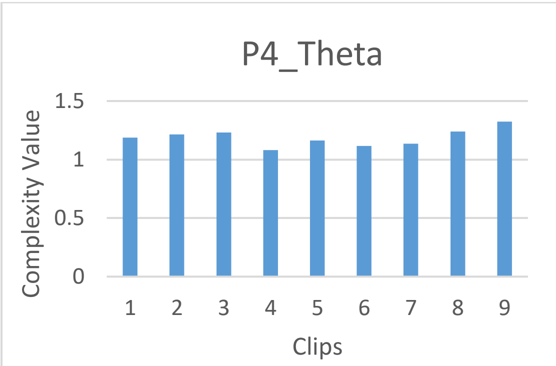


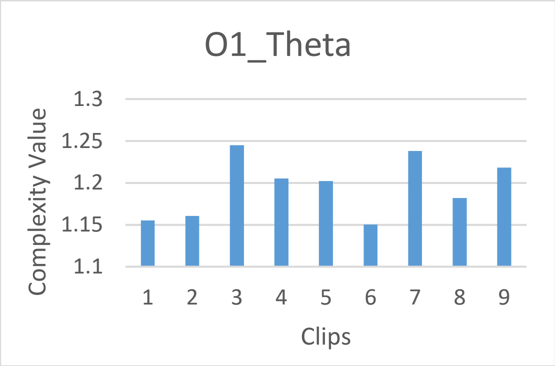
Figure 8.3.1.3: Complexity Variation in Parietal Electrodes Clip-wise

In P3, the values of w are varying with each clip. It is to be noted that the clip 8 with a value of 1.272 is the highest and clip 4 with a value of 1.082 is the lowest. Once again, it is seen that the clip with highest complexity value is denoting a positive emotion- calm and the lowest denoting yet another positive emotion but the activation is less- romantic.

In P4, for all the clips the multifractal width is almost similar. The value of w ranges from 1.080 to 1.324. Again, since the values are similar and neck to neck, a definite conclusion cannot be formed from this given graph.

Here in this experiment the subject is exposed to colors and their EEG recordings are then taken. In this particular set, we are primarily focusing on matching colors like discussed earlier. Now we are taking into consideration the occipital lobe, a very important one.

Occipital lobe is the visual processing area of the brain. It helps process all the visual information, depth and distance, perception as well as color determination. Let us see how the complexities vary in this lobe for each of the 9 clips.



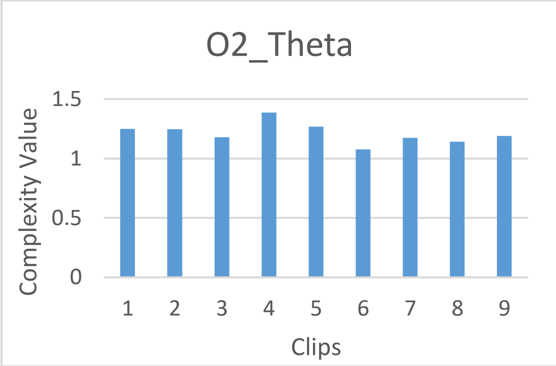


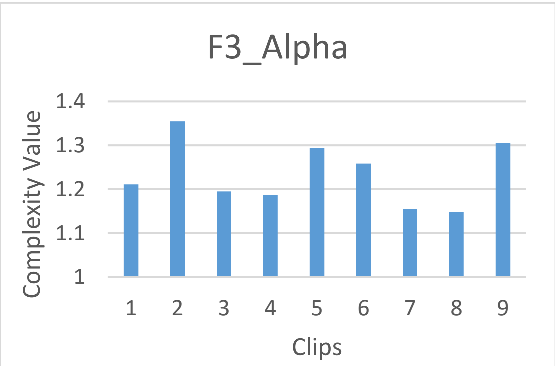
Figure 8.3.1.4: Complexity Variation in Occipital Electrodes Clip-wise

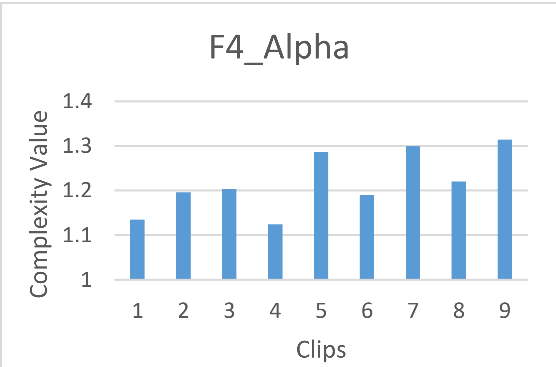
In O1, a good amount of variation can be seen in each of the clip. Starting from the highest value of 1.244 of clip 3, this value corresponds to the clip which invokes a sense of happiness and pleasant emotions in the minds of the human. The lowest complexity value is 1.150 of the clip 6, although the value is very low but this also represents the emotion of happiness.

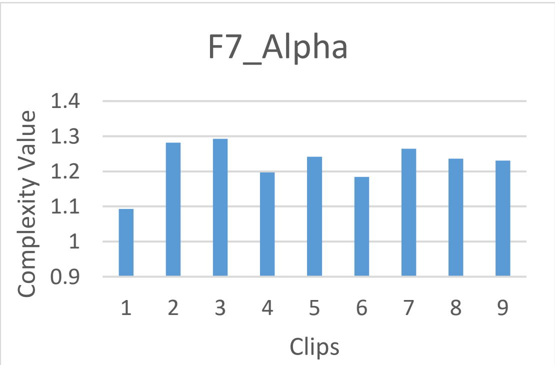
In O2, all the clips exhibit almost similar complexities. The value varies from 1.076 to 1.385. Since the values are very close enough, no concrete observations can be made from this graph.

All the above discussed graphs have been calculated taking into account the Theta waves of the brain. We also need to discuss the complexity variations in the brain for all these clips for the Alpha waves.

In the next section, we are discussing the impact of Alpha waves on the brain when the same stimulus is shown to the subject along with the matching colors.







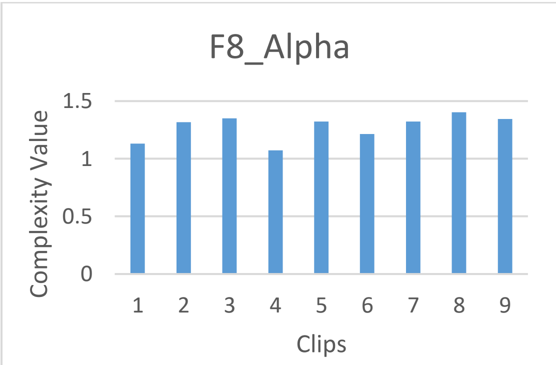


Figure 8.3.1.5: Complexity Variation in Frontal Electrodes Clip-wise

In F3, Clip 2 is having the highest w value of 1.354 while clip 8 has the value of 1.148 which is the lowest among the all. We can observe that clip 7 and 8 have similar value, both are denoting two different emotions of sadness and calmness but both the emotions have low activation. While clips 2,5 and 9 have high and similar complexity levels and they are denoting emotions of high activation.

In F4, clips 5,7 and 9 have similar complexity values with the highest value being of clip 9: 1.314. the similarity in these 3 clips is that all the emotions invokes by these clips are lying in the high activation region. The clips 1,2,3 and 4 have similar w values and it is seen that the emotions depicted in these clips are those with high activation.

In F7, the variation is not as strong as other electrodes but we can see that it has a highest w value of 1.292 corresponding to clip 3 which marks happy, a high activation and pleasant emotion. Clips 8 and 9 have almost similar values and both of them invoke emotions of calmness and happiness.

In F8, not much variation can be seen. The complexity value lies between 1.072 to 1.404. Since the complexity values are not that different a conclusive result cannot be drawn from this.

Coming next, we are going to analyze the electrodes attached to the temporal lobe of the brain:

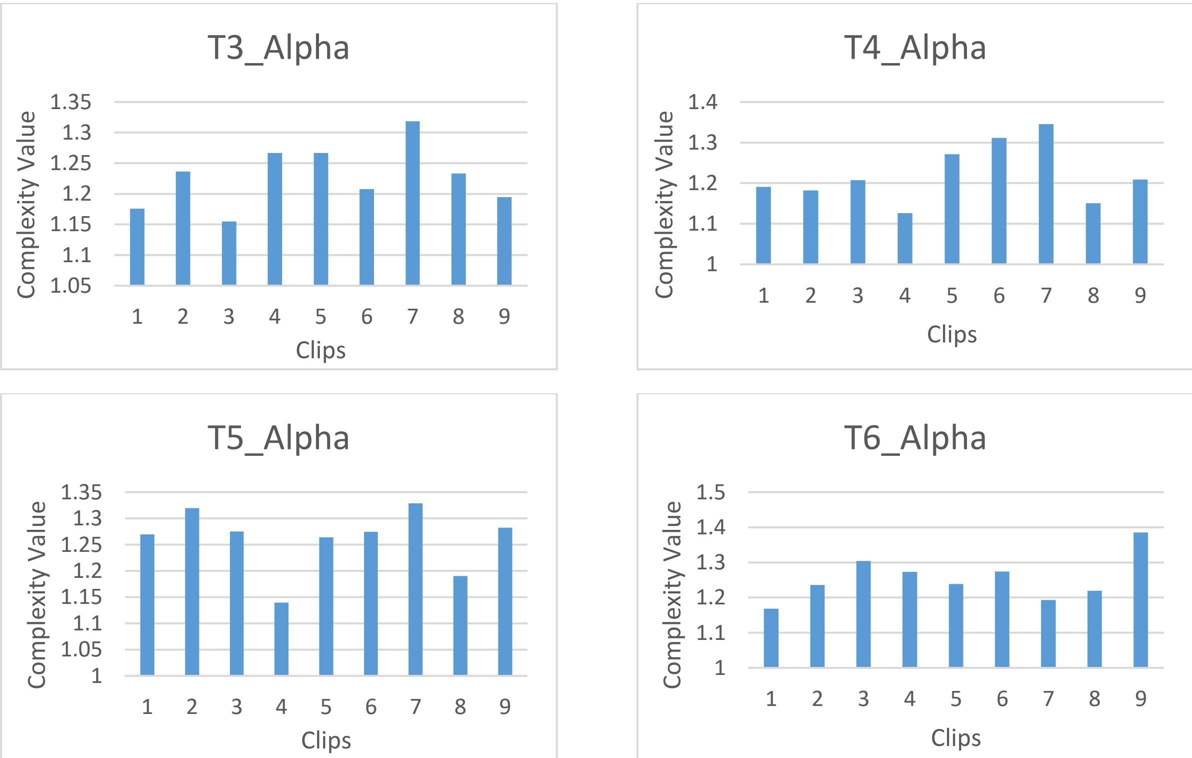


Figure 8.3.1.6: Complexity Variation in Temporal Electrodes Clip-wise

In T3, clip 7 has the highest multifractal width of 1.318 while clip 3 having the lowest of 1.550. It is to be notes that these two clips invoke the opposite of emotions, the highest invoking happiness while the lowest invoking sadness. Clips 6 and 9 having almost similar complexity values depicts happiness same goes for clip 1 and 3.

In T4, there is a similarity in the first three clips, all of them are involved with emotions of happiness and devotion, basically on the pleasant half of the circumplex model. The clip with the lowest complexity invokes romantic emotions and the highest complexity clip invokes sadness. In this electrode T4, we can see a major difference as the higher the complexity the negative is the emotion unlike other electrodes discussed above.

In T5, most clips have a similar complexity level. Clips 1,2,3 and 7 have mixed emotions of happy and sad, but it is to be noted that the activation level of both the emotions is low. Clip 4 having the lowest complexity with a value of 1.139 is denoting romantic emotions.

In T6, the average multifractal width of each clip can be seen as similar. The only standing out clip is 9 which has a happy emotion, but other than than the other emotions although being positive have lower complexities.

In the next section we are going to discuss the multifractal widths of electrodes attached to the parietal lobe of the brain.

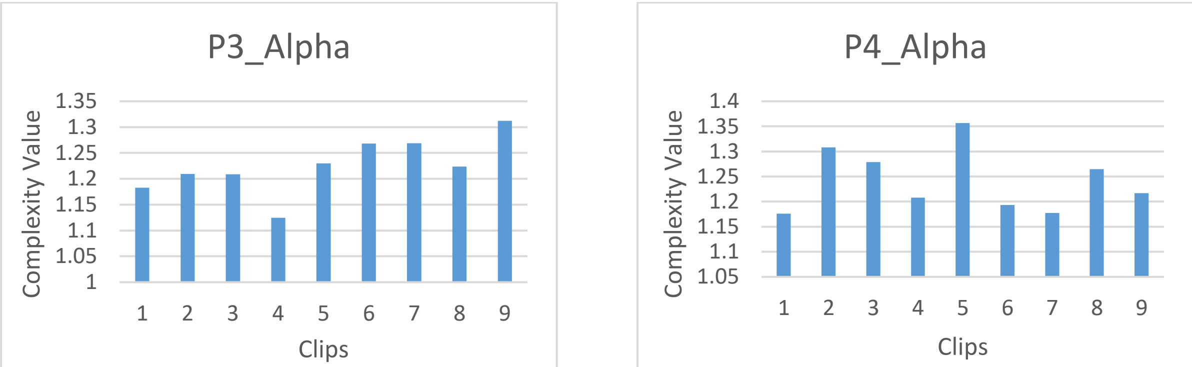


Figure 8.3.1.7: Complexity Variation in Parietal Electrodes Clip-wise

In P3, it can be observed that with a complexity value of 1.312 clip 9 is the highest amongst the rest, it involves a positive emotion of happiness while clip 4 having a value of 1.124 being the lowest, denotes the emotion of romance. It is to be noted that the highest complexity and the lowest complexity is direction proportional to the levels of activation.

In P4, clip 5 has the largest w value of 1.356 denoting a highly activated level of emotion that is anger. The lower complexity clips such as 6 and 7 are the emotions which have low activation.

Lastly, we are going to take a look on the occipital electrodes and see if the colors are making any strong impact on the EEG readings or not.

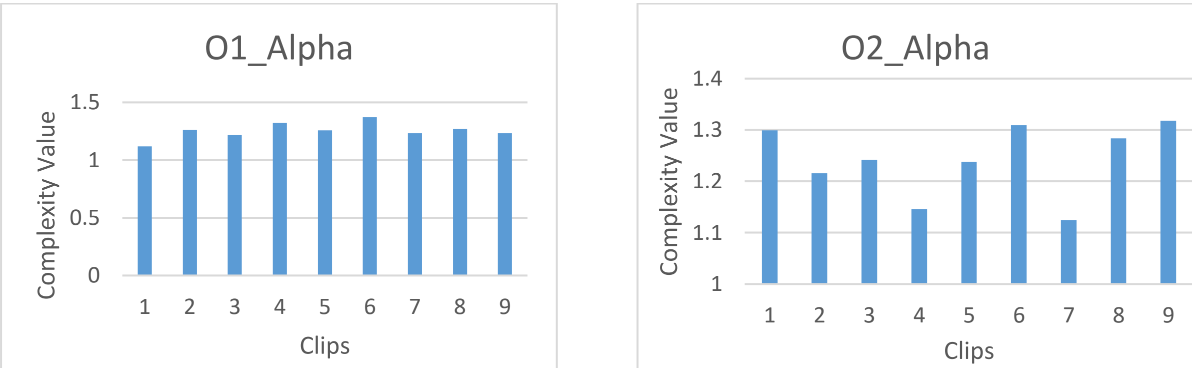


Figure 8.3.1.8: Complexity Variation in Occipital Electrodes Clip-wise

In O1, the average complexity values are comparable. The range of values lies between 1.118 and 1.370. Since the complexity values are too close to each other, we cannot make any definite observations from the given graph.

In O2, the complexity values of clips 1,6 and 9 are similar as well as high, the highest having the value of 1.318. All these clips have a common emotion which a happy- a low activation as well as a pleasant emotion. The lowest complexity value 1.124 of clip 7, can be seen as depicting a negative emotion-sadness.

In the above graphs, we have observed each electrode individually and have made the comments on them. Now, the same electrodes have been combined according to their different lobes and a comparative study has been done. It will help us see which clip as well as which emotion is causing the maximum changes and which lobe. This comparison is also done in two parts; one comparison of the lobes considering the Theta wave and the other considering the Alpha waves.

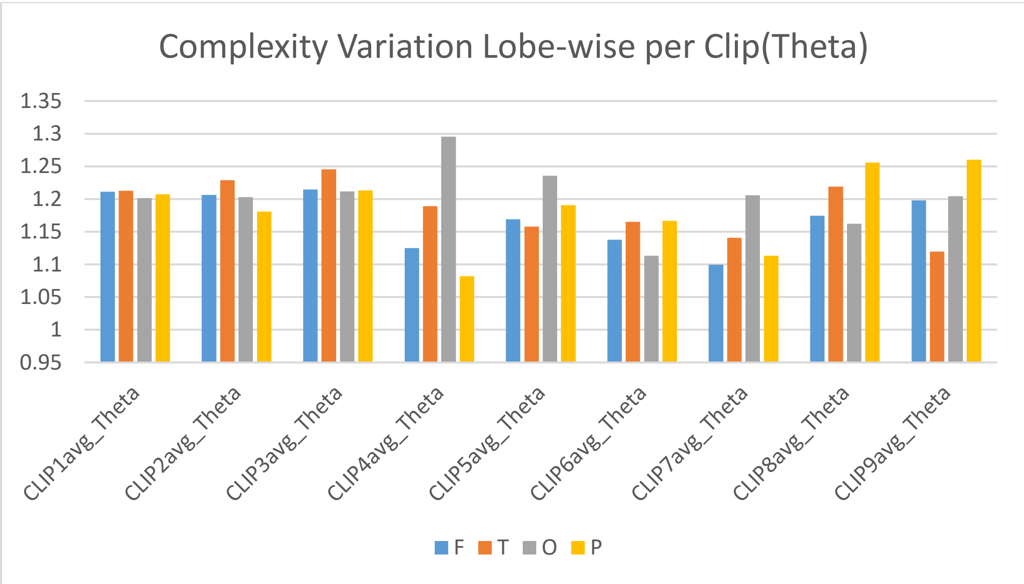


Figure 8.3.1.9: Complexity Variation Lobe-wise per clip (for theta)

In figure 3.1.9, let us observe the changes clip-wise. Clip 1,2 and 3 have almost similar changes lobe-wise. Clip 4 has very observable changes in the lobe-wise activation, the occipital lobe is having the maximum complexity value (1.295) while the parietal lobe having the lowest complexity value(1.081). Clip 4 invoking a pleasant and low activation emotion of romance, the complexity value can be seen as relatively high for the occipital lobe. Again in clip5, the occipital lobe has relatively high complexity value (1.235), this clip is supposedly invoked the emotions of Anger.Next again in clip 7, we can see a jump in the w values in occipital region, this clip invokes sadness, an unpleasant yet low activation emotion. Lastly, clips 8 and 9 have lower levels of occipital activation but the parietal activation is much higher. The clips are invoking calm and happy emotions, which are towards the lower activation zones.

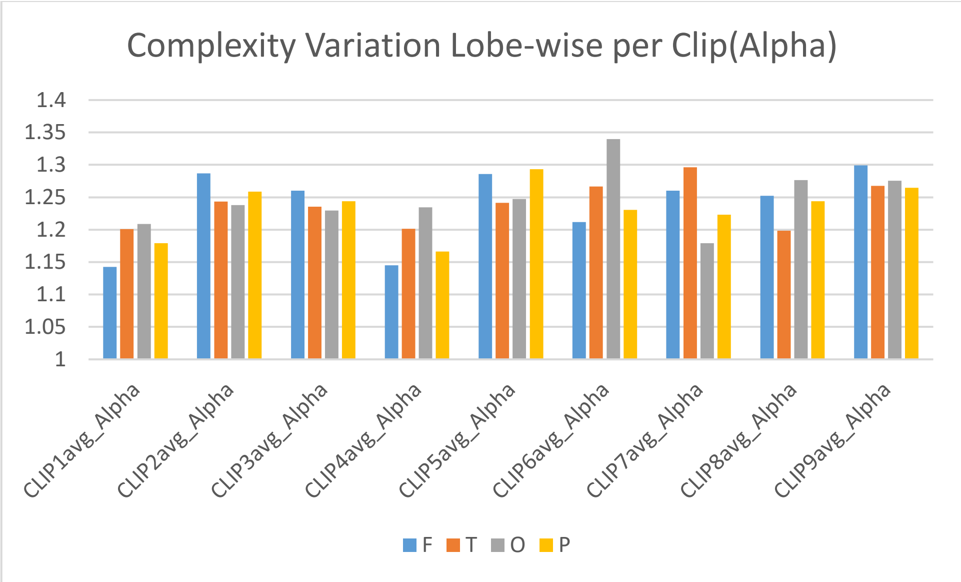


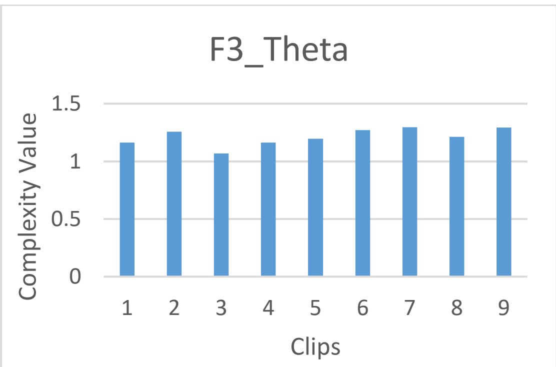
Figure 8.3.1.10: Complexity Variation Lobe-wise per clip(for alpha)

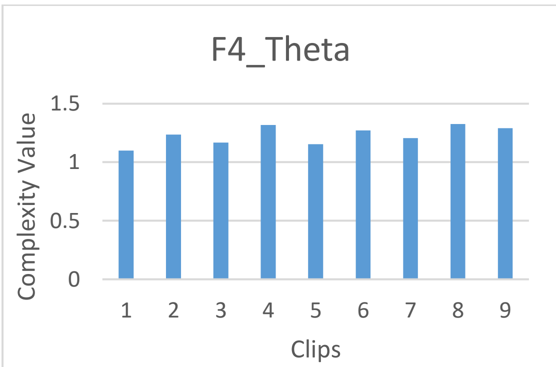
In figure 3.1.10, clip 1 has lower values of complexity in general, this clip denotes the emotion of devotion. Clip 2 and 3, have comparable values of complexity these include the emotions of happiness and anxiety, activated emotions. In clip 4, again we can the overall values are low but amidst the other lobes the occipital lobe has the highest w value (1.234). Clip 4 resembles emotions of romantic nature. In clip 6, the occipital lobe has a very high value (1.339), this clip denotes the pleasant emotion of happiness. Interestingly enough, in clip 7 the occipital values are lower than the rest of the lobe while this clip is for sadness. Again clip 8 and 9, have comparable levels of complexity.

8.3.2. Set-2: Contrasting Colors:

In this and the following sections, we will be discussing about the same things as discussed earlier. The electrode wise changes in the 9 clips for both the alpha and theta range of values and then finally do the lobe-wise comparison for the same. The only thing that will be different in this section is the stimuli shown to the subject has been altered. The stimuli now shows contrasting colors before every clip, contrasting to the emotion that has been portrayed. We are going to see if exposure to a color and listening to an audio clip where both the emotions invoked are different makes any observable changes or not.

Starting the analysis with the individual electrode graphs of the EEG recordings that were taken for the Theta waves of the brain.





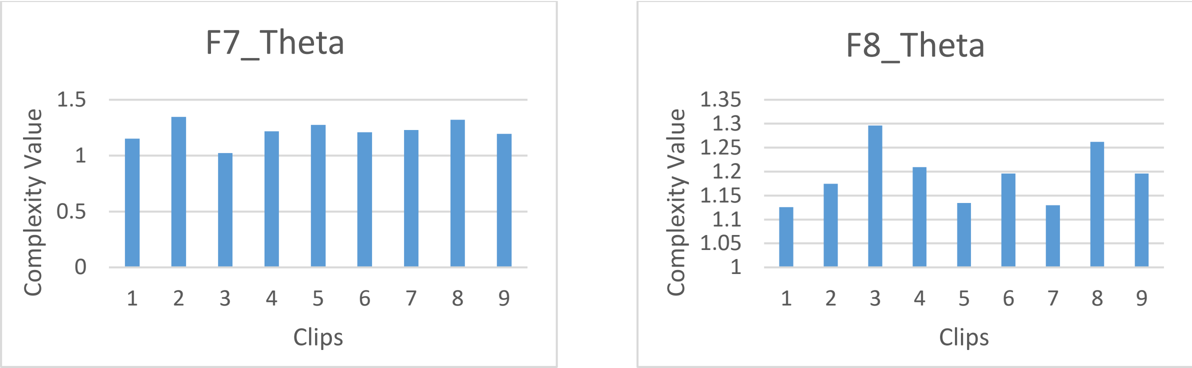


Figure 8.3.2.1: Complexity Variation in Frontal Electrodes Clip-wise

In F3, the complexity values are almost same for all the clips. The values ranges from 1.067 to 1.296. Since the variations is very minimum, we cannot derive a concrete observation out of it.

In F4, again the complexity variation is very marginal and individual observations cannot be drawn. The w value varies from 1.100 to 1.326.

In F7, the complexity variation is a bit more. The lowest value is 1.024 which corresponds to clip 3 which denotes a positive emotion while the highest value of complexity is 1.347 belonging to clip 2 which induces an emotion of anxiety which is a high activation emotion.

In F8, the complexity variation is strong. The highest value is for clip 3(1.296), this clip resembles the emotion of happiness and the lowest the value went is 1.130. This clip denotes the negative emotion of sadness, which is unpleasant.

Next, the discussions for the electrode attached to the temporal lobe of the brain:

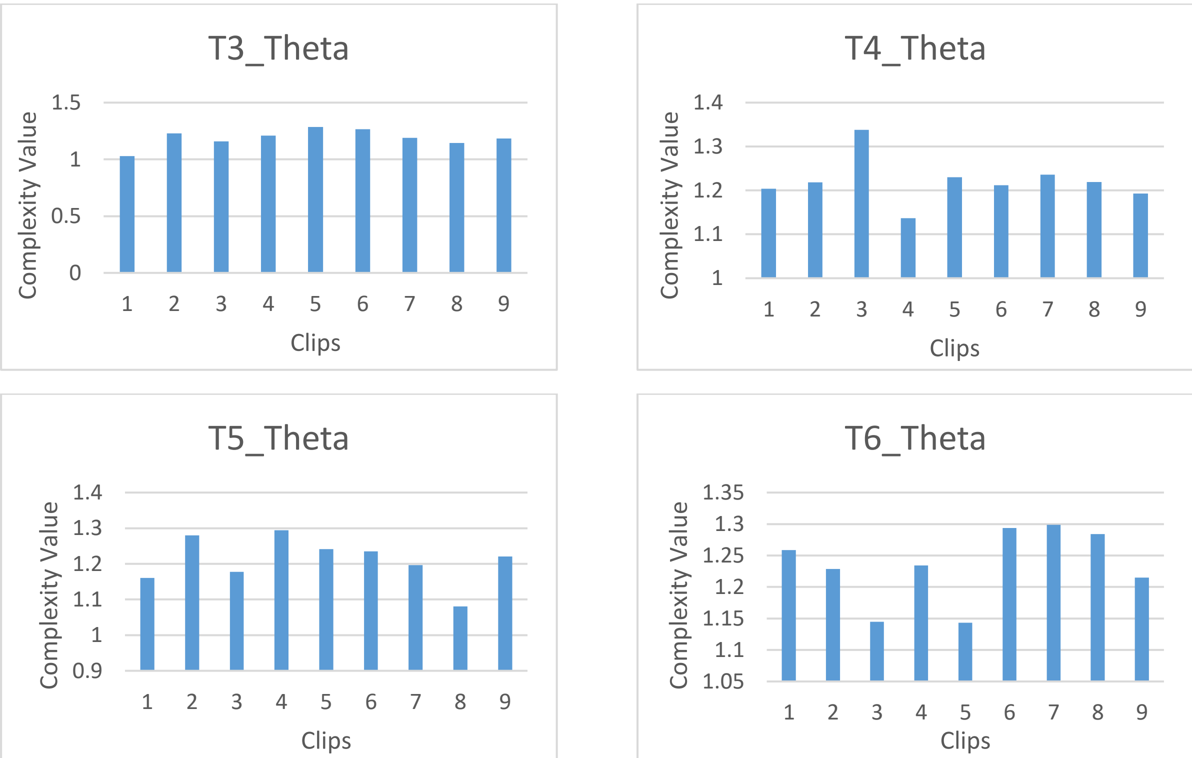


Figure 8.3.2.2: Complexity Variation in Temporal Electrodes Clip-wise

In T3, all the clips have comparable complexity values. The value w varies from 1.027 to 1.286. Clips 2,5 and 6 have very similar values of complexity which resemble the positive emotions i.e. the emotions on the pleasant side of the graph.

In T4, most clips are valued around 1.2, with a drastic change in clip 3 valued at 1.338 and clip 4 which has the value 1.136. Here, clip 3 has a very high complexity which resembles the emotion of happiness while clip 4 having a low complexity value is corresponding to romance. Hence, the complexity is varying with the varying levels of activation.

In T5, the complexity variation is quite erratic. Clip 4 is having the highest level of complexity (1.294) and the lowest level of complexity can be seen in clip 8(1.080). With high levels of complexity, clip 4 matches with the emotion of romance and clip 8 with calm. We can see lower the level of activation, lower is the multifractal width value.

In T6, clips 6,7 and 8 have similar complexity values, these clips invoke emotions of lower activation level- happy and calm. While clips 3 and 5 have the lowest w value where clip 3 is for happy and clip 5 is for anger.

In the next section, we are going to discuss the multifractal widths of electrodes attached to the parietal lobe of the brain.

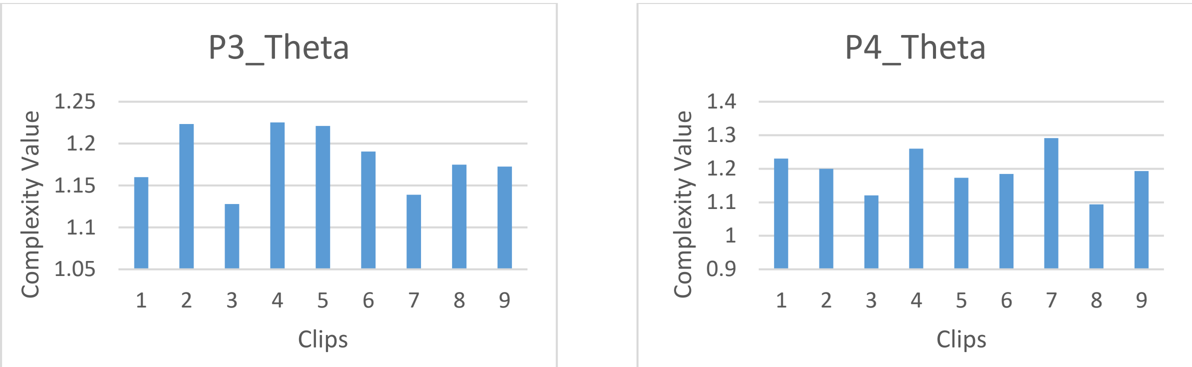


Figure 8.3.2.3: Complexity Variation in Parietal Electrodes Clip-wise

In P3, It can be observed that the clips 2,4 and 5 have comparable levels of complexity all around the value of 1.22. Although these signify varying emotions such as anxious, romantic and anger. The clips with lower values of complexity such as 3 and 7, denote the emotions of low activation- happiness and sadness.

In P4, there is not much difference in the values of complexity of the clips. Clips 1,4 and 7 have similar values these match with the emotions of lower activation. While clips 3 and 8 with further lower complexity values are for emotions whose activation is even lower.

Lastly, coming to the occipital lobe of the brain. We will be discussing how the activity has varied electrode wise in this particular lobe:

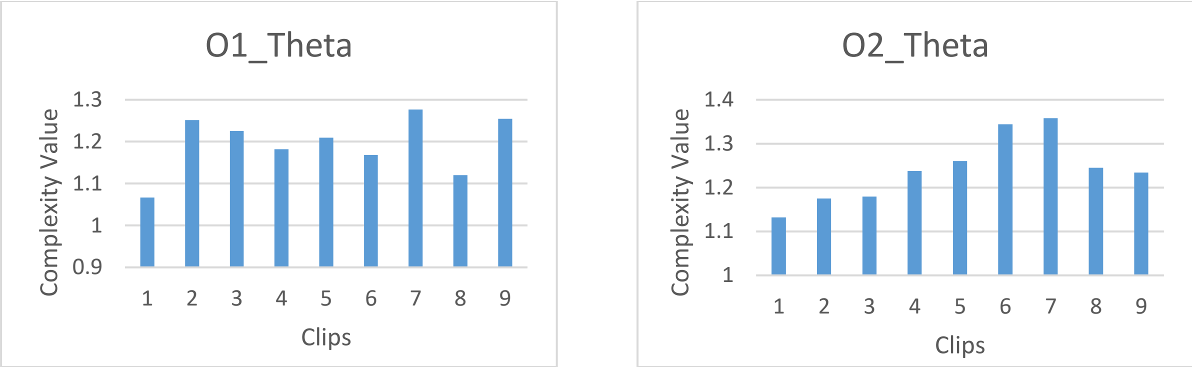


Figure 8.3.2.4: Complexity Variation in Occipital Electrodes Clip-wise

In O1, the complexity values of clip 2, 7 and 9 are almost similar, they are around 1.27, they can be mapped to the emotions who have the activation level slightly higher. Clip 1 has the lowest complexity level with a value of 1.066, denoting the emotion of devotion- highly pleasant and deactivated emotion.

In O2, we can see a general trend of low complexity values. Though clip 6 with a complexity value of 1.344 and clip 7 with a complexity value of 1.357 are quite high on the level. Both these clips derive the emotion of happiness and sadness simultaneously but they can be seen as having complimentary levels of activation.

In the above section we have analyzed the multifractral width of the individual electrodes in the Theta range of values, now we are going to discuss about the values during the alpha waves.

Starting off with the electrodes in the frontal lobe:

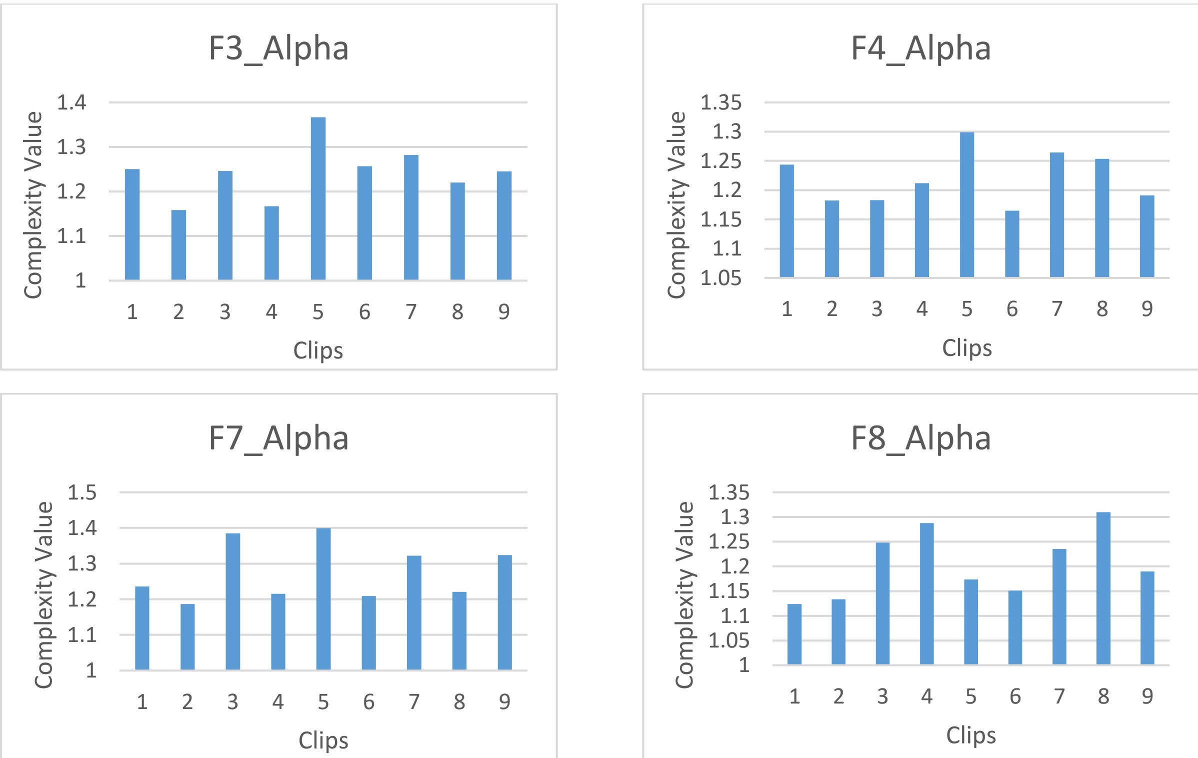


Figure 8.3.2.5: Complexity Variation in Frontal Electrodes Clip-wise

In F3, the clip with highest value of complexity (1.366) is clip 5 demonstrating an emotion of anger. Clip 2 having the lowest value of complexity of 1.158 and it matched with the emotion of anxiety.

While clip 6 and 9 having almost similar levels of complexity, both denote the same positive emotion of happiness.

In F4, clip 5 is having the complexity value of anger and it is the highest among the rest of the clips. The lowest value of 1.165 can be seen in clip 6, this clip is mapped with happiness. Clips 2 and 3 have similar complexity values but have varying emotions of happiness and anxiety but both in the pleasant side of the model.

In F7, in this graph we can see a clear difference. Clips 2,4,6 and 8 have a similar level of complexity whereas clips 3 and 5 have a similar level of complexity. It is seen that the former set has the clips having positive emotions and that of low activation, the latter ones are of happy and anger, different emotions, different activation levels. Again clip 7 and clip 9 have similar complexity values and both the clips can be mapped to happiness.

In F8, Clip 8 is having the clear highest value of complexity (1.309), this clip has been marked as invoking a calm emotion according to the human response. Clips 1, 2 and 6 have similar low values of complexity which are mostly for the positive emotions.

Moving next to the individual electrodes at the temporal lobe of the brain, for the alpha waves specifically:

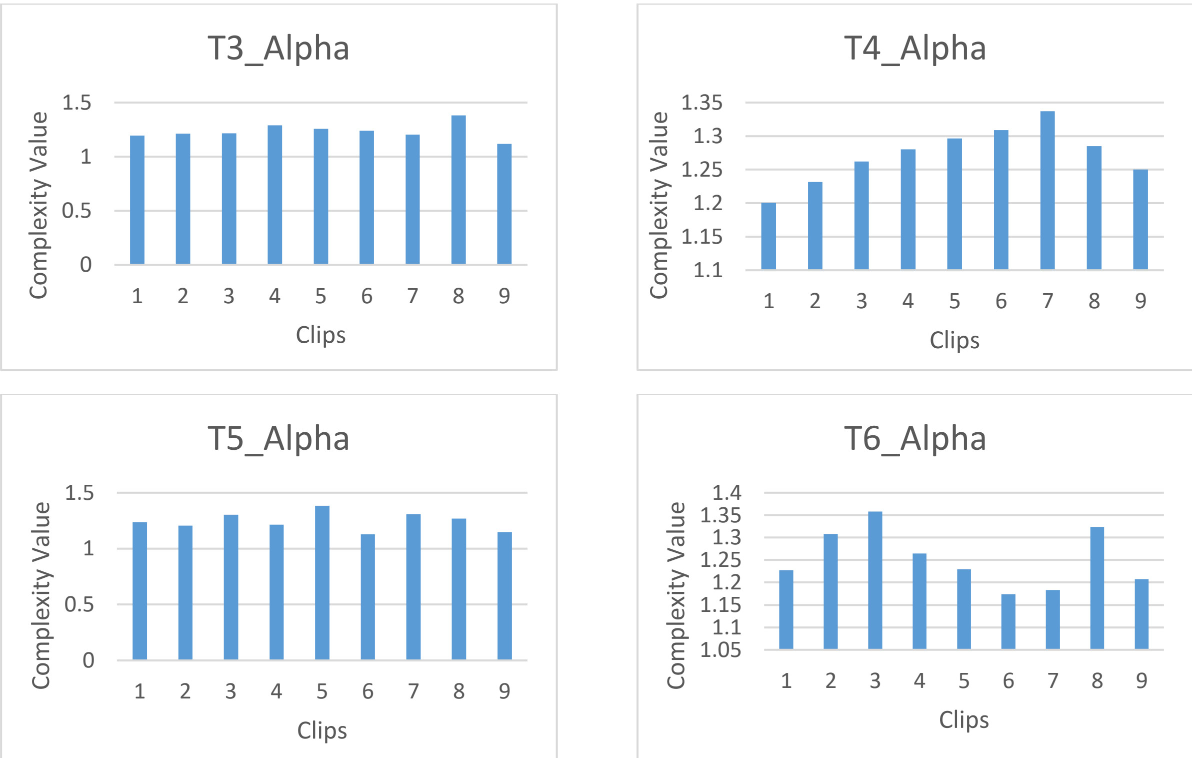


Figure 8.3.2.6: Complexity Variation in Temporal Electrodes Clip-wise

In T3, all the clips have similar complexity values ranging from 1.194 to 1.381. The only noticeable change that can be seen in the graph is for clip 8 which has a higher level of complexity than the rest of the clips. Clip 8 is supposed to be invoking emotions of calmness.

