Emotional Response Detection via HRV Analysis of Audiovisual Stimuli: A Study Based on Time, Frequency, and Non-Linear Features

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Submitted by

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I hereby declare that this thesis contains a literature survey and original research work by the undersigned candidate, as part of his Master of Engineering in Biomedical Engineering studies during the academic session 2022-2024.

All information in this document has been obtained and presented following academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referred all material and results that are not original to this work.

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Preface

Human emotions play a pivotal role in stress management. Understanding these emotions, particularly through the lens of physiological responses, can significantly benefit society by providing effective strategies for managing stress. Analyzing Heart Rate Variability (HRV) characteristics from Electrocardiogram (ECG) data is one of the most promising approaches to determining emotional states. This recognition is instrumental in developing tools and techniques for stress management. This experiment was conducted by analyzing emotional responses to audiovisual stimuli.

In the first chapter, a brief introduction to human emotions and their impact on physiological changes is presented. This chapter explores the relationship between emotions, ECG, and HRV, highlighting how these elements are interconnected.

The second chapter provides a thorough literature review encompassing all aspects of this study. It describes signal acquisition, the relation between emotions and HRV and ECG, as well as several HRV characteristics, such as the frequency domain, time domain, and non-linear parameters. The experiment involved analyzing emotional responses to various audiovisual stimuli to observe their effects on HRV.

In the third chapter, the methodology and experimental procedures are detailed. This chapter describes all steps followed during the study, including the signal acquisition systems used, signal processing techniques, and the analysis of ECG signals about emotions. It also discusses the extraction of HRV features across time, frequency, and non-linear domains.

The fourth chapter presents the experimental results. This consists of the study's conclusions, which include the extraction and analysis of the non-linear parameters, time domain, frequency domain HRV components, and the detection of QRS using the Pan-Tompkins method.

In the final chapters, the HRV's feature results are discussed from a physiological perspective, leading to certain conclusions. These conclusions underscore the significance of HRV feature extraction from ECG signals in recognizing emotional states and their potential applications in stress management.

Contents

PUBLICATION ---------- **I**
PREFACE ---------- **II**
CONTENTS ---------- **III**
LIST OF FIGURES ---------- **V**
LIST OF TABLES ---------- **VII**
1. INTRODUCTION ---------- **1**
1.1. HUMAN EMOTION: PHYSIOLOGICAL REACTION AND BIO-SIGNAL ---------- 2
1.1.1. Emotions & Physiological Reaction ---------- *2*
1.1.2. Analyzing Bio-signals to Determine Physiological Responses ---------- *3*
1.1.3. ECG, Emotion & Responses ---------- *3*
1.1.4. The Correlation Between Various Emotions & ECG ---------- *4*
1.2. ELECTROCARDIOGRAM AND ELECTROCARDIOGRAPHY ---------- 4
1.2.1. Heart & Conduction Mechanism ---------- *5*
1.2.2. The Electrocardiogram Waveform ---------- *6*
1.2.3. The Significance of Physiology ---------- *7*
1.3. RELATIONSHIP BETWEEN HRV AND ECG ---------- 8
1.3.1. The Autonomic Nervous System & HRV ---------- *8*
1.3.2. HRV's Time-Domain Parameters ---------- *9*
1.3.3. HRV's Frequency-Domain Parameters ---------- *9*
1.3.4. HRV's Non-Linear Parameters ---------- *10*
1.3.5. Physiological Significance ---------- *10*
1.4. MOTIVATION BEHIND THE WORK ---------- 11
1.5. OBJECTIVE OF THE WORK ---------- 12
2. LITERATURE REVIEW ---------- **13**
2.1. ANALYZING EMOTIONS WITH EEG ---------- 14
2.2. ANALYZING EMOTIONS WITH ECG ---------- 15
2.3. STUDYING EMOTIONS FROM HRV ---------- 16
2.4. ANALYZING EMOTIONS THROUGH TIME DOMAIN FEATURES OF HRV ANALYSIS ---------- 18

2.5. ANALYZING EMOTIONS THROUGH FREQUENCY DOMAIN FEATURES OF HRV ANALYSIS 19
2.6. ANALYZING EMOTIONS THROUGH HRV ANALYSIS OF NON-LINEAR FEATURES ----------20

3. METHODOLOGY ----------22

3.1. SIGNAL ACQUISITION ----------22
3.2. SIGNAL PROCESSING ----------24
3.3. ANALYSIS ECG SIGNAL WITH STIMULI ----------24
3.3.1. QRS RECOGNITION USING PAN TOMKINS ALGORITHM ----------24
3.3.2. IDENTIFY R-R & NN INTERVALS ----------26
3.3.3. ANALYSIS of HRV ----------26
3.4. HRV'S FEATURES EXTRACTION ----------27
3.4.1. TIME DOMAIN PARAMETERS ----------27
3.4.2. FEATURES of FREQUENCY DOMAIN ----------29
3.4.3. NON-LINEAR FEATURES ----------32

4. RESULT ----------38

4.1. PAN TOMKINS ALGORITHM FOR QRS DETECTION ----------38
4.2. HEART RATE ----------40
4.2.1. Heat Plot of The Heart Rate ----------41
4.3. HRV FEATURES ----------43
4.3.1. Time domain ----------43
4.3.2. Analysis of Frequency Domain ----------49
4.3.3. Non-Linear Features Analysis ----------59

5. DISCUSSION ----------66

6. CONCLUSION ----------72

7. FUTURE SCOPE ----------73

8. REFERENCE ----------74

List of Figures

1. Figure 1. 1 Diagram of the Cardiac Conduction System 5
2. Figure 1. 2 Graphical representation of ECG Wave with the component waves labeled. 7
3. Figure 1. 3 ECG Waveforms of electrical signals associated with different parts of the heart. 7
4. Figure 1. 4 Block Representation of Plan of Work 12

5. Figure 3. 1 Overall Block diagram of Experimental setup 22
6. Figure 3. 2 Representation of ECG's electrode placement for the Einthoven Leads system [69] 23
7. Figure 3. 3 Pan Tompkins QRS detection algorithm flowchart 24
8. Figure 3. 4 Sample PSD computed using the Welch's method [87] 30
9. *Figure 3. 5 Sample PSD computed using the Lomb-Scargle periodogram [89]* 31
10. Figure 3. 6 Poincare plot for three Different RR intervals: Fig: (a) Poincare plots demonstrative of a healthy subject with a comet pattern, (b) a heartbeat irregularity in a subject with a torpedo pattern, and (c) another heartbeat irregularity in a subject with a complex pattern [103] 33
11. Figure 3. 7 Poincare plot of a coordinate plane [104] 34
12. Figure 3. 8 DFA representation of the short (Red) & long (green) term fluctuations [115] 37

13. Figure 4.1. 1 Pan-Tomkins Algorithm for QRS Detection 38
14. Figure 4.1. 2 Pan-Tomkins Algorithm for QRS Detection 39

15. Figure 4.2. 1 Heart Rate Distribution 40
16. Figure 4.2. 2 Heart Rate Heat plot while watching Nature Video 41
17. Figure 4.2. 3 Heart Rate Heat plot while watching a Comedy Video 42
18. Figure 4.2. 4 Heart Rate Heat plot while watching Suspense Video 43

19. Figure 4.3. 1 SDNN values for each subject and phase 44
20. Figure 4.3. 2 RMSSD values for each subject and phase 46
21. Figure 4.3. 3 pNN50 values for each subject and phase 47

22. FIGURE 4.3. 4 PSD ESTIMATION USING WELCH'S METHOD WHILE WATCHING A NATURE VIDEO 49
23. FIGURE 4.3. 5 PSD COMPARISONS ESTIMATION USING WELCH'S METHOD WHILE WATCHING A NATURE VIDEO 50
24. FIGURE 4.3. 6 PSD ESTIMATION USING WELCH'S METHOD WHILE WATCHING A COMEDY VIDEO 51
25. FIGURE 4.3. 7 PSD COMPARISON ESTIMATION USING WELCH'S METHOD WHILE WATCHING A COMEDY VIDEO 51
26. FIGURE 4.3. 8 PSD ESTIMATION USING WELCH'S METHOD WHILE WATCHING A SUSPENSE VIDEO 52
27. FIGURE 4.3. 9 PSD COMPARISONS ESTIMATION USING WELCH'S METHOD WHILE WATCHING A SUSPENSE VIDEO 52
28. FIGURE 4.3. 10 PSD ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A NATURE VIDEO 53
29. FIGURE 4.3. 11 PSD COMPARISONS ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A NATURE VIDEO 54
30. *FIGURE 4.3. 12 PSD ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A COMEDY VIDEO* 55
31. FIGURE 4.3. 13 PSD COMPARISONS ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A COMEDY VIDEO 55
32. FIGURE 4.3. 14 PSD ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A SUSPENSE VIDEO 56
33. FIGURE 4.3. 15 PSD COMPARISONS ESTIMATION USING LOMB SCARGLE'S METHOD WHILE WATCHING A SUSPENSE VIDEO 56
34. FIGURE 4.3. 16 LF/HF VALUES FOR EACH SUBJECT AND PHASE 57
35. FIGURE 4.3. 17 POINCARE PLOT OF NATURE VIDEO 59
36. FIGURE 4.3. 18 POINCARE PLOT OF COMEDY VIDEO 59
37. FIGURE 4.3. 19 POINCARE PLOT OF SUSPENSE VIDEO 59
38. FIGURE 4.3. 20 SAMPLE ENTROPY VALUES FOR EACH SUBJECT AND PHASE 61
39. FIGURE 4.3. 21 DFA FOR NATURE VIDEO 63
40. FIGURE 4.3. 22 DFA FOR COMEDY VIDEO 64
41. FIGURE 4.3. 23 DFA FOR SUSPENSE VIDEO 65

List of Tables

1. TABLE 1 - SDNN VALUES OF ALL SUBJECTS 44
2. TABLE 2 - RMSSD VALUES OF ALL SUBJECTS 45
3. TABLE 3 – PNN50 VALUES OF ALL SUBJECTS 47
4. TABLE 4 – LF/HF VALUES OF ALL SUBJECTS 57
5. TABLE 5 – SAMPLE ENTROPY VALUES OF ALL SUBJECTS 61

CHAPTER-I

1. Introduction

In human daily life, individuals in various professions encounter unique sources of stress. Students feel a lot of pressure about their studies, tests, and future jobs. Working professionals have to handle tough career duties, deadlines, and balancing work and personal life. Young people often battle various types of depression and anxiety from social, school, or money pressures. As a result, stress is a big problem that affects mental and physical health every day.

Recognizing the widespread impact of stress, I, as a biomedical master's student, became determined to contribute to the field of stress management. As I watched, understanding emotions is the first big step in grasping the problem. Emotions mainly play a major role in how we perceive and cope with stress, and closely related to the changes in our body. These physiological changes can be measured through bio-signals, which are mainly physiological measurements that provide valuable information on the state of the body.

The electrocardiogram, or ECG, is one of the most significant bio-signals as it mainly detects the electrical impulses of the heart. Heart rate variability (HRV), a crucial marker of the autonomic nervous system (ANS) in human physiology, can be obtained from the ECG.

In addition to ECG, the electroencephalogram (EEG) is another valuable tool for studying emotional responses. The EEG measures the brain's electrical activity and can identify patterns associated with different emotional states. While EEG is effective, it is tedious and complex compared to ECG, which presents a more straightforward, easy, and accessible acquisition technique [1].

I am motivated to investigate the use of ECG-based HRV analysis as opposed to the current reliance on EEG for emotion recognition due to the potential that this simpler and more practical

method has in detecting and analyzing emotional states [2]. The approach towards the assessment of emotional states based on bio-signals could really help society in numerous applications.

So, the motivation behind this research work is determined by the wish to address the universal issue of stress in daily life by advancing our understanding of the physiological responses of emotions and developing innovative tools for their assessment. By using ECG, these research objectives are to make a difference in stress management and improve the good of individuals in various professions and walks of life.

1.1. Human Emotion: Physiological Reaction and Bio-signal

Human emotions are complex and involve psychological, physiological, and behavioral components. Emotions can affect a variety of physiological systems, and these changes can be measured through bio-signals [3]. Bio-signals are physiological measurements that replicate the state of the body and are crucial for understanding the physiological responses associated with different emotional states [4].