In T4, the lowest complexity that can be observed is for clip 1 which has a value of 1.200, this clip is mapped with the emotion of devotion i.e low activation. The highest being clip 7 with a complexity value of 1.337 and invoking an emotion of sadness, which in comparison has higher levels of activation than devotion.

In T5, the complexity variation is very minimum and all the clips for this electrode have given almost similar levels of complexity. In comparison the highest complexity value has been achieved by clip 5 which has been mapped to the emotion of anger.

In T6, the complexity variation is pretty erratic, it can be observed that clip 3 has the highest level complexity with a value of 1.357, this can be mapped to the emotions of happiness. The lowest complexity value can be seen of clip 6 with a value of 1.174, interestingly enough, both the highest as well as the lowest complexity values are for the emotion happy. Clips 4, 5 and 6 have their complexity levels in the descending order and analyzing their emotions it can be said that the clips are also in the increasing order of their activation.

In the next section we have to discuss about the variations in the complexity levels for the individual electrodes in the parietal regions of the brain:

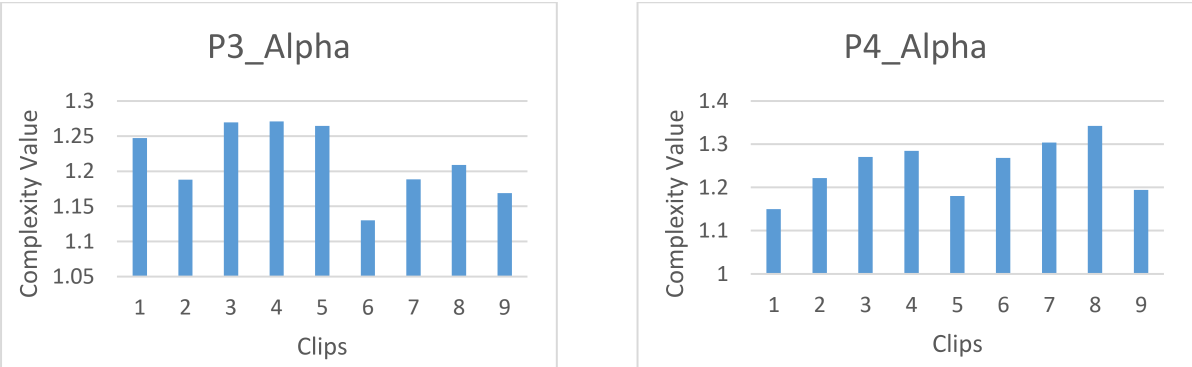


Figure 8.3.2.7: Complexity Variation in Parietal Electrodes Clip-wise

In P3, the first thing to notice is that clips 3,4 and 5 have very comparable complexity values (near 1.27), here clips 3 and 4 are giving emotions such happy and romantic but clip 5 invokes emotions of anger. Clip 6 which invokes happiness have the lowest complexity value of 1.130 and clips 7 , 8 and 9 have similar values and they invoke emotions of lower activation.

In P4, the lowest complexity value can be seen in clip 5 with a value of 1.180, this clip can be mapped to the emotion- anger. The highest value of complexity is 1.342 of clip 8 and it can be mapped to calmness or emotions of very low activation. Clips such as 3 and 6 have similar values as well as they invoke the same feeling of happiness.

Lastly for this section, we are going to take into account the occipital lobe electrodes and are going to discuss the results and findings in the same:

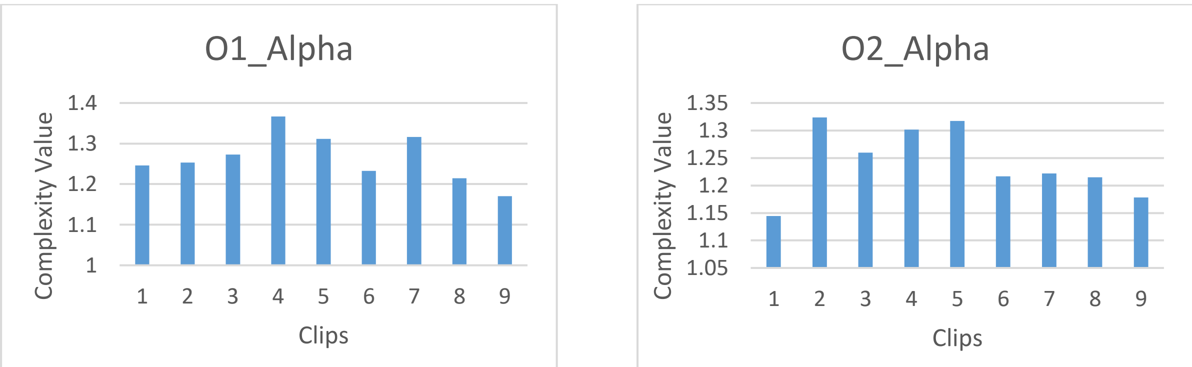


Figure 8.3.2.8: Complexity Variation in Occipital Electrodes Clip-wise

In O1, the complexity values are similar for the first 3 clips (around 1.25), these clips are mapped to the emotions of low activation- happiness and devotion. Clip 4 having the highest complexity value 1.367, this clip has been seen to invoke the feelings of romance, hence it resembles to very low activation state. Clips 5 and 7 have similar complexity levels they invoke the emotions of anger and sadness, both of which lie in the unpleasant side of the circumplex model.

In O2, clip 2 and 5 have comparable complexity levels valued at around 1.32. Both of these clips are mapped to emotions which are high in activation level. Clips 6, 7 and 8 have similar levels, these clips can be mapped to emotions of lower activation region. In this electrode, it's seen that the complexity rises with rising level in activation.

In the above section, we have observed each electrode individually and have made the comments on them. Now, the same electrodes have been combined according to their different lobes and a comparative study has been done. It will help us determine clips as well as emotions causing different levels of changes in the lobes. This comparison is also done in two parts: one comparison of the lobes considering the Theta wave and the other considering the Alpha waves.

The comparison lobe-wise for the theta waves of the brain considering that the color stimuli that have been exposed to the subject are of contrasting color and emotions.

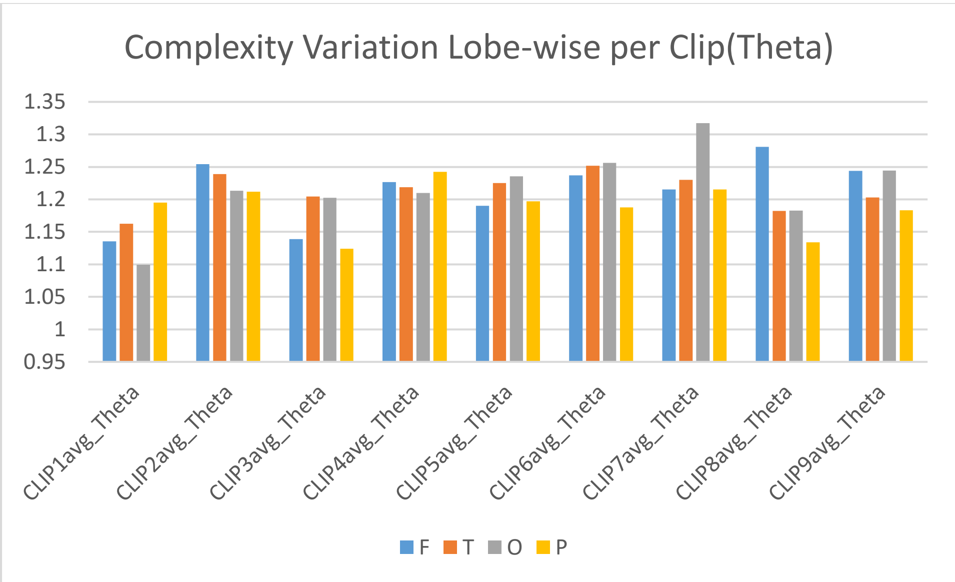


Figure 8.3.2.9: Complexity Variation Lobe-wise per clip (for theta)

In figure 8.3.2.8, we will be discussing clip-wise to get a better understanding of what is happening in the lobes. In clip 1, all the lobes have almost similar levels of complexity except for that of the occipital lobe which has a very low complexity value of 1.099. Clip 2 has the complexity levels of all the lobes comparable. In clip 3, it is observed that the complexity levels of the frontal and parietal lobes are remarkably less in comparison to the other two lobes. Clips 4, 5,6 have similar levels of complexity within their lobes. Coming to clip 7, the complexity of occipital lobe is very high in comparison to others. It is even the highest among all the 9 clips. It has a complexity of 1.317, this clip has been mapped to the emotion of sadness- a low activation unpleasant emotion. In clip 8, the complexity of frontal lobe is a bit higher than the rest, this clip has been mapped to the emotion calm which has a lower level of activation. Lastly, clip 9 has comparable levels of complexity in frontal and occipital lobes and similar levels in temporal and parietal lobes.

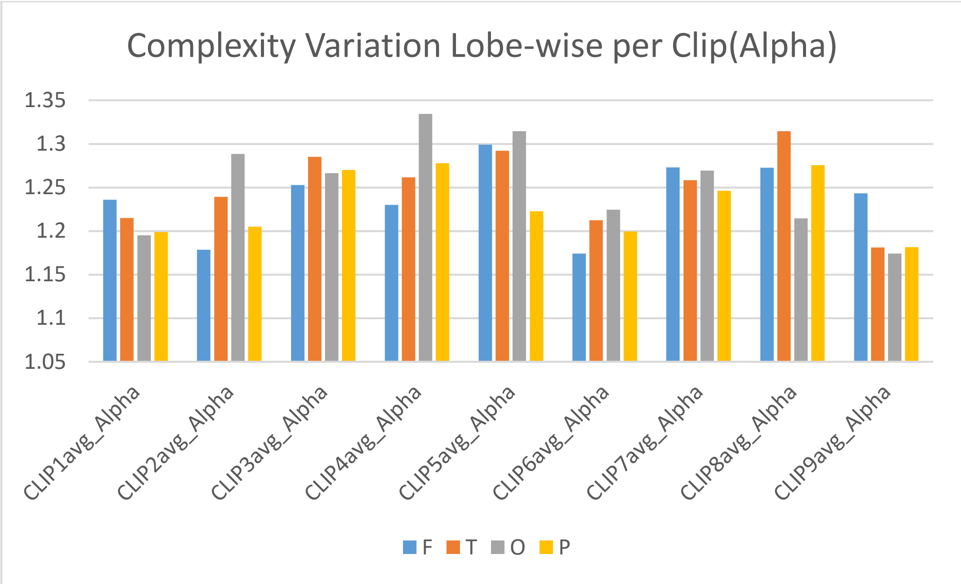


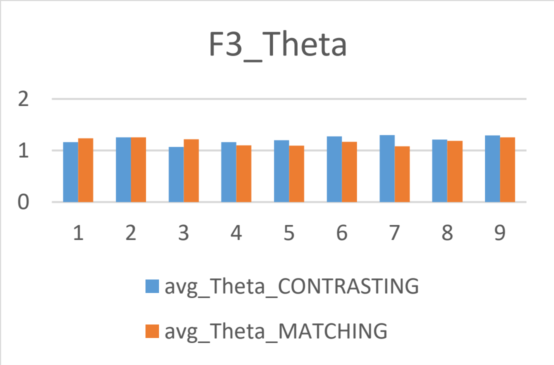
Figure 8.3.2.10: Complexity Variation Lobe-wise per clip (for alpha)

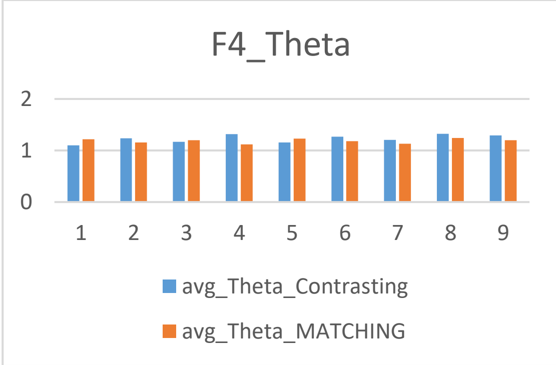
In figure 8.3.2.9, the lobe-wise comparison is done for the alpha waves. In clip 1, the complexity values of each lobe are lower in comparison to the rest of the clips. Clip 2 has a high complexity value (1.2885) in the occipital lobe, if we look into the emotion that is invoked by this clip, it is anxiety- an emotion with high activation level. Clip 3 and clip 5 have comparable levels of complexity with the latter having low complexity in the parietal region. In clip 4, invoking emotions of romantic feeling the occipital lobe has higher complexity. Clips 6 and 7, have comparable complexities not much that can be observed as a group. Next clip 8, all the lobes have comparable complexities except for that of occipital lobe which has a complexity value of 1.215, this clip can be mapped with emotion of calmness i.e. for low activation. Lastly, in clip 9 all the lobes have similar complexity except for the frontal lobe which has a high complexity value (1.243).

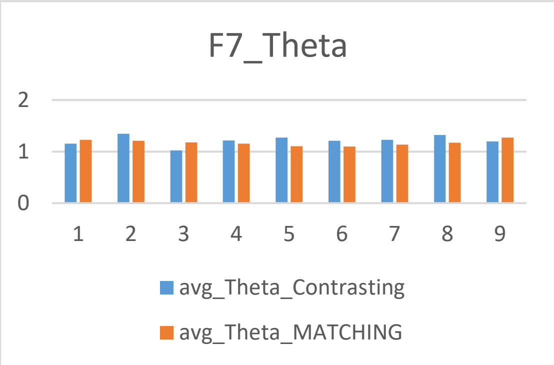
In this experiment, as it has been mentioned multiple times that we are focusing on two types of stimuli primarily- Matching Colors and Contrasting Colors. In the above sections, we have made comparisons with individual electrodes for both the brain wave frequencies separately for both the types, we have also done a comparative study for both the frequencies with respect to the lobes that have been affected (again for matching as well as contrasting colors). To complete the entire picture of comparison lastly, a comparative study has been done for the each brain wave individually where the values of contrasting as well as matching colors have been plotted together.

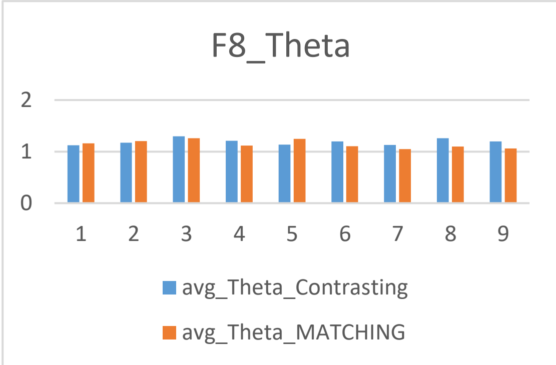
8.3.3. Set-3: Comparative study between Matching and Contrasting Colors:

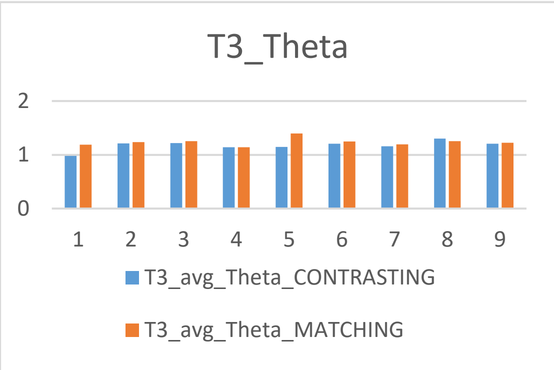
The electrode wise study has given us a fair idea about the complexity variation in each lobe for individual clips. In the next section, we have taken the same plots for matching and contrasting colors both and compared them simultaneously. This will give us an idea about the change in the multifractal width values in context to the color situations. As we have done it for earlier, first we will be looking at the comparison in the theta range of frequencies and there after the comparison in alpha range of frequencies will be done.

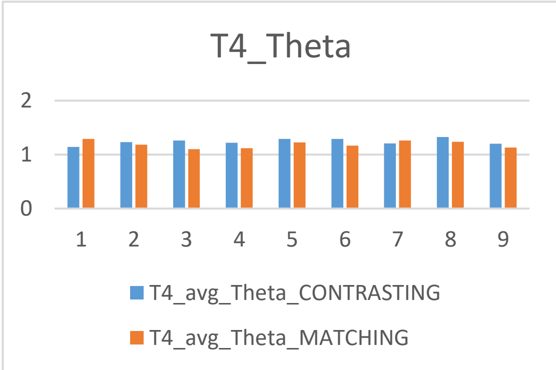

F3_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_CONTRASTING
avg_Theta_MATCHING

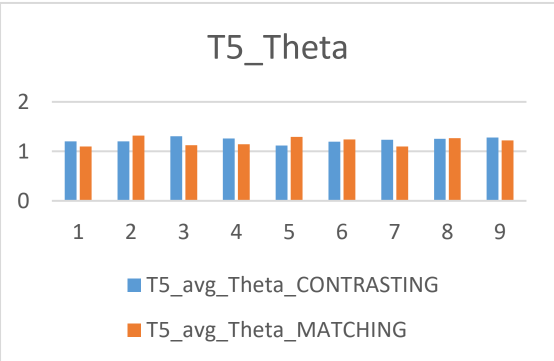

F4_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_Contrasting
avg_Theta_MATCHING

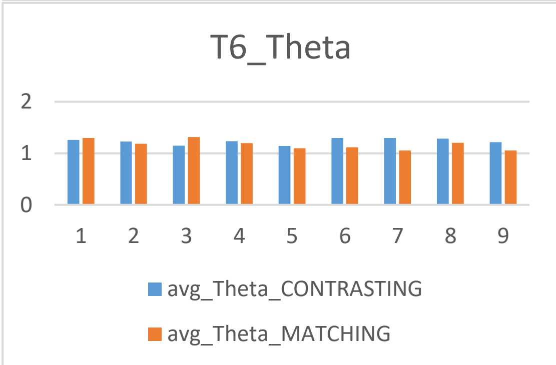

F7_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_Contrasting
avg_Theta_MATCHING

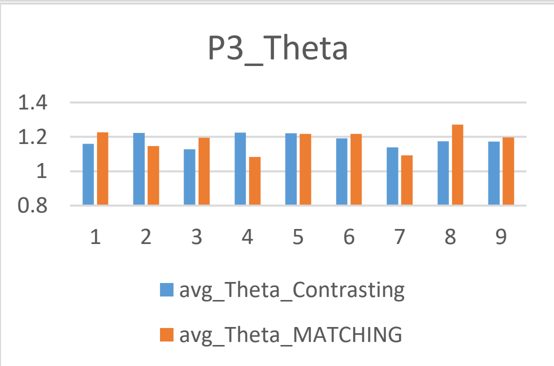

F8_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_Contrasting
avg_Theta_MATCHING

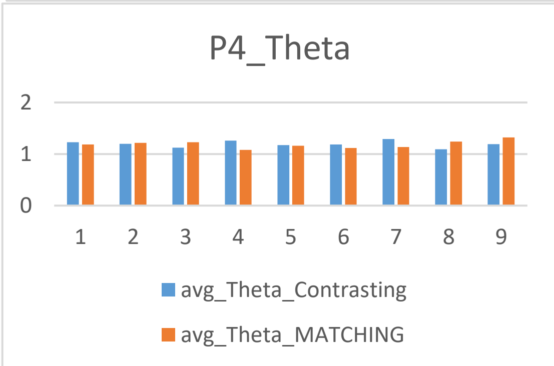

T3_Theta
2
1
0
1 2 3 4 5 6 7 8 9
T3_avg_Theta_CONTRASTING
T3_avg_Theta_MATCHING


T4_Theta
2
1
0
1 2 3 4 5 6 7 8 9
T4_avg_Theta_CONTRASTING
T4_avg_Theta_MATCHING


T5_Theta
2
1
0
1 2 3 4 5 6 7 8 9
T5_avg_Theta_CONTRASTING
T5_avg_Theta_MATCHING


T6_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_CONTRASTING
avg_Theta_MATCHING


P3_Theta
1.4
1.2
1
0.8
1 2 3 4 5 6 7 8 9
avg_Theta_Contrasting
avg_Theta_MATCHING


P4_Theta
2
1
0
1 2 3 4 5 6 7 8 9
avg_Theta_Contrasting
avg_Theta_MATCHING

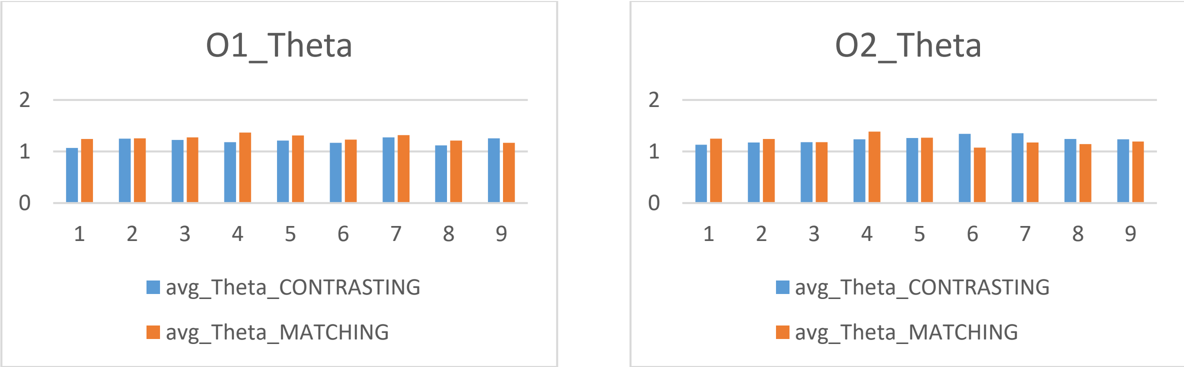


Figure 8.3.3.1: Complexity Variation of Matching and Contrasting colors clip-wise (for theta)

In figure 8.3.3.1, we have considered each electrode individually and then compared their complexity values in alpha and theta range of frequencies. Starting from the electrodes in the frontal lobe, not much variations can be seen in the values of contrasting and matching colors. Next in temporal lobe, variations can be seen. There is some amount of variations in all the electrodes of them temporal regions, it is to be noticed that the variations in electrode T4 is the highest. The difference between the complexity values of Theta and Alpha ranges has varied a lot, especially for the clips 1, 3, 5 and 8. For the Parietal region, there are slight differences in the values. More clearly in the electrode P3, we can see prominent differences between the colored stimuli. Lastly, in occipital region not much variation can be observed between the two different stimuli.

We will be doing the same kind of comparison for all the electrodes individually but this time for the Alpha range of brain waves.

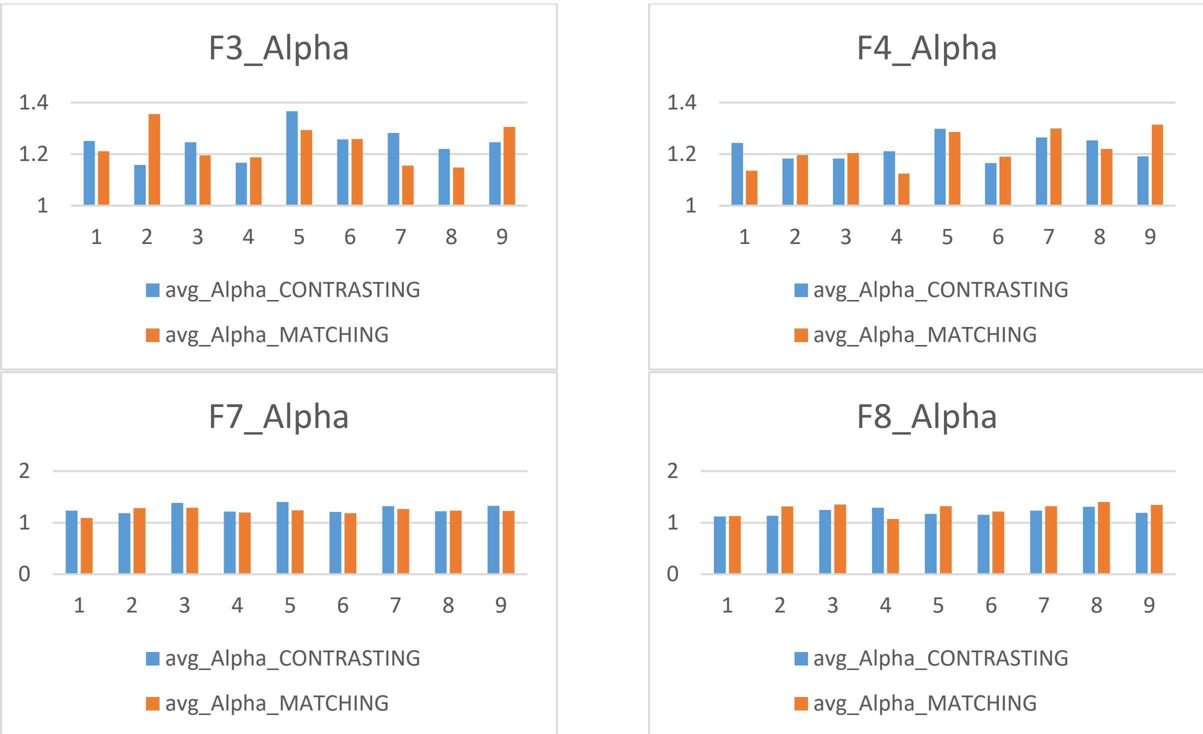


Figure 8.3.3.2: Complexity Variation of Matching and Contrasting colors clip-wise (for alpha)

In figure 8.3.3.2, taking into consideration the frontal lobe, a good amount of variation can be seen between the two different stimuli for the electrodes F3 and F4. For the F3 electrode, the clips 2, 5, 7 and 8 portray a lot of variations and for F4 the clips 1,4,8 and 9. The other two electrodes of the frontal lobes do not show much variation. In temporal region, variations can be observed in electrode T4, specifically in the clips 2, 3, 4 and 8 and along with this in electrode T6. One prominent observation that can be made is that the individual values of complexities in T6 is the lowest among all the other electrodes where the values are large. In Parietal lobe, both the electrodes have some kind of variation between the different stimuli. For electrode P3, this variation can be considerably noticed in clips of 4, 6 and 9 while in electrode P4 variations can be seen in clips 4, 5, 6 and 7. Lastly coming to the occipital region, the electrode O1 does not have much variation but the electrode O2 has large variations especially in the clips 1,2,4,7 and 9.

These were the observations that have been drawn from the data that has been received from EEG collection of several subjects. The observations have been divided electrode-wise, lobe-wise, frequency-wise as well as lastly stimuli-wise. The objective of drawing so many observations is because the human brain in a complex in-deterministic system. Vast amount of studies has to be done in order to find even the slightest pattern. Through the above observations, we have gathered some amount of solid data which can be used to govern the relation between complexity of an audio clip and the human emotion involved in it. We can also draw a conclusion with respect to the color stimuli that the subjects have been exposed to. Since the matching and contrasting colors have given, us contrasting data for particular electrodes.

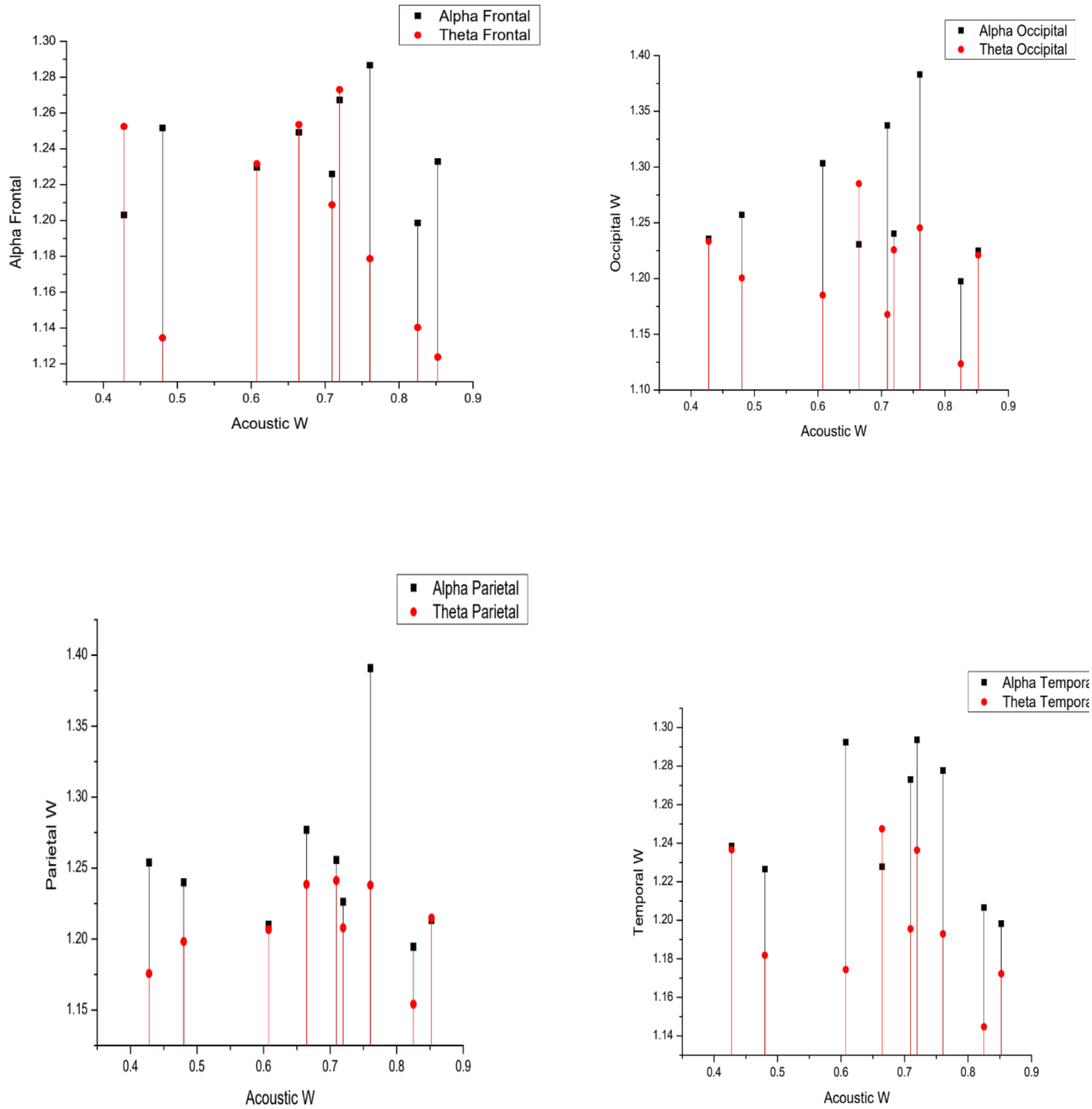


Figure 8.3.3.3: Lobe wise Complexity Variation against the complexity of the acoustic stimuli (for both theta & alpha range)

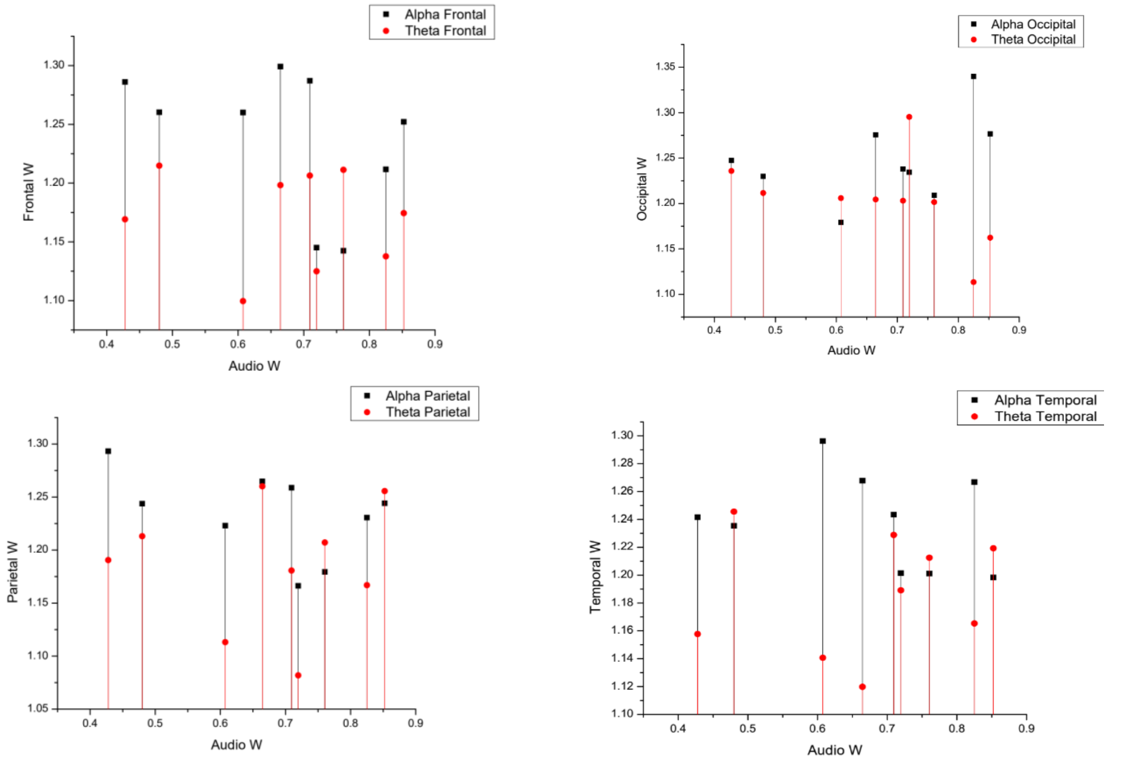


Figure 8.3.3.4: Lobe wise Complexity Variation against the complexity of the acoustic stimuli for matching colors (for both theta & alpha range)

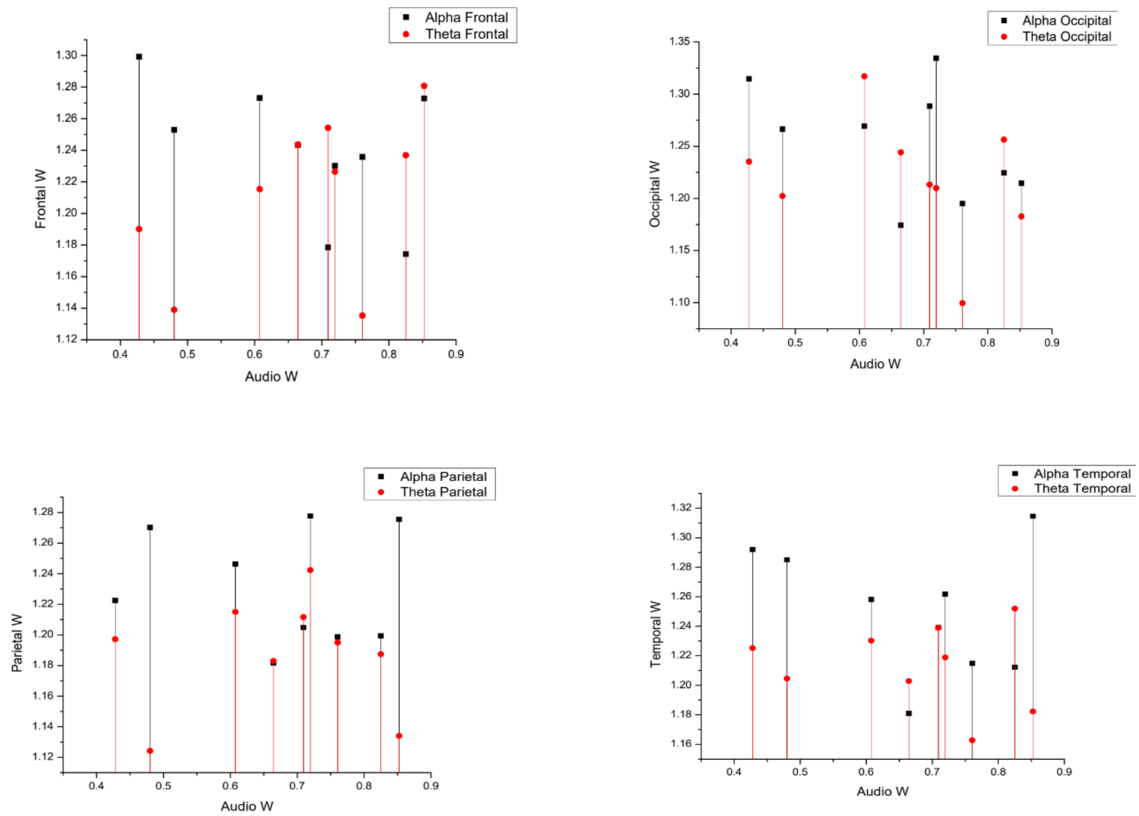


Figure 8.3.3.5: Lobe wise Complexity Variation against the complexity of the acoustic stimuli for contrasting colors (for both theta & alpha range)

8.4. Conclusion

To summarise our entire experiment, we focused on investigating the relationship between audio and visual stimuli in the form of poems along with the various colours depicting the necessary emotions and their impact on brain activity, as measured through EEG readings. The scientifical method that we used to understand the changes in brain activity is Multifractal Detrended Fluctuation Analysis (MFDFA). The observations in our research shed light on the intricate connections between audio and visual stimuli and emotional processing within the brain. We have observed distinct patterns in brain activity across different regions of the brain and for various emotional states.

We had established this experiment under two broad categories: Matching colors and Contrasting colors, let us explain the observation in that domain itself. Starting from matching colors, in the alpha frequencies variations can be seen in frontal region (especially F3, F4), occipital region (O2), and parietal region (P4). While in theta frequencies, variation has been observed in the entire frontal lobe, most of the temporal lobe (T3, T4, and T5), occipital lobe (O1) and parietal lobe (P3). We can infer that alpha and theta frequencies work in separate lobes. Alpha frequencies do not activate temporal region while theta frequencies main target is the temporal region. Likewise occipital and parietal regions are also different for each frequency. Evaluating contrasting colors, for the alpha frequencies again we can see all the regions are being activated except for temporal region and for theta, a similar pattern is observed. Hence, on the basis of activation of region whether during the alpha waves (calm state) or theta waves (meditative state), we can conclude that color (contrasting or matching) activate the same regions.

When we are comparing the contrasting and matching color readings, it is observed that in the theta range of frequencies, whether or not the subject is shown a color resembling the emotion in the clip, the complexity does not vary much. But considering the alpha frequencies, there is a lot of deviation in complexity due to the type of image shown. Hence, the second conclusion that can be drawn is for analysis of color and emotion, the subject must be in a calm state (brain functioning in the alpha frequencies). The most amount of complexity variations can be seen in the following electrodes: F3, F4, T4, T6, P3, P4 and O2.

As described in Russell’s circumplex model, emotions can be mapped on two axes- valence and activation. For matching colors, it has been seen that emotions which have a positive level of activation such as happy, anger or anxiety contain a higher level of multifractal width or w complexity whereas emotions like romantic, sad or calm which are in the negative activation region have w complexity values very low.

We have done a quantitative analysis of the relationship between audio-visual stimuli and human emotions, this has provided valuable insights that can be used to drive advancements in various technological domains. By understanding how particular audio-visual cues evoke emotional responses in individuals, we can leverage this knowledge to build personalised and high emotional quotient products. Emotionally intelligent systems and devices such as emotion based personalised chat bots and companions, mental health monitoring devices or emotion based driving safety management and the list continues.

8.5. References

[1] Sreeja, P. S., and G. S. Mahalakshmi. "Perc-an emotion recognition corpus for cognitive poems." *2019 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2019.

[2] Liu, Sannyuya, et al. "Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement." *Computers & Education* 181 (2022): 104461.

[3] Johnson-Laird, Philip N., and Keith Oatley. "How poetry evokes emotions." *Acta Psychologica* 224 (2022): 103506.

[4] Freeman, Margaret H. *The poem as icon: A study in aesthetic cognition*. Oxford University Press, 2020.

[5] Farsi, Roghayeh. "Cognitive appraisal and coping in poetry." *Journal of Narrative and Language Studies* 9.18 (2021): 339-356.

[6] Dzedzickis, Andrius, Artūras Kaklauskas, and Vytautas Bucinskas. "Human emotion recognition: Review of sensors and methods." *Sensors* 20.3 (2020): 592.

[7] Dewaele, Jean-Marc, and Chengchen Li. "Emotions in second language acquisition: A critical review and research agenda." *Foreign Language World* 196.1 (2020): 34-49.

[8] Kosti, Ronak, et al. "Context based emotion recognition using emotic dataset." *IEEE transactions on pattern analysis and machine intelligence* 42.11 (2019): 2755-2766.

[9] Zhong, Ke, Tianwei Qiao, and Liqun Zhang. "A study of emotional communication of emoticon based on Russell's circumplex model of affect." *Design, User Experience, and Usability. Design Philosophy and Theory: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part I 21*. Springer International Publishing, 2019.

[10] Patnaik, Suprava. "Speech emotion recognition by using complex MFCC and deep sequential model." *Multimedia Tools and Applications* 82.8 (2023): 11897-11922.

[11] Rai, Amod Kumar. "Bharatmuni's Natyasastra: A contemporary pertinence." *An International Refereed Journal of English Language and Literature* 8.2 (2022): 17.

[12] Pandey, Pankaj, et al. "Identifying Dominant Emotion in Positive and Negative Groups of Navarasa Using Functional Brain Connectivity Patterns." *Neural Information Processing: 29th International Conference, ICONIP 2022, Virtual Event, November 22–26, 2022, Proceedings, Part II*. Cham: Springer International Publishing, 2023.

[13] Casillo, Stephanie M., Diego D. Luy, and Ezequiel Goldschmidt. "A history of the lobes of the brain." *World Neurosurgery* 134 (2020): 353-360.

[14] Leblanc, Richard. "Pavlov, Penfield, and the physiology of the mind." *Neurology* 92.12 (2019): 575-578.

[15] Hu, Li, and Zhiguo Zhang, eds. *EEG signal processing and feature extraction*. Singapore: Springer Singapore, 2019.

[16] Martínez, Jorge Luis Morales, et al. "A modified multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation." *Physica A: Statistical Mechanics and its Applications* 565 (2021): 125611.

[17] Gorjão, Leonardo Rydin, et al. "MFDFA: Efficient multifractal detrended fluctuation analysis in python." *Computer Physics Communications* 273 (2022): 108254.

[18] David, Sergio Adriani, et al. "A combined measure to differentiate EEG signals using fractal dimension and MFDFA-Hurst." *Communications in Nonlinear Science and Numerical Simulation* 84 (2020): 105170.

[19] Sarkar, Uddalok, et al. "Language Independent Emotion Quantification using Non linear Modelling of Speech." *arXiv preprint arXiv:2102.06003* (2021).

[20] Avramidis, Kleanthis, et al. "Multiscale fractal analysis on EEG signals for music-induced emotion recognition." *2021 29th European Signal Processing Conference (EUSIPCO)*. IEEE, 2021.

[21] Jonauskaite, Domicele, et al. "Universal patterns in color-emotion associations are further shaped by linguistic and geographic proximity." *Psychological Science* 31.10 (2020): 1245-1260.

[22] Jonauskaite, Domicele, et al. "What color do you feel? Color choices are driven by mood." *Color Research & Application* 44.2 (2019): 272-284.

[23] Zhang, Rui, Cairang Jia, and Jian Wang. "Text emotion classification system based on multifractal methods." *Chaos, Solitons & Fractals* 156 (2022): 111867.

[24] Basu, Medha, et al. "Neural Quantification of Timbre and Emotions from Indian Classical Music a Multifractal Exploration." *Available at SSRN 4374657*.

[25] Ahirwal, Mitul Kumar, and Mangesh Ramaji Kose. "Audio-visual stimulation based emotion classification by correlated EEG channels." *Health and Technology* 10.1 (2020): 7-23.

[26] Feradov, Firgan, Iosif Mporas, and Todor Ganchev. "Evaluation of features in detection of dislike responses to audio–visual stimuli from EEG signals." *Computers* 9.2 (2020): 33.

[27] DAŞDEMİR, YAŞAR, and RÜSTEM ÖZAKAR. "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning." *Turkish Journal of Electrical Engineering and Computer Sciences* 30.7 (2022): 2707-2724.

[28] Rodriguez-Larios, Julio, et al. "From thoughtless awareness to effortful cognition: alpha-theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic." *Scientific Reports* 10.1 (2020): 1-11.

[29] Lin, Sen, et al. "A flexible, robust, and gel-free electroencephalogram electrode for noninvasive brain-computer interfaces." *Nano letters* 19.10 (2019): 6853-6861.

[30] Yean, Choong Wen, et al. "Emotional states analyze from scaling properties of EEG signals using hurst exponent for stroke and normal groups." *Intelligent Manufacturing and Mechatronics: Proceedings of the 2nd Symposium on Intelligent Manufacturing and Mechatronics–SympoSIMM 2019, 8 July 2019, Melaka, Malaysia*. Springer Singapore, 2020.

[31] Guo, Fu, et al. "Research on color optimization of tricolor product considering color harmony and users' emotion." *Color Research & Application* 45.1 (2020): 156-171.

[32] Zeileis, Achim, et al. "colorspace: A toolbox for manipulating and assessing colors and palettes." *arXiv preprint arXiv:1903.06490* (2019).

[33] Shrestha, Badri, and Louese Dunn. "The declaration of Helsinki on medical research involving human subjects: a review of seventh revision." *Journal of Nepal Health Research Council* 17.4 (2019): 548-552.

[34] Farrens, Jaclyn L., et al. "Electroencephalogram (EEG) recording protocol for cognitive and affective human neuroscience research." (2021).

[35] Dilena, Robertino, et al. "Consensus protocol for EEG and amplitude-integrated EEG assessment and monitoring in neonates." *Clinical Neurophysiology* 132.4 (2021): 886-903.

CHAPTER 9

SPEECH-RECITATION-SONG: ACOUSTICAL & NEURO-COGNITIVE EXPLORATION USING NONLINEAR APPROACH

The Music is a vibration in the brain rather than the ear"

Amy Clampitt

9.1 Introduction:

In the realm of poetry, art and music, the power of words transcends mere linguistic communication and delves into the domains of emotion and cognition [1]. This research explores the acoustical and neuro-cognitive aspects of prosodic variations between pieces of one of the most revered and noted poets of Bengal till date, Rabindranath Tagore. Tagore's works have left an indelible mark on the literary landscape, captivating readers with his profound verses in multiple languages, and is rightfully considered to be the greatest of his era, if not of all time. The domain of our work spans irrespective of a time frame, as the only considerations for our work are three different compositions of Tagore with varying prosodies or renditions.

The primary focus of this study is to examine the difference in cognitive engagement evoked by the different stimuli [2]. Our stimuli constituted of three pieces of composition, each from the same poet, incorporating the same syntax and semantics, but with three different forms of prosodies: the same piece was played as a stimuli to our subjects in the form of a speech, recitation and as a song [3]. By analysing the impact of these audio clips on the neurocognitive engagement and subsequently the human mind, we aim to shed light on the intricate relationship between different kinds of renditions and the human cognition [4-6]. It has been previously reported by virtue of multiple researches that the cognitive engagement for stimuli as in this experiment has always been the greatest in case of a singing rendition [7-8]. Reinstating the importance of our work, we aim to establish a qualitative-to-quantitative parity between the human psyche and the technical aspect of the brain's cognition [9-11].

In conjunction, we seek to explore the neuro-cognitive processes associated with these emotions invoked by the stimuli, measuring the cognitive engagements from a bio-physical perspective [12-13]. Based on the human responses recorded beforehand, our aim was to non-linearly measure and analyse the change in the different lobes of the human brain invoked by these stimuli, and in achieving the same, we employed the use of Electroencephalography or EEG [14]. Our analysis encompasses four specific lobes of the brain: the frontal, temporal, occipital, and parietal lobes. Utilizing EEG will enable us to examine the patterns of responses associated with these cognitive engagements.

The analysis of EEG readings from the aforementioned lobes follows a non-linear approach using the tried and tested mechanism of Multifractal Detrended Fluctuation Analysis (MFDFA). An algorithm for non-linear super-complex systems, this technique enables us to analyse the intricate complexities of the brain's response to the stimuli presented during the recitation of various poems[15-19].

The primary analytical tool that has been employed in this study to assess the changes in cognitive engagements is the Multifractal Width (w) of the stimuli (audio clips) as well as the recorded EEG brain waves [20-22]. By virtue of this parameter, we can undertake the neuro-cognitive analyses to quantify and compare the multifractality of aforementioned cognitive patterns [23-24].

To ensure a comprehensive analysis, we seek to establish a parity between the qualitative assessments derived from collection human responses to the stimuli and the technical analysis of the same. This parallel evaluation will enable us to bridge the subjective nature of human perception with objective scientific measurements, ultimately enhancing our understanding of the neuro-cognitive effects of art and literature.

9.2 Experimental Details:

9.2.1 Methodology

Understanding the human brain's response to different stimuli is fundamental to cognitive and neuroscience analysis and research. As discussed earlier, this paper aims to study the brain activity of subjects by exposing the individuals to various audio and visual stimuli while recording that data using Electroencephalography (EEG) [25-27]. EEG is a popular non-invasive technique that can measure and record the electrical activity of the brain. It can provide valuable information about cognitive processes and brain functioning by capturing brain wave patterns. During an EEG recording, there are multiple brain waves that can be observed. These brain waves represent different patterns of electrical activity in the brain and can be categorized based on their frequency ranges which are- Delta waves (0.5-4 Hz), Theta waves(4-7 Hz), Alpha waves(8-12 Hz), Beta waves(12-30 Hz) and Gamma waves(30-100 Hz) [28].

Alpha waves are associated with relaxed wakefulness and a calm state of mind. They are usually observed when individuals close their eyes or meditate. Additionally, Theta waves are prominent during periods of deep relaxation, meditation, and early stages of sleep. They are linked to creativity, memory formation, and deep emotional states.

Here, our focus is going to be analysing Alpha and Theta waves because these states comprise the brain activity during calm, non-aroused, and alert states of mind, and thus can provide insights into cognitive processes and emotional states.

To accomplish our goal, we have used a 19-10 electrode cap to record data, this cap is specifically designed for EEG purposes. It consists of 13 electrodes that are strategically placed on the different lobes of our brain [29].

1. Frontal Lobe: The frontal lobe plays a crucial role in decision-making, executive functions, problem-solving, and cognitive control. Electrodes placed on the frontal lobes will capture brain activity associated with these processes, thus allowing researchers to examine cognitive states during stimulus exposure. 4 electrodes were placed in this particular region namely- F3, F4, F7 and F8.

2. Parietal Lobe: The parietal lobe plays a pivotal role in various sensory integration processes, spatial awareness, attention, and perception. Electrodes placed on the parietal lobes enable the monitoring of brain activity associated with the attentional allocation and the integration of various visual and auditory stimuli. We placed 2 electrodes in this particular region namely- P3 and P4.

3. Occipital Lobe: The occipital lobe is mainly responsible for visual processing and perception. Electrodes placed on the occipital lobe capture brain activity associated with visual stimuli, allowing researchers to study visual perception and processing during stimulus exposure. 2 electrodes were placed in this particular region namely- O1 and O2.

4. Temporal Lobe: The temporal lobe plays a major role in auditory processing, language understanding, and memory functions. Electrodes placed on the temporal lobe enable the study of auditory perception, language-related processes, and memory formation during the presentation of audio stimuli. We placed 4 electrodes in this particular region namely- T3, T4, T5 and T6[13].

The acquired EEG data of two separate frequencies (alpha and theta) from the subject are to be processed and analysed using a mathematical non-linear analysis technique called MFDFA (Multifractal Detrended Fluctuation Analysis).This method is specifically designed to understand the complex nature of EEG signals by evaluating their fractal properties (self-similarities) and long-range correlations.

The technique involves several steps- detrending: the data is detrended to remove any present patterns, fluctuation calculation: fluctuations in segments of varying lengths is calculated, scaling analysis:

analysis of the fluctuations and lastly the exponent calculation: giving the degree of self-similarity. Using the fluctuation function obtained from the MFDFA algorithm, Hurst exponent (H) is also calculated. It helps to quantify the degree of self-similarity or self-affinity present in the given data. The value of H has different interpretations: H> 0.5 -indicates a persistent or positively correlated time series (having long term trends), H= 0.5- indicates uncorrelated time series (random or no trend) and H < 0.5- indicates an anti-persistent or negatively correlated time series (oscillatory trend) [30].

9.2.2 Stimuli Details:

We have carefully chosen three poems by well-known poet Rabindranath Tagore who have made significant contributions to Bengali literature over the past years as part of our research. These poems are a rich and diverse representation of the literary heritage of the Bengali language. Segments from each of these three poems were extracted and used to create a controlled stimulus for our study, ensuring that each segment is approximately 30-35 seconds long. These poems are then used in the stimuli where the syntax as well as semantics are kept same but changes are made in the prosodic. To be clear, the same poem is played three times to the subject- once in the form of speech, recitation and as a song. These meticulously curated snippets allow us to maintain consistency and precision in our experimental design while also capturing the essence and emotional depth of the original poems.

Here are brief descriptions of the poems that were used as stimuli:

Clip 1: ‘Amar praner pore chole gelo k’: This writing expresses a deep sense of longing, heartbreak, and unanswered questions. This extract is of the category (parjaay) ‘Prem’. It is composed in the Taal ‘Ar-khemta’, Raag is ‘Pilu-Kalingara-Paraj-Kirtan’ and Anga is ‘kirtan’. This was written in 1883. In this clip, the prosodic followed is speech.

Clip 2: ‘Amar praner pore chole gelo k’: The prosodic followed is recitation.

Clip 3: ‘Amar praner pore chole gelo k’- The prosodic followed is Song

Clip 4: ‘Hare rere rere amay chhere de re’: This is a very moving piece where the writer expresses a longing for freedom and liberation from restrictive circumstances. Few notable composition details are: category (parjaay) - Bichitro, Taal is ‘Ektaal’ and Raag is ‘Iman-Bhupali’. It was written in 1907. The prosodic followed here is speech.

Clip 5: ‘Hare rere rere amay chhere de re’: The prosodic followed is recitation.

Clip 6: ‘Hare rere rere amay chhere de re’: The prosodic followed is song.

Clip 7: ‘Sankochero bihwalata nijere apomaan’: This excerpt explores the internal conflict and self-doubt that arises when someone feels a sense of shame or humiliation. Details of the composition of the clip are: category (parjaay) ‘Swadesh’, Taal is ‘Dadra’, Raag is ‘Iman-Kalyan, written in the year of 1930. The prosodic followed is speech.

Clip 8: ‘Sankochero bihwalata nijere apomaan’- The prosodic followed is recitation

Clip 9: ‘Sankochero bihwalata nijere apomaan’- The prosodic followed is song.

Henceforth the audio clips will be referred to as Clip along with their respective number to maintain consistency and for easy understanding.

9.2.3 Participant Details:

A total of 10 individuals between the ages of 18 and 23 participated in this experiment to provide us with EEG recordings. Participants were reached out individually from personal contacts and word-of-mouth. All the participants were requested to provide their consent prior to the involvement in this study. To ensure the privacy and confidentiality of each of the participants, unique identification number were assigned to them, and their personal information was hidden and securely stored separately from the research data[31].

The participants consisted of young adults, comprising of both males and females. Each participant reported having right-handed dominance, indicating a right-handed preference. All participants had normal visual ability, with a vision of 6/6, indicating normal or optimal vision. Participants reported having proper hearing ability. Participants did not disclose any prevailing medical conditions that could potentially influence their responses or impact the validity of the study. It is worth mentioning that the participants were of sound body and mind, indicating that they were in good overall physical and mental health. This ensured that the data collected and later on the analysis was not disturbed by any underlying health issues that could influence the results.

To look after the safety and well-being of the participants, the experiments were conducted with proper precautions and following the ethical guidelines. All participants provided informed consent, indicating their voluntary involvement. Their consent was obtained prior to their engagement.

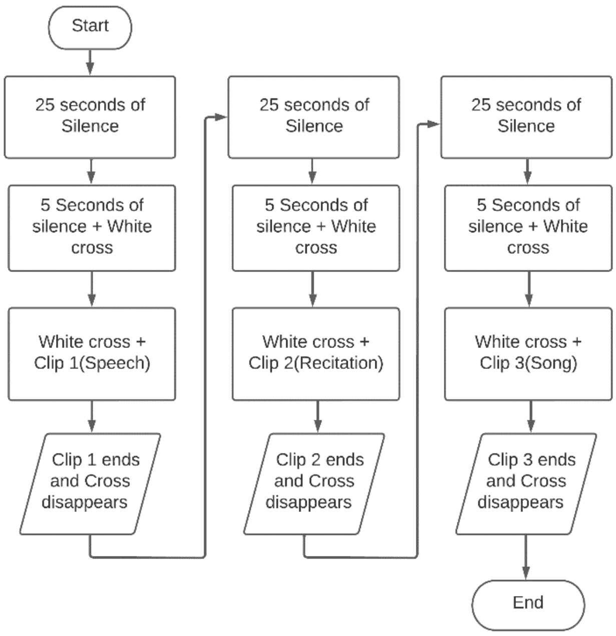
9.2.4 Protocol and Data Recording:

We began the process of capturing EEG recordings from the subjects following a standardized and uniform protocol while collecting human responses, to ensure consistency and reliability, each subject underwent the EEG procedure in the same way. The aim of this approach was to establish a solid foundation for data analysis and interpretation. During the EEG sessions, electrodes were carefully placed in specific locations on the participants' scalps, following the international 10-20 system for electrode placement. This systematic approach ensured comprehensive data collection by allowing us to capture electrical activity from multiple regions of the brain simultaneously after the EEG recordings were obtained, the next step was to extract relevant data for further analysis. To extract meaningful insights from the collected EEG data, we used a computational technique known as Multifractal Detrended Fluctuation Analysis (MFDFA) [16]. This method enabled us to investigate the complex temporal patterns and fluctuations within the EEG signals.

The nine audio clips were arranged in a particular manner which is very important to the experiment. The nine audio clips has been categorized into three sets on the basis of the poem. First set comprising of the first poem clips 1 through 3. Second set comprising of clips 4 through 6, and the third set comprising of clips 7 to 9, all written by Rabindranath Tagore and in each set, each clip has a different prosodic.

Each set follows the same protocol of the arrangement of the clips. Taking Set 1 as an example. As discussed set 1 has 3 clips, these clips need to be arranged in proper intervals of silence followed by audio. Beginning the clip with 25 seconds of complete silence, then there's 5 seconds of silence but along with this silence a white cross is shown on screen to draw back the attention of the subject. After these 5 seconds, the first clip is played, while the clip is being played the white cross should stay on the screen till the end of the clip. As soon as the clip ends, the white cross also disappears. There is again silence of another 25 seconds, followed by silence along with the white cross sign for 5 seconds. Then comes the 2nd clip which is again played along with the white cross and it cross disappears as soon as the clip ends. Lastly, another interval of silence for 25 seconds, 5 seconds of silence and cross followed by the 3rd audio clip and the cross. In the end, when the last audio clip finishes, the cross also disappears but another silence of 30 seconds to be maintained so as to not disrupt or activate the brain activity unnecessarily. In Fig. 2.1, the protocol is explained in the form of a flowchart for one set, this entire set up is repeated for set 2 and set 3 without any interval.

This protocol is followed for all the sets of poems and this is maintained throughout to extract the EEG readings from all the subjects. This is done so as to maintain a uniformity in the procedure. The silence intervals are placed in such a way that the brain activity is maximum and focused during the interval of the audio clip.



Flowchart of the Protocol

It is very important to maintain a proper protocol along with creating an optimal environment for each participant to ensure that we get accurate and reliable results [32-33]. The following guidelines were strictly followed to attain the best possible conditions for data collection:

1.) Sitting in a relaxed and comfortable position: The subjects were instructed to sit in a comfortable and relaxed position throughout the experiment to minimize physical discomfort or distractions that could potentially affect the emotional responses.

2.) Having no contact with the floor of the room: To prevent any grounding or interference from external sources, subjects were advised to keep their feet on a mat i.e avoid direct contact with the floor of the room.

3.) In a dark and cool environment: Subjects were taken in an environment with controlled lighting conditions. The room was kept in darkness to minimize visual distractions and to help focus attention on the experiment. Additionally, maintaining a cool temperature in the room to ensure the subjects' comfort and less distraction due to heat.

4.) In a noise-free zone: To create an environment for concentration and to minimize distractions, subjects were kept in a noise-free zone. Background noise, such as external conversations or environmental sounds, was tried to be blocked out to maintain a quiet and serene environment during the experiment.

5.) Focusing on the computer monitor only: Subjects were instructed to direct their attention on the computer monitor solely, where the stimuli were presented.

6.) Able to consume the video protocol files: Subjects were provided with the necessary equipment to effectively consume the video protocol files. This ensured that the audio-visual stimuli were presented to participants in a clear and accessible manner

By strictly adhering to these guidelines and maintaining a standardized protocol, we tried to create a controlled experimental environment for each subject. This helped to eliminate any possible errors that might have surfaced in the readings.

9.2.5 Calculation of Parameters:

After the data collection phase, the next important phase was the analysis of the obtained data. The EEG recordings were properly extracted into .csv. The extracted EEG data was meticulously labelled and organized to prevent any inaccurate or redundant data.

These excel files helped to process the data efficiently and the data was further analyzed using appropriate algorithms and Multifractal Detrended Fluctuation Analysis (MFDFA). These computational methods helped us to quantify the complexity of the brain activity. By calculating the average multifractal width, we were able to obtain a measure of the complexity for each audio clip. This complexity metric served as a basis for comparing and contrasting the different audio stimuli utilized in the study.

To get a comprehensive analysis, the data was needed to be arranged in a manner that helped us make visual representation such as graphs. Graphs were drawn to visually represent the findings and provide a clearer understanding of the patterns and relationships in the data. Firstly, we created an individual electrode-wise analysis, examining the contributions of each electrode. Furthermore, we performed lobe-wise analysis, focusing on the frontal, parietal, occipital, and temporal lobes. By examining the EEG data specific to these regions, we had observations into the activity of different brain areas during the processing of the stimuli. For both the alpha and theta frequency bands, graphs were plotted to visualize and explore the patterns, trends, and variations in brain wave activity.

From these graphs, we extracted key findings and results, which are presented in this research paper. These findings help us understand about the neural responses evoked by the stimuli and enable a deeper understanding of the emotional and cognitive processes associated with the audio clips.

The combination of human responses and EEG data analysis allowed us to establish a comprehensive study for investigating the relationship between the audio files and emotions. The utilization of multifractal analysis and graphical representations enhanced our ability to explain the intricacies of brain wave activity and derive meaningful insights from the collected data.

9.3 Results and Discussions:

9.3.1. Results from acoustic analysis of clips: The errors are not shown in the figures as they are too small to appreciate.

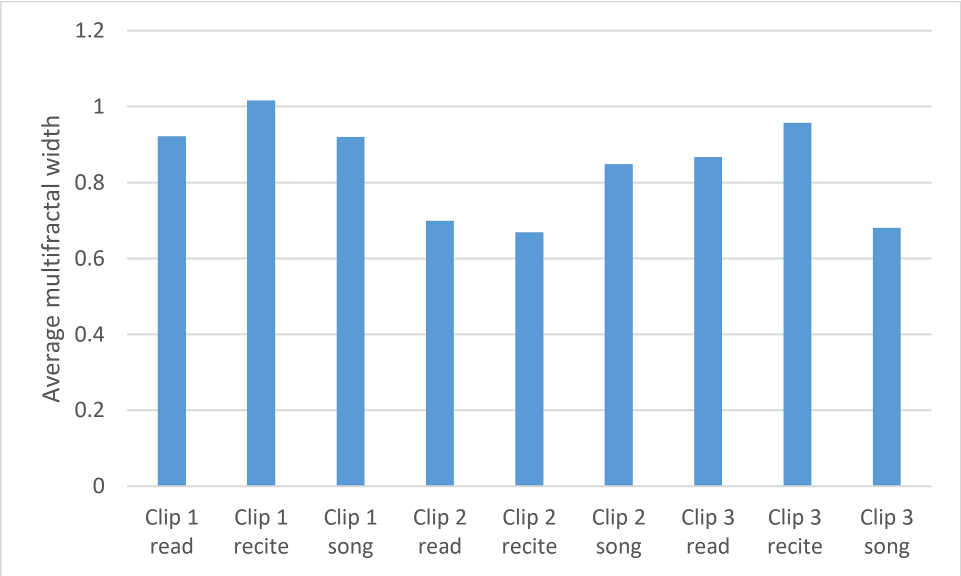
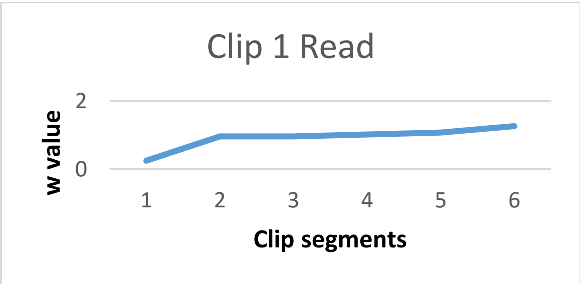


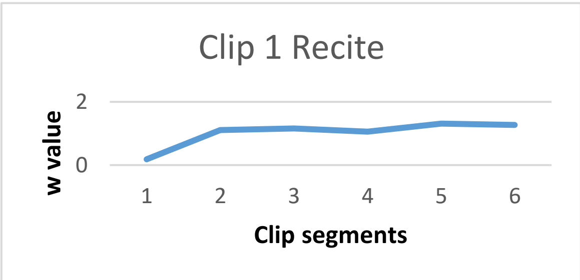
Fig.9.3.1: AVERAGE MULTIFRACTAL WIDTH (w) OF THE CLIPS

Observations:

- In case of clip 1, average w is similar in speech and singing, for reading whereas it is lower in clip 2 and higher in clip 3 in comparison of singing.
- In case of clip 2, average w is lowest for recitation, whereas it is highest in case of clips 1 and 3.
- In case of clip 3, average w is lowest for singing, whereas it is highest in case of clips 1 and 2.
- So, for clip 2, reading shows lower presence of long-range correlations and for clip 3, reading shows higher presence of long-rage correlations. Therefore, clip 2 getting lower and clip 3 getting higher complexity in comparison to clip 1.
- So, for clips 1 and 3, recitation shows higher presence of long-range correlations and therefore, higher complexity.
- So, for clips 1 and 2, singing shows higher presence of long-range correlation and therefore, higher complexity.

Now, for the change in w-patterns for each clip:





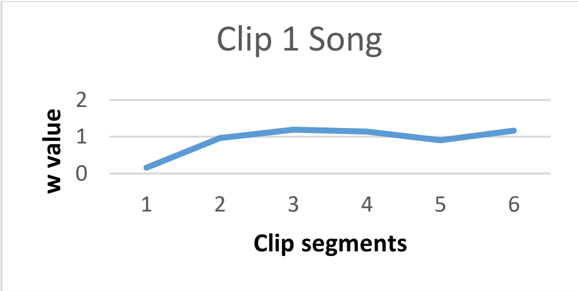


Fig.9.1.2: Change in w-patterns for clip 1

Evidently, clip 1(Fig 9.1.2) shares similar patterns of w changes in reading and recitation renditions in comparison of singing.

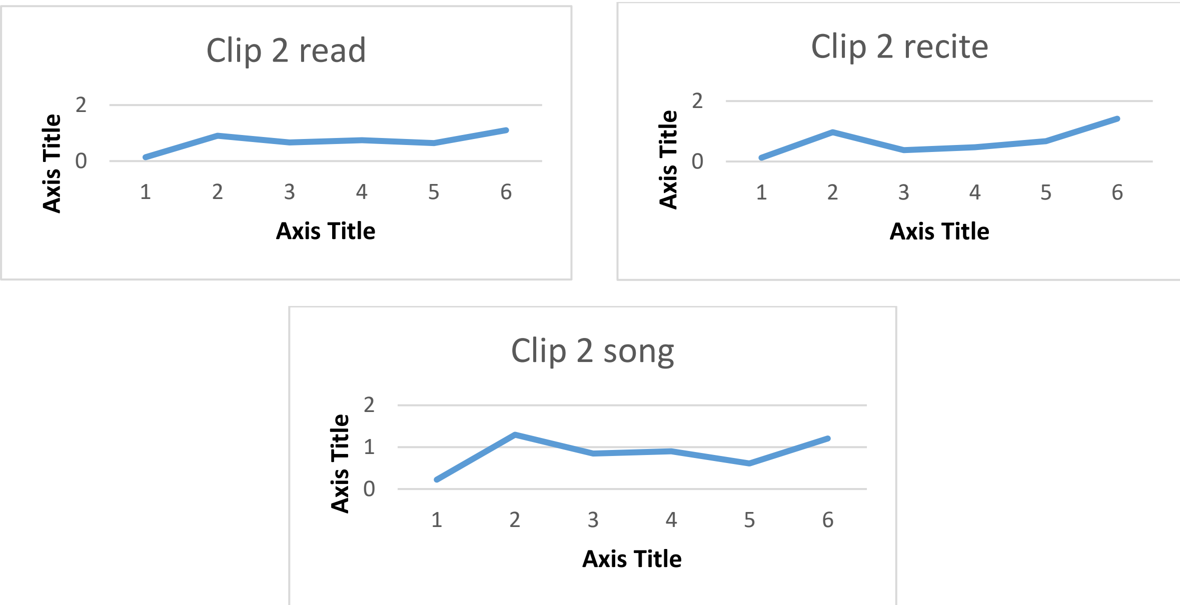


Fig. 9.1.3: Change in w-patterns for clip 2

Here, clip 2(Fig.9.1.3) shares similar patterns in reading and recitation but not in the song rendition.

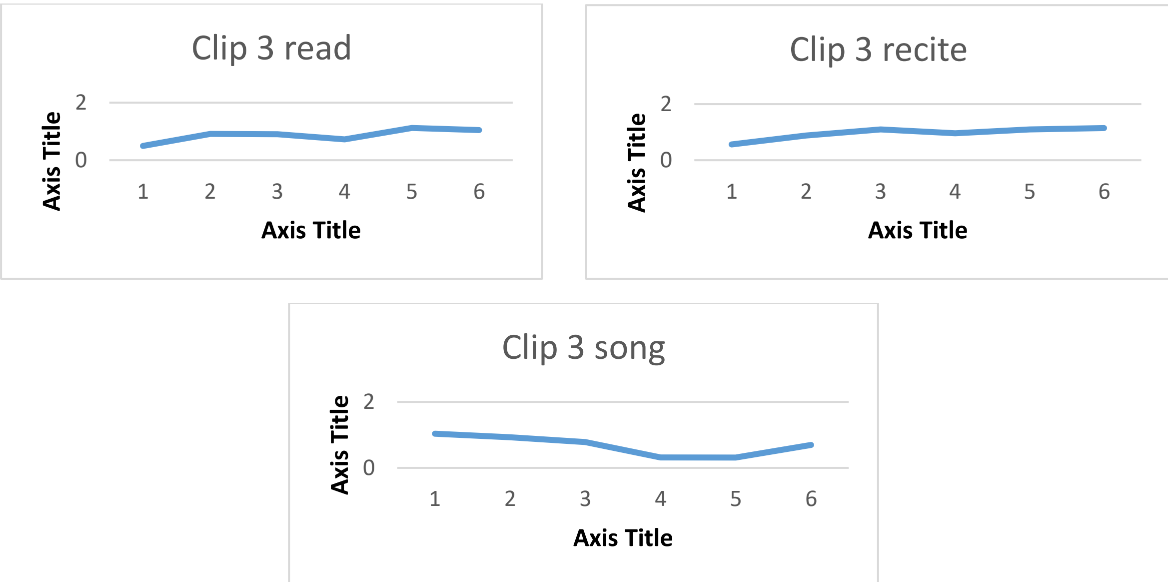


Fig.9.1.4: Change in w-patterns for clip 3

Now, for clip 3(Fig.1.4) also has distinctively dissimilar w changing patterns in song rendition than reading or recitation.

This indicates that the addition of melodic content in the song rendition tends to lower the long-range temporal correlations compared to reading or reciting modes.

9.3.2. Lobe-wise EEG Analyses of the Theta Range of brainwaves:

Let us now consider the lobe-wise variations observed for the theta range of brainwaves after performing EEG on the subjects with the 9 different clips as the stimuli. In the following figures, you will see the 'w' value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition. The clips are referred according to the following legend:

1. Item 1 speech
2. Item 1 recitation
3. Item 1 song
4. Item 2 speech
5. Item 2 recitation
6. Item 2 song
7. Item 3 speech
8. Item 3 recitation
9. Item 3 song

9.3.2.1 Frontal lobe:

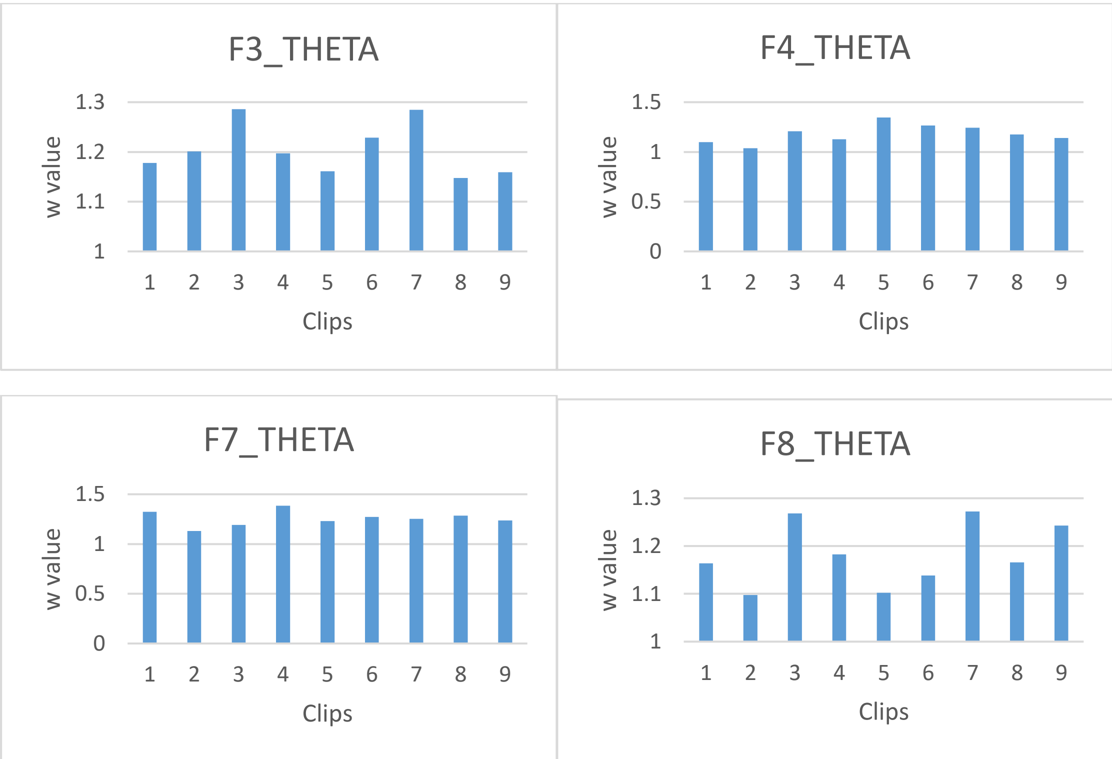


Figure 9.1.5: Lobe-wise variation for Frontal electrodes

From the above figures, we case that the variation in theta values of F3 and F8 are significantly more than that for F7 and F4. For the F3 electrode of the Frontal lobe, the 3rd and 7th clips show similar yet highest values of 'w' at 1.2859 and 1.2848. In case of F4, clip 5 produces the highest 'w' value of 1.345 although not much of variation was observed between the different clips. Similarly in case of F7, the

4th clip produces the maximum value of 1.3848, while in case of F8, both the 3rd and 7th clips again have similar albeit maximum value of 1.2685 and 1.2726 respectively. The lowest values were exhibited for F3 by the 8th clip with a value of 1.14735, for F4 by the 2nd clip with a value of 1.0375, for F7 by the 2nd clip with a value of 1.1295 and for F8 by the 2nd clip with a value of 1.0973. We also observe a trend between the F3 and F8 electrodes, where clips 3 and 7 have significantly higher values than that of the others. For the F7 electrode, we see that there is minimal variation among the clips for their complexity values.

9.3.2.2. Temporal Lobe:

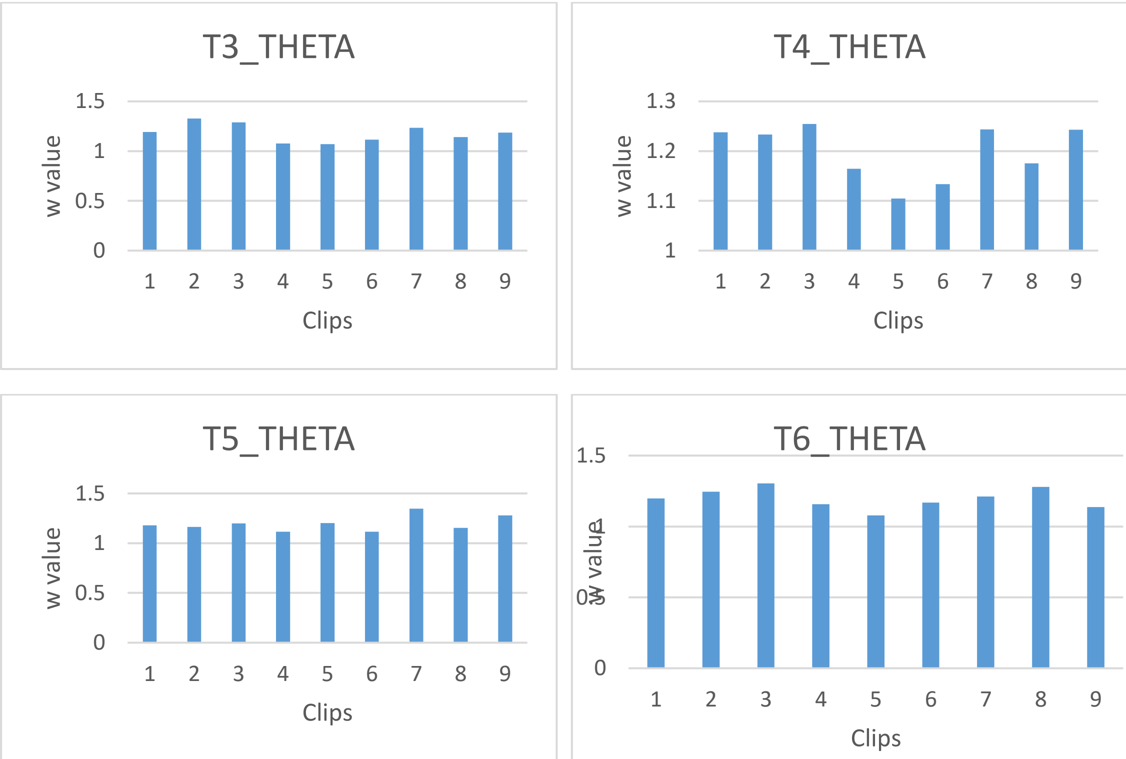


Figure 9.1.6: Lobe-wise variation for Temporal electrodes

From the above figures, we case that the variation in theta values T5 is significantly less than that of T3, T4 and T6. For the T3 electrode of the Temporal lobe, the 5th and 8th clips exhibit the highest values with 1.38462 and 1.38186 respectively. For T4, the 6th and 8th clips exhibit the highest values with 1.2916 and 1.2873 respectively. For T5, clip 3 exhibits the highest complexity with a value of 1.37344 while for T6, the 4th clip shows the highest value of 1.37345.