1.1.1. Emotions & Physiological Reaction

When somebody experiences emotions, The body faces several physiological changes. The autonomic nerve system (ANS), which regulates involuntary body processes which include heart rate, breathing, and digestion, is responsible for these alterations [5]. Two branches within the ANS are the Parasympathetic Nervous System and the Sympathetic Nervous System.

- Sympathetic Nervous System (SNS): This all comes down to regulating the ‘fight or flight’ reaction, which formulates the body to react to stressful situations. When stressful situations present then our heart rate goes up, blood pressure rises, breathing gets faster and stress hormones like adrenaline and cortisol get released [6].
- Parasympathetic Nervous System (PNS): The PNS helps relaxation and recovery mainly in control of the ‘rest and digest’ reaction. Activation of the PNS refers to a decrease in heart rate, and it helps with digestion and energy conservation [7].

1.1.2. Analyzing Bio-signals to Determine Physiological Responses

Bio-signals are important tools for measuring the physiological responses associated with emotions [8]. Prominent bio-signals used in emotional research are:

- Electroencephalogram (EEG): EEG is connected with emotion recognition by measuring the brain's electrical activity to identify patterns related to different emotional states.
- Electrocardiogram (ECG): ECG measures the electrical impulse of the heart and gives valuable information about heartbeat and variability of heart rate.
- Electrodermal Activity (EDA): It measures deviations in skin conductance, which are generated by sweat glands and linked with arousal and stress.
- Respiration Rate (RP): It measures the rate of breathing, which can change with emotional states.
- Blood Pressure (BP): It detects the force of blood against artery walls, which can rise in times of stress or excitement.

1.1.3. ECG, Emotion & Responses

The ECG is a widely used bio-signal for studying emotional responses [9]. It records the electrical activity heart and gives valuable information about heart rate and HRV parameters, both of which are influenced by emotional states.

- Heart Rate: It is the count of heartbeats that occur in a minute. Heart rate usually rises in response to emotional excitation, such as excitement, fear, or tension. On the other hand, relaxation and quietness are linked with a decreased heartbeat.

- Heart Rate Variability (HRV): It’s the variation in time between consecutive heartbeats. HRV is an important parameter of ANS [10]. High HRV is associated with a healthy, responsive autonomic system and is linked to positive emotional states, while low HRV is linked with anxiety, stress, and negative emotional states.

1.1.4. The Correlation Between Various Emotions & ECG

Emotional states influence the ANS, which affects the electrical response of the heart. These changes are recorded by the ECG, which enables researchers to examine the physiological underpinnings of emotion [11]. For instance:

- Stress and Anxiety: These emotional responses of the SNS, lead to an increase in the rate of heart and a decrease in HRV. This can be observed as shorter RR intervals (the interval between successive ECG R-waves) and reduced variability in the ECG waveform.
- Relaxation and Calmness: These conditions activate the PNS, leading to a reduction the heart rate and a rise in the HRV. This results in longer RR intervals and greater variability in the ECG waveform.

So, using the ECG, researchers can gain an understanding of the physiological responses associated with different emotional states. This information is most valuable for developing interventions aimed at improving emotional regulation and overall well-being. Moreover, ECG-based HRV analysis is a non-invasive process and an important method for measuring emotional health, making it a valuable tool for both clinical and everyday applications [12]. The activity of these counterpart divisions plays a critical role in heart rate regulation, which can be observed and analyzed using HRV analysis methods. For instance, it is known that physical or emotional stress results in an increase in HR which can be indexed as increased activity of the SNS [13]. This alteration in HR is the fundamental information used in HRVA, from which a series of features can be derived to identify the dominant physiological mechanisms

1.2. Electrocardiogram and Electrocardiography

The Electrocardiogram (ECG) represents a fundamental signal from the human body, encapsulating the combined electrical activity within the heart's tissue, which initiates the heart's pumping action specifically the heartbeat. This signal is the outcome of an ECG recording [14], a crucial and often used technique for cardiac monitoring, wherein the electrical activity from cardiac contractions is gauged with dedicated ECG sensors and surface electrodes placed on the skin. The unique shape of the ECG signal is a consequence of the sequential contractions of distinct segments of the cardiac tissue, each contributing to the overall waveform [15].

The human heart is a powerful pump that helps blood flow throughout the body to supply tissues with nutrition and oxygen while expelling waste. This movement is dictated by a series of synchronized electrical impulses stemming from specialized cardiac cells. Understanding the electrical patterns of the heart is necessary for understanding the waveform of an electrocardiogram, which contains of the P, QRS, and T waves. Delving deeper, I explore the physiological mechanisms governing the heart's operation, starting from the sinoatrial (SA) node to the bundle of His, and elucidating how these processes give rise to the distinctive ECG waveform.

1.2.1. Heart & Conduction Mechanism

Sinoatrial (SA) Node: It is a natural pacemaker, and located in the right atrium close to the entry of the superior vena cava [16]. In a healthy person who is at rest, it produces electrical impulses at regular intervals, usually 60 to 100 times per minute. The heart's contraction cycle starts with these impulses [17]. **Atrial Conduction**: The atria contract as a result of atrial depolarization followed by the electrical impulse that originates from the SA node and spreads across them [18]. Blood is pushed into the ventricles by this atrial contraction. The P wave indicates the depolarization of the atria.

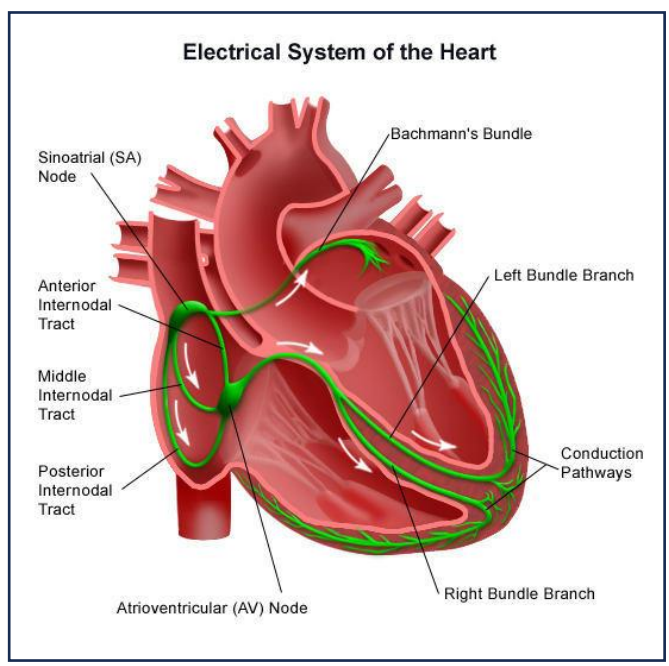


Figure 1. 1 Diagram of The Cardiac Conduction System [18]