The variation between the highest and lowest values of complexity are similar in case of all 4 lobes, with the lowest values for T3 given by the 7th clip at 1.1601, for T4 by the 5th clip at 1.0888, for T5 by the 1st clip at 1.129 and for T6 by the 9th clip at 1.1667.

9.3.2.3. Occipital Lobe:

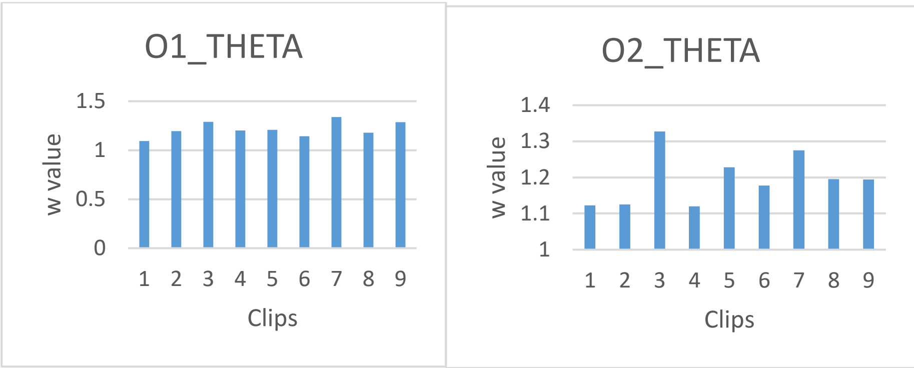


Figure 9.1.7: Lobe-wise variation for Occipital electrodes

In case of the occipital lobe, we are only considering the O1 and O2 electrodes. As you can see from the figure above, O2 exhibits greater variation between the clips than O1. The maximum complexity for O1 was observed by the 7th clip at a value of 1.338, and the 9th and 3rd clips with similar values. In case of O2 the maximum value is exhibited by the 3rd clip with a complexity value of 1.3272.

Once again with a similar maxima-minima variation, the lowest value for O1 is by the 1st clip with a value of 1.09207; and for O2 by the 4th clip with a complexity value of 1.119705.

9.3.2.4. Parietal lobe:

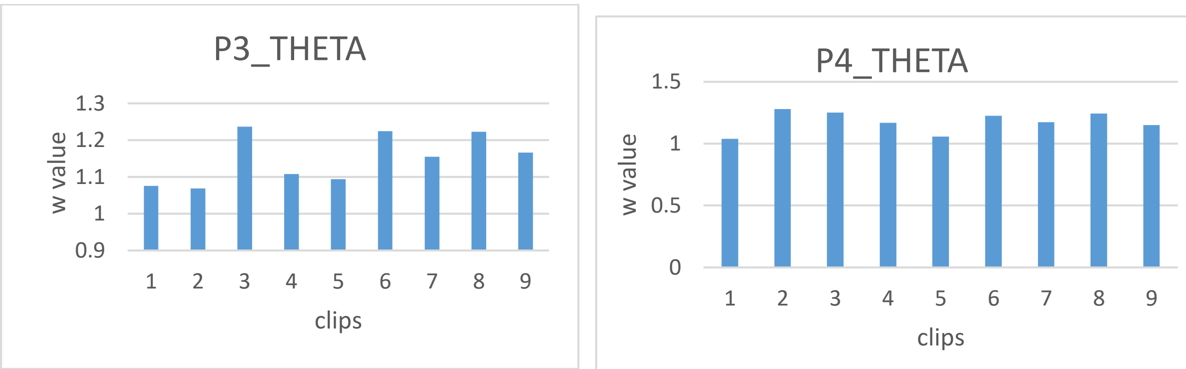


Figure 9.1.8: Lobe-wise variation for Parietal electrodes

In case of the parietal lobe, we are only considering the P3 and P4 electrodes. As we can see from the figure above P3 exhibits a greater variation between the clips than P4. The maximum complexity for P3 was observed by the third clip with a value of 1.2363 and the maximum value for P4 was observed by the second clip with a value of 1.27938.

Minimum value for P3 was observed by the 2nd clip with a value of 1.068 and the minimum value of P4 was observed by the 1st clip with a value of 1.03966.

9.3.3. Lobe-wise EEG Analyses of the Alpha Range of brainwaves:

Let us now consider the lobe-wise variations observed for the alpha range of brainwaves after performing EEG on the subjects with the 9 different clips as the stimuli. In the following figures, you will see the 'w' value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition. The clips are referred according to the following legend:

9.3.3.1. Frontal Lobe:

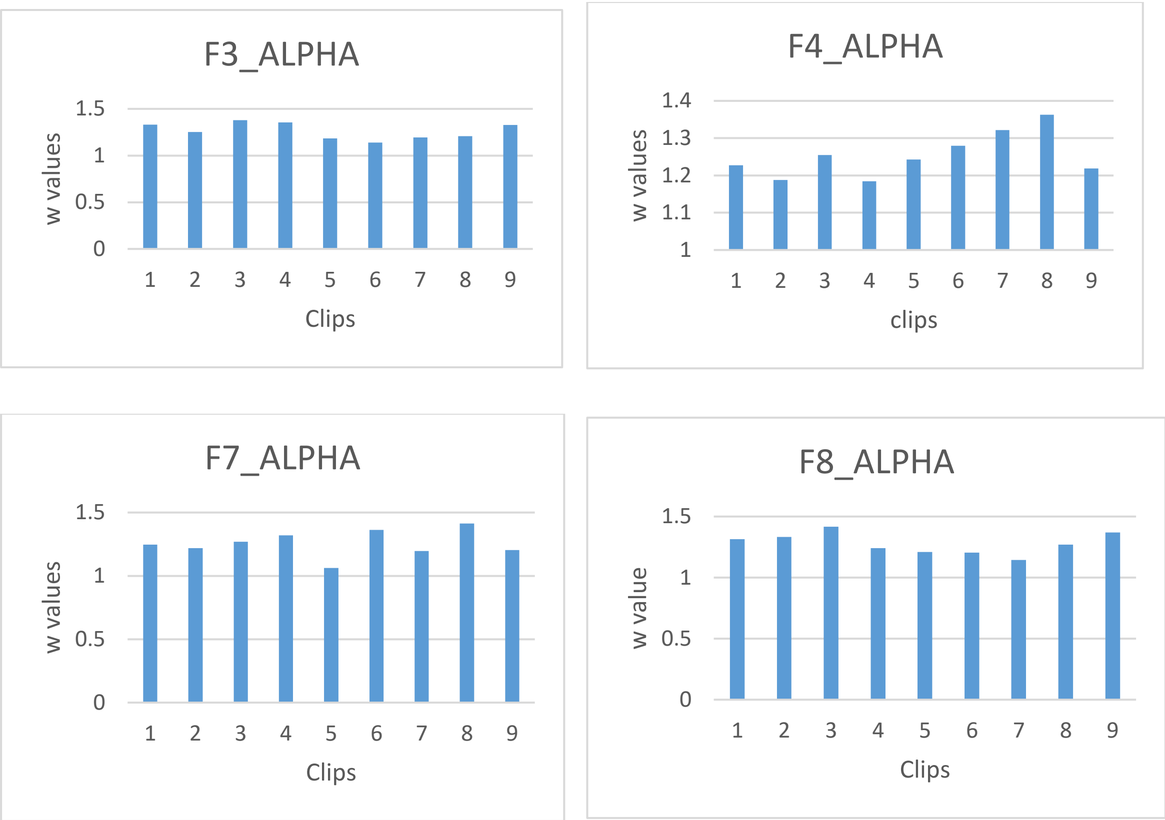


Figure 9.1.9: Lobe-wise variation for Frontal electrodes

From the above figures we see that in case of the Frontal lobes, variation is observed significantly more for the F4 electrode in comparison to the others. The maximum value of complexity for F3 is observed by the third clip with a value of 1.3779, although the fourth clip is very close behind at 1.35353. The maximum value of complexity for the F4 electrode is observed by the 8th clip with a value of 1.3628 while the maximum value of F7 is observed by the 8th clip again with the value of 1.41293. The maximum complexity for F8 is exhibited by the third clip with a value of 1.41590 with not much variation among the others.

The minimum value for F3 is observed by the 6th clip with the value of 1.1406 while the minimum value for F4 is observed by the 4th clip for the value of 1.1839. The minimum complexity for F7 is exhibited by the fifth clip with the value of 1.06365 and the minimum value of F8 is exhibited by the 7th clip with a value of 1.14303.

From the above figures we can see that in case of F7 the clip 5 has a remarkably a lower value of complexity in comparison to the other nine clips, and F4 exhibits the maximum variation in complexities of alpha waves.

9.3.3.2. Temporal Lobe:

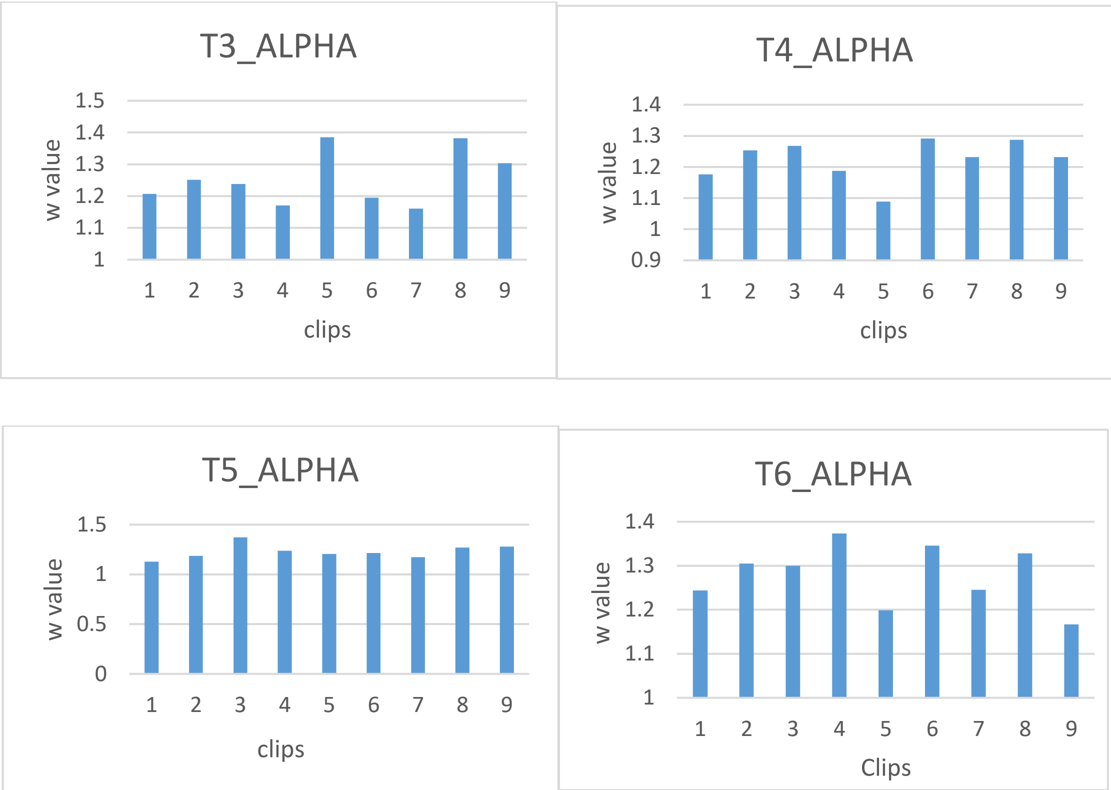


Figure 9.1.10: Lobe-wise variation for Temporal electrodes

In case of the temporal lobe, we see from the above figures that for the T3 electrode, the maximum value is exhibited by the fifth clip with a complexity of 1.3462. For the T4 electrode the maximum complexity value is observed by the 6th clip with 1.29160 while for the T5 electrode the 3rd clip exhibits the maximum complexity with the value of 1.37344. The 4th clip shows maximum complexity for T6 with a value of 1.37345.

The minimum value for the T3 electrode is exhibited by the 7th clip with a complexity of 1.16 while the fifth clip for T4 has the minimum of 1.088. The first clip exhibits the lowest for T5 electrode with a value of 1.1290 and for T6 the 9th clip exhibits lowest complexity of 1.166.

We observe in case of T3 that the fifth and eighth clips have significantly higher complexities in comparison to the other clips, while in case of T4 the opposite is opposite trend is observed, where the fifth clip as a significantly lower value compared to its other contemporary clips.

For T6, the 9th clip can be seen having a significantly lower value in comparison to the others, closely followed by the 5th clip which also has a lower value compared to the others. In case of T4 we can also see that the fifth clip has a lower value then the other clips.

9.3.3.3. Occipital Lobe:

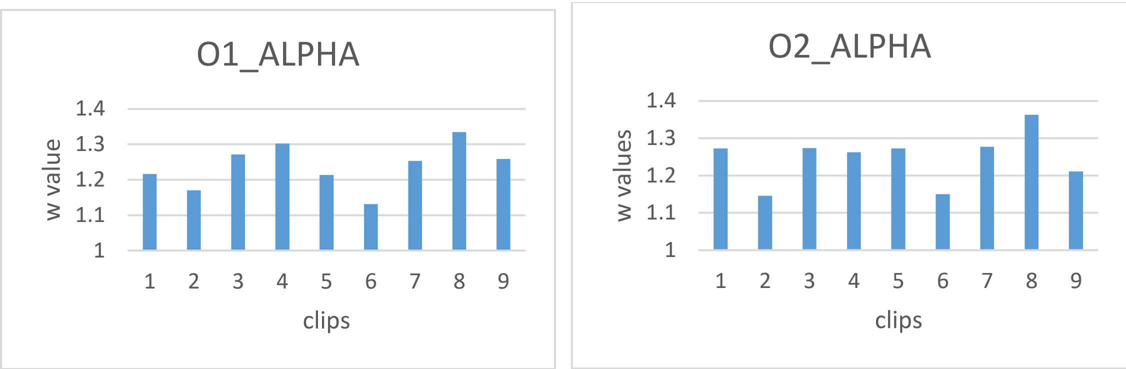


Figure 9.1.11: Lobe-wise variation for Occipital electrodes

For O1 electrode, it is observed that the 8th clip has a maximum value of 1.33477. For the O2 electrode we can see the maximum value is once again exhibited by the 8 clip with a complexity of 1.362399. The minimum for O1 is observed by the 6th clip with the complexity of 1.1314 and the minimum value for O2 electrode is observed by the second clip with 1.14539. For both the electrodes O1 and O2 we can see a trend where the 2nd and 6th clips have significantly lower values in comparison to the other clips. The 8th clip in both electrodes have higher values than its neighboring clips.

9.3.3.4. Parietal Lobe:

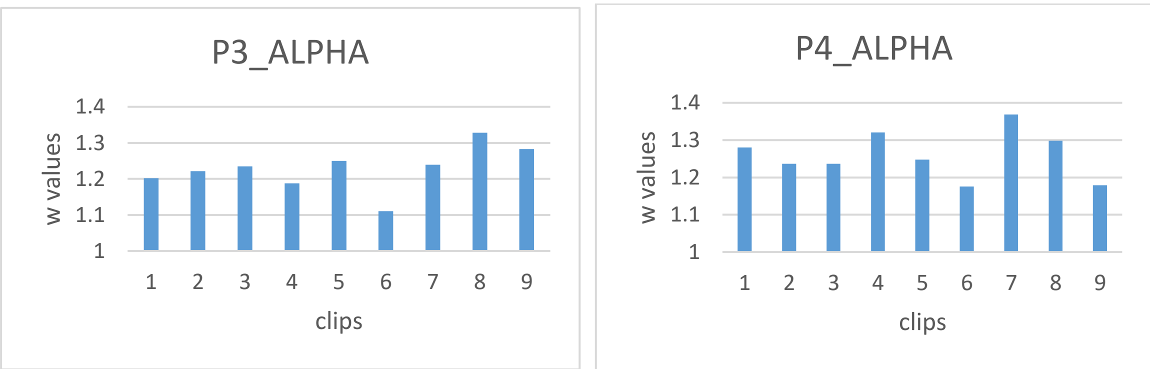


Figure 9.1.12: Lobe-wise variation for Parietal electrodes

We can see that the P3 electrode has a maximum complexity for the 8th clip at 1.32789 and P4 electrode has the maximum complexity for the seventh clip and 1.36859. The minimum values are given by the 6th clip for P3 electrode at 1.11022 and by the 6th clip again at a value of 1.17579.

We can also see that in case of both the P3 and P4 electrodes the 6th clip has a lower complexity when compared to the other clips and for the 9th clip we see a contrasting behaviour between the P3 and P4 electrode where for the 9th clip where it exhibits one of the highest values for P3 while for the P4, it is one of the lowest.

9.3.4. Prosodic-wise variation in each electrode for the three items:

Let us now consider the variation in cognitive engagement for the three different kinds of prosodies for all of the items. The X-axis represents the EEG electrodes, while the Y-axis represents the w values for complexity. The blue bars represents the complexity valued for theta range of brainwaves while the orange bars represent the complexity values for alpha waves.

9.3.4.1. Item 1:

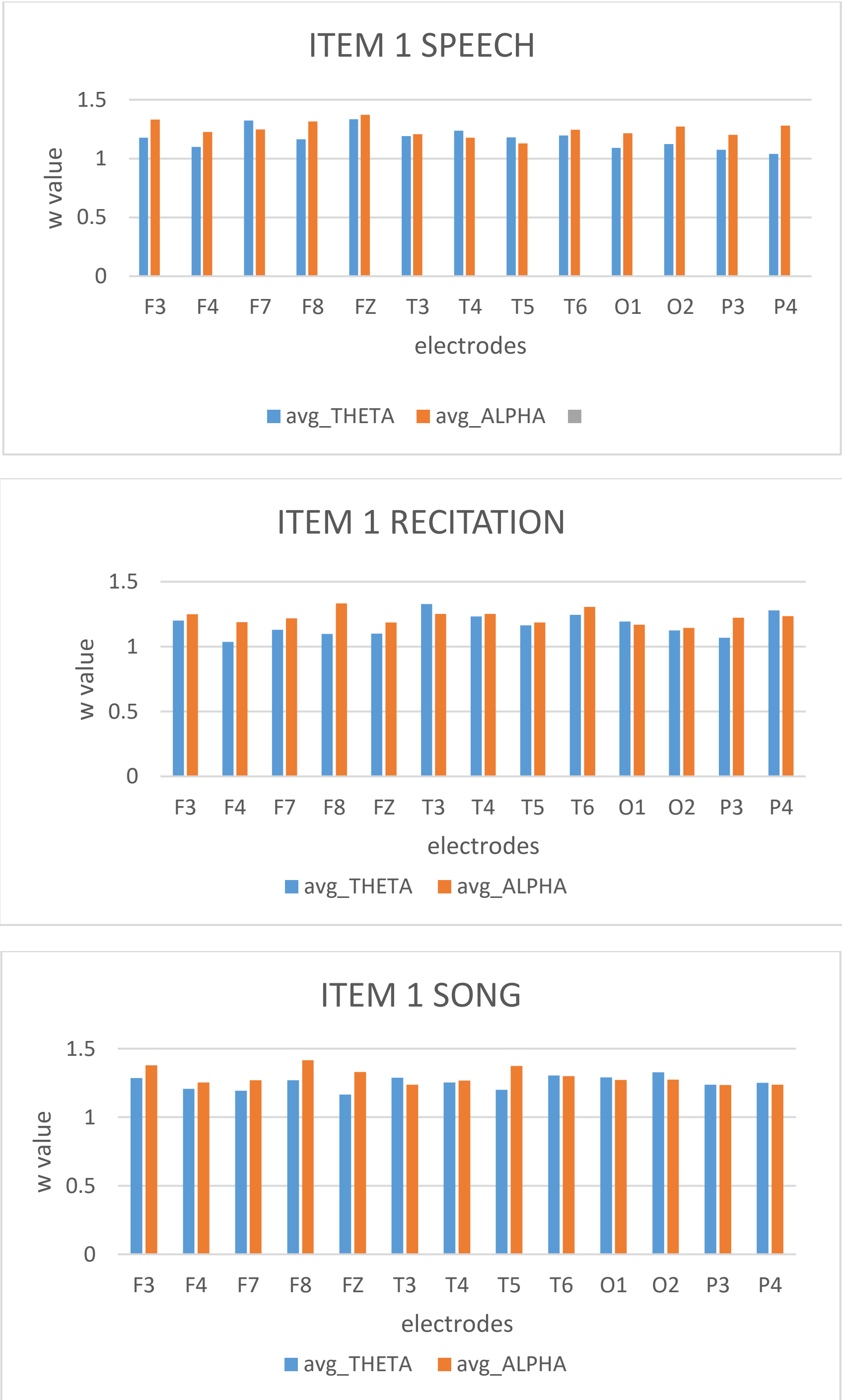


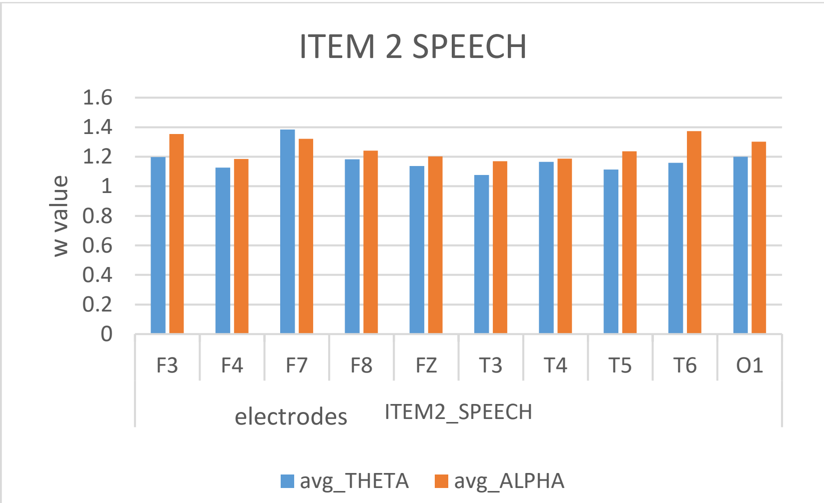
Figure 9.1.13: Prosodic-wise variation between the different electrodes for item 1

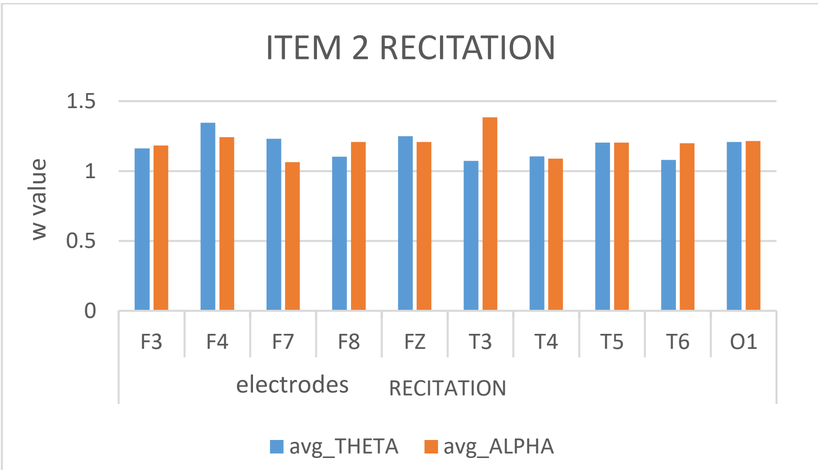
Here for the speech prosody we see in most cases that the alpha waves dominate over the theta waves. We see that the F3 electrode possesses the maximum value for alpha complexity at 1.33243, while the maximum theta complexity was observed for F7 at 1.32402. We see the minimum alpha activation in case of the T5 electrode at 1.29005, while a minimum theta value was observed for P4 at 1.03966.

In case of the recitation prosody we see a similar trend where the alpha waves have a greater value against the theta waves. The maximum complexity for alpha waves was observed by the F8 electrode with a value of 1.3324 and a maximum theta activation by the T3 electrode at 1.32825. The minimum alpha complexity was exhibited by the O2 electrode with a value of 1.14539 and a minimum theta value of 1.03759 by the F4 electrode.

For the song prosody, the most important takeaway is that there is an overall greater activation in all electrodes in comparison to the other two prosodies. The maximum alpha activation was observed in the F8 electrode with a value of 1.4159 and the maximum theta complexity was observed in the O2 electrode with a value of 1.32724. The minimum value of alpha activation was observed for P4 with a value of 1.23636 while for theta, it was the T5 electrode with a complexity of 1.19962. Again from the numerical values we can see that the song prosody has a greater cognitive engagement with the lowest values of theta and alpha coming in with a range of values higher than the other two prosodies.

9.3.4.2. Item 2:





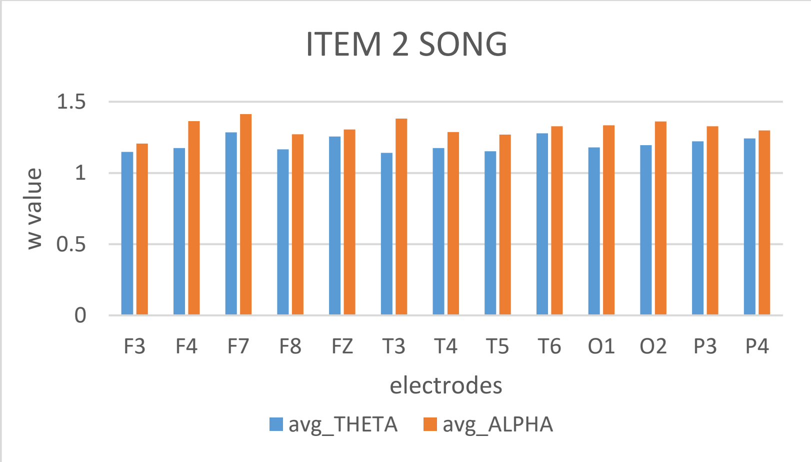


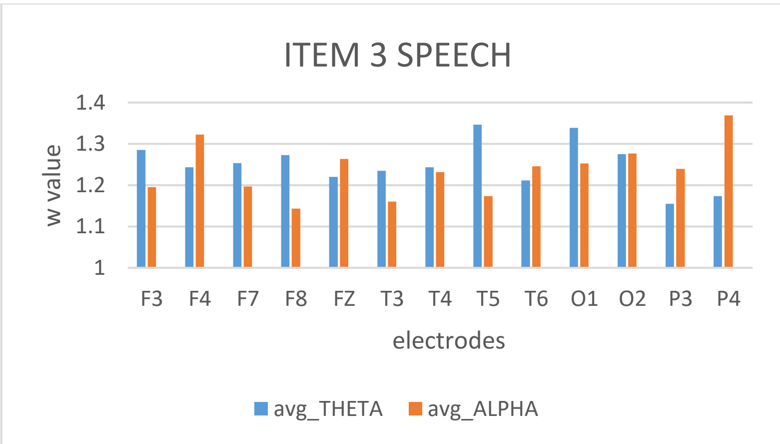
Figure 9.1.14: Prosodic-wise variation between the different electrodes for item 2

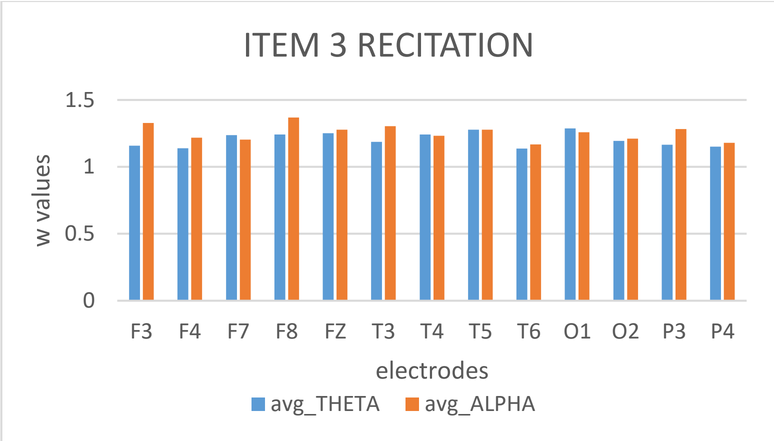
For the speech prosodic, we can see from the above figures that the T6 electrode exhibits the maximum value for alpha wave complexity at 1.37345, while F7 exhibits a maximum theta wave complexity of 1.38486. Meanwhile, the T3 electrode exhibits both the minimum values for alpha and theta engagement, at 1.17-3 and 1.07605 respectively.

In case of recitation we can see that there is a very ambiguous difference between theta and Alpha, wherein some electrodes exhibit a theta complexity dominating over alpha and the other way round in other electrodes. T3 electrode can be seen with a maximum Alpha complexity of 1.846 but a very low theta value of 1.0717. But in case of the F4 electrode we can see a maximum theta complexity of 1.24305.

For the song prosodic, a similar trend is observed by all the electrodes, having a generally higher complexity when compared to speech and recitation. The F7 electrode can be seen with a maximum alpha complexity of 1.4129 and maximum theta value of 1.2854.

9.3.4.3. Item 3:





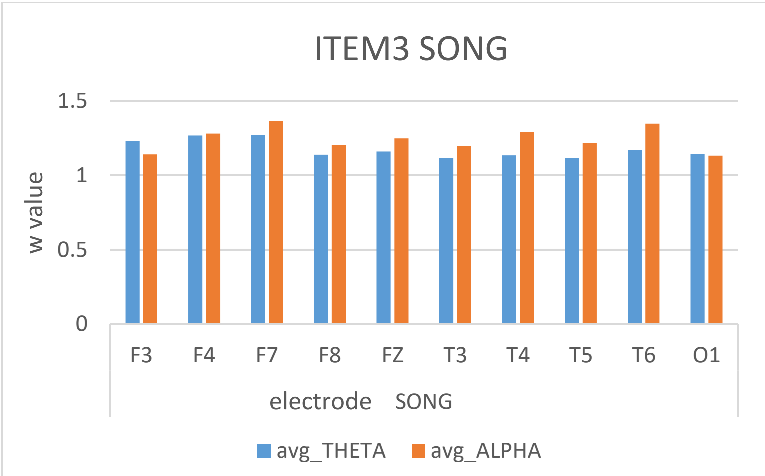


Figure 9.1.15: Prosodic-wise variation between the different electrodes for item 3

For the third item's speech prosodic, we see an incredibly high Alpha complexity for the P4 electrode with a value of 1.3685 and an incredibly high value of theta in case of T5 electrode with 1.3463. We can also observe that the O1 electrode also has in similar theta value of 1.3389, and a trend of both alpha and theta dominating over each other for different electrodes can be observed.

A case of recitation we can again see there is similar trend between the theta and Alpha values of all electrodes. The F8 electrode has a maximum alpha complexity value of 1.36829 while the O1 electrode has a maximum theta value of 1.28674. Interestingly in case of T5 electrode here we can see that both the theta and alpha have very similar values, albeit Alpha edging out theta by an extremely small margin.

In case of the song prosodic, we can see a similar range of values, mostly comparable to the other prosodic but Alpha here has a marginally greater than theta for most electrodes. We can see that the maximum values of theta were seen for the F4 and F7 electrodes where F7 possesses a maximum Alpha complexity of 1.3626 and maximum theta value of 1.2714.

9.3.5. Lobe-wise comparison between the three prosodies for theta waves:

Let us draw a comparison between the different lobes of the brain and the three different prosodies of our stimuli. The lobe-wise values were obtained by averaging the w complexities observed from every electrode of the F: Frontal, T: Temporal, O: Occipital, P: Parietal lobes and associating them with the letters. The blue bar refers to speech prosody, the orange refers to the recitation and grey to the song prosody.

9.3.5.1. Item 1:

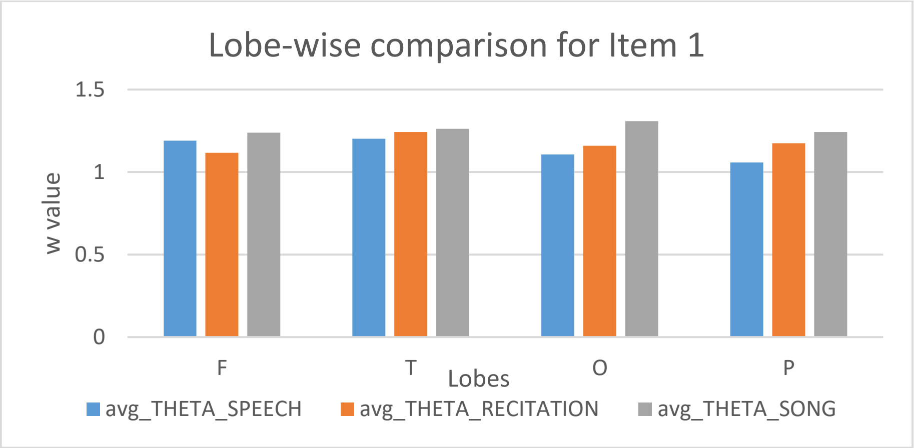


Figure 9.1.16: Lobe-wise variation between prosodies for Item 1

Here were can see that the song prosody has a greater w complexity in all of the lobes compared to the speech or recitation renditions. Except for the frontal lobe, the speech rendition exhibits the lowest level of engagement elsewhere and recitation subsequently the middle value. The occipital lobe exhibits the maximum w value for songs at 1.30845. The parietal lobe was observed to have the lowest value for speech at 1.05778, and the lowest value for recitation prosody was seen with the frontal lobe at 1.11638.

9.3.5.2. Item 2:

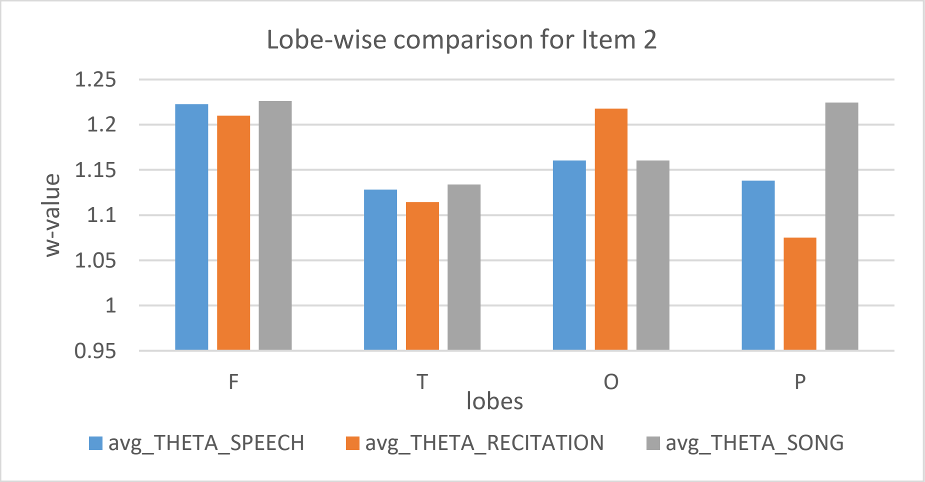


Figure 9.1.17: Lobe-wise variation between prosodies for Item 2

Here we can see that the complexity of the song prosodic dominates over the others in only the frontal temporal and parietal lobes, while in case of the frontal and temporal lobes the difference between that and the speech prosodic is very minimal. In case of the parietal lobe, we can see the maximum complexity for song is 1.2244 meanwhile for the frontal lobe the maximum value for the same is 1.2261.

We can also see that the overall activation for the temporal lobe is very low compared to the others and in case of the occipital lobe, recitation can be seen with the maximum complexity value of 1.2176. We can see also that the theta complexity of the speech prosodic is not the minimum for all of the all of the lobes, as was observed in case of the first item.

9.3.5.3. Item 3:

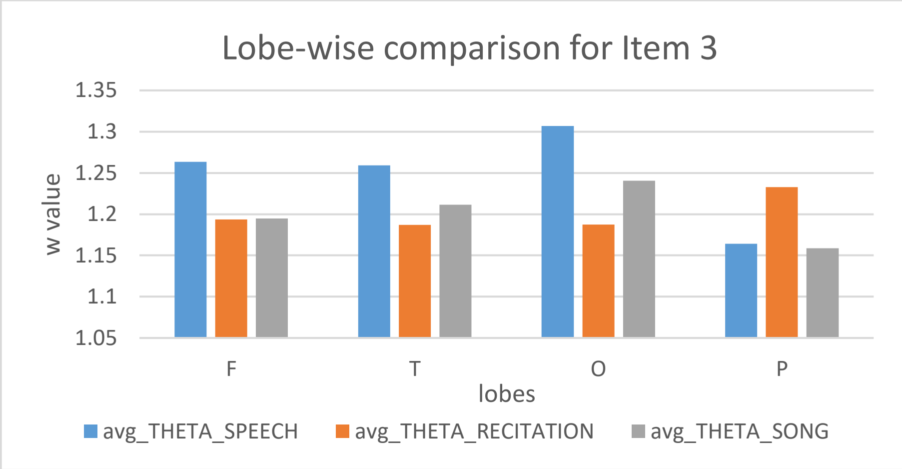


Figure 9.1.18: Lobe-wise variation between prosodies for Item 3

Here for the third item we see the maximum complexity for speech prosodic in the frontal, temporal and occipital lobes. In case of the parietal lobe, recitation exhibits the maximum complexity. In fact here we see that in most of the lobes the maximum complexity has been obtained by the speech prosodic only. For the frontal lobe, we can see that the recitation and song has a similar value of complexity while for the temporal lobe, although similar, the song slightly greater value. Interestingly we can also observe that in case of the parietal lobe, the speech and song have a similar value. The maximum complexity for speech was obtained by the occipital lobe with 1.3068 while the maximum value for recitation was observed for the parietal lobe with a value of 1.2328. The maximum complexity of the song was also observed for the occipital lobe with a value of 1.2406.

9.3.6. Lobe-wise comparison between the three prosodies for alpha waves:

Similarly as in case of theta waves, let us draw a comparison between the different lobes of the brain and the three different prosodies of our stimuli. The lobe-wise values were obtained by averaging the w complexities observed from every electrode of the F: Frontal, T: Temporal, O: Occipital, P: Parietal lobes and associating them with the letters. The blue bar refers to speech prosody, the orange refers to the recitation and grey to the song prosody.

9.3.6.1. Item 1:

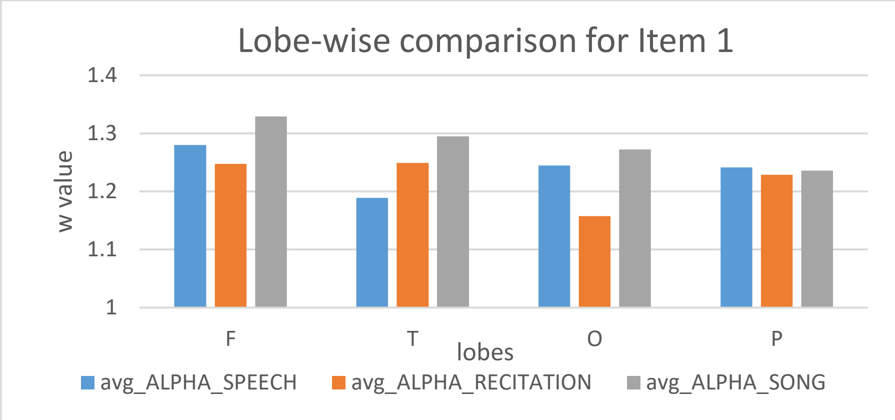


Figure 9.1.19: Lobe-wise variation between prosodies for Item 1

In a similar fashion to the theta waves, we see that the song prosodic have a higher complexity for the frontal, temporal and occipital lobes, but not for the parietal lobe for alpha wave complexity. Similarly, the speech also has a higher complexity for the frontal, occipital and parietal lobes, but not for the temporal lobe. The maximum activation can be observed for the song prosodic in the frontal lobe, with a complexity value of 1.32922 as well as the maximum activation for speech. The temporal lobe exhibited the maximum recitation value of 1.24895 albeit with frontal and parietal having very similar margins.

9.3.6.2. Item 2:

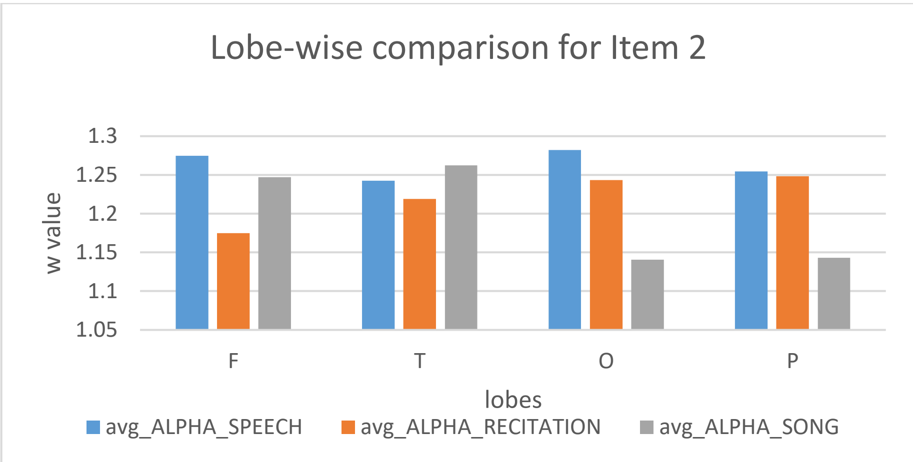


Figure 9.1.20: Lobe-wise variation between prosodies for Item 2

In case of the 2nd Item, we see a significantly low song rendition activation for both the occipital and parietal lobes, a drastic change in trend. The maximum value is observed in the temporal lobe with a complexity of 1.2622, but the maximum overall activation was observed for speech in the occipital lobe with a complexity value of 1.28200. The parietal lobe showed the maximum complexity for recitation, at 1.24846.

9.3.6.3. Item 3:

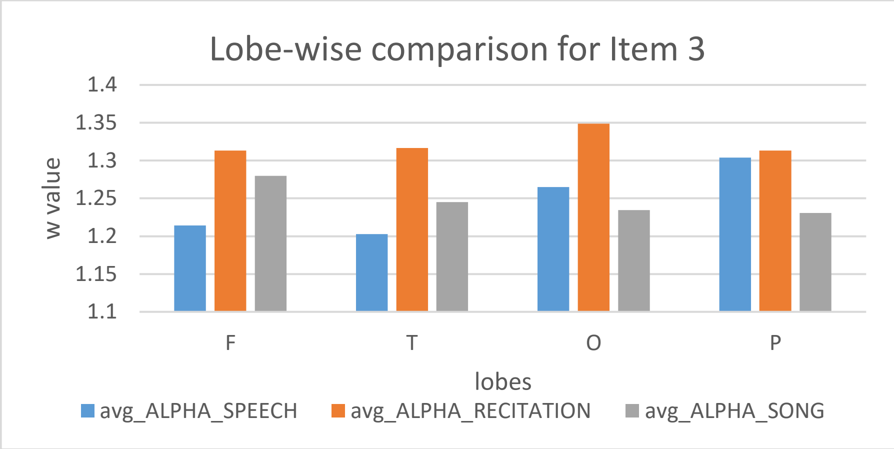


Figure 9.1.21: Lobe-wise variation between prosodies for Item 3

In a complete sway of trends, recitation was observed to provide the most cognitive engagement for all the lobes, with the occipital lobe exhibiting a value of 1.34858. Meanwhile, the parietal lobe showed the maximum value for speech at 1.30387, while the frontal lobe showed the maximum value of complexity for song prosodic at 1.2797.

9.4 Conclusion

In our conclusive experiment, the objective was to analyze the effect of prosody or renditions in the level of cognitive engagements observed in the human mind, and an analysis of the subsequent human emotions. We employed the tried and tested algorithm of Multifractal Detrended Fluctuation Analysis (MFDFA), a scientific approach used to understand the intricacies of non-linear and complex systems and their long range correlations, to examine alterations in brain activity. Our study findings have yielded significant understanding of the intricate links between auditory stimuli and the emotional processing in the brain. We identified unique brain activity patterns in different regions of the human brain, suggesting the impact of diverse emotional states.

Our experiment involved in the usage of stimuli with three different prosodies, speech, recitation and song, of the same three pieces, and then performed a graphical analysis of the cognitive engagement based on the multifractal width (w) obtained from EEG readings. The study includes variation distributions in item-wise as well as lobe-wise configurations, so as to understand the complete purview of the experiment.

Now, we know that with a higher complexity or a higher ‘w’ value, one can expect a higher level of cognitive engagement. In fact, we can see that the recitation prosodies for the 1st and 3rd items in this experiment have the highest level of complexity, thus with the most amount of variations in frequencies and elements in the audio clip.

Considering how alpha waves refer to a focused state of mind and theta refer to a more subconscious state, from the experiments it was observed that for all sorts of stimuli, both alpha and theta waves were present, albeit to varying values. In some cases alpha was found to be dominating over theta while in other cases it was observed to be the other way around. For songs, it was seen that theta was more prominent, but with an overall greater level of w values in comparison to the speech and recitation prosodies. Meanwhile, to reinstate our findings, alpha wave complexity were seen to be especially more in case of the speech and recitations, with the same being corroborated from our electrode-wise analyses. It was seen that if considered on an overall level, the w complexity of songs were of a greater range of values than it was for recitation and speech, indicating a generally higher level of engagement.

The temporal and frontal lobes were mostly found to be comparable in values, with in some cases the former dominating in activation over the other, indicating a region activation in both the lobes for all the stimuli. Interestingly, the theta activation for the temporal lobe was observed to be relatively lesser for item 2, signifying a lesser cognitive engagement for audio stimuli for audio such as these. The parietal lobe exhibited maximum theta engagement in case of songs.

Thus it has been established that the cognitive engagement of the human mind with respect to the prosodies is the maximum when songs are the stimuli. In addition to that, we can also see that the mind starts to focus more when a song is played in the rendition of a speech or recitation, while it tends to relax more when the song is played.

9.5 References:

[1] Sreeja, P. S., and G. S. Mahalakshmi. "Perc-an emotion recognition corpus for cognitive poems." *2019 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2019.

[2] Kang, Jin-Ae, Sookyeong Hong, and Glenn T. Hubbard. "The role of storytelling in advertising: Consumer emotion, narrative engagement level, and word-of-mouth intention." *Journal of Consumer Behaviour* 19.1 (2020): 47-56.

[3] Cummins, Fred. "The territory between speech and song: A joint speech perspective." *Music Perception* 37.4 (2020): 347-358.

[4] Johnson-Laird, Philip N., and Keith Oatley. "How poetry evokes emotions." *Acta Psychologica* 224 (2022): 103506.

[5] Freeman, Margaret H. *The poem as icon: A study in aesthetic cognition*. Oxford University Press, 2020.

[6] Farsi, Roghayeh. "Cognitive appraisal and coping in poetry." *Journal of Narrative and Language Studies* 9.18 (2021): 339-356.

[7] Russo, Frank A. "Motor system involvement in the perception of singing." *The Routledge companion to interdisciplinary studies in singing*. Routledge, 2020. 276-288.

[8] Howlin, Claire, Alison Stapleton, and Brendan Rooney. "Tune out pain: Agency and active engagement predict decreases in pain intensity after music listening." *PloS one* 17.8 (2022): e0271329.

[9] Cross, Emily S., et al. "A neurocognitive investigation of the impact of socializing with a robot on empathy for pain." *Philosophical Transactions of the Royal Society B* 374.1771 (2019): 20180034.

[10] Jaquess, Kyle J., et al. "Self-controlled practice to achieve neuro-cognitive engagement: Underlying brain processes to enhance cognitive-motor learning and performance." *Journal of Motor Behavior* 52.5 (2020): 544-557.

[11] Zmigrod, Leor. "A neurocognitive model of ideological thinking." *Politics and the Life Sciences* 40.2 (2021): 224-238.

[12] Casillo, Stephanie M., Diego D. Luy, and Ezequiel Goldschmidt. "A history of the lobes of the brain." *World Neurosurgery* 134 (2020): 353-360.

[13] Leblanc, Richard. "Pavlov, Penfield, and the physiology of the mind." *Neurology* 92.12 (2019): 575-578.

[14] Hu, Li, and Zhiguo Zhang, eds. *EEG signal processing and feature extraction*. Singapore: Springer Singapore, 2019.

[15] Martínez, Jorge Luis Morales, et al. "A modified multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation." *Physica A: Statistical Mechanics and its Applications* 565 (2021): 125611.

[16] Gorjão, Leonardo Rydin, et al. "MFDFA: Efficient multifractal detrended fluctuation analysis in python." *Computer Physics Communications* 273 (2022): 108254.

[17] David, Sergio Adriani, et al. "A combined measure to differentiate EEG signals using fractal dimension and MFDFA-Hurst." *Communications in Nonlinear Science and Numerical Simulation* 84 (2020): 105170.

[18] Sarkar, Uddalok, et al. "Language Independent Emotion Quantification using Non linear Modelling of Speech." *arXiv preprint arXiv:2102.06003* (2021).

[19] Avramidis, Kleanthis, et al. "Multiscale fractal analysis on EEG signals for music-induced emotion recognition." *2021 29th European Signal Processing Conference (EUSIPCO)*. IEEE, 2021.

[20] Banerjee, Archi, et al. "A novel study on perception–cognition scenario in music using deterministic and non-deterministic approach." *Physica A: Statistical Mechanics and its Applications* 567 (2021): 125682.

[21] Basu, Medha, et al. "Does musical training affect neuro-cognition of emotions? An EEG study with Indian Classical Instrumental Music." *Proceedings of Meetings on Acoustics 182ASA*. Vol. 46. No. 1. Acoustical Society of America, 2022.

[22] Scheuber, Sephra H. *Emotional and neurological responses to timbre*. University of Central Oklahoma, 2019.

[23] Zhang, Rui, Cairang Jia, and Jian Wang. "Text emotion classification system based on multifractal methods." *Chaos, Solitons & Fractals* 156 (2022): 111867.

[24] Basu, Medha, et al. "Neural Quantification of Timbre and Emotions from Indian Classical Music a Multifractal Exploration." *Available at SSRN 4374657*.

[25] Ahirwal, Mitul Kumar, and Mangesh Ramaji Kose. "Audio-visual stimulation based emotion classification by correlated EEG channels." *Health and Technology* 10.1 (2020): 7-23.

[26] Feradov, Firgan, Iosif Mporas, and Todor Ganchev. "Evaluation of features in detection of dislike responses to audio–visual stimuli from EEG signals." *Computers* 9.2 (2020): 33.

[27] DAŞDEMİR, YAŞAR, and RÜSTEM ÖZAKAR. "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning." *Turkish Journal of Electrical Engineering and Computer Sciences* 30.7 (2022): 2707-2724.

[28] Rodriguez-Larios, Julio, et al. "From thoughtless awareness to effortful cognition: alpha-theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic." *Scientific Reports* 10.1 (2020): 1-11.

[29] Lin, Sen, et al. "A flexible, robust, and gel-free electroencephalogram electrode for noninvasive brain-computer interfaces." *Nano letters* 19.10 (2019): 6853-6861.

[30] Yean, Choong Wen, et al. "Emotional states analyze from scaling properties of EEG signals using hurst exponent for stroke and normal groups." *Intelligent Manufacturing and Mechatronics: Proceedings of the 2nd Symposium on Intelligent Manufacturing and Mechatronics–SympoSIMM 2019, 8 July 2019, Melaka, Malaysia*. Springer Singapore, 2020.

[31] Shrestha, Badri, and Louese Dunn. "The declaration of Helsinki on medical research involving human subjects: a review of seventh revision." *Journal of Nepal Health Research Council* 17.4 (2019): 548-552.

[32] Farrens, Jaclyn L., et al. "Electroencephalogram (EEG) recording protocol for cognitive and affective human neuroscience research." (2021).

[33] Dilena, Robertino, et al. "Consensus protocol for EEG and amplitude-integrated EEG assessment and monitoring in neonates." *Clinical Neurophysiology* 132.4 (2021): 886-903.

CHAPTER 10

SPEECH-RECITATION-SONG: ACOUSTICAL & COLOUR-BASED NEURO-COGNITIVE EXPLORATION USING NONLINEAR APPROACH

"Professional musicians, in general, possess what most of us would regard as remarkable powers of musical imagery. Many composers, indeed, do not compose initially or entirely at an instrument but in their minds"

Oliver Sacks

10.1 Introduction:

In the world of poetry, art, and music, the power of words goes beyond simple linguistic communication and extends to the realms of emotion and thinking [1]. This research investigates the acoustic and neurocognitive aspects of variations in prosody between different works of Rabindranath Tagore, one of Bengal's most revered and well-known poets. Tagore's works have had a lasting impact on literature, captivating readers with his profound verses in multiple languages, and he is rightly regarded as one of the greatest poets of his time, if not of all time. Our study is not limited to any specific time frame; instead, we focus only on three different compositions by Tagore, each with distinct prosodic renditions.

The main objective of this study is to examine the differences in cognitive engagement elicited by these different renditions [2]. Our stimuli consist of three compositions by the same poet, using the same syntax and semantics but employing three different forms of prosody: the same piece is presented as a speech, a recitation, and a song [3]. Additionally, the stimuli include the association of matching and contrasting colours based on previous research. By analysing the impact of these audio clips and their colour associations on cognitive engagement and subsequent effects on human emotions, we aim to uncover the intricate relationship between different renditions, colours, and human cognition [4-6].

This study aims to analyse the correlation between different prosodies when accompanied by matching or contrasting colours. In doing so, we can draw conclusions about how both colours and prosodies can influence the neurocognitive engagement of the human mind [7-9], establishing a qualitative-to-quantitative relationship between the two. Previous researches have already shown that cognitive engagement tends to be higher in singing renditions [10-11], further justifying the need for our research.

We seek to explore the neurocognitive processes associated with the emotions evoked by the stimuli, measuring cognitive engagement from a biophysical perspective [12-13]. Our goal is to non-linearly measure and analyse changes in different lobes of the human brain that are influenced by these stimuli. To achieve this, we employed Electroencephalography (EEG) [14], a technique that records electrical activity in the brain. Our analysis focuses on four specific lobes: the frontal, temporal, occipital, and parietal lobes. By utilizing EEG, we can examine the patterns of responses associated with these cognitive engagements.

The analysis of EEG readings from the mentioned lobes follows a non-linear approach using Multifractal Detrended Fluctuation Analysis (MFDFA), a proven algorithm for studying non-linear complex systems. This technique allows us to analyse the intricate complexities of the brain's response to the stimuli presented during the recitation of various poems and their colour associations [15-19].

The primary analytical tool used in this study to assess changes in cognitive engagement is the Multifractal Width (w) of the stimuli (audio clips) and the recorded EEG brain waves [20-22]. Through this parameter, we can conduct neurocognitive analyses to quantify and compare the multifractality of the aforementioned cognitive patterns [23-24].

To ensure a comprehensive analysis, we aim to establish a connection between the subjective assessments of human emotions and the technical analysis of the same. This parallel evaluation will enable us to bridge the subjective nature of human perception with objective scientific measurements, ultimately enhancing our understanding of the neurocognitive effects of art, colour, and literature.

9.2 Experimental Details:

9.2.1 Methodology:

Understanding the human brain's response to different stimuli is fundamental to cognitive and neuroscience analysis and research. As discussed earlier, this paper aims to study the brain activity of subjects by exposing the individuals to various audio and visual stimuli while recording that data using Electroencephalography (EEG) [25-27]. EEG is a popular non-invasive technique that can measure and record the electrical activity of the brain. It can provide valuable information about cognitive processes and brain functioning by capturing brain wave patterns. During an EEG recording, there are multiple brain waves that can be observed. These brain waves represent different patterns of electrical activity in the brain and can be categorized based on their frequency ranges which are- Delta waves (0.5-4 Hz), Theta waves (4-7 Hz), Alpha waves (8-12 Hz), Beta waves (12-30 Hz) and Gamma waves (30-100 Hz) [28].

Alpha waves are associated with relaxed wakefulness and a calm state of mind. They are usually observed when individuals close their eyes or meditate. Additionally, Theta waves are prominent during periods of deep relaxation, meditation, and early stages of sleep. They are linked to creativity, memory formation, and deep emotional states.
Here, our focus is going to be analysing Alpha and Theta waves because these states comprise the brain activity during calm, non-aroused, and alert states of mind, and thus can provide insights into cognitive processes and emotional states.

To accomplish our goal, we have used a 19-10 electrode cap to record data, this cap is specifically designed for EEG purposes. It consists of 13 electrodes that are strategically placed on the different lobes of our brain [29].

1. Frontal Lobe: The frontal lobe plays a crucial role in decision-making, executive functions, problem-solving, and cognitive control. Electrodes placed on the frontal lobes will capture brain activity associated with these processes, thus allowing researchers to examine cognitive states during stimulus exposure. 4 electrodes were placed in this particular region namely- F3, F4, F7 and F8.

2. Parietal Lobe: The parietal lobe plays a pivotal role in various sensory integration processes, spatial awareness, attention, and perception. Electrodes placed on the parietal lobes enable the monitoring of brain activity associated with the attentional allocation and the integration of various visual and auditory stimuli. We placed 2 electrodes in this particular region namely- P3 and P4.
3. Occipital Lobe: The occipital lobe is mainly responsible for visual processing and perception. Electrodes placed on the occipital lobe capture brain activity associated with visual stimuli, allowing researchers to study visual perception and processing during stimulus exposure. 2 electrodes were placed in this particular region namely- O1 and O2.

4. Temporal Lobe: The temporal lobe plays a major role in auditory processing, language understanding, and memory functions. Electrodes placed on the temporal lobe enable the study of auditory perception, language-related processes, and memory formation during the presentation of audio stimuli. We placed 4 electrodes in this particular region namely- T3, T4, T5 and T6 [13].

The acquired EEG data of two separate frequencies (alpha and theta) from the subject are to be processed and analysed using a mathematical non-linear analysis technique called MFDFA (Multifractal Detrended Fluctuation Analysis).This method is specifically designed to understand the complex nature of EEG signals by evaluating their fractal properties (self-similarities) and long-range correlations.

The technique involves several steps- detrending: the data is detrended to remove any present patterns, fluctuation calculation: fluctuations in segments of varying lengths is calculated, scaling analysis: analysis of the fluctuations and lastly the exponent calculation: giving the degree of self-similarity. Using the fluctuation function obtained from the MFDFA algorithm, Hurst exponent (H) is also calculated. It helps to quantify the degree of self-similarity or self-affinity present in the given data. The value of H has different interpretations: H> 0.5 -indicates a persistent or positively correlated time series (having long term trends), H= 0.5- indicates uncorrelated time series (random or no trend) and H < 0.5- indicates an anti-persistent or negatively correlated time series (oscillatory trend) [30].

9.2.2 Stimuli Details:

We have carefully chosen three poems by well-known poet Rabindranath Tagore who have made significant contributions to Bengali literature over the past years as part of our research. These poems are a rich and diverse representation of the literary heritage of the Bengali language. Segments from each of these three poems were extracted and used to create a controlled stimulus for our study, ensuring that each segment is approximately 30-35 seconds long. These poems are then used in the stimuli where the syntax as well as semantics are kept same but changes are made in the prosodic. To be clear, the same poem is played three times to the subject- once in the form of speech, recitation and as a song. These meticulously curated snippets allow us to maintain consistency and precision in our experimental design while also capturing the essence and emotional depth of the original poems.

Here are brief descriptions of the poems that were used as stimuli:

Clip 1: ‘Amar praner pore chole gelo k’: This writing expresses a deep sense of longing, heartbreak, and unanswered questions. This extract is of the category (parjaay) ‘Prem’. It is composed in the Taal ‘Ar-khemta’, Raag is ‘Pilu-Kalingara-Paraj-Kirtan’ and Anga is ‘kirtan’. This was written in 1883. In this clip, the prosodic followed is speech.

Clip 2: ‘Amar praner pore chole gelo k’: The prosodic followed is recitation.

Clip 3: ‘Amar praner pore chole gelo k’- The prosodic followed is Song

Clip 4: ‘Hare rere rere amay chhere de re’: This is a very moving piece where the writer expresses a longing for freedom and liberation from restrictive circumstances. Few notable composition details are: category (parjaay)- Bichitro, Taal is ‘Ektaal’ and Raag is ‘Iman-Bhupali’. It was written in 1907. The prosodic followed here is speech.

Clip 5: ‘Hare rere rere amay chhere de re’: The prosodic followed is recitation.

Clip 6: ‘Hare rere rere amay chhere de re’: The prosodic followed is song.

Clip 7: ‘Sankochero bihwalata nijere apomaan’: This excerpt explores the internal conflict and self-doubt that arises when someone feels a sense of shame or humiliation. Details of the composition of the clip are: category (parjaay) ‘Swadesh’, Taal is ‘Dadra’, Raag is ‘Iman-Kalyan’, written in the year of 1930. The prosodic followed is speech.

Clip 8: ‘Sankochero bihwalata nijere apomaan’- The prosodic followed is recitation

Clip 9: ‘Sankochero bihwalata nijere apomaan’- The prosodic followed is song.

Henceforth the audio clips will be referred to as Clip along with their respective number to maintain consistency and for easy understanding.

Now we are introducing more visual stimuli in this experiment. It has been found out through various studies that colors can invoke emotions as well. Specific colors are responsible for invoking specific emotions in human beings. We have tried to implement this idea while preparing the stimuli. We have obtained a set of emotions corresponding to individual clips, using these emotions we have found out the color that is invoked by these emotions. These colors are in the standardized RGB format. Now two sets of color schemes are to be formulated. One being the Matching Colors and another being Contrasting Colors [31-32].

Matching Colors- In this scheme, during the 25 seconds of silence we are prompting a color on the screen. This is not just any color but the color which corresponds to the emotion that will be invoked by the following audio clip.

Contrasting Colors- in this scheme, like the previous one during the 25 seconds of silence we are prompting a color on the screen. This time this color is a contrasting color corresponding to the emotion that will be invoked by the following clip. We have found out the matching color and using other studies transformed the matching color into a contrasting one.

These colors are displayed before all the 9 clips once for obtaining the results for the matching set and once for obtaining the results for the contrasting set.

Clip Number	Matching Color	Contrasting Color
1	G	R
2	B	R
3	R	B
4	G	R
5	B	R
6	B	R
7	B	R
8	R	G
9	R	B

Table 10.1: Color Distribution for clips

10.2.3 Participant Details:

A total of 10 individuals between the ages of 18 and 23 participated in this experiment to provide us with EEG recordings. Participants were reached out individually from personal contacts and word-of-mouth. All the participants were requested to provide their consent prior to the involvement in this study. To ensure the privacy and confidentiality of each of the participants, unique identification number were assigned to them, and their personal information was hidden and securely stored separately from the research data[33].

The participants consisted of young adults, comprising of both males and females. Each participant reported having right-handed dominance, indicating a right-handed preference. All participants had normal visual ability, with a vision of 6/6, indicating normal or optimal vision. Participants reported having proper hearing ability. Participants did not disclose any prevailing medical conditions that could potentially influence their responses or impact the validity of the study. It is worth mentioning that the participants were of sound body and mind, indicating that they were in good overall physical and mental health. This ensured that the data collected and later on the analysis was not disturbed by any underlying health issues that could influence the results.

To look after the safety and well-being of the participants, the experiments were conducted with proper precautions and following the ethical guidelines. All participants provided informed consent, indicating their voluntary involvement. Their consent was obtained prior to their engagement.

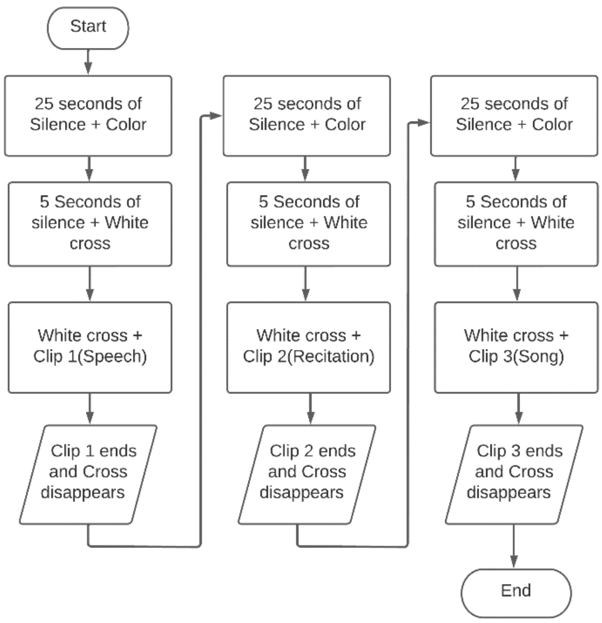
10.2.4 Protocol and Data Recording:

We began the process of capturing EEG recordings from the subjects following a standardized and uniform protocol while collecting human responses, to ensure consistency and reliability, each subject underwent the EEG procedure in the same way. The aim of this approach was to establish a solid foundation for data analysis and interpretation. During the EEG sessions, electrodes were carefully placed in specific locations on the participants' scalps, following the international 10-20 system for electrode placement. This systematic approach ensured comprehensive data collection by allowing us to capture electrical activity from multiple regions of the brain simultaneously after the EEG recordings were obtained, the next step was to extract relevant data for further analysis. To extract meaningful insights from the collected EEG data, we used a computational technique known as Multifractal Detrended Fluctuation Analysis (MFDFA)[16]. This method enabled us to investigate the complex temporal patterns and fluctuations within the EEG signals.

The nine audio clips were arranged in a particular manner which is very important to the experiment. The nine audio clips has been categorized into three sets on the basis of the poem. First set comprising of the first poem clips 1 through 3. Second set comprising of clips 4 through 6, and the third set comprising of clips 7 to 9, all written by Rabindranath Tagore and in each set, each clip has a different prosodic.

Each set follows the same protocol of the arrangement of the clips. Taking Set 1 as an example. As discussed set 1 has 3 clips, these clips need to be arranged in proper intervals of silence followed by audio. Beginning the clip with 25 seconds of complete silence along with the matching/contrasting color of clip1, then there’s 5 seconds of silence but along with this silence just a white cross is shown on screen to draw back the attention of the subject. After these 5 seconds, the first clip is played, while the clip is being played the white cross should stay on the screen till the end of the clip. As soon as the clip ends, the white cross also disappears. There is again silence of another 25seconds with a color on the screen depending on the matching or contrasting set, followed by silence along with the white cross sign for 5 seconds. Then comes the 2nd clip which is again played along with the white cross and it cross disappears as soon as the clip ends. Lastly, another interval of silence for 25 seconds with color, 5 seconds of silence and cross followed by the 3rd audio clip and the cross. In the end, when the last audio clip finishes, the cross also disappears but another silence of 30s to be maintained so as to not disrupt or activate the brain activity unnecessarily. In Fig. 2.1, the protocol is explained in the form of a flowchart for one set, this entire set up is repeated for set 2 and set 3 without any interval.

This protocol is followed for all the sets of poems and this is maintained throughout to extract the EEG readings from all the subjects. This is done so as to maintain a uniformity in the procedure. The silence intervals are placed in such a way that the brain activity is maximum and focused during the interval of the audio clip.



10.2.5: Flowchart of the Protocol

It is very important to maintain a proper protocol along with creating an optimal environment for each participant to ensure that we get accurate and reliable results [34-35]. The following guidelines were strictly followed to attain the best possible conditions for data collection:

1.) Sitting in a relaxed and comfortable position: The subjects were instructed to sit in a comfortable and relaxed position throughout the experiment to minimize physical discomfort or distractions that could potentially affect the emotional responses.

2.) Having no contact with the floor of the room: To prevent any grounding or interference from external sources, subjects were advised to keep their feet on a mat i.e. avoid direct contact with the floor of the room.

3.) In a dark and cool environment: Subjects were taken in an environment with controlled lighting conditions. The room was kept in darkness to minimize visual distractions and to help focus attention on the experiment. Additionally, maintaining a cool temperature in the room to ensure the subjects' comfort and less distraction due to heat.

4.) In a noise-free zone: To create an environment for concentration and to minimize distractions, subjects were kept in a noise-free zone. Background noise, such as external conversations or environmental sounds, was tried to be blocked out to maintain a quiet and serene environment during the experiment.

5.) Focusing on the computer monitor only: Subjects were instructed to direct their attention on the computer monitor solely, where the stimuli were presented.

6.) Able to consume the video protocol files: Subjects were provided with the necessary equipment to effectively consume the video protocol files. This ensured that the audio-visual stimuli were presented to participants in a clear and accessible manner

By strictly adhering to these guidelines and maintaining a standardized protocol, we tried to create a controlled experimental environment for each subject. This helped to eliminate any possible errors that might have surfaced in the readings.

10.2.5 Calculation of Parameters:

After the data collection phase, the next important phase was the analysis of the obtained data. The EEG recordings were properly extracted into .csv. The extracted EEG data was meticulously labelled and organized to prevent any inaccurate or redundant data.
These excel files helped to process the data efficiently and the data was further analyzed using appropriate algorithms and Multifractal Detrended Fluctuation Analysis (MFDFA). These computational methods helped us to quantify the complexity of the brain activity. By calculating the average multifractal width, we were able to obtain a measure of the complexity for each audio clip. This complexity metric served as a basis for comparing and contrasting the different audio stimuli utilized in the study.

To get a comprehensive analysis, the data was needed to be arranged in a manner that helped us make visual representation such as graphs. Graphs were drawn to visually represent the findings and provide a clearer understanding of the patterns and relationships in the data. Firstly, we created an individual electrode-wise analysis, examining the contributions of each electrode. Furthermore, we performed lobe-wise analysis, focusing on the frontal, parietal, occipital, and temporal lobes. By examining the EEG data specific to these regions, we had observations into the activity of different brain areas during the processing of the stimuli. For both the alpha and theta frequency bands, graphs were plotted to visualize and explore the patterns, trends, and variations in brain wave activity.
From these graphs, we extracted key findings and results, which are presented in this research paper. These findings help us understand about the neural responses evoked by the stimuli and enable a deeper understanding of the emotional and cognitive processes associated with the audio clips.

The combination of human responses and EEG data analysis allowed us to establish a comprehensive study for investigating the relationship between the audio files and emotions. The utilization of multifractal analysis and graphical representations enhanced our ability to explain the intricacies of brain wave activity and derive meaningful insights from the collected data.

10.3. Results and Discussions

3.1 Lobe-wise EEG Analyses of Theta Range of brainwaves for matching colour:

Let us now consider the lobe-wise variations observed for the theta range of brainwaves after performing EEG on the subjects with the 9 different clips and corresponding matching colour as the stimuli. In the following figures, you will see the ‘w’ value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition.

10. 3.1.1. Frontal lobe:

In EEG we are using only four electrodes for the frontal lobe which are denoted as electrodes F3, F4, F7 and F8. The errors are not shown in the figures as they are too small to appreciate.

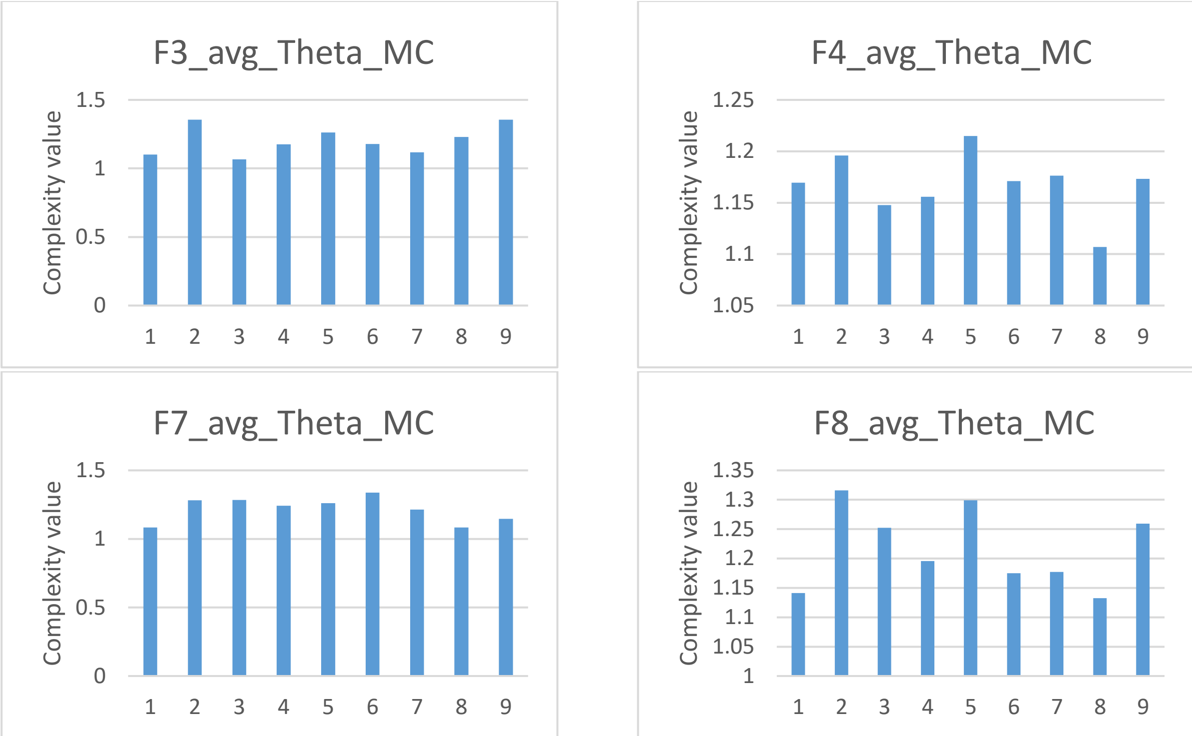
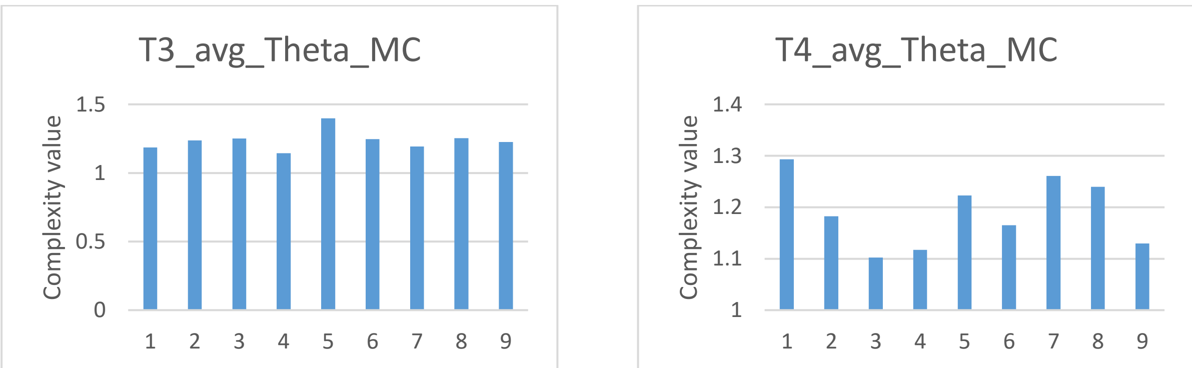


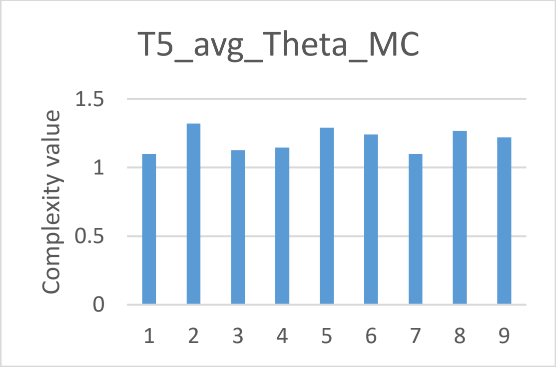
Fig.10. 3.1.1: Lobe-wise variation for Frontal electrodes for matching colour

Upon careful examination, it is evident that the graphs of F4 and F8 display higher levels of fluctuation compared to F3 and F5. In the case of F3, the lowest theta value is observed during the singing of clip 1, recording a value of 1.06589. On the other hand, the highest theta value is observed during the singing of clip 3, reaching a value of 1.35635. Shifting our attention to F4, the lowest theta value is observed during the recitation of clip 3, measuring 1.10703, while the highest theta value is observed during the recitation of clip 2, amounting to 1.21498. Likewise, in F7, the lowest theta value is observed during the recitation of clip 3, registering 1.08382, whereas the highest theta value is found during the singing of clip 2, amounting to 1.33735. In the case of F8, the lowest theta value is observed during the recitation of clip 3, with a value of 1.13253, while the highest theta value is observed during the recitation of clip 1, measuring 1.31617.

10.3.1.2 Temporal lobe:

In EEG we are using four electrodes for the temporal lobe which are denoted as electrodes T3, T4, T5 and T6.





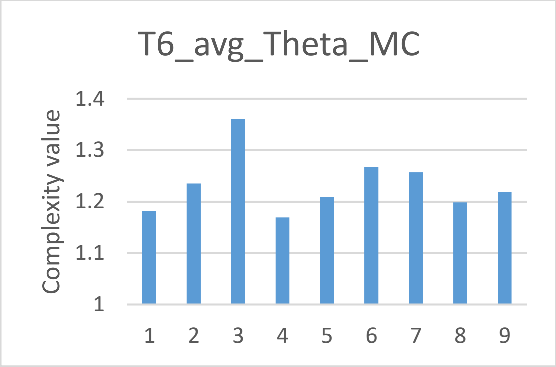
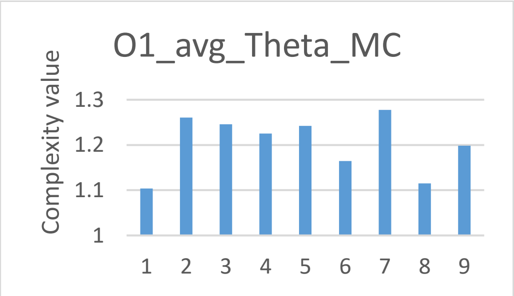


Fig.10.3.1.2- Lobe-wise variation for Temporal electrodes for matching colour

Upon analysis, it is apparent that the graphs of T4 and T6 exhibit higher levels of fluctuation compared to T3 and T5. In the case of T3, the lowest theta value is observed during the reading of clip 2, with an average theta value of 1.14298. Conversely, the highest theta value is observed during the recitation of clip 2, recording an average theta value of 1.39843. Shifting our attention to T4, the lowest theta value is observed during the singing of clip 1, measuring an average theta value of 1.18227, while the highest theta value is observed during the reading of clip 1, amounting to an average theta value of 1.29332. Likewise, in T5, the lowest theta value is observed during the reading of clip 3, registering an average theta value of 1.09886, while the highest theta value is found during the recitation of clip 1, with an average theta value of 1.31941. In the case of T6, the lowest theta value is observed during the reading of clip 2, with an average theta value of 1.16941, while the highest theta value is observed during the singing of clip 1, amounting to an average theta value of 1.36055.

10.3.1.3 Occipital lobe:

Now, in EEG we are using two electrodes for the occipital lobe which are denoted as electrodes O1 and O2. Also, we are using the matching colour for each prosodic of the clip.



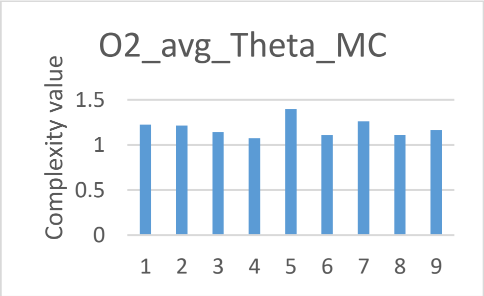
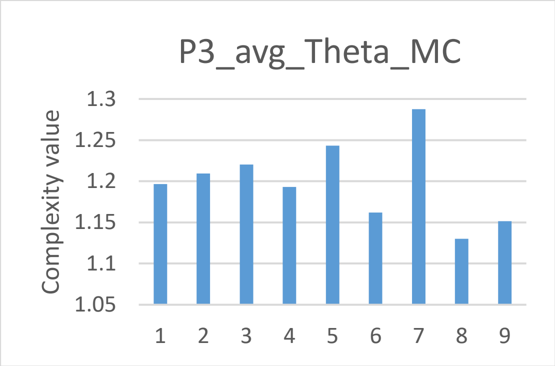


Fig.10.3.1.3- Lobe-wise variation for Occipital electrodes for matching colour

Upon observation, it is evident that the graph of O1 displays higher levels of fluctuation compared to O2. In O1, the lowest theta value is observed during the reading of clip 1, with an average theta value of 1.10392. On the other hand, the highest theta value is observed during the reading of clip 3, recording an average theta value of 1.27788. Shifting our attention to O2, the lowest theta value is observed during the reading of clip 2, measuring an average theta value of 1.07231, while the highest theta value is observed during the recitation of clip 2, with an average theta value of 1.39794.