Atrioventricular (AV) Node: It is situated at the meeting point of the ventricles and atria and is where the pulse next arrives. To make sure the ventricles are filled with blood and the atria are fully constricted, the AV node acts as a gatekeeper by slightly delaying the impulse. This delay is crucial for the efficiency of the heart's pumping action. **Bundle of His**: The impulse reaches the AV node and travels to the bundle of His, where the branches of the bundle separate into the left and right. These branches comportment the impulse toward the ventricles. **Purkinje Fibers**: The bundle branches are again divided into a network of Purkinje fibers that spread throughout the hole ventricles. The fast conduction through these fibers ensures the main simultaneous contraction of the ventricular muscle cells [19].

1.2.2. The Electrocardiogram Waveform

The waveform [20] is a graphic representation of the heart's electrical impulse as seen on the skin's surface [21]. It is made up of the following parts:

- **P Wave**: Generated by the SA node, the P wave represents the atrial depolarization. It is a small, rounded wave that precedes the main complex.

- **QRS Complex**: The ventricular depolarization is symbolized by the QRS complex. Ventricles have more muscle mass than the P wave, for that reason QRS complex is noticeably bigger. It is made up of three separate parts:
- **Q**: A deviation downward that follows the P.
- **R**: A huge rising deflection demonstration of ventricular depolarization.
- **S**: A downward deflection that follows the R wave and signifies the ventricular depolarization's final phase.

- **T Wave**: Ventricular repolarization represents the T wave, where the ventricles prepare for the next contraction. It is usually a modest upward wave following the QRS complex.

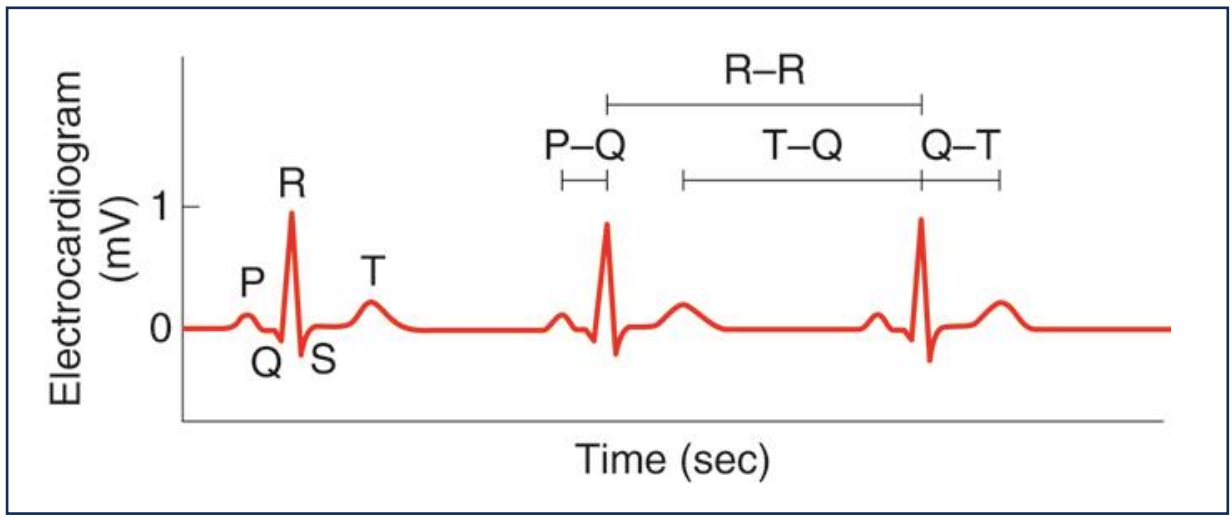


Figure 1. 2 Graphical representation of ECG Wave with the component waves labeled [21]

1.2.3. The Significance of Physiology

Conduction from SA to AV Node: The electrical impulse is generated from the SA node and spreads over the atria to the AV node. This pathway confirms the atria contract and pushes blood into the ventricles before the ventricles contract [16].