10.3.1.4 Parietal lobe:

In EEG we are using only two electrodes for the parietal lobe which are denoted as electrodes P3 and P4.



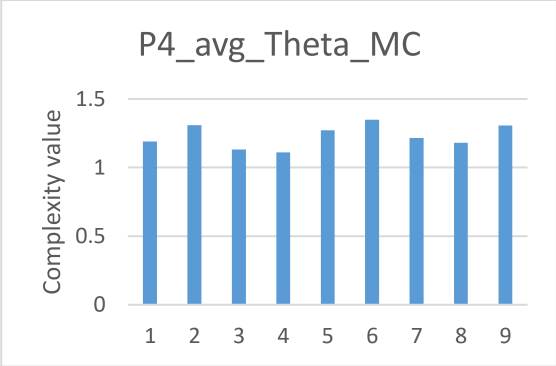


Fig 10. 3.1.4- Lobe-wise variation for Parietal lobe electrodes for matching colour

Upon observation, it is evident that the graph of P3 displays higher levels of fluctuation compared to P4. In P3, the lowest theta value is observed during the recitation of clip 3, with an average theta value of 1.13031. On the other hand, the highest theta value is observed during the reading of clip 3, recording an average theta value of 1.28741. Shifting our attention to P4, the lowest theta value is observed during the reading of clip 2, measuring an average theta value of 1.10967, while the highest theta value is observed during the singing of clip 2, with an average theta value of 1.34916.

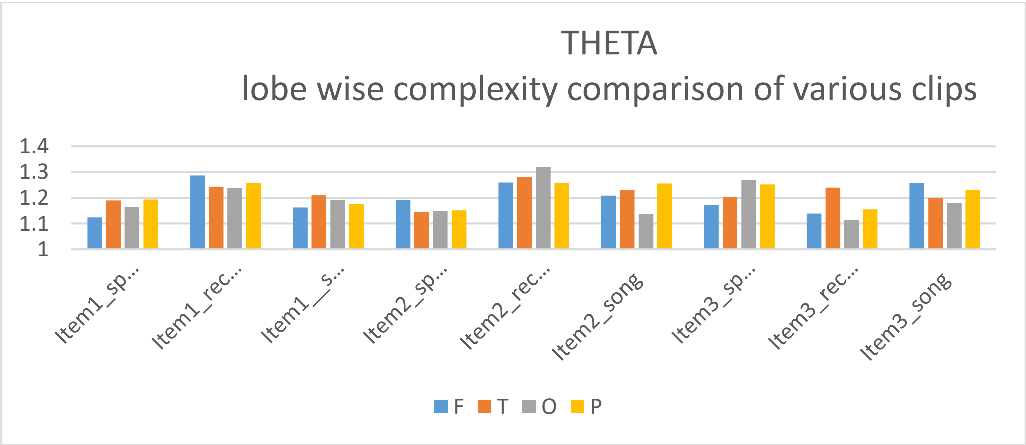


Figure 10. 3.1.5: Complexity Variation Lobe-wise per clip for matching color

In Figure 3.1.5, let's examine the changes on a clip-by-clip basis. During the reading of clip 1, the frontal lobe exhibits the lowest complexity value of 1.12386, while the parietal lobe has the highest complexity value of 1.19326. When reciting clip 1, the frontal lobe reaches the highest complexity value of 1.28709. Turning to clip 1 singing, the temporal lobe demonstrates the highest complexity value of 1.21025, whereas the frontal lobe has the lowest complexity value of 1.16316. Moving on to clip 2 reading, the frontal lobe records the maximum complexity value of 1.19255. During the recitation of clip 2, the occipital lobe displays the highest complexity value of 1.320138, while the frontal lobe exhibits the lowest complexity value of 1.25932. In the case of clip 2 singing, the occipital lobe showcases the lowest complexity value of 1.13665.

Shifting our attention to clip 3 reading, the occipital lobe presents the highest complexity value of 1.26934, and the frontal lobe records the lowest complexity value of 1.17111. For clip 3 recitation, the temporal lobe exhibits the highest complexity value of 1.23994. Finally, in clip 3 singing, the frontal lobe demonstrates the highest complexity value of 1.25813, while the occipital lobe shows the lowest complexity value of 1.180605.

3.2. Lobe-wise EEG Analyses of the Alpha Range of brainwaves for matching colour:

Let us now consider the lobe-wise variations observed for the theta range of brainwaves after performing EEG on the subjects with the 9 different clips and corresponding matching colour as the stimuli. In the following figures, you will see the ‘w’ value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition.

10.3.2.1. Frontal Lobe:

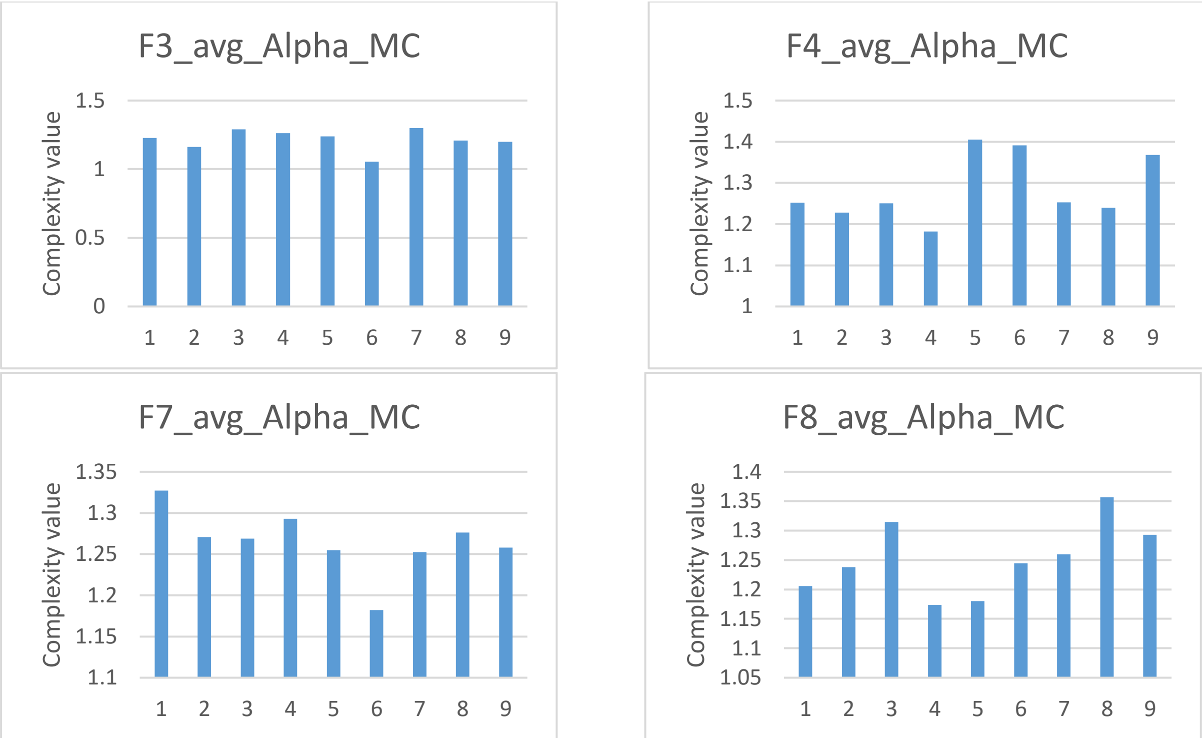


Fig.10.3.2.1- Lobe-wise variation for Frontal electrodes for matching colour

We observe that the graphs of F4, F7, and F8 exhibit higher levels of fluctuation compared to F3. In F3, the lowest alpha value is observed during the singing of clip 2, with an average alpha value of 1.06589. Conversely, the highest alpha value is observed during the reading of clip 3, recording an average alpha value of 1.29948. Shifting our attention to F4, the lowest alpha value is observed during the reading of clip 2, measuring an average alpha value of 1.40551, while the highest alpha value is observed during the recitation of clip 1, with an average alpha value of 1.22827.

Turning our focus to F7, the lowest alpha value is observed during the singing of clip 2, with an average alpha value of 1.182261, whereas the highest alpha value is observed during the reading of clip 1, recording an average alpha value of 1.32711. Similarly, in F8, the lowest alpha value is observed during the reading of clip 2, measuring an average alpha value of 1.17341, while the highest alpha value is observed during the recitation of clip 3, with an average alpha value of 1.356804.

10.3.2.2. Temporal lobe:

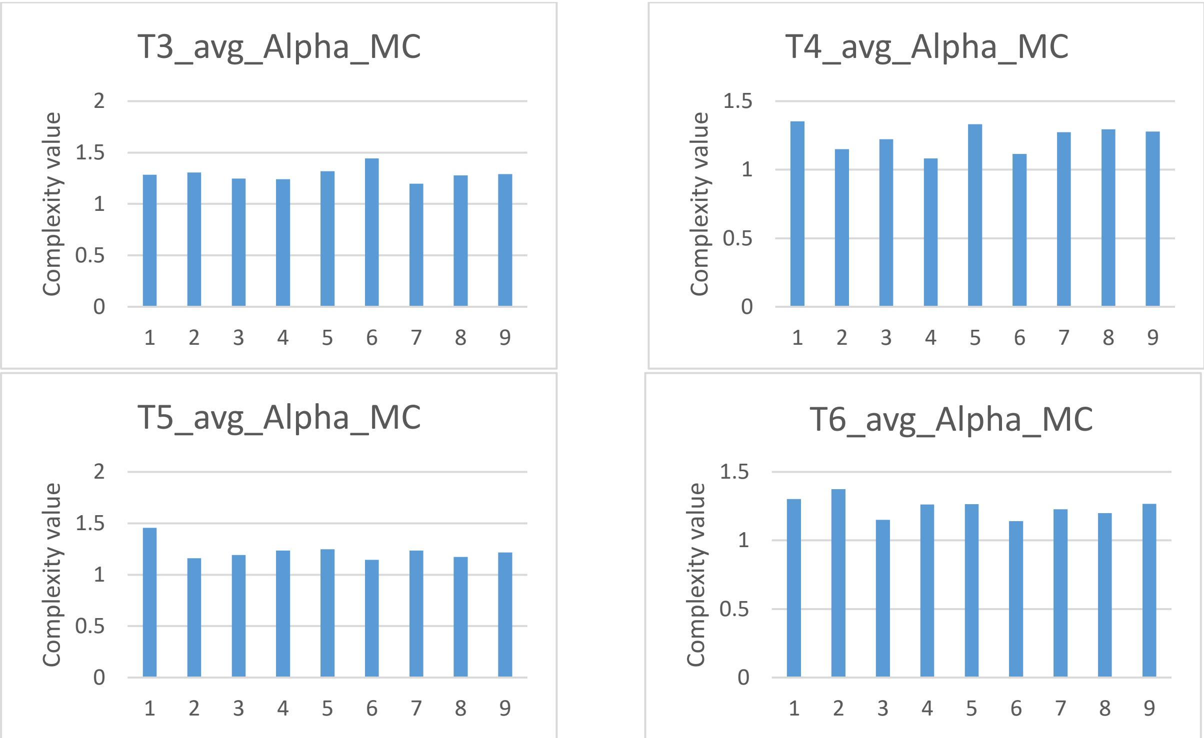
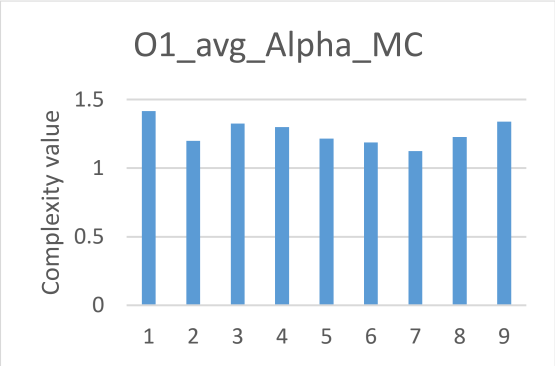


Fig.10.3.2.2- Lobe-wise variation for Temporal electrodes for matching colour

The fluctuation levels in the graph of T4 are higher compared to T3, T5, and T6. In T3, the lowest average alpha value of 1.14298 is observed during the reading of clip 2, while the highest average alpha value of 1.39843 is observed during the singing of clip 2. Shifting our focus to T4, we find that the average alpha value is lowest during the reading of clip 2 (1.08125) and highest during the reading of clip 1 (1.35403).

Examining T5, the lowest average alpha value of 1.14491 is observed during the singing of clip 2, while the highest average alpha value of 1.2486 is observed during the reading of clip 1. Similarly, in T6, the lowest average alpha value of 1.13972 is observed during the singing of clip 2, and the highest average alpha value of 1.3742 is observed during the recitation of clip 1.

10.3.2.3 Occipital lobe:



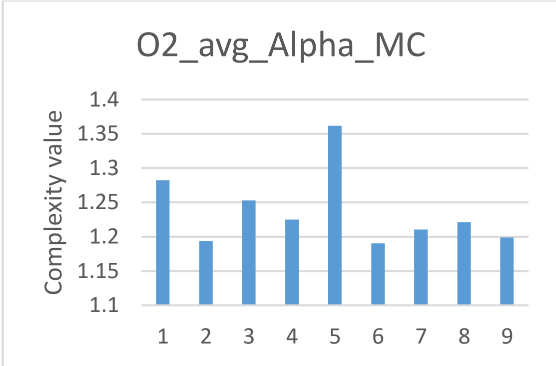
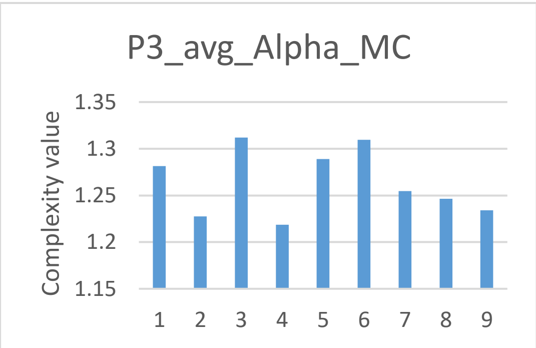


Fig.10.3.2.3- Lobe-wise variation for Occipital electrodes for matching colour

We observe that the graph of O2 exhibits higher levels of fluctuation compared to O1. In O1, the lowest alpha value is observed during the reading of clip 3, with an average alpha value of 1.12344. On the other hand, the highest alpha value is observed during the reading of clip 1, recording an average alpha value of 1.4168. Shifting our attention to O2, the lowest alpha value is observed during the singing of clip 2, measuring an average alpha value of 1.19026, while the highest alpha value is observed during the recitation of clip 2, with an average alpha value of 1.39187

10. 3.2.4 Parietal lobe:

In EEG we are using only two electrodes for the parietal lobe which are denoted as electrodes P3 and P4.



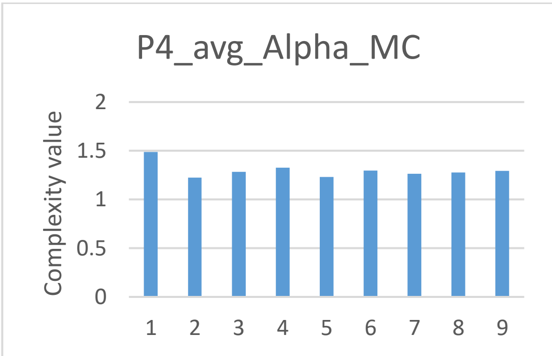


Fig.10.3.2.4- Lobe-wise variation for Parietal lobe electrodes for matching colour

We observe that the graph of P3 exhibits higher levels of fluctuation compared to P4. In P3, the lowest alpha value is observed during the reading of clip 2, with an average alpha value of 1.21868. Conversely, the highest alpha value is observed during the singing of clip 1, recording an average alpha value of 1.3118. Shifting our attention to P4, the lowest alpha value is observed during the recitation of clip 2, with an average alpha value of 1.23199. On the other hand, the highest alpha value is observed during the reading of clip 1, with an average alpha value of 1.48682.

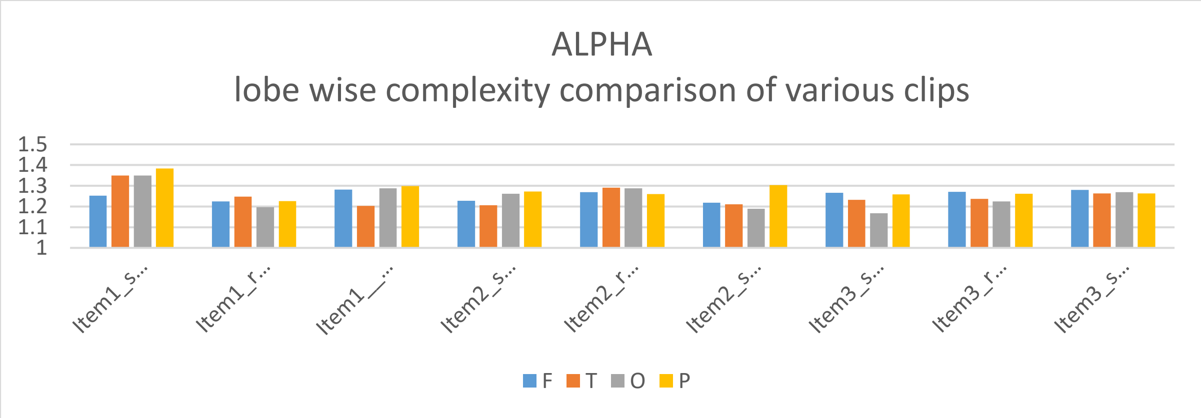


Figure 10.3.2.5: Complexity Variation Lobe-wise per clip for matching colour

Let's analyse the changes in Figure 3.2.5 on a clip-by-clip basis. During the reading of clip 1, the frontal lobe has the lowest complexity value of 1.25288, while the parietal lobe has the highest complexity value of 1.38419. When reciting clip 1, the temporal lobe shows the highest complexity value of 1.24815.

Moving on to clip 1 singing, the parietal lobe exhibits the highest complexity value of 1.29862, whereas the temporal lobe has the lowest complexity value of 1.20226.

For clip 2 reading, the parietal lobe records the maximum complexity value of 1.27224. In clip 2 recitation, the parietal lobe again shows the highest complexity value of 1.30393, while the occipital lobe has the lowest complexity value of 1.18875.

During clip 2 singing, the occipital lobe exhibits the lowest complexity value of 1.18875.

Moving to clip 3 reading, the occipital lobe shows the lowest complexity value of 1.16708, while the frontal lobe records the highest complexity value of 1.26621. In clip 3 recitation, the frontal lobe displays the highest complexity value of 1.27022.

Lastly, for clip 3 singing, the fluctuations in complexity values are not as pronounced.

10. 3.3. Lobe-wise EEG Analyses of Theta Range of brainwaves for Contrasting colour:

Let us now consider the lobe-wise variations observed for the theta range of brainwaves after performing EEG on the subjects with the 9 different clips and corresponding contrasting colour as the stimuli. In the following figures, you will see the 'w' value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition.

10.3.3.1. Frontal lobe:

In EEG we are using only four electrodes for the frontal lobe which are denoted as electrodes F3, F4, F7 and F8.

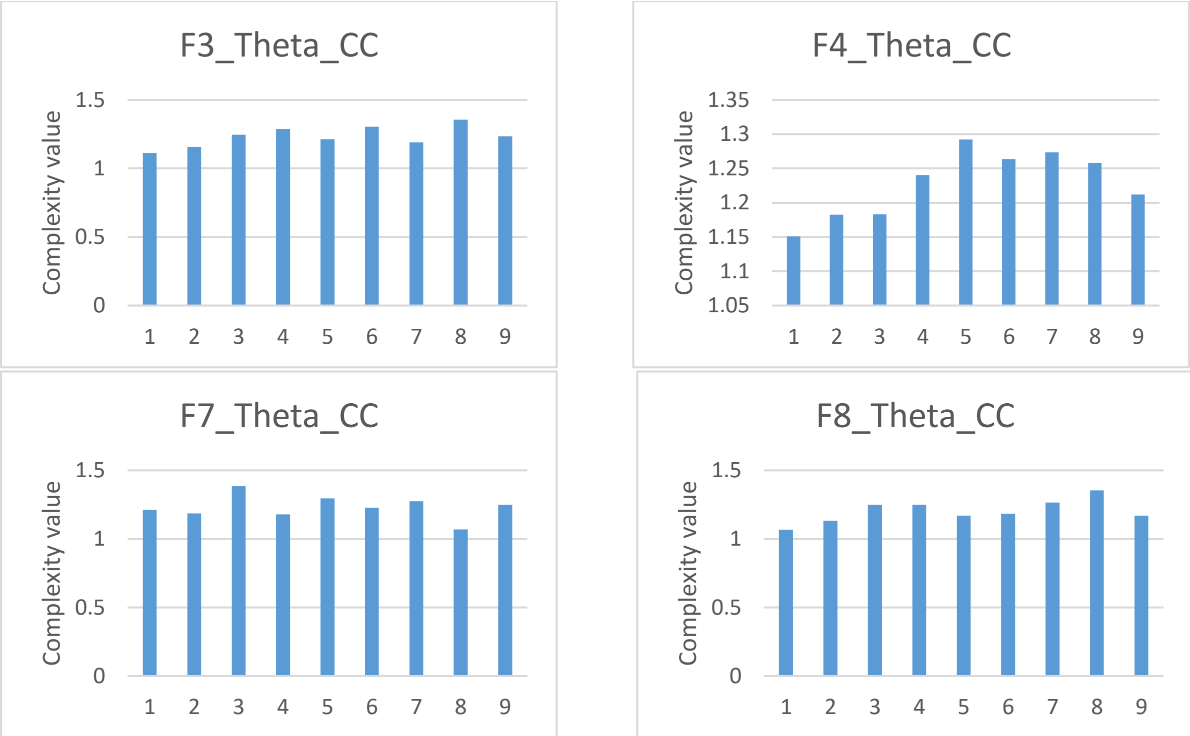
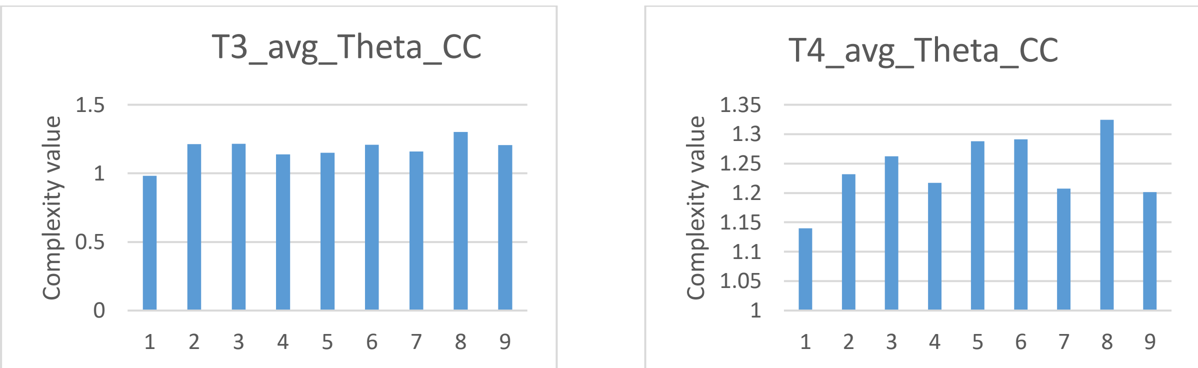


Fig.10.3.3.1: Lobe-wise variation for Frontal electrodes for Contrasting colour

We observe that the graph of F4 exhibits higher levels of fluctuation compared to F3, F7, and F8. In F3, the lowest theta value is observed during the reading of clip 1, with an average theta value of 1.11373, while the highest theta value is observed during the recitation of clip 3, with an average theta value of 1.35587943. Shifting our attention to F4, the lowest theta value is observed during the reading of clip 1, measuring an average theta value of 1.150933, while the highest theta value is observed during the recitation of clip 2, with an average theta value of 1.29209.

Turning our focus to F7, the lowest theta value is observed during the recitation of clip 3, with an average theta value of 1.06981, while the highest theta value is observed during the reading of clip 2, recording an average theta value of 1.34877. Similarly, in F8, the lowest theta value is observed during the reading of clip 1, measuring an average theta value of 1.06665, while the highest theta value is observed during the recitation of clip 3, with an average theta value of 1.35356.

10. 3.3.2 Temporal lobe:



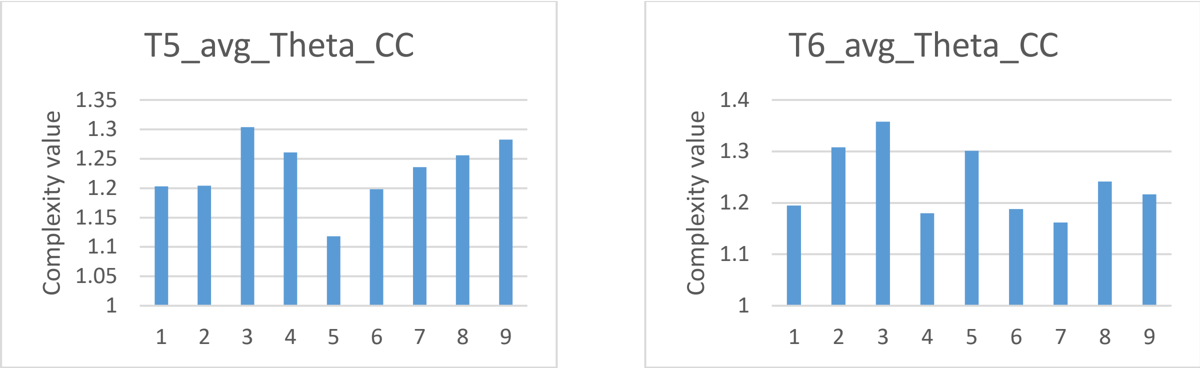


Fig.10.3.3.2- Lobe-wise variation for temporal electrodes for Contrasting colour

The fluctuations in the graphs of T4, T5, and T6 are more pronounced compared to T3. When analysing T3, we find that the lowest theta value is observed during the reading of clip 1, with an average theta value of 0.98143. On the other hand, the highest theta value is observed during the recitation of clip 3, recording an average theta value of 1.30121.

Moving on to T4, we observe that the lowest theta value is found during the reading of clip 1, with an average theta value of 1.14011. Conversely, the highest theta value is observed during the recitation of clip 3, with an average theta value of 1.32433. Similarly, in T5, the lowest theta value is observed during the reading of clip 2, measuring an average theta value of 1.11792, while the highest theta value is observed during the singing of clip 1, with an average theta value of 1.304.

Examining T6, we find that the lowest theta value is observed during the reading of clip 2, with a value of 1.17973, while the highest theta value is observed during the singing of clip 1, recording an average theta value of 1.35788.

10.3.3.3. Occipital lobe:

Now, in EEG we are using two electrodes for the occipital lobe which are denoted as electrodes O1 and O2. Also, we are using the contrasting colour for each prosodic of the clip.

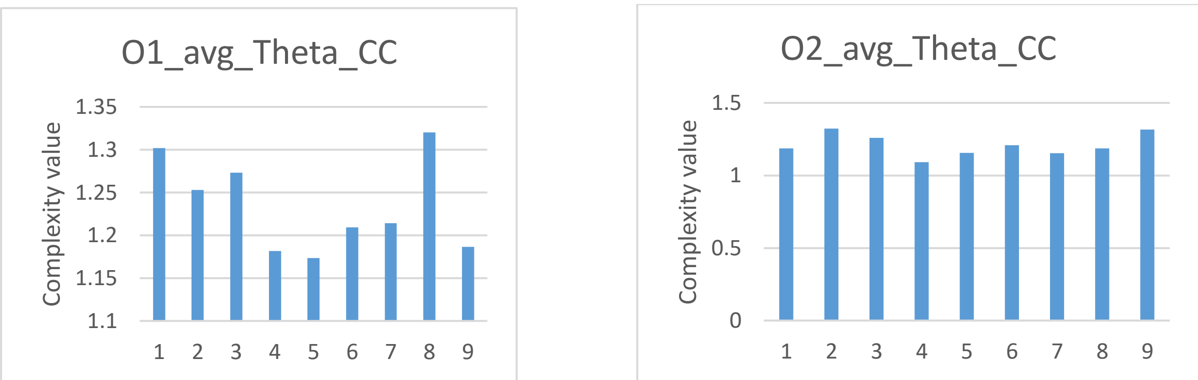
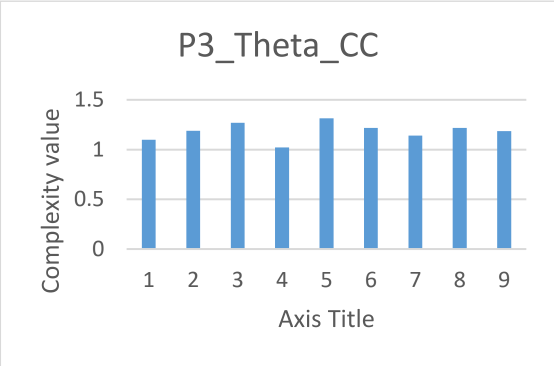


Fig.10.3.3.3-- Lobe-wise variation for Occipital electrodes for Contrasting colour

We can observe that the fluctuations in the graph of O1 are more pronounced compared to O2. In O1, the lowest theta value is observed during the recitation of clip 2, with a theta value of 1.1736. On the other hand, the highest theta value is observed during the recitation of clip 3, with a theta value of 1.32031. Turning our attention to O2, the lowest theta value is observed during the reading of clip 2, with a theta value of 1.09159. Conversely, the highest theta value is observed during the singing of clip 3, with a theta value of 1.31699.

10.3.3.4. Parietal lobe:

In EEG we are using only two electrodes for the parietal lobe which are denoted as electrodes P3 and P4.



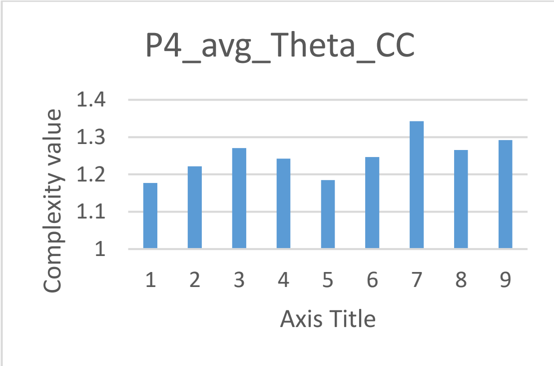


Fig.10.3.3.4-- Lobe-wise variation for Parietal electrodes for Contrasting colour

We can observe that the fluctuations in the graph of P4 are more pronounced compared to P3. In P3, the lowest theta value is observed during the reading of clip 2, with an average theta value of 1.01994. On the other hand, the highest theta value is observed during the recitation of clip 2, recording an average theta value of 1.31423. Shifting our attention to P4, the lowest theta value is observed during the recitation of clip 2, with an average theta value of 1.09474. Conversely, the highest theta value is observed during the reading of clip 3, with an average theta value of 1.34263.

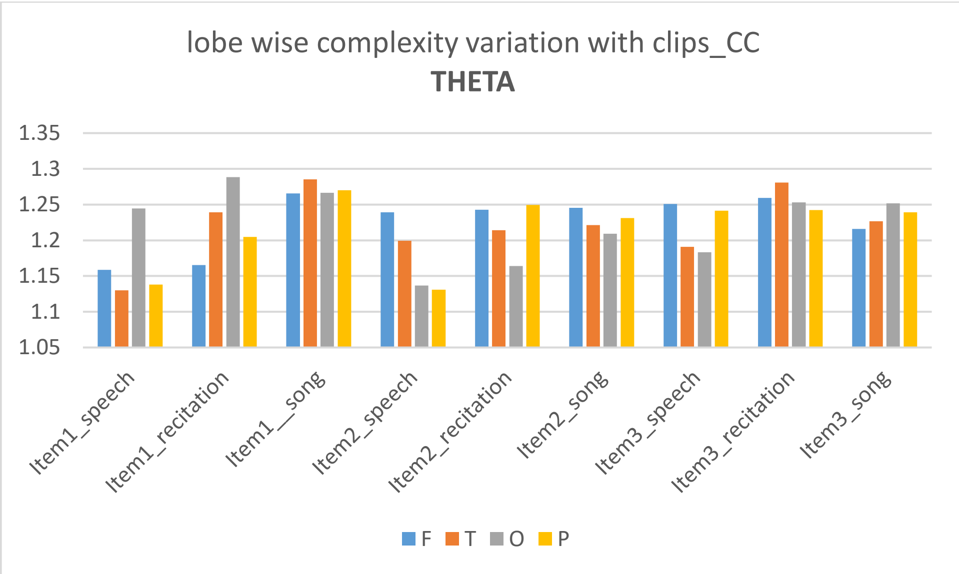


Figure 10.3.3.5: Complexity Variation Lobe-wise per clip for contrasting colour

In Figure 3.3.5, let's analyse the changes clip-wise. During the reading of clip 1, the temporal lobe exhibits the lowest complexity value of 1.12979, while the occipital lobe has the highest complexity value of 1.24446. When reciting clip 1, the occipital lobe shows the highest complexity value of 1.28847.

Moving on to clip 1 singing, the temporal lobe records the highest complexity value of 1.28510, whereas the frontal lobe has the lowest complexity value of 1.26575.

For clip 2 reading, the frontal lobe displays the maximum complexity value of 1.23934. In clip 2 recitation, the parietal lobe exhibits the highest complexity value of 1.24944, while the occipital lobe has the lowest complexity value of 1.16421.

During clip 2 singing, the occipital lobe shows the lowest complexity value of 1.20918.

Moving to clip 3 reading, the occipital lobe exhibits the lowest complexity value of 1.18337, while the frontal lobe records the highest complexity value of 1.250596. In clip 3 recitation, the temporal lobe displays the highest complexity value of 1.280683.

Lastly, for clip 3, the complexity value is highest in the occipital lobe with a value of 1.25179 and the lowest value is found in the frontal lobe with a value of 1.21588.

10.3.4. Lobe-wise EEG Analyses of Alpha Range of brainwaves for Contrasting colour:

Let us now consider the lobe-wise variations observed for the theta range of brainwaves after performing EEG on the subjects with the 9 different clips and corresponding contrasting colour as the stimuli. In the following figures, you will see the ‘w’ value of the EEG readings along the Y-axis with the clip number along X–axis, with all three pieces varying in terms of rendition.

10.3.4.1. Frontal lobe:

In EEG we are using only four electrodes for the frontal lobe which are denoted as electrodes F3, F4, F7 and F8.

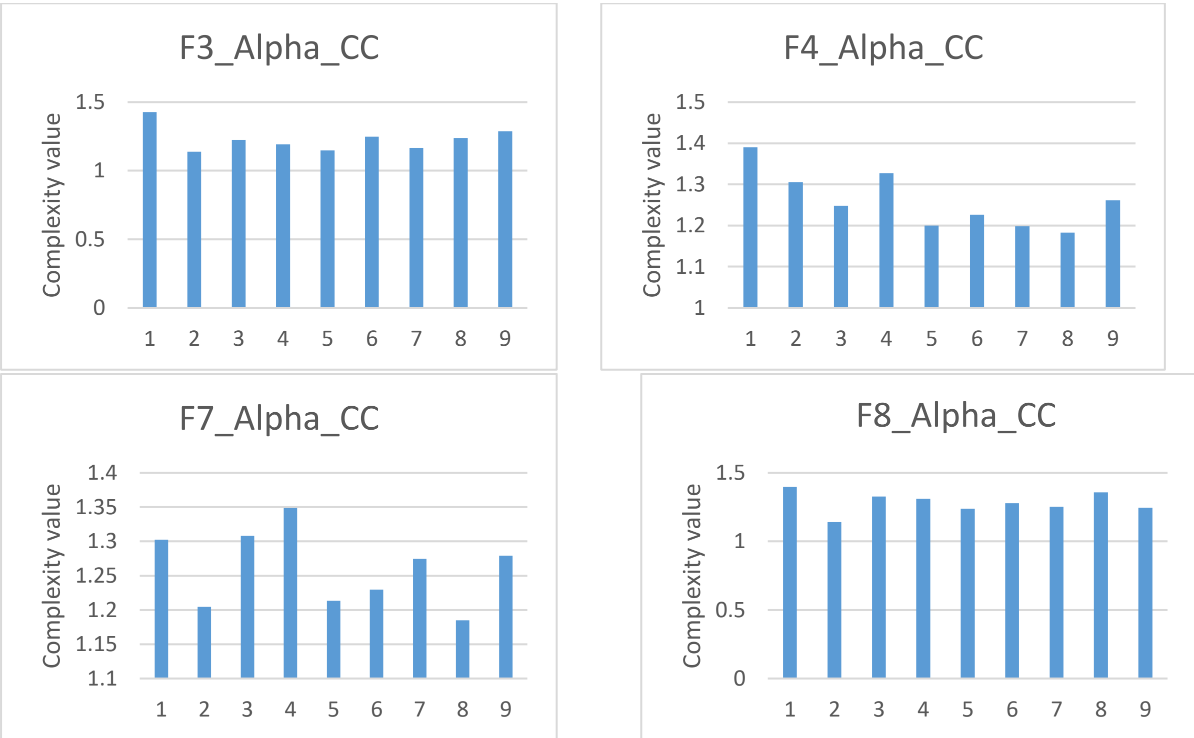


Fig.10.3.4.1: Lobe-wise variation for Frontal electrodes for Contrasting colour

The fluctuation levels in the graphs of F4 and F7 are more pronounced compared to F3 and F8. In F3, the lowest alpha value is observed during the recitation of clip 1, with an average alpha value of 1.13772. On the other hand, the highest alpha value is observed during the reading of clip 1, with an average alpha value of 1.42819. Turning our focus to F4, the lowest alpha value is observed during the recitation of clip 3, measuring an average alpha value of 1.19995, while the highest alpha value is observed during the reading of clip 1, with an average alpha value of 1.39039.

Similarly, in F7, the lowest alpha value is observed during the recitation of clip 3, with an average alpha value of 1.18474, while the highest alpha value is observed during the reading of clip 2, recording an average alpha value of 1.34877. In contrast, in F8, the lowest alpha value is observed during the recitation of clip 1, with an average alpha value of 1.13991, while the highest alpha value is observed during the reading of clip 1, measuring an average alpha value of 1.39771.

10.3.4.2 Temporal lobe:

In EEG we are using four electrodes for the temporal lobe which are denoted as electrodes T3, T4, T5 and T6.

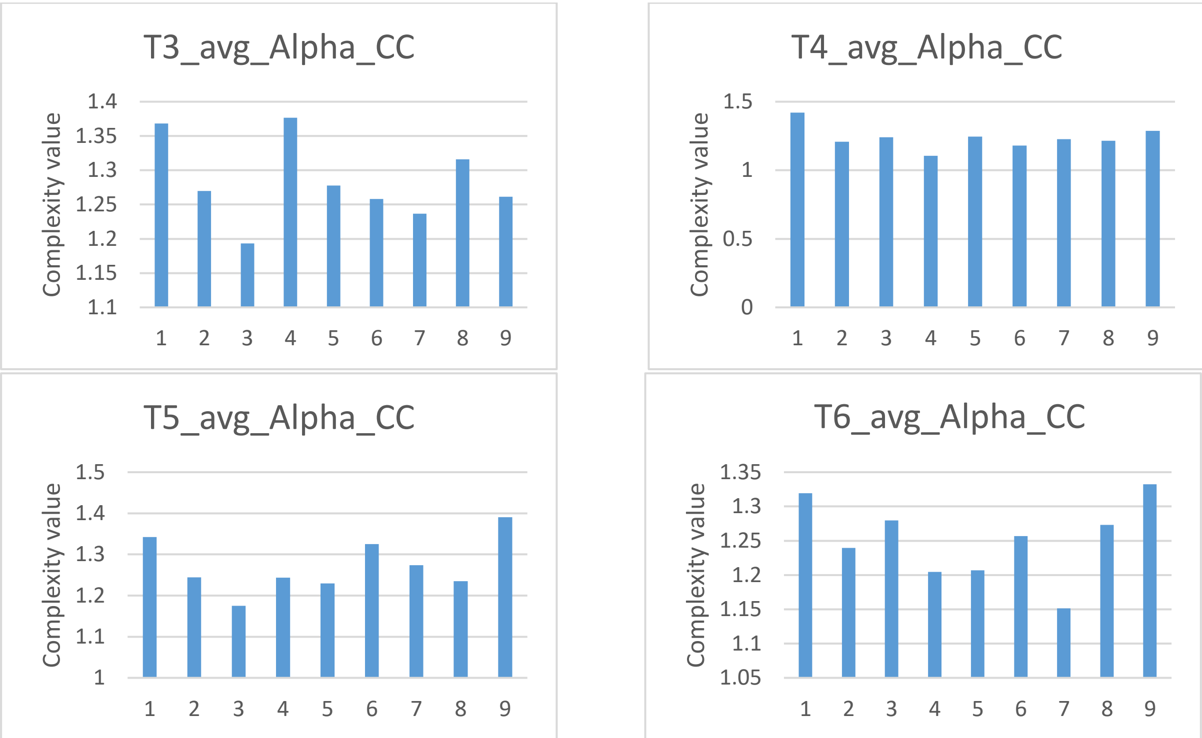
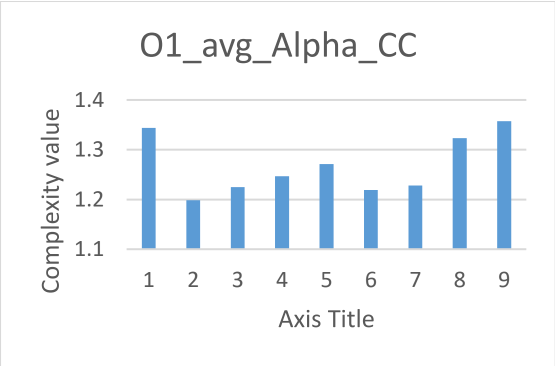


Fig.10.3.4.2: Lobe-wise variation for Temporal electrodes for Contrasting colour

The level of fluctuation in the graph of T4 is comparatively lower than that of T3, T5, and T6. In T3, the lowest alpha value is observed during the singing of clip 1, with an alpha value of 1.19338. Conversely, the highest alpha value is observed during the reading of clip 2, recording an alpha value of 1.37659. Shifting our attention to T4, the lowest alpha value is observed during the reading of clip 2, measuring an alpha value of 1.10598, while the highest alpha value is observed during the reading of clip 1, with an alpha value of 1.4211.

Likewise, in T5, the lowest alpha value is observed during the singing of clip 1, with an alpha value of 1.17539, while the highest alpha value is observed during the singing of clip 3, having an alpha value of 1.39058. Similarly, in T6, the lowest alpha value is observed during the reading of clip 3, measuring an alpha value of 1.15143, while the highest alpha value is observed during the singing of clip 3, recording an alpha value of 1.3217.

10.3.4.3 Occipital Lobe:



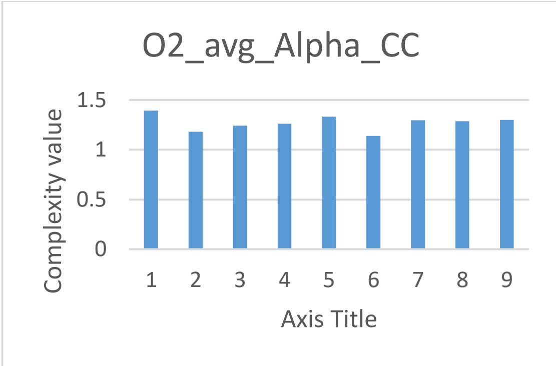
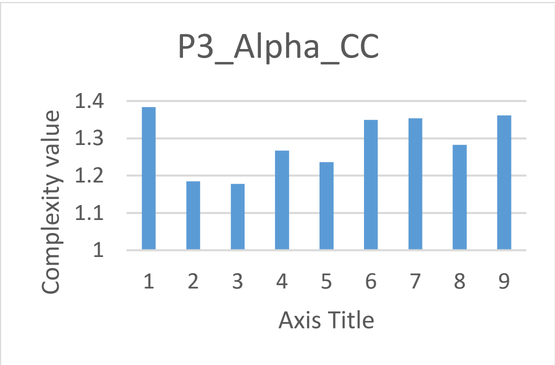


Fig.10.3.4.3: Lobe-wise variation for Occipital electrodes for Contrasting colour

The level of fluctuation in the graph of O2 is higher than that of O1. In O1, the lowest alpha value is observed during the recitation of clip 1, with an alpha value of 1.1983. On the other hand, the highest alpha value is observed during the singing of clip 3, recording an alpha value of 1.35732. Shifting our focus to O2, the lowest alpha value is observed during the singing of clip 2, measuring an alpha value of 1.13709, while the highest alpha value is observed during the reading of clip 1, with an alpha value of 1.39388.

10.3.4.4 Parietal lobe:

In EEG we are using only two electrodes for the parietal lobe which are denoted as electrodes P3 and P4.



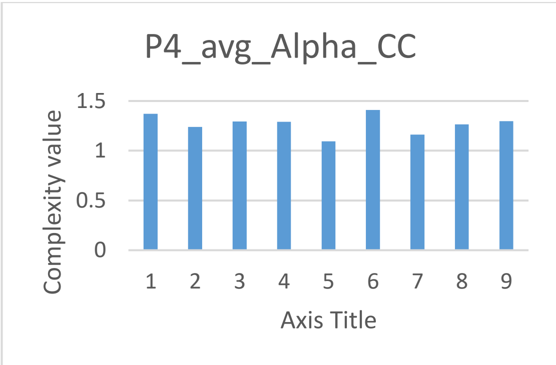


Fig.10.3.4.4: Lobe-wise variation for Parietal electrodes for Contrasting colour

The level of fluctuation in the graph of P3 is higher than that of P4. In P3, the lowest alpha value is observed during the singing of clip 1, recording an alpha value of 1.17814. Conversely, the highest alpha value is observed during the reading of clip 1, with an alpha value of 1.38330. Shifting our focus to P4, the lowest alpha value is observed during the recitation of clip 2, measuring an alpha value of 1.09474, while the highest alpha value is observed during the singing of clip 2, with an alpha value of 1.40838.

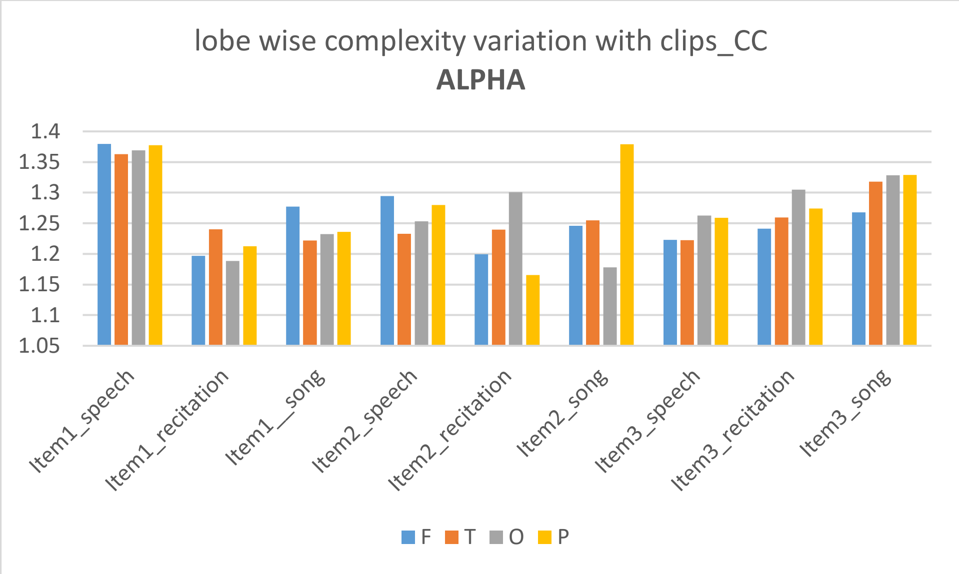


Figure 10.3.4.5: Complexity Variation Lobe-wise per clip for contrasting colour

n Figure 3.4.5., let's examine the changes clip-wise. During the reading of clip 1, there is not much fluctuation in the complexity value across each lobe. When reciting clip 1, the temporal lobe displays the highest complexity value of 1.24027.

Moving on to clip 1 singing, the frontal lobe records the highest complexity value of 1.277, while the temporal lobe has the lowest complexity value of 1.22203.

For clip 2 reading, the frontal lobe exhibits the maximum complexity value of 1.294627. In clip 2 recitation, the occipital lobe shows the highest complexity value of 1.30064, while the parietal lobe has the lowest complexity value of 1.16552.

During clip 2 singing, the occipital lobe displays the lowest complexity value of 1.17804.

Moving to clip 3 reading, the temporal lobe exhibits the lowest complexity value of 1.22219, while the occipital lobe records the highest complexity value of 1.26279. In clip 3 recitation, the occipital lobe displays the highest complexity value of 1.30510.

Lastly, for clip 3, the frontal lobe exhibits the lowest complexity value with a value of 1.26800.

10.3.5. EEG comparison between Matching Colour and Contrasting Colour in the Theta range:

10.3.5.1. Frontal lobe:

In EEG we are using only four electrodes for the frontal lobe which are denoted as electrodes F3, F4, F7 and F8.

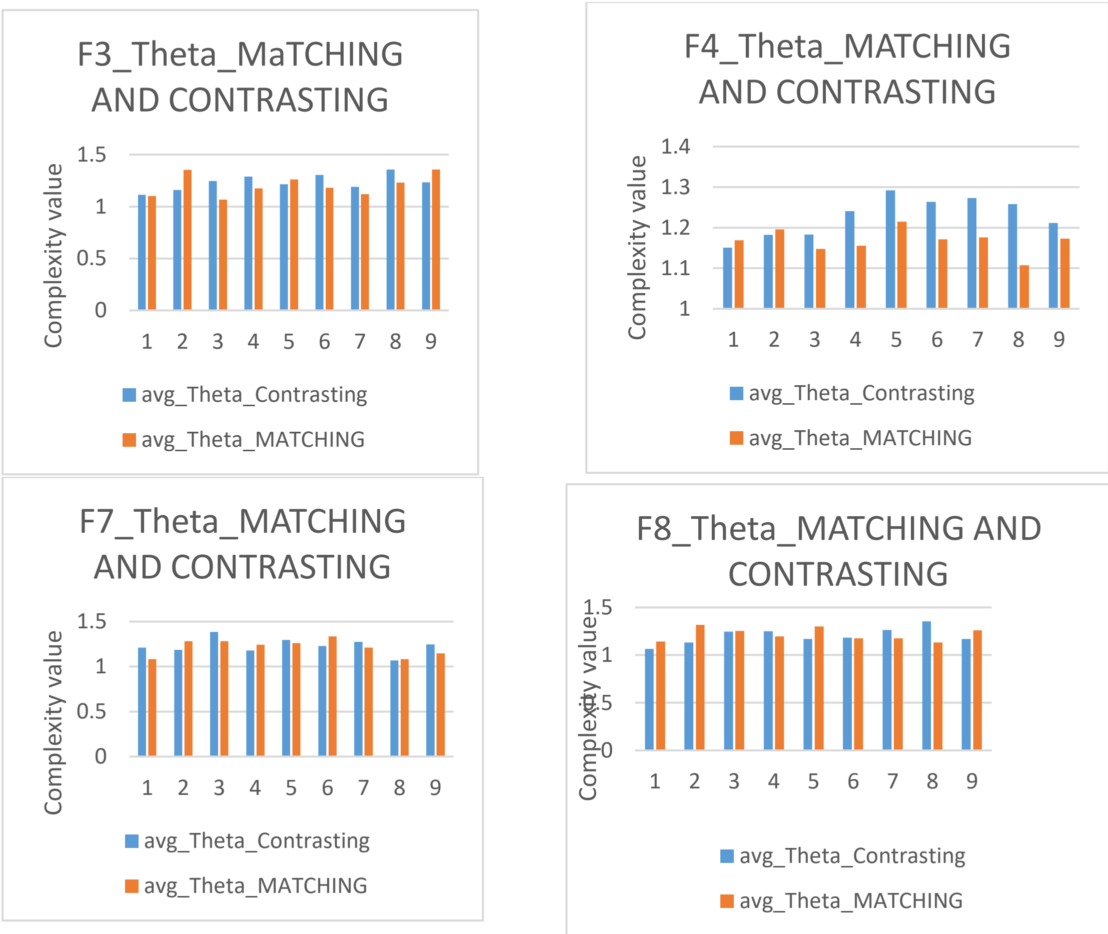


Fig.10.3.5.1-Comparison Between Matching colour and Contrasting Colour for Frontal lobe

In the reading of clip 1, the theta values of the matching colour are higher in the F4 and F8 electrodes, while they are lower for the F7 electrode. This pattern is consistent with the contrasting colour in the F3 electrode.

During the recitation of clip 1, the theta values of the matching colour are higher in all electrodes.

When it comes to the singing of clip 1, the theta values of the contrasting colour are higher in the F3, F4, and F7 electrodes, while they are almost the same as the matching colour in the F8 electrode.

During the reading of clip 2, the theta values of the contrasting colour are higher in the F3, F4, and F8 electrodes, while they are lower for the F7 electrode.

During the recitation of clip 2, the theta values of the contrasting colour are higher in the F3 and F8 electrodes, while they are lower in the F4 and F7 electrodes.

When it comes to the singing of clip 2, the theta values of the matching colour are lower in the F3, F4, and F8 electrodes, while they are higher in the F7 electrode.

During the reading of clip 3, the theta values of the matching colour are lower for all electrodes.

During the recitation of clip 3, the theta values of the contrasting colour are higher in the F3, F4, and F8 electrodes, while they are the same as the matching colour in the F7 electrode.

During the singing of clip 3, the theta values of the contrasting colour are higher in the F4 and F7 electrodes, while they are lower in the F3 and F8 electrodes.

10.3.5.2. Temporal lobe:

In EEG we are using four electrodes for the temporal lobe which are denoted as electrodes T3, T4, T5 and T6.

1. **Theta values:**

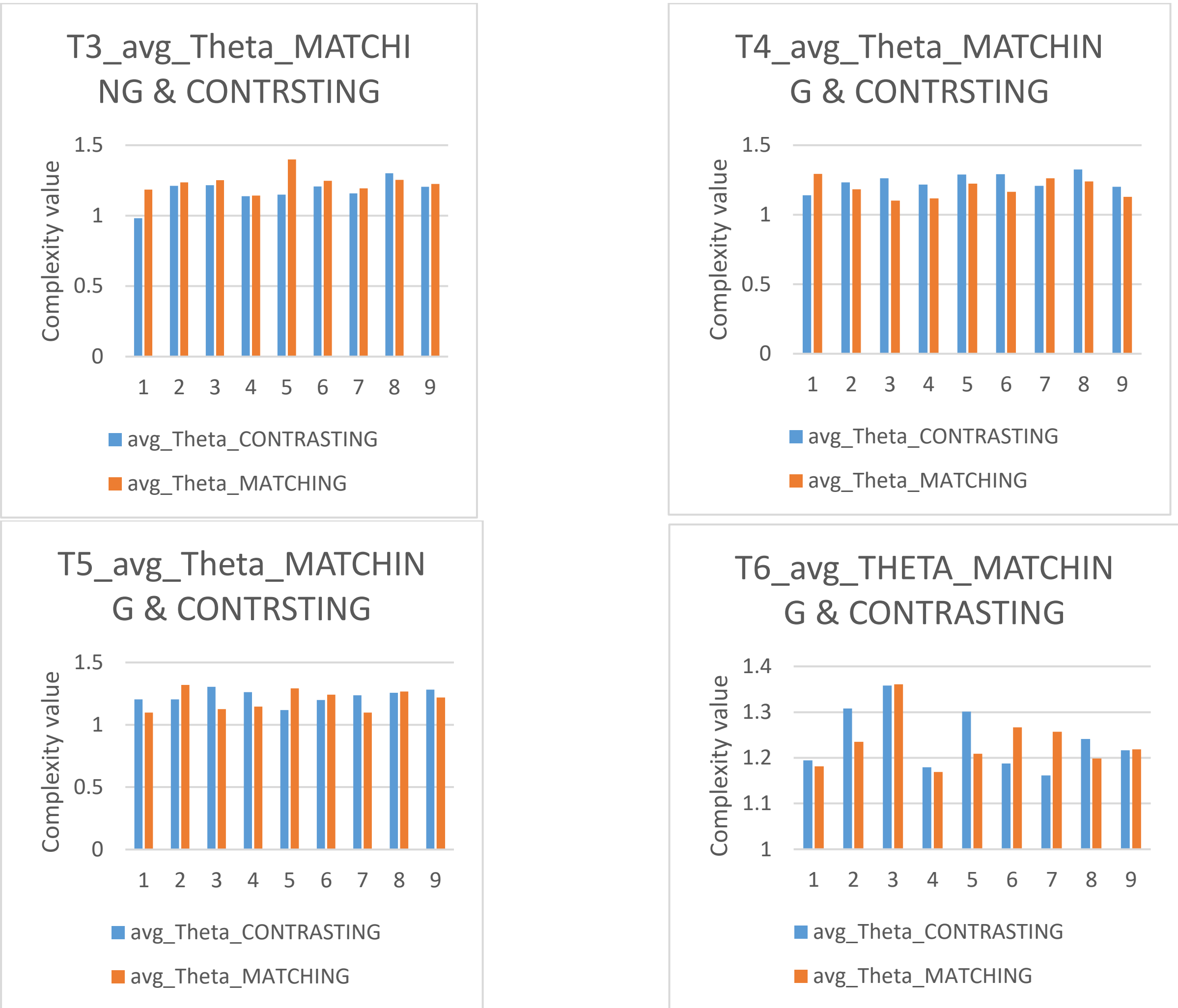


Fig.10.3.5.2-AVERAGE THETA VALUE COMPARISON OF TEMPORAL LOBE

In the context of clip 1, we observe that the theta values associated with the matching colour are notably higher in the T3 and T4 electrodes, while they are relatively lower in the T5 and T6 electrodes. On the other hand, during recitation of clip 1, the theta values represented by the contrasting colour exhibit higher amplitudes in the T4 and T6 electrodes, contrasting with the lower values observed in the T3 and T5 electrodes. Shifting to the singing segment of clip 1, we note that the theta values associated with the contrasting colour are prominently higher in the T4 and T5 electrodes, demonstrating a comparable level to the theta values represented by the matching colour in the T3 and T6 electrodes.

Transitioning to the reading session of clip 2, the theta values of the matching colour align closely with those of the contrasting colour in the T3 and T6 electrodes, while displaying lower magnitudes in the

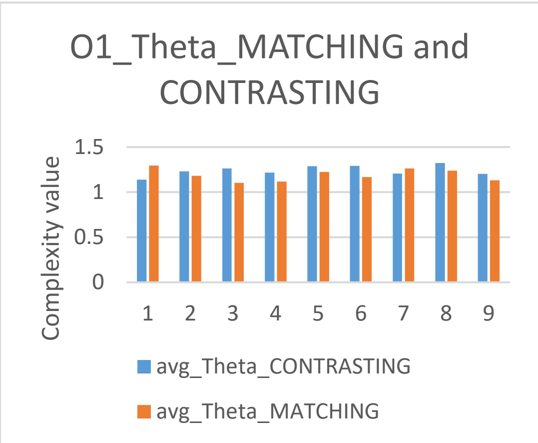
T4 and T5 electrodes. Similarly, during the recitation phase of clip 2, the contrasting colour manifests higher theta values in the T4 and T6 electrodes, whereas the T3 and T5 electrodes depict lower values. In the singing portion of clip 2, the theta values corresponding to the matching colour exhibit an elevated profile in the T3, T5, and T6 electrodes, while displaying lower amplitudes in the T4 electrode.

Shifting to the reading sequence of clip 3, we observe that the theta values associated with the matching colour show an increased magnitude in the T3, T4, and T6 electrodes, while exhibiting lower values in the T5 electrode. During the recitation phase of clip 3, the contrasting colour displays higher theta values in the T3, T4, and T6 electrodes, while aligning closely with the matching colour in the T5 electrode. Finally, in the singing segment of clip 3, the contrasting colour reveals higher theta values in the T4 and T5 electrodes, while showcasing a similar pattern to the matching colour in the T3 and T6 electrodes.

10.3.5.3. Occipital lobe:

Now, in EEG we are using two electrodes for the occipital lobe which are denoted as electrodes O1 and O2. Also, we are using the matching colour for each prosodic of the clip.

1. **Theta values:**



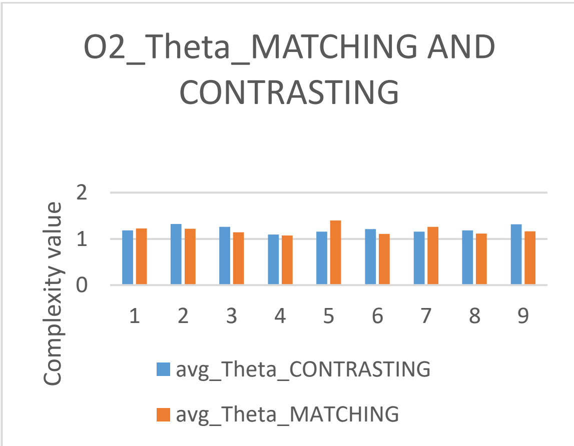


Fig 10.3.5.3-AVERAGE THETA VALUE COMPARISON OF OCCIPITAL LOBE

The O1 and O2 graphs show consistent patterns in comparing the theta values of matching and contrasting colours. However, there are slight variations, especially in the 4th and 5th bars representing the reading and recitation of clip 2. In reading clip 2, O1 has higher theta for the contrasting colour, while O2 shows similar values. In recitation clip 2, O1 has higher theta for the contrasting colour, while O2 has lower theta. These differences indicate varying responses to stimuli in different electrodes.

3.5.4. Parietal lobe:

In EEG we are using only two electrodes for the parietal lobe which are denoted as electrodes P3 and P4.

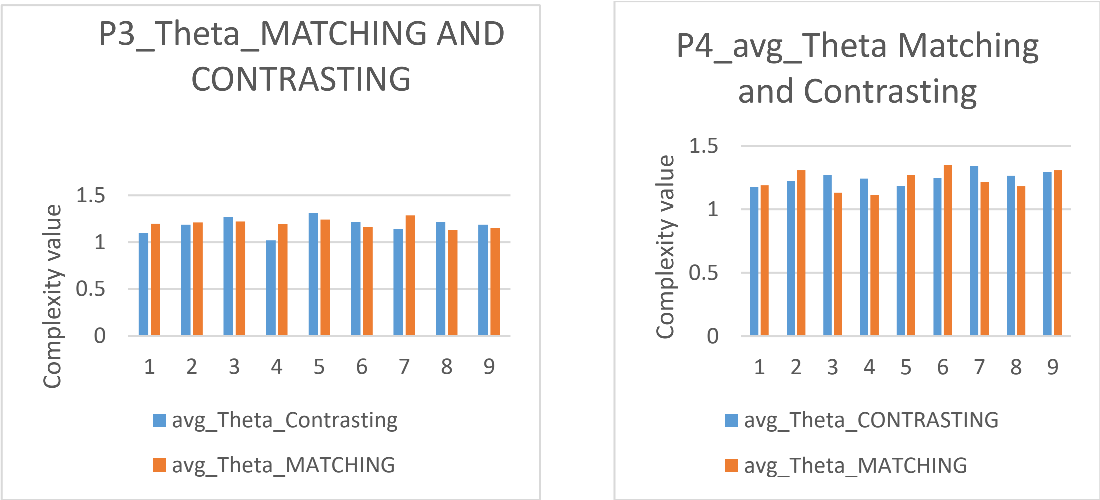


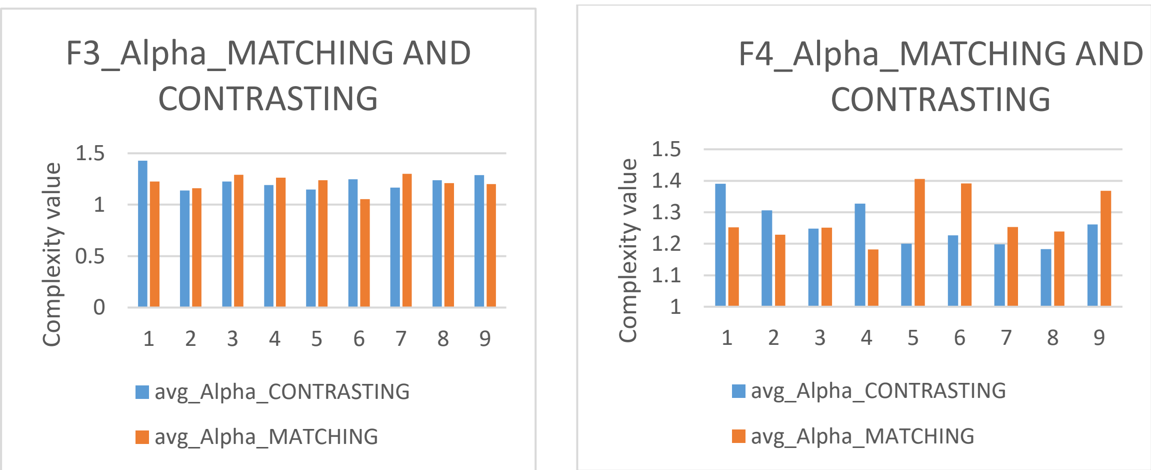
Fig.10.3.5.4-AVERAGE THETA VALUE COMPARISON OF PARETIAL LOBE

The theta values in the reading of clip 2 and clip 3 exhibit opposite patterns in P3 and P4 electrodes. In P3, the matching colour has higher theta values compared to the contrasting colour, while in P4, the matching colour has lower theta values than the contrasting colour. Similarly, in the singing of clip 2, the contrasting colour shows higher theta values in the P3 electrode, whereas it has lower theta values in the P4 electrode. These differences indicate distinct responses to the matching and contrasting colours in the two electrodes.

10.3.6. EEG comparison between Matching Colour and Contrasting Colour in the Theta range:

10.3.6.1. Frontal lobe:

In EEG we are using only four electrodes for the frontal lobe which are denoted as electrodes F3, F4, F7 and F8.



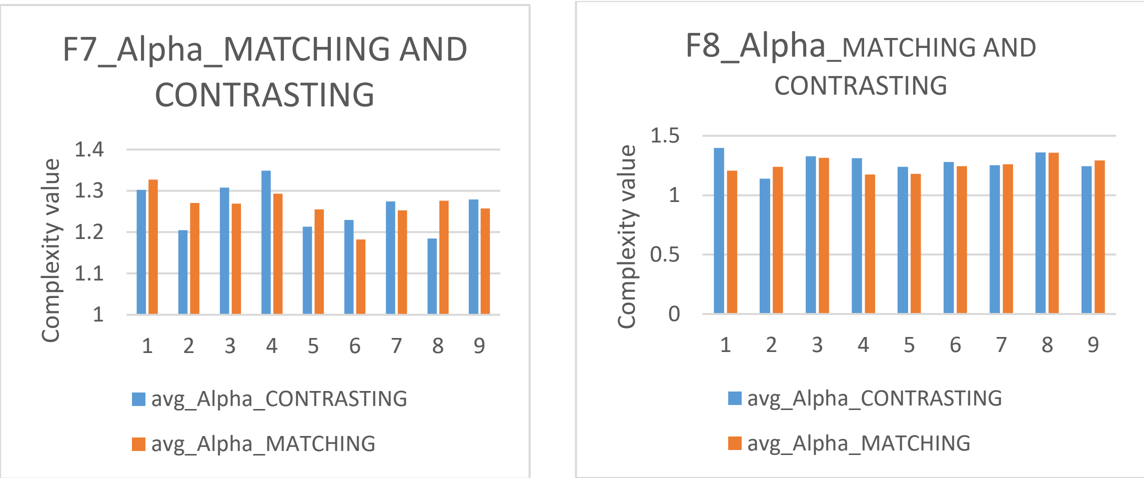


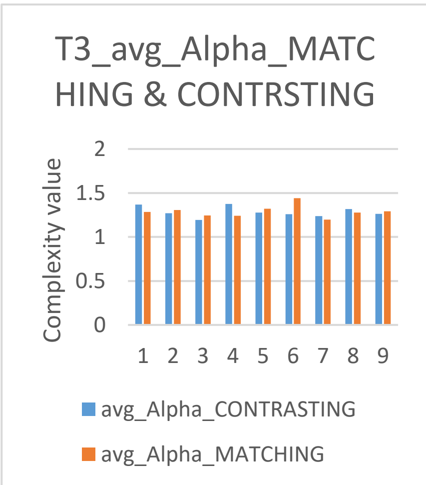
Fig.10.3.6.1-AVERAGE ALPHA VALUE COMPARISION OF FRONTAL LOBE

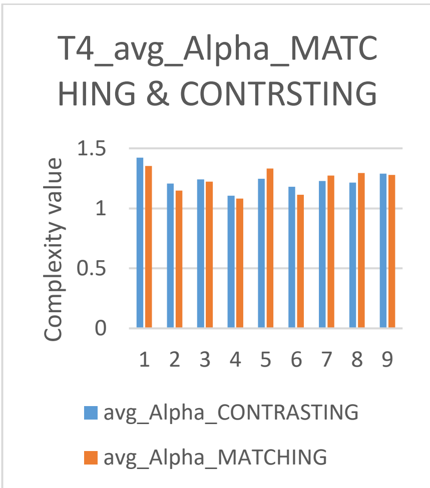
In the reading of clip 1, the alpha values of the matching colour are higher in the F7 electrode and lower in the F3, F4, and F8 electrodes. During the recitation of clip 1, the alpha values of the contrasting colour are higher in the F4 electrode and lower in the F3, F7, and F8 electrodes. When singing clip 1, the alpha values of the contrasting colour are the same as the matching colour in the F4 and F8 electrodes, higher in the F7 electrode, and lower in the F3 electrode.

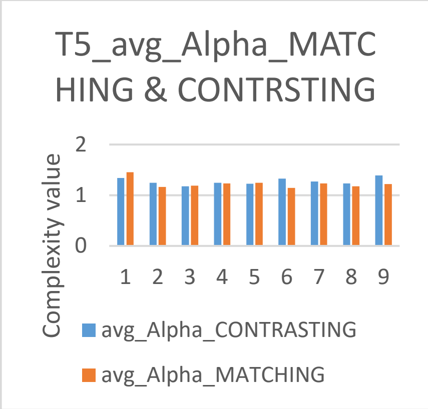
In the reading of clip 2, the alpha values of the contrasting colour are higher in the T3 and T4 electrodes and almost the same as the matching colour in the T5 and T6 electrodes. During the recitation of clip 2, the alpha values of the contrasting colour are lower in the F3, F4, and F7 electrodes and the same as the matching colour in the F8 electrode. When singing clip 2, the alpha values of the matching colour are higher in the F3, F4, and F7 electrodes and the same as the contrasting colour in the F8 electrode.

For the reading of clip 3, the alpha values of the matching colour are higher in the F3 and F4 electrodes and the same as the contrasting colour in the F7 and F8 electrodes. During the recitation of clip 3, the alpha values of the contrasting colour are lower in the F3 and F7 electrodes and the same as the matching colour in the F4 and F8 electrodes. When singing clip 3, the alpha values of the contrasting colour are higher in the F3 and F7 electrodes and lower in the F4 and F8 electrodes.

10.3.6.2. Temporal Lobe:







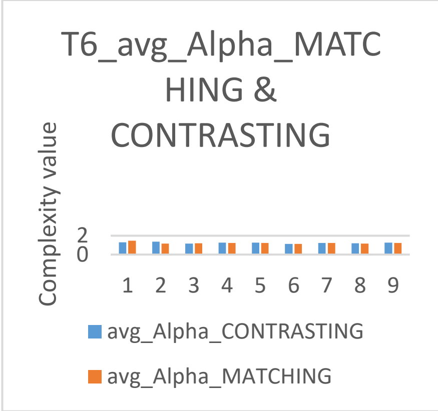
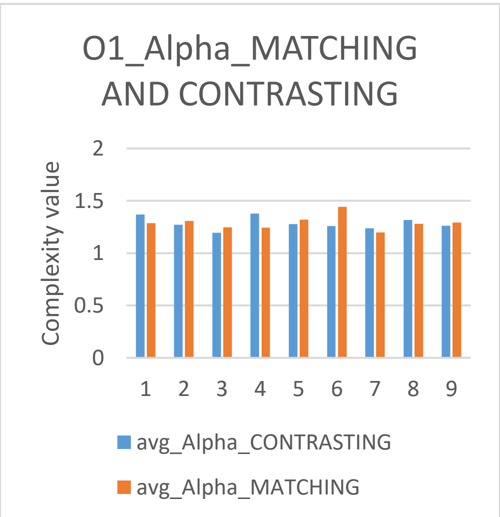


Fig.10.3.6.2-AVERAGE ALPHA VALUE COMPORISON OF TEMPORAL LOBE

During the reading task of clip 1, the alpha values indicate higher activation for the matching colour in the T5 and T6 electrodes, while the T3 and T4 electrodes exhibit lower activation. In the recitation task of clip 1, the alpha values show increased activation for the contrasting colour in the T4, T5, and T6 electrodes, while the T3 electrode displays lower activation. Interestingly, in the singing task of clip 1, the alpha values for both the matching and contrasting colours are identical across all electrodes. Moving to clip 2, during the reading task, the alpha values reveal elevated activation for the contrasting colour in the T3 and T4 electrodes, whereas the T5 and T6 electrodes demonstrate similar activation levels for both the matching and contrasting colours. For the recitation task of clip 2, the alpha values indicate reduced activation for the contrasting colour in the T3, T4, and T5 electrodes, while the T6 electrode exhibits comparable activation for both colours. In the singing task of clip 2, the alpha values show higher activation for the matching colour in the T3 electrode, lower activation for the matching colour in the T4 and T5 electrodes, and equivalent activation for both colours in the T6 electrode. Turning to clip 3, during the reading task, the alpha values indicate greater activation for the matching colour in the T4 electrode, and lower activation for the matching colour in the T5 and T3 electrodes, while the T6 electrode shows similar activation for both colours. In the recitation task of clip 3, the alpha values demonstrate increased activation for the contrasting colour in the T5 electrode, decreased activation in the T4 electrode, and equivalent activation for both colours in the T3 and T6 electrodes. Finally, in the singing task of clip 3, the alpha values reveal higher activation for the contrasting colour in the T5 electrode, and comparable activation for both colours in the T3, T4, and T6 electrodes.

10.3.6.3. Occipital Lobe:



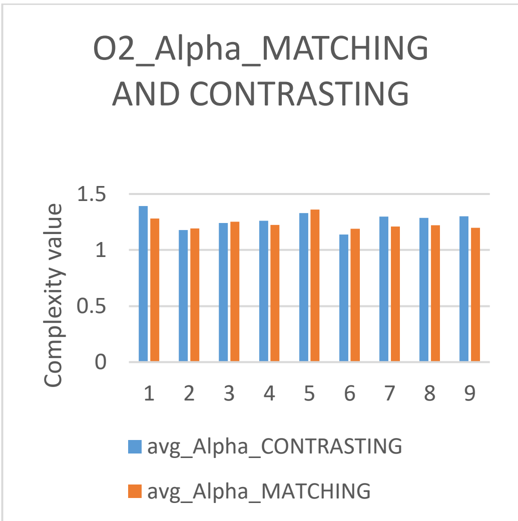


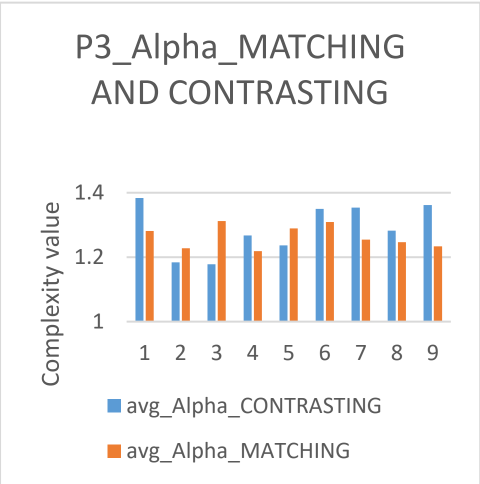
Fig 10.3.6.3-AVERAGE ALPHA VALUE COMPARISON OF OCCIPITAL LOBE

The alpha values recorded in the O1 and O2 electrodes exhibit noticeable distinctions. During the singing of clip 2, the difference in alpha values between the matching colour and contrasting colour is relatively smaller in the O1 electrode compared to the O2 electrode. This implies that the O1 electrode is less responsive to the colour contrast presented in clip 2, while the O2 electrode shows a more pronounced differentiation between the two colours.

In the case of singing clip 3, contrasting patterns emerge between the O1 and O2 electrodes. The O1 electrode displays a higher alpha value for the matching colour, indicating a stronger neural response to the matching colour during clip 3. On the other hand, the O2 electrode exhibits a lower alpha value for the matching colour, suggesting a reduced sensitivity to the matching colour in clip 3.

These findings highlight the distinct neural processing of visual stimuli between the O1 and O2 electrodes during the singing of clip 2 and clip 3, with the O1 electrode demonstrating differential sensitivity to colour contrast and the matching colour.

10.3.6.4. Parietal Lobe:



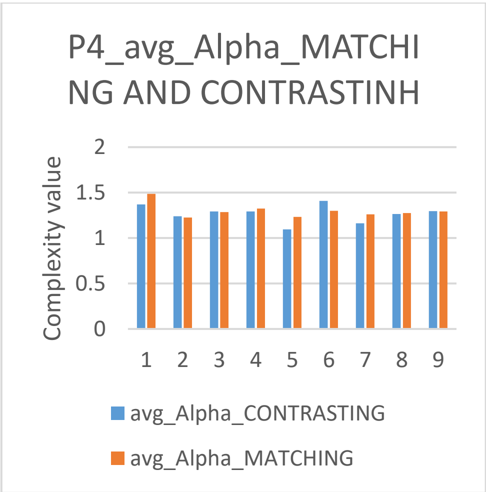


Fig 10.3.6.4-AVERAGE ALPHA VALUE COMPARISON OF PARETIAL LOBE

In the P3 electrode, the alpha values for the contrasting colour are consistently higher during the reading of clip 1, clip 2, and clip 3, whereas they are either lower or the same in the P4 electrode. Specifically, during the recitation of clip 1 and clip 2, the P3 electrode exhibits lower alpha values for the matching colour and higher alpha values for the contrasting colour, while the P4 electrode shows similar alpha values for both colours. In the case of singing clip 1, the P3 electrode demonstrates a high alpha value for the matching colour, whereas the P4 electrode has a low alpha value. Interestingly, for the singing of clip 3, we observe an opposite pattern between the two electrodes.