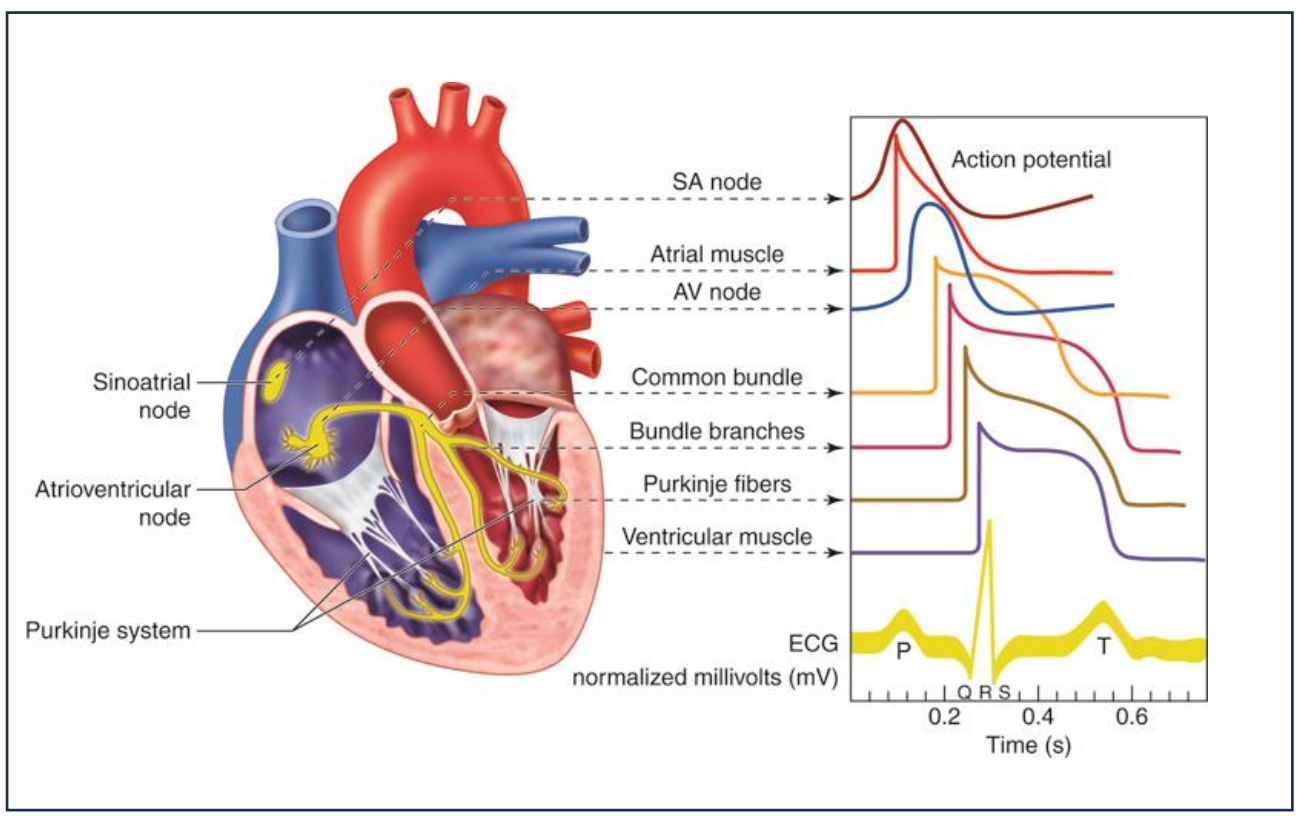


Figure 1. 3 ECG Waveforms of electrical signals associated with different parts of the heart [21]

AV Node Delay: The AV node delays the impulse to allow complete ventricular filling. This delay is replicated in the PR intervals, the period between the onset of the wave P and the start of the QRS complex. **Ventricular Depolarization and Contraction**: The rapid transmission of the impulse through the bundle of His and fibers of Purkinje ensures the synchronized contraction of the ventricles, which is crucial for effective blood ejection. **Repolarization**: The ventricles repolarize and get ready for the subsequent cycle, which is shown by the T wave on the ECG, after contraction. This repolarization phase is essential for maintaining the heart's rhythm and readiness for subsequent beats [17].

Understanding the intricate processes of cardiac conduction and ECG waveform generation provides valuable insights into heart function and health. This knowledge is fundamental for diagnosing and managing various cardiac conditions, ensuring effective medical interventions.

1.3. Relationship between HRV and ECG

Variability of Heart Rate indicates the fluctuations in intervals of time between successive heartbeats that are generated from the ECG. HRV is impacted by the ANS [22], which oversees physical functions like digestion, breathing, heart rate, and more. The parasympathetic nervous system and the sympathetic nervous system compose the ANS, which contradict each other's effects on heart performance. The examination of HRV offers insights into the equilibrium and operation of these systems and can be done through various time-related, frequency-related, and non-linear parameters.

1.3.1. The Autonomic Nervous System & HRV

A. **Sympathetic Nervous System (SNS)**: The Sympathetic Nervous System makes the body for ‘fight or flight’ reactions in times of stress or emergency [23]. It increases heart rate and decreases HRV by promoting shorter intervals between heartbeats. This response is mediated through the release of neurotransmitters like norepinephrine, which bind to adrenergic receptors in the heart.

B. **Parasympathetic Nervous System (PNS)**: The PNS responsible for 'rest and digest' activities, slowing the heart rate and increasing HRV by promoting longer intervals between heartbeats. This response is mediated through the release of acetylcholine from the vagus nerve, which binds to muscarinic receptors in the heart.

HRV is a dynamic marker of the interplay between the SNS and PNS [24]. High HRV typically indicates a healthy balance with dominant parasympathetic activity, while low HRV suggests dominant sympathetic activity or reduced parasympathetic function, often associated with stress, fatigue, or cardiac conditions.

1.3.2. HRV's Time-Domain Parameters

Time domain methods involve statistical study of the intervals between successive heartbeats, commonly known as RR intervals [25].

I. **Standard Deviation of NN Intervals**: SDNN determines the standard deviation of normal-to-normal heartbeats in a given period. It demonstrates overall HRV and is influenced by both long and short-term variations.
II. **Root Mean Square of Successive Differences**: RMSSD is the square root of the mean of the squares of successive differences between adjacent NN intervals. It mainly reflects short-term HRV and is a pointer to parasympathetic activity.
III. **pNN50**: The number of consecutive normal-to-normal heartbeat pairs that differ by more than 50 milliseconds is counted by pNN50, which also represents this count as a percentage of all NN intervals. These measures also reflect parasympathetic activity.

1.3.3. HRV's Frequency-Domain Parameters

Using spectral analysis, frequency-domain techniques examine how absolute or relative power is distributed across various frequency bands [26].

I. **Very Low Frequency or VLF**: VLF band power reflects long-term regulation mechanisms, including the renin-angiotensin and thermoregulation system. It is influenced by both parasympathetic and sympathetic activity. The VLF Band range is less than **0.04 Hz.**

II. **Low Frequency or LF**: LF band power is considered a marker of parasympathetic and sympathetic activity between the frequency range of **0.04 Hz to 0.15 Hz**, although it is often interpreted as reflecting sympathetic modulation when normalized.

III. **High Frequency or HF**: HF band power is the response for respiratory sinus arrhythmia that reflects parasympathetic (vagal) activity. It is influenced by patterns of breathing. HF frequency band between **0.15 Hz to 0.40 Hz.**

IV. **LF/HF Ratio**: This ratio is the equilibrium between parasympathetic and sympathetic activity. Whereas a smaller ratio indicates parasympathetic dominance, a larger ratio indicates sympathetic dominance.

1.3.4. HRV's Non-Linear Parameters

Non-linear methods capture the complexity and unpredictability of HRV, offering insights beyond traditional linear methods [27].

I. **Poincare Plot**: It is a graphical illustration of the relationship between successive RR intervals. It gives qualitative insights into HRV by revealing patterns and structures that linear methods might miss. SD1 is short-term and SD2 is long-term variability using these quantitative measures derived from the Poincare plot.

II. **Sample Entropy (SamEn)**: It measures the regularity and unpredictability of the RR interval of the time series. Lower values demonstrate more predictable, regular patterns (lower complexity), while higher values indicate more irregularity (higher complexity).

III. **Detrended Fluctuation Analysis or DFA**: It evaluates the properties of fractals in RR intervals, recognizing the correlations of long-range in a time series data frame. It provides insights into the intrinsic dynamics of HRV.

1.3.5. Physiological Significance

HRV study provides significant information into the heart's autonomic operation and total cardiovascular health. More HRV is generally linked with a healthy autonomic balance, greater resilience to stress, and better cardiovascular fitness [28]. Conversely, low HRV is linked to stress, anxiety, depression, and a higher risk of cardiovascular diseases.

By studying HRV through ECG, researchers and clinicians can gain a deeper understanding of how the autonomic nervous system responds to various stimuli [29], including emotional and physical stressors. This knowledge can inform interventions aimed at improving autonomic function and overall health.

1.4. Motivation Behind the Work

The motivation behind this work arises from the increasing recognition of the profound impact emotions have on physiological health and with the rising prevalence of stress-related disorders, there is an urgent requirement for reliable methods to assess and monitor emotional well-being. In contemporary society, stress has become a pervasive factor affecting daily life, leading to a surge in stress-related disorders. Consequently, there is an urgent need for reliable and accessible methods to assess and monitor emotional well-being.

Current methods of emotional state recognition often rely on electroencephalography (EEG), which, although effective, can be cumbersome and complex to implement. On the other hand, emotional states have a noteworthy impact on cardiovascular health, emphasizing the urgency for dependable techniques to assess emotional well-being. Electrocardiography (ECG) provides a simpler and more accessible option for detecting emotional states. The process of acquiring ECG data is less invasive and more straightforward, making it a practical choice for wide adoption.

Through the utilization of ECG, this study aims to examine HRV's understandable and a well-established sign of ANS activity and emotional states. Incorporating audio-visual stimuli into ECG-based HRV analysis offers a holistic approach to detecting and interpreting emotional states. This methodology not only shows promise in clinical settings for diagnosing and managing mental health conditions but also offers valuable insights for enhancing emotional self-awareness and coping strategies in everyday life.

1.5. Objective of the work

The main motivation of this research work is to assess people's emotional state by analyzing their response to audio-visual stimuli using ECG's HRV analysis. The study focuses on accurately determining individuals' emotional reactions in various scenarios.

Develop a protocol for inducing various emotional states using standardized audio-visual stimuli. Collect and analyze ECG data to extract HRV features that correlate with different emotional states. Establish a relationship between specific HRV patterns and distinct emotional states. Validate the findings through experimental studies involving human participants. Explore potential applications of this methodology in clinical and non-clinical settings for emotional assessment and management.

This pursues of research contributes to the rising field of affective computing by providing new insights into the physiological underpinnings of emotions and developing innovative tools for their assessment.

Here is the block presentation of the overall plan of the work:

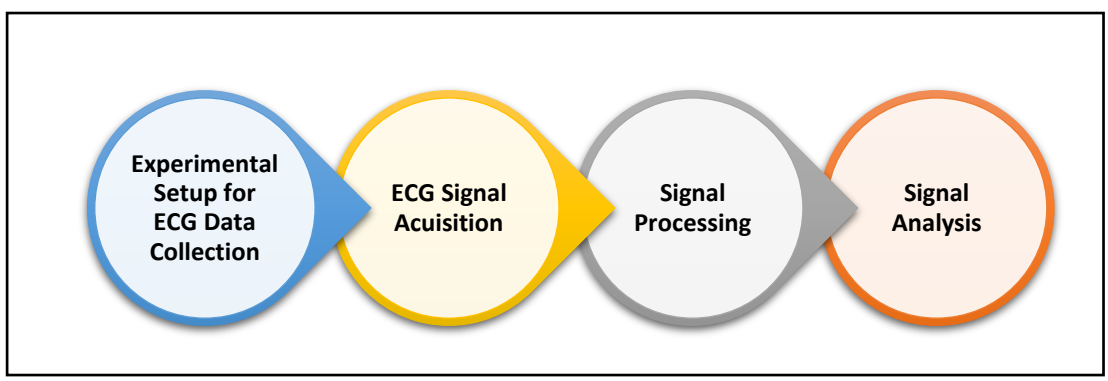


Figure 1. 4 Block Representation of Plan of Work

CHAPTER-II

2. Literature Review

The exploration of how people react emotionally to things they see and hear has caught the attention of folks in psychology, neuroscience, and biomedical engineering. Learning about these reactions can give us real clues about how humans act, think, and feel. One way to measure these emotional responses is by looking at Heart Rate Variability (HRV) analysis taken from Electrocardiograms (ECGs). HRV is all about how the time between heartbeats changes, which is linked to the ANS and demonstrations how well the body deals with stress and what's going on around it.

The early observations show that ancient Greek doctors & scientists measured pulse rates first, although they were unable to detect beat-to-beat variations [30]. In 1733, Reverend Stephen Hales noticed that pulse rates changed with breathing. After that, Carl Ludwig recorded respiratory sinus arrhythmia in 1847 - heart rate going up when breathing in and down when breathing out and then the electrocardiogram (ECG) invention in 1895 made it easier to measure ECG's R-R intervals and HRV more precisely.

In the 1960s, the first Time-Domain parameters came into play. These parameters were basic stats obtained from the series of Inter-Beat-Interval (IBI). In the next thirty years, HRV characteristics saw some new time domain additions, along with various frequency analyses and non-linear assessment methods. The issue is directly addressed in the HRV recommendations, which were published in 1996. They pick out the right parameters based on what was known back then about clinical standards and how our bodies work [30][31].

In [32][33] it was seen that HRV changes a lot depending on how we feel, showing how our autonomic nervous system reacts to emotions. Research proves that feelings like joy and sorrow impact HRV measures, displaying unique patterns of autonomic activity.

2.1. Analyzing Emotions with EEG

Studying emotions using EEG plays an important role in determining it. Research EEG signals can sort emotions triggered by visuals and findings in low-frequency bands like delta and theta work well for this EEG is also used to study stress and anxiety showing its potential to info about brain areas linked to stress [34][35].

The research paper [36] focuses on EEG-based emotional state detection using visual stimuli and common spatial patterns (CSP). EEG has been widely used in emotion recognition due to its high temporal resolution and non-invasiveness, making it suitable for studying emotional responses. Previous studies have shown that emotional responses are linked to specific patterns in EEG signals, such as changes in power spectral density across different frequency bands.

The paper [37] addressed the challenge of boosting emotional intelligence in automatic systems by picking up on emotions through physiological signals, with a special focus on electroencephalography (EEG). The research highlights the importance of analyzing spectral power in different frequency bands of the EEG spectrum to classify emotional states, with beta waves showing the best accuracy rates for valence and arousal detection. They've used sequential forward selection methods to pinpoint the key brain regions linked to valence and arousal detection, uncovering how crucial frontal areas are for valence and posterior regions are for identifying arousal. Emotions are a crucial part of how humans behave and communicate with each other. Text, talking, faces, and movements are ways to understand feelings. Researchers have also investigated the impact of using various frequency bands and naming conventions on the effectiveness of emotion analysis models, as seen in the primary objective of this paper [38].

In [39]the study focuses on utilizing Electroencephalography (EEG) to analyze neuronal activity related to emotions, highlighting the importance of understanding emotional states in daily life. Deep learning techniques were reviewed for extracting spatial elements from EEG data, emphasizing the functional connections between different brain regions during emotional events. The dataset used in the study was generated through the MUSE EEG headband, which has 4 electrode resolutions. It included emotional states categorized as effective, neutral, and poor, induced by video clips with clear valence and neutral resting data.

In [40]the study focuses on emotion detection using EEG-based Brain-Computer Interaction (BCI), a growing research area in human-computer interaction and neuroscience. Mainly EEG signals are used by researchers to classify emotions such as joy, sadness, repulsion, and anxiety, demonstrating the potential of EEG in emotion recognition. Studies have also investigated the use of machine learning algorithms to analyze EEG data for emotion detection, showing promising results in accurately identifying emotional states based on brain activity patterns.

2.2. Analyzing Emotions with ECG

A common approach to identifying emotional states through biological signals involves utilizing Electroencephalography (EEG) signals. Nevertheless, the process of obtaining EEG signals is quite time-consuming. Conversely, Electrocardiography (ECG) presents a more straightforward method with promise for emotional state recognition.

In [41] Research in this area focuses on understanding the information carried in different physiological signals by developing methods for feature selection and emotion classification. Physiological bio-signal, such as an electrocardiogram (ECG), is collected during emotional conditions to analyze reactions like joy, fear, and neutral states. The study highlights that emotional stimuli provoke variations in heartbeat with other ECG features, leading to distinct reactions to emotions.

In this paper [41] discusses recent advances in research using ECG signals based on emotion recognition. The combination of several features has been studied in this area, where feature extraction techniques like non-linear transformations and fractal transformations like Fast Fourier Transform are applied to ECG signals for emotion recognition. Several methods are used such as Local Ternary Patterns, Local Pattern Description techniques, and Local Binary Patterns for feature extraction and classification.

The research paper [42] digs into ECG-based affective computing, looking at how human emotions connect with ECG signals. They checked out using Logistic Regression and Artificial Neural Network machine learning to tell apart emotional states in humans. Participants were exposed to movies evoking different emotions (neutral, fear, disgust), and their ECG activity was

recorded for analysis. The paper [43] talks about the issue of making models that work for everyone in recognizing emotions because ECG signals differ a lot from person to person and over time. By picking out details from ECG readings, they told the difference between fear, disgust, and feeling neutral. Emotion recognition is a big deal in human-computer interaction. People use machine learning and different signals like sound, sight, or body stuff to figure out feelings. Before, scientists mostly used EEG signals for this, which well but had some problems because it was intrusive. However, studies [44]show that ECG signals could work too, and are not as intrusive as EEG. This study talks about how emotion recognition from ECG signals is better by using wavelet transformation for signal information to understand various emotions. By looking at features from ECG using wavelet thingies, this method gets high accuracy rates like 88.8% for valence, 90.2% for arousal, and 95.3% for two types of emotions together, doing better than other studies. The study also talks about how cool it would be to use wearable gadgets to know feelings and how this method can help in real-life situations.

In this paper [45] Detrended Fluctuation Analysis (DFA) has been utilized in emotion recognition tasks to understand power-law correlations and similarity properties in signals. The combination of DFA with machine learning classifiers like Extreme Gradient Boost (XG Boost) has shown promise in classifying emotions based on ECG signals. Research has shown that ECG signals of different emotions exhibit long-range correlations and self-similarity properties, making them suitable for emotion classification. Features such as Hurst exponent and DFA intercept extracted from ECG signals have been used to differentiate between emotions like scary and boring. The proposed approach in the paper demonstrates an accuracy of 80.5% in classifying scary and boring emotions, indicating the potential of wearable emotion recognition systems in mental health care.

2.3. Studying Emotions from HRV

Heart Rate Variability (HRV) calculation for analyzing emotional responses is a valuable method for comprehending human emotions. Research indicates that emotional triggers can notably impact HRV markers, where negative emotions result in reduced overall HRV and increased breathing irregularities, while positive emotions yield the opposite outcome [46][47]. HRV features derived from inter-beat intervals reflect autonomic nervous system processes and have correlations with mental processes like stress, amusement, and relaxation [48].

The paper [49] focuses on emotional data visualization for well-being through biofeedback training, aiming to help individuals manage their emotions effectively to prevent mental illness. It addresses the challenges of utilizing existing technologies to understand human emotions in exhibition settings and determining the appropriate form of manifestation to evoke emotional resonance. Analysis to measure anxiety and stress levels, highlighting the significance of physiological data in assessing emotional states using HRV. By visualizing emotional data on a wall composed of 64 bionic scales, the study demonstrates how biofeedback systems can guide individuals into a meditative state, prompting reflection on emotional regulation and ultimately supporting mental health.

The research paper [50] studied how to figure out human emotions by looking at heart rate changes. They use different parts of the heart rate data depending on how fast someone breathes. The paper explains why it's important to also look at blood pressure, skin temperature, and skin response data along with ECG and breathing signals to get the best results for emotion recognition. It suggests that future research could include additional HRV indices, particularly nonlinear ones, to enhance the accuracy of classifying emotions based on ANS activity. The research suggests that traditional definitions of the high frequency (HF) band may not be appropriate when the RF falls outside the 0.15-0.4 Hz range, highlighting the importance of aligning the HF band with RF for more precise HRV analysis.

In [51] the study investigates using HRV analysis how negative emotions impact heart health in older adults, highlighting the impact of emotions on cardiac function. Scientists in the psychophysiology field have linked psychology to changes in heart activity, especially through HRV analysis. Various emotional theories, including Lang's discrete and dimensional models and Ekman's classification of six basic emotions, are explored concerning emotional recognition and its effects on heart health among the elderly.

The paper [52] focuses on developing a mathematical model to recognize the relationship between HRV, emotion, and respiration. It addresses the argument that the HRV’s low-frequency (LF) component and its potential as an objective measurement of emotions for bio-signal applications. The model integrates various facts such as emotion, the nervous system, and the cardiovascular system to simulate experimental results related to HRV, and respiratory sinus arrhythmia. The study recommends that the heart rate delay is controlled by the parasympathetic

activity acts as an LPF or low-pass filter, leading to higher respiration frequency due to a decrease in HRV total power. It also proposes that the HRV's LF component is generated as the response of the baroreflex feedback control to emotional stimuli, highlighting the role of the baroreflex in controlling homeostasis. Furthermore, the model shows that focusing on breathing to reduce respiration rate can lead to a reduction in the LF/HF ratio, and can impact emotional status, emphasizing the interconnectedness of emotion, respiration, and HRV.

The article [53] delves into two big ideas that explain how HRV affects emotions, highlighting its importance in social situations and mental disorders. Research shows that higher HRV is linked to better emotional control, while lower HRV is tied to struggles with emotions, anxiety, and feeling down. The polyvagal theory and the model of neurovisceral integration are key theories that stress the significance of HRV in expressing and controlling emotions. Studies suggest that analyzing HRV can help us understand pain sensitivity, handle emotions, and determine how early life experiences impact our body's regulation systems.

2.4. Analyzing Emotions through Time Domain Features of HRV Analysis

HRV's Time-domain analysis is vital for evaluating emotional responses and mental stress. Numerous studies have investigated the effectiveness of HRV in identifying emotional reactions to various stimuli [54].

Time domain features are essential in influencing emotional responses as they offer valuable insights into the physiological changes linked to various emotional states. In study [55] examination of electrocardiogram (ECG) signals utilizing time-domain characteristics aided in identifying specific emotions such as enjoyable, uninteresting, calming, and frightening. Key features for classification included the average of peaks, changes in slope sign, range of dynamics, and mean of the first derivative. A systematic review [56] focused on examining HRV as an indicator of stress among healthcare providers facing medical emergencies discovered that time-domain parameters such as RMSSD, Standard Deviation of NN interval, and Pnn50 displayed consistent reactions to the stress of medical crises. This finding supports the validity and reliability of HRV as a noninvasive marker of stress.

In [54] studied HRV is well-defined as the brief variation in the end heart rate estimated at various intervals, ranging from long-range HRV intervals to ultra-short HRV. The ANS plays a crucial role in maintaining physiological homeostasis by regulating the momentary heart rate (MHR) and the end heart rate (EHR) within the normal range of 60–100 bpm. The study emphasizes the importance of HRV features, such as Mean, RMSSD, Standard Deviation of NN interval, and pNN50 in reflecting autonomic modulation of the heart and expecting cardiovascular risk.

2.5. Analyzing Emotions through Frequency Domain Features of HRV Analysis

Frequency domain HRV parameters like VLF power, LF power, HF power, and the LF/HF ratio have been used to assess emotional responses to various stimuli, including audiovisual media and immersive virtual reality scenarios [57].

HF power is linked to parasympathetic nervous system activity and respiratory sinus arrhythmia, reflecting emotional regulation. LF power is related to sympathetic nervous system activity and baroreflex control. The LF/HF ratio is demonstrated as an indicator of autonomic balance, though its interpretation is controversial [58].

This study [59] shows the utilization of HRV's frequency domain characteristics for identifying emotional states during the watching of video clips. The researchers assess three HRV parameters such as LF power, HF power, and the LF/HF ratio to distinguish between various emotional reactions. Findings suggest that particular frequency domain features exhibit a strong correlation with specific emotional states, highlighting the potential of HRV analysis in detecting emotions.

In [60] The research delves into evaluating emotional reactions in real-time during virtual reality exposure therapy by utilizing wearable sensors to measure HRV metrics. Through an analysis of features in the frequency domain, the study demonstrates how alterations in HF and LF power can mirror different emotional arousal and regulation levels. The results affirm the effectiveness of HRV analysis in overseeing and improving therapeutic approaches for emotional disorders.

This article [61] discusses HRV utilization as biofeedback to estimate and enhance emotional regulation by studying the aspects of the HRV frequency domain. It points out the correlation between HF power and parasympathetic function, and LF power with sympathetic function, underscoring their significance in managing emotions. The research suggests that HRV biofeedback proves to be a valuable technique for improving emotional regulation and overall quality of life.

The research [62] focuses on using wearable devices to recognize emotions through heart rate variability analysis, particularly frequency domain features. By analyzing HF and LF power, the study demonstrates how these HRV metrics can identify different emotional states with significant accuracy. The results underscore the potential of wearable technology in real-time emotion recognition and its applications in various fields.

2.6. Analyzing Emotions through HRV Analysis of Non-Linear Features

This study [27] examines a various range of non-linear features, such as Poincare plot, sample entropy (SampEn), approximate entropy, and detrended fluctuation analysis (DFA), demonstrating their effectiveness in recognizing delicate changes in heart rate dynamics that traditional linear methods might miss. These metrics offer valuable insights into the intricacy and unpredictability of HRV, which play a significant role in comprehending autonomic regulation and cardiovascular well-being.

In their 2018 study, Li and colleagues [63] investigated the utilization of machine learning methods for identifying emotions using HRV analysis. By applying non-linear features such as Poincare plots and entropy metrics, they attained a high level of accuracy in distinguishing various emotional states. This research highlights the efficacy of combining non-linear HRV characteristics with sophisticated computational techniques for emotion recognition.

In the study [64], the