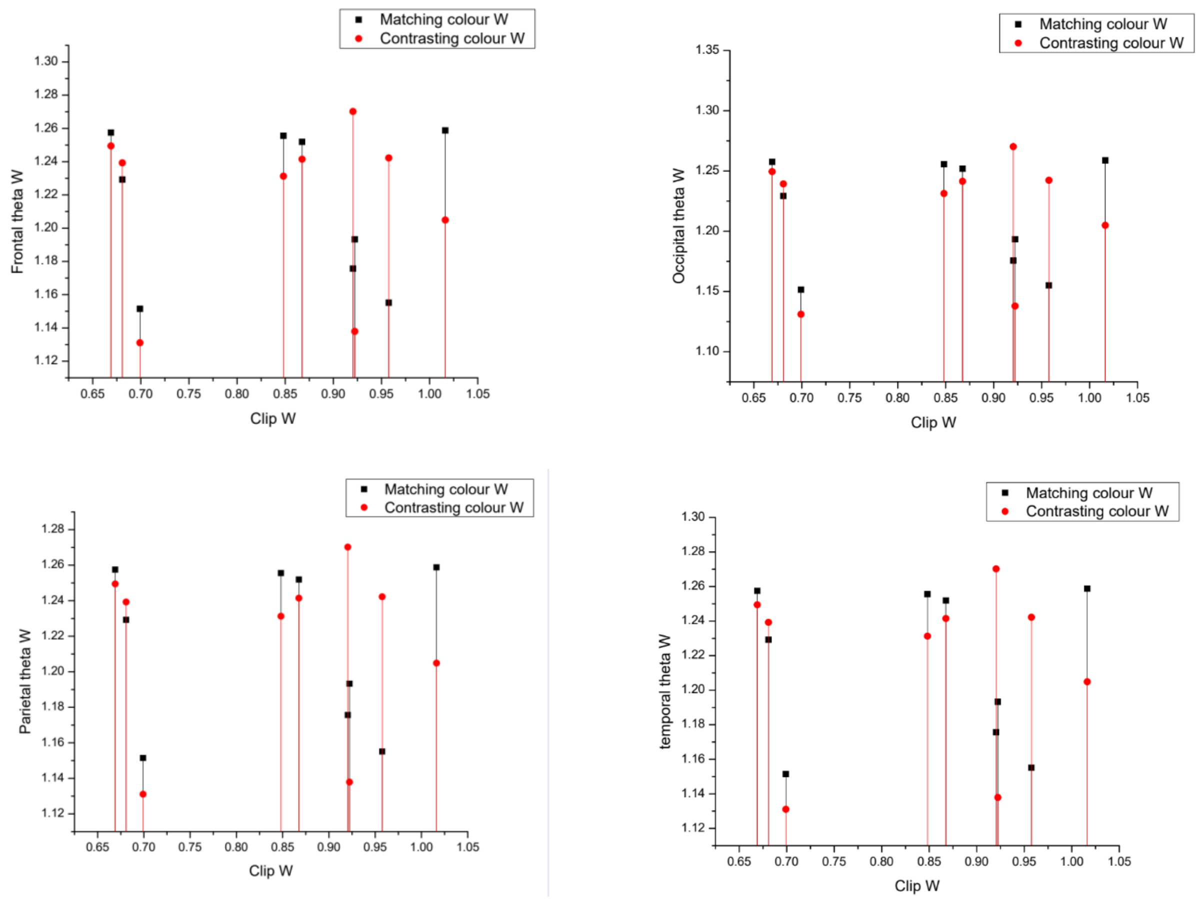
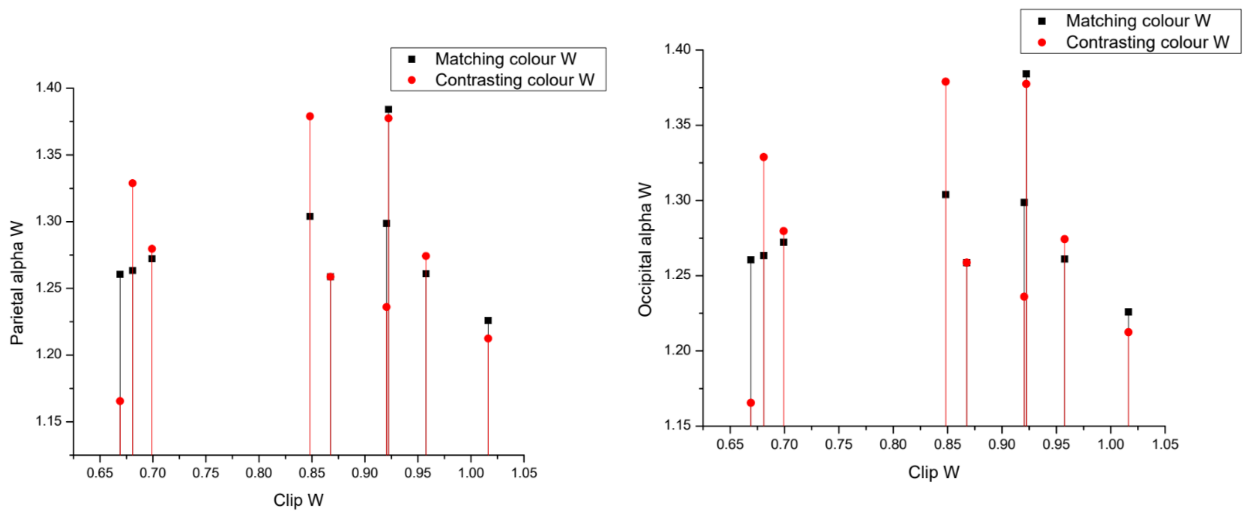


Fig 10.3.6.5-Lobe wise complexity variation against color stimuli and acoustic signals for theta range



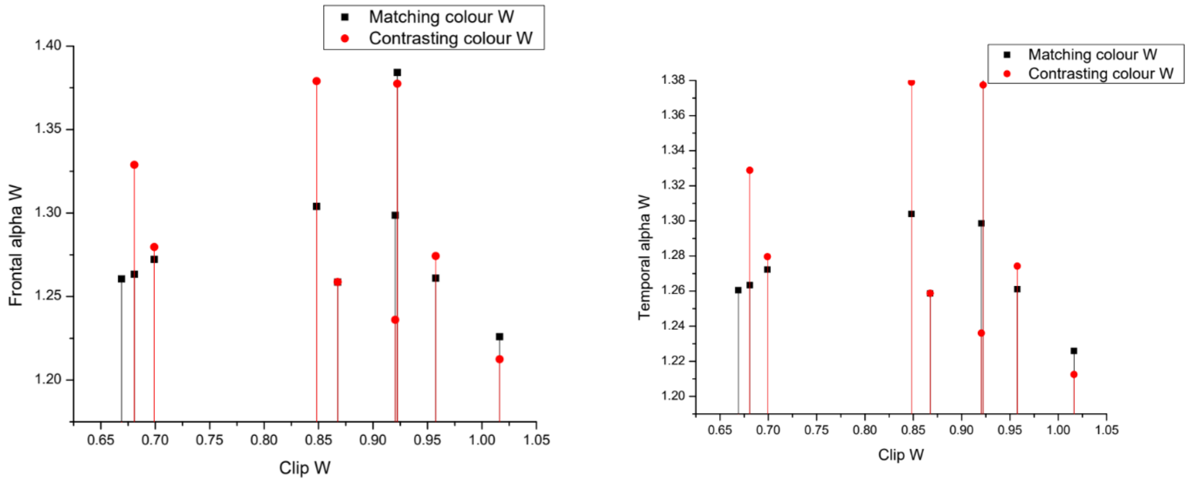


Fig 10.3.6.6-Lobe wise complexity variation against color stimuli and acoustic signals for alpha range

10.4. Conclusion:

In summary, our comprehensive experiment's main objective was to explore the correlation between audio and visual stimuli, specifically when the prosody of the same item is changed and their effects on brain activity as measured by EEG readings. To analyse the changes in brain activity, we employed the scientific approach of Multifractal Detrended Fluctuation Analysis (MFDFA). The results from our research have provided valuable insights into the connections between audio-visual stimuli and the emotional processing that occurs within the brain along with the importance of prosodic. Notably, we observed distinct patterns of brain activity across different brain regions and in relation to various emotional states. These findings contribute to our understanding of how audio and visual cues impact emotional processing in the brain.

We had established this experiment under two broad categories: Matching colours and Contrasting colours, let us explain the observation in that domain itself. Starting from matching colours, in the alpha frequencies variations can be seen in frontal region (especially F4, F7and F8), not that much in temporal region, occipital region (O2), and parietal region (P3). While in theta frequencies, variation has been observed in the frontal lobe (F4, F8), most of the temporal lobe (T4 and T6), occipital lobe (O1) and parietal lobe (P3). We can infer that alpha and theta frequencies work in separate lobes. Alpha frequencies do not activate temporal region while theta frequencies main target is the temporal region. Likewise occipital and parietal regions are also differ from each other while comparing frequencies. Evaluating contrasting colours, for the theta frequencies again we can see all the regions are being activated except for frontal region and for alpha, a similar pattern is observed, except temporal region. Hence, on the basis of activation of region whether during the alpha waves (calm state) or theta waves (meditative state), we can conclude that colour (contrasting or matching) activate the same regions.

When we are comparing the contrasting and matching colour readings, it is observed that in the theta range of frequencies, whether or not the subject is shown a colour resembling the emotion in the clip, the complexity vary too much. But considering the alpha frequencies, there is a lot of deviation in complexity due to the type of image shown. Hence, the second conclusion that can be drawn is for analysis of colour and emotion, the subject must be in a calm state (brain functioning in the alpha frequencies).

Another interesting aspect of our experiment was the change in prosodies. We have gathered some interesting results from the analysis. For Item 1, in alpha frequencies: song and speech has been invoking the maximum complexity in most of the lobes, in theta frequencies: song is affecting most of the lobes. For item 2, in alpha frequencies: Speech and recitation has been majorly activating the lobes of the brain whereas in theta frequencies: all the prosodies have been actively targeting different regions of the brain. For item 3, in alpha regions: recitation has been dominantly activating the lobes and in theta frequencies: speech is activating the various lobes of the brain. We can conclude that, in the alpha range of frequencies (calm state) mostly speech and recitation are the two prosodies which are responsible for activating different parts of the brain. Same analysis can be done in the theta range of frequencies (meditative state) where it is observed- speech, recitation and song all the three prosodies collectively activate the entire brain.

Through our quantitative analysis, we have explored the connection between audio-visual stimuli and prosody of literature, obtaining valuable insights with potential implications for advancements in various technological fields. By gaining an understanding of how specific audio-visual cues relate to various prosodies, we can harness this knowledge to develop personalized products that prioritize emotional engagement. This opens up possibilities for the creation of emotionally intelligent systems and devices, our data can be of use to speech recognition and natural language processing technologies where prosody plays a crucial role, and even in the future, methods can be developed to relate prosody to human emotions and create various emotion recognition devices. The potential applications of this research extend beyond what has been mentioned, paving the way for further innovations in the field.

10.5. References

[1] Sreeja, P. S., and G. S. Mahalakshmi. "Perc-an emotion recognition corpus for cognitive poems." *2019 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2019.

[2] Kang, Jin-Ae, Sookyeong Hong, and Glenn T. Hubbard. "The role of storytelling in advertising: Consumer emotion, narrative engagement level, and word-of-mouth intention." *Journal of Consumer Behaviour* 19.1 (2020): 47-56.

[3] Cummins, Fred. "The territory between speech and song: A joint speech perspective." *Music Perception* 37.4 (2020): 347-358.

[4] Johnson-Laird, Philip N., and Keith Oatley. "How poetry evokes emotions." *Acta Psychologica* 224 (2022): 103506.

[5] Freeman, Margaret H. *The poem as icon: A study in aesthetic cognition*. Oxford University Press, 2020.

[6] Farsi, Roghayeh. "Cognitive appraisal and coping in poetry." *Journal of Narrative and Language Studies* 9.18 (2021): 339-356.

[7] Cross, Emily S., et al. "A neurocognitive investigation of the impact of socializing with a robot on empathy for pain." *Philosophical Transactions of the Royal Society B* 374.1771 (2019): 20180034.

[8] Jaquess, Kyle J., et al. "Self-controlled practice to achieve neuro-cognitive engagement: Underlying brain processes to enhance cognitive-motor learning and performance." *Journal of Motor Behavior* 52.5 (2020): 544-557.

[9] Zmigrod, Leor. "A neurocognitive model of ideological thinking." *Politics and the Life Sciences* 40.2 (2021): 224-238.

[10] Russo, Frank A. "Motor system involvement in the perception of singing." *The Routledge companion to interdisciplinary studies in singing*. Routledge, 2020. 276-288.

[11] Howlin, Claire, Alison Stapleton, and Brendan Rooney. "Tune out pain: Agency and active engagement predict decreases in pain intensity after music listening." *PloS one* 17.8 (2022): e0271329.

[12] Casillo, Stephanie M., Diego D. Luy, and Ezequiel Goldschmidt. "A history of the lobes of the brain." *World Neurosurgery* 134 (2020): 353-360.

[13] Leblanc, Richard. "Pavlov, Penfield, and the physiology of the mind." *Neurology* 92.12 (2019): 575-578.

[14] Hu, Li, and Zhiguo Zhang, eds. *EEG signal processing and feature extraction*. Singapore: Springer Singapore, 2019.

[15] Martínez, Jorge Luis Morales, et al. "A modified multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation." *Physica A: Statistical Mechanics and its Applications* 565 (2021): 125611.

[16] Gorjão, Leonardo Rydin, et al. "MFDFA: Efficient multifractal detrended fluctuation analysis in python." *Computer Physics Communications* 273 (2022): 108254.

[17] David, Sergio Adriani, et al. "A combined measure to differentiate EEG signals using fractal dimension and MFDFA-Hurst." *Communications in Nonlinear Science and Numerical Simulation* 84 (2020): 105170.

[18] Sarkar, Uddalok, et al. "Language Independent Emotion Quantification using Non linear Modelling of Speech." *arXiv preprint arXiv:2102.06003* (2021).

[19] Avramidis, Kleanthis, et al. "Multiscale fractal analysis on EEG signals for music-induced emotion recognition." *2021 29th European Signal Processing Conference (EUSIPCO)*. IEEE, 2021.

[20] Banerjee, Archi, et al. "A novel study on perception–cognition scenario in music using deterministic and non-deterministic approach." *Physica A: Statistical Mechanics and its Applications* 567 (2021): 125682.

[21] Basu, Medha, et al. "Does musical training affect neuro-cognition of emotions? An EEG study with Indian Classical Instrumental Music." *Proceedings of Meetings on Acoustics 182ASA*. Vol. 46. No. 1. Acoustical Society of America, 2022.

[22] Scheuber, Sephra H. *Emotional and neurological responses to timbre*. University of Central Oklahoma, 2019.

[23] Zhang, Rui, Cairang Jia, and Jian Wang. "Text emotion classification system based on multifractal methods." *Chaos, Solitons & Fractals* 156 (2022): 111867.

[24] Basu, Medha, et al. "Neural Quantification of Timbre and Emotions from Indian Classical Music a Multifractal Exploration." *Available at SSRN 4374657*.

[25] Ahirwal, Mitul Kumar, and Mangesh Ramaji Kose. "Audio-visual stimulation based emotion classification by correlated EEG channels." *Health and Technology* 10.1 (2020): 7-23.

[26] Feradov, Firgan, Iosif Mporas, and Todor Ganchev. "Evaluation of features in detection of dislike responses to audio–visual stimuli from EEG signals." *Computers* 9.2 (2020): 33.

[27] DAŞDEMİR, YAŞAR, and RÜSTEM ÖZAKAR. "Affective states classification performance of audio-visual stimuli from EEG signals with multiple-instance learning." *Turkish Journal of Electrical Engineering and Computer Sciences* 30.7 (2022): 2707-2724.

[28] Rodriguez-Larios, Julio, et al. "From thoughtless awareness to effortful cognition: alpha-theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic." *Scientific Reports* 10.1 (2020): 1-11.

[29] Lin, Sen, et al. "A flexible, robust, and gel-free electroencephalogram electrode for noninvasive brain-computer interfaces." *Nano letters* 19.10 (2019): 6853-6861.

[30] Yean, Choong Wen, et al. "Emotional states analyze from scaling properties of EEG signals using hurst exponent for stroke and normal groups." *Intelligent Manufacturing and Mechatronics: Proceedings of the 2nd Symposium on Intelligent Manufacturing and Mechatronics–SympoSIMM 2019, 8 July 2019, Melaka, Malaysia*. Springer Singapore, 2020.

[31] Guo, Fu, et al. "Research on color optimization of tricolor product considering color harmony and users' emotion." *Color Research & Application* 45.1 (2020): 156-171.

[32] Zeileis, Achim, et al. "colorspace: A toolbox for manipulating and assessing colors and palettes." *arXiv preprint arXiv:1903.06490* (2019).

[33] Shrestha, Badri, and Louese Dunn. "The declaration of Helsinki on medical research involving human subjects: a review of seventh revision." *Journal of Nepal Health Research Council* 17.4 (2019): 548-552.

[34] Farrens, Jaclyn L., et al. "Electroencephalogram (EEG) recording protocol for cognitive and affective human neuroscience research." (2021).

[35] Dilena, Robertino, et al. "Consensus protocol for EEG and amplitude-integrated EEG assessment and monitoring in neonates." *Clinical Neurophysiology* 132.4 (2021): 886-903.

CHAPTER 11

DEVELOPMENT OF AN EMOTION RECOGNIZER: CLIENT ATTITUDE TRACKING A NOVEL BI ANALYTICS

"The whole is other than the sum of the parts".

Kurt Koffka

11.1 INTRODUCTION

Final chapter of the thesis deals with the implementation of detecting emotions out of audio signals using the nonlinear tool MFDFA. Studies report that Emotion recognition in conversations (ERC) is a hard job that has become more popular lately because of the ways it could be used. But until now, there hasn't been a big, multimodal, multi-party collection of emotional conversations with more than two people per discussion. Facial expression mood recognition is a natural way to tell what a person is thinking and feeling, and it is one of the most important ways to communicate with other people. It can be used in a lot of different areas, like psychology. As a famous person in old China, Zeng Guofan knew how to read people's emotions by looking at their faces. In his book Bing Jian, he summarizes eight ways to figure out who someone is, especially how to choose the right one. For example, "look at the eyes and nose for evil and righteousness, the lips for truth and falsehood; the temperament for success and fame, the spirit for wealth and fortune; the fingers and claws for ideas, the hamstrings for setbacks; if you want to know his conviction, you can pay attention to what he has said." People say that a person's face shows his or her attitude, thought, and whether they are good or bad. But because people's facial expressions of emotion are complicated and vary, standard facial expression emotion recognition technology has problems with not being able to pull out enough features and being affected by the outside world. Here we propose a simple yet extremely impactful model for detection customer satisfaction by comparing the complexities of his tone with the company operator. This is an extremely powerful tool that finds extensive applications in Business Intelligence.

One of the most effective communication in form of text, helping people detect emotions, tones and sentiments from other forms of human expression including text, vocal gestures and facial expressions. Understanding computationally the complete range of available data –fact and feelings respectively – to meet ones' situational needs is ambitious but an achievable project.

Business Process Organizations (BPOs) record huge amounts of telephone calls or telephone quality speech samples. These can be processed for attitude prediction and emotion extraction. Customer's opinions on various trends can be mined through attitude prediction and emotion extraction, which helps the corporate companies in their decision making.

11.2 ABC MODEL OF ATTITUDE

COMPONENT	MEASURED BY	EXAMPLE
Affect	Physiological indicators, verbal statements about feelings	I don't like my boss
Behavioral Intentions	Observed behavior, Verbal Statements about intentions	I want transfer in some other department
Cognition	Attitude scales, Verbal statement about beliefs	I believe my boss plays his favorites

11.3 Detection of Basic Emotion

The European culture views its primary feelings as being shared by all people. They consist of feelings such as happiness, sadness, anger, fear, surprise, and disgust. They are often manifested through facial expressions, body language, and vocal signs, and it is believed that they evolved to facilitate the rapid communication of an individual's internal state to others in the context of social settings. These feelings are known to elicit physiological responses such as increased heart rate, perspiration, and dilated pupils, which highlights the significance of these feelings in human connection. Understanding these feelings is necessary for effective communication and social interaction.

In Western countries, identifying fundamental feelings is done in a more overt manner than in Eastern cultures. Emotions felt by humans are still taken into account. The Eastern philosophical perspective on emotions is that they are malleable and cannot be labeled. According to Taoism, feelings are a natural part of the human experience and should be welcomed without criticism. According to Buddhist thought, feelings are fleeting experiences that can be managed by practices such as mindfulness and meditation. Affective neuroscience is a field that aims at understanding the underlying emotional processes of neural networks and their effects on cognition, physiology, and behavior. The historical focus has been on describing human emotions universally, clearly defining the cause of emotional processes, and also the role of the body and interoception of feelings and emotions.

Emotions have a social, or motivational, or adaptive role in human life, producing different characteristics which are indicative of human behavior. Decision-making, perception, human interactions, and human intelligence, as well as human health and work efficiency - are all affected by emotions. There are three components that influence the psychological behavior of humans: personal experiences, physiological responses, and behavioral or expressive responses. Emotions are consistent or discrete responses to events that are considerable for a being, corresponding to a coordinated set of responses that are brief in duration. To better understand emotions expressed daily, they can be analyzed from a dimensional or categorical point of view.

The categorical point of view is based on the idea of basic emotions that are implanted in human physiology. There are different proposals for the number and type of basic emotions, ranging from six to ten. With advancements in brain-computer interface and neuroimaging technology, it is possible to record brainwave signals non-intrusively and measure or control device motions virtually or physically. New applications, including neuroinformatics, which is the study of classification of emotions by collecting brainware signals are being actively developed using Artificial Intelligence and Machine Learning. This would in-turn aid in the development of Human Computer Interfaces (HCI) that cater to niche human needs.

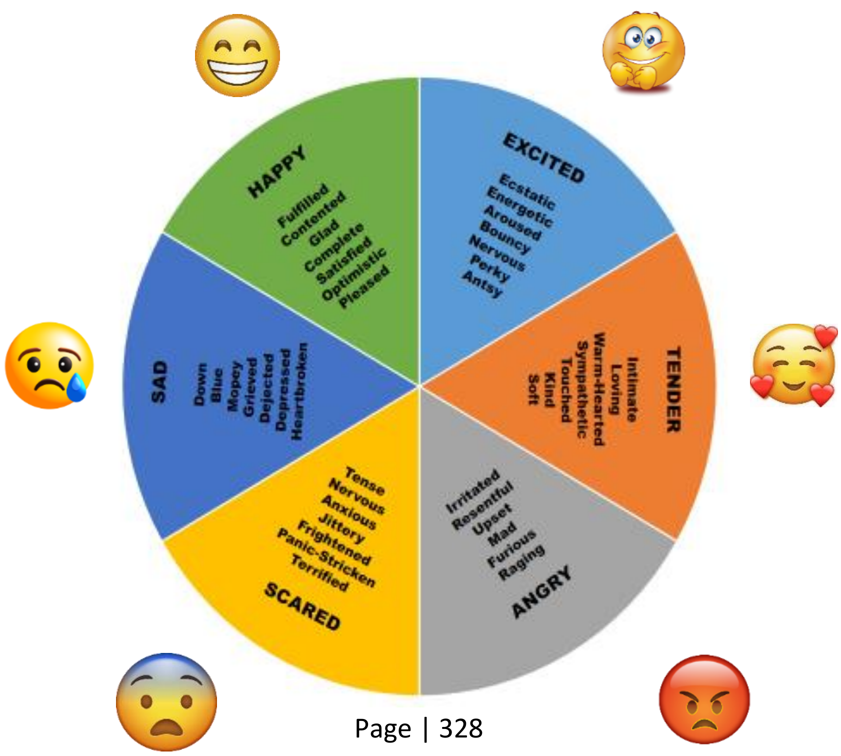


Fig 11.1 Detailed Model of emotional mapping

11.4 MODE OF COMMUNICATION

Fig 11.2 pictorial representation of Emotion detection through Text, Speech & Face

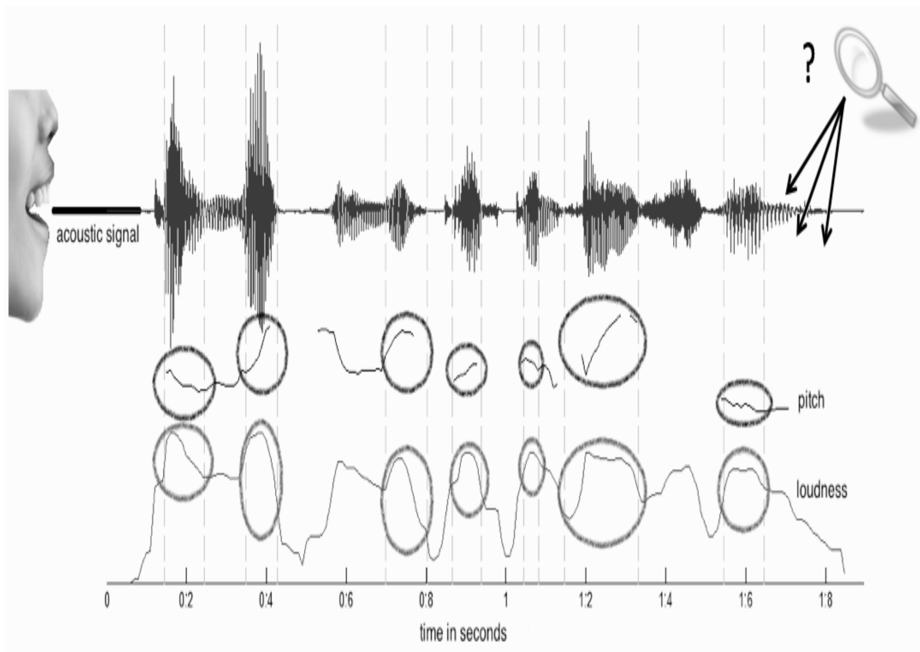


Fig 11.3 Detection of emotion through recorded audio of client/ customer and analyzing through nonlinear tools MFDFA/ MFDXA

Detection of human emotions can always be achieved through Facial expressions, speech signals and reading out text messages. out of these three options, text is apparently most difficult. doing a video call with the client and recording it for their responses analysis is also not a feasible option at all, but most of the BPOs have a declared terms and conditions that call recording can be done for quality improvement and training purposes. in the given scenario, recording the call with a customer and analyzing his tone and intonations is the easiest way of identifying emotions from the client's or the customer's end. In the given periphery we will try to identify the customer or the client satisfaction by analyzing the audio signal recorded during the conversation between the tele caller of the company and the customer and we will be analyzing these tools with MFDFA and we can further compare the two subsequent responses from the same client for a same service by checking the cross correlation among them. So MFDFA and MFDXA are the tools for the entire process to achive desired results. we have tried to represent the entire process in a pictorial format through figure 11.2, 11.3 and 11.4.

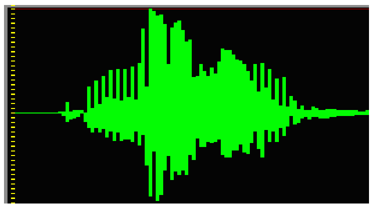
11.5 ASSETMENT THROUGH VARIOUS MODES OF COMMUNICATION

pictorial presentation of the pilot project

1 **TEXT**

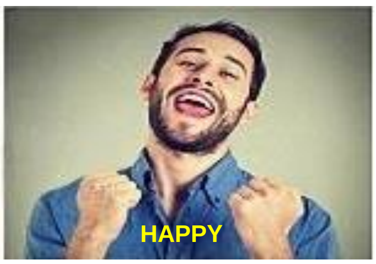
TOUGHEST

2 **SPEECH**



ACHIEVABLE

3 **FACE**



EASY

INTERACTION - 1

CLIENT 1

Speech/Voice

(Phone)

RECORD (3 min)

DIGITIZE

TOOLKIT 1

EMOTION RECOGNITION

INTERACTION - 2

CLIENT 2

Speech/Voice (Phone)

RECORD (3 min)

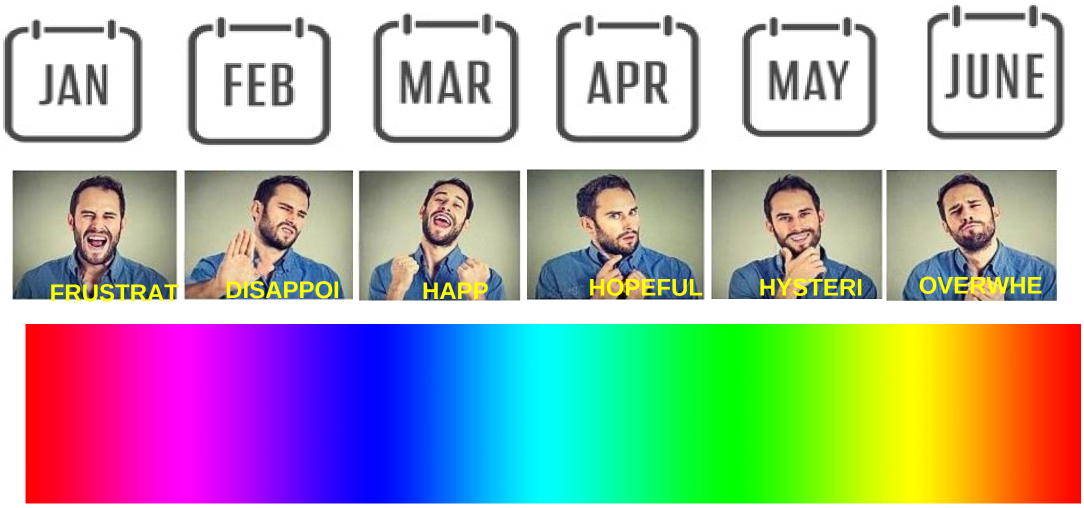
DIGITIZE

EMOTION TOOLKIT 1

EMOTIONAL TOOLKIT 2

EMOTION

11.6 CLIENT ATTITUDE TRACKING



CHANGE OF ATTITUDE CAN BE LINKED WITH COLOUR

ATTITUDE SURVEILLANCE MANAGER

11.6 References

Ahmadlou, M., & Adeli, H. (2011). Functional community analysis of brain: A new approach for EEG-based investigation of the brain pathology. *Neuroimage*, *58*(2), 401-408.

Ahmadlou, M., Adeli, H., & Adeli, A. (2010). New diagnostic EEG markers of the Alzheimer's disease using visibility graph. *Journal of neural transmission*, *117*(9), 1099-1109.

Ahmadlou, M., Adeli, H., & Adeli, A. (2012). Fractality analysis of frontal brain in major depressive disorder. *International Journal of Psychophysiology*, *85*(2), 206-211.

Banerjee, A., Sanyal, S., Patranabis, A., Banerjee, K., Guhathakurta, T., Sengupta, R., ... & Ghose, P. (2016). Study on brain dynamics by non linear analysis of music induced EEG signals. *Physica A: Statistical Mechanics and its Applications*, *444*, 110-120.

Bigerelle, M., & Iost, A. (2000). Fractal dimension and classification of music. *Chaos, Solitons & Fractals*, *11*(14), 2179-2192.

Gao, T. T., Wu, D., Huang, Y. L., & Yao, D. Z. (2007). Detrended fluctuation analysis of the human EEG during listening to emotional music. *Journal of Electronic Science and Technology*, *5*(3), 272- 277.

Hsü, K. J., & Hsü, A. J. (1990). Fractal geometry of music. *Proceedings of the National Academy of Sciences*, *87*(3), 938-941.

Hwa, R. C., & Ferree, T. C. (2002). Scaling properties of fluctuations in the human electroencephalogram. *Physical Review E*, *66*(2), 021901.

Kiselev, V. G., Hahn, K. R., & Auer, D. P. (2003). Is the brain cortex a fractal?. *Neuroimage*, *20*(3), 1765-1774.

Kumar, A., & Mullick, S. K. (1996). Nonlinear dynamical analysis of speech. *The Journal of the Acoustical Society of America*, *100*(1), 615-629.

Lee, J. M., Kim, D. J., Kim, I. Y., Park, K. S., & Kim, S. I. (2002). Detrended fluctuation analysis of EEG in sleep apnea using MIT/BIH polysomnography data. *Computers in biology and medicine*, *32*(1), 37-47.

Lee, M. (2015). *György Ligeti's" Désordre" and" L'escalier du Diable": Compositional style and method of practice*. The Ohio State University.

Ligeti, G. (2003). *Etudes, books I and II*. Naxos.

Linkenkaer-Hansen, K., Nikouline, V. V., Palva, J. M., & Ilmoniemi, R. J. (2001). Long-range temporal correlations and scaling behavior in human brain oscillations. *Journal of Neuroscience*, *21*(4), 1370-1377.

Lochhead, J. (2001). Hearing Chaos. *American Music*, 210-246.

Lopes, R., & Betrouni, N. (2009). Fractal and multifractal analysis: a review. *Medical image analysis*, *13*(4), 634-649.

Maity, A. K., Pratihar, R., Mitra, A., Dey, S., Agrawal, V., Sanyal, S., ... & Ghosh, D. (2015). Multifractal detrended fluctuation analysis of alpha and theta EEG rhythms with musical stimuli. *Chaos, Solitons & Fractals*, *81*, 52-67.

Mandelbrot, B. (1967). How long is the coast of Britain? Statistical self-similarity and fractional dimension. *science*, *156*(3775), 636-638.

Mölle, M., Marshall, L., Lutzenberger, W., Pietrowsky, R., Fehm, H. L., & Born, J. (1996). Enhanced dynamic complexity in the human EEG during creative thinking. *Neuroscience Letters*, *208*(1), 61-64.

Natarajan, K., Acharya U, R., Alias, F., Tiboleng, T., & Puthusserypady, S. K. (2004). Nonlinear analysis of EEG signals at different mental states. *Biomedical engineering online*, *3*(1), 1-11.

Pressing, J. (1988). Improvisation: methods and models. *Generative processes in music*, 129-178.

Salter, J. R. (2009). *Chaos in music: Historical developments and applications to music theory and composition*. The University of North Carolina at Greensboro.

Sengupta, R., Dey, N., Datta, A. K., Ghosh, D., & Patranabis, A. (2010). Analysis of the signal complexity in sitar performances. *Fractals*, *18*(02), 265-270.

Su, Z. Y., & Wu, T. (2006). Multifractal analyses of music sequences. *Physica D: Nonlinear Phenomena*, *221*(2), 188-194.

Tong, S., Huang, H., Luan, J., & Chen, H. (2005). Dimensional complexity analysis of human EEG in visual processing. *Neurocomputing*, *67*, 297-305.

Voss, R. F., & Clarke, J. (1975). '1/f noise in music and speech. *Nature*, *258*(5533), 317-318.

Weiss, B., Clemens, Z., Bódizs, R., & Halász, P. (2011). Comparison of fractal and power spectral EEG features: Effects of topography and sleep stages. *Brain research bulletin*, *84*(6), 359-375.

CHAPTER 12
CONTRIBUTION OF THE WORK

The greater the ambiguity, the greater the pleasure"

Milan Kundera

This thesis focused on a few interesting ideas, which will be quickly summed up in this part. It started by looking at how visual and audio stimuli affect the brain and how they affect thinking. Biosignals, such as EEG and fMRI, show exactly how an input changes the way the brain works. And changes in the thinking area show up indirectly in how people talk, act, and make decisions. In two different ways, both of these ways were used. Ghosh et al. (2018) wrote about how a sensory input like music can change cellular markers and how complicated they are. In fact, the trigger is very close to itself and has long-range associations (Hsü & Hsü, 1991). The next question that comes to mind is whether these bodily changes caused by a trigger also have effects on thinking. Also, do these processing networks interact with other perceptual networks, such as those that deal with seeing and understanding what you see? Because of this, researchers looked at how the visual connection of a sound input affected how the brain thought about it. It was found that the subjects' color choices are affected by how hard the information is to understand. Next, the EEG readings were used to look at the direct effects of visual stimuli on the brain. This was done to study how stimuli affect the brain. Using Grey as a starting point, subjects were shown seven colors of VIBGYOR, and the biosignals they produced were observed. The study of the same showed that the general level of difficulty went up from Blue to Red to Green. It was also found that the processing of perceptual information is not domain-specific, even at the temporal level. In this case, the Frontal, Parietal, and Occipital parts of the brain were all involved in the process at the same time. It has also been found that the right side of the brain is more active than the left when it comes to interpreting visual information. These studies give us new information about how the brain and mind work together to process stimuli. But what is it about a stimulation that makes it arousing? Every piece of writing is made up of a subset of the words that are used in that language as a whole. But the book doesn't make you feel anything, while a Shakespeare play does. Then, is it the language that makes you feel so much? Semantics? Or perhaps the setting? Could it be because the reader expected something to happen (a word, a phrase, a literary term, a pattern in a story) and it did or didn't? In the same way, a piece of music is made of the same amount of notes as another piece of music. What sets them apart? Is it just the way the notes are put together? More importantly, how do they make people feel such different emotions, even though they have the same basic structure? Because of these questions, people looked into the structure of music to find clues that could help them figure out how it makes people feel. In a new way, Indian Classical Music and its many forms were studied using hard-core statistical tools. Based on how musical notes are used now and in the past, these methods have found factors that can identify previously intangible or qualitative features. It can measure how fast or slow the performance is, how "close" the performance is to the traditional methods used, how complicated the notation language is, how free the performance is, and how open or closed the performance is to decoration and expressive movements ("musical analyticity"). Some of the most important things that make a piece of music beautiful are listed here. Also, the factors could be used to put styles, singers, and Ragas into groups. Lastly, the question of whether or not traditional theories and logics are enough to explain thought and awareness was looked into. It was shown that the Boolean logic doesn't work when it comes to how we hear things, which isn't always clear. This makes a case for a theory that is better than the traditional ones, which is what quantum cognition models offer. This is a different method.

From quantum neural models, which try to use quantum theory to explain where thought and awareness come from a phenomenological point of view. Quantum cognition uses the mathematical structure of quantum theory (probability amplitudes, actualization of potentials, and quantum operators) to explain the cognitive domain and answer non-Boolean puzzles. Later, this method is used to describe a model of creative thinking that puts ambiguity (or the ability to deal with ambiguity) at the top of the list of important factors. All of the studies and methods discussed in this thesis have one thing in common: they all have to do with how people feel. A factor that gives us a natural edge in how we perceive events and is still one of the most important parts of how we understand them. Science hasn't been able to directly measure this human idea yet, which makes us wonder if this kind of unity is even possible. This thesis makes it possible to combine fields like physics, music, color perception, psychology, cognition, and neuroscience, and the author thinks that doing so could help answer some of these tough questions in the future.

Physics is proud of being able to explain the most of reality with the fewest ideas and rules. From a science point of view, the areas of thought, awareness, and feeling are too far away and hazy. But Sir Isaac Newton, one of the founders of modern physics, took on such a job and called it "spiritual substance" (Dempsey, 2006). His efforts didn't work, and since then, this kind of talk has been left to philosophers and scientists. Recent progress in neuroscience has brought these back into the world of "hard science." Scanning technologies like PET, fMRI, MEG, and EEG are getting better at showing what's going on in a person's brain when they actually have an experience. This brings the field a step closer to finding the neural correlates of subjective truth. Grossberg and Levine (1987) say that feelings are caused by nerve signals that link areas of the brain that deal with instinct and those that deal with ideas. They tell mental awareness and understanding processes about innate wants. Their job is to drive behavioral and mental representation-models, which relate to things or events that might meet natural needs, so that these models get more attention and processing power in the brain. So, feelings judge ideas so that instincts can be satisfied. Many emotions are involved in our higher cognitive skills. These include learning, emotions in the way we speak, emotions caused by cognitive dissonances, and artistic emotions. Some cognitive differences, like how we see space, colors, the pitch of sounds, tastes, numbers, objects, and movements, depend on changes in the brain that help us generalize and put things into groups. When it comes to studies on brain, linguistics and music also play bigger parts than they used to. Chomsky tried to separate language from thinking, but language is so important to thinking that it is hard to imagine what thinking would be like without language (Chomsky, 1957). Do we think with words, or do we only use words to name parts of our thoughts when they are finished? There are almost an endless number of possible connections between words and things, so how does every child learn to make the right connections? What happens to a child's brain when he or she learns a language? Science needs to figure out how language and thought work together and why they are so connected but also so different. Another edge is how language makes people feel. Language and its most important way of working, speech, can only work if the sounds of words are felt. If the sound of a word doesn't make you feel or do anything, it doesn't mean anything.

Even if it's not recognized, the emotional tone of a person's voice changes the whole the mind and even the society. This is still something that needs to be looked into. In the same way, understanding music is also important. Honing et al. (2015) still don't know how people learn to understand music. A lot has been learned about where emotions come from and what affects they have. Answers to these questions can help us understand how music makes us feel or why its emotional traits are so widely appealing. Traditionally, a lot of these problems belonged to subjective reality, which was usually outside of scientific objectivity. With the rise of cognitive psychology in the 1960s, scientists began to talk about the possibility and necessity of putting subjective experience back into scientific study. They also came up with experimental methods and theoretical models to help them understand the hidden mental machinery of human perception, cognition, and action. To quote the great E. P. Wigner (1995): "Both Physics and Psychology claim to be all-encompassing disciplines; the first because it tries to explain all of nature and the second because it studies all mental events, and nature only exists for us because we know about it. Both fields could still be combined into one without putting too much pressure on our ability to think abstractly. In physics, the first test of a scientific theory is how elegant and beautiful it is. This means that it should be able to explain a large body of knowledge using only a few basic principles and make statements that can be tested in the real world. Future study in the cognitive sphere should use all the big guns, like physics, neuroscience, and psychology, to create a mutual environment where ideas and their testability can grow beyond intellectual gatekeeping. This thesis hopes to get the ball going in that way and be the starting point for such a huge project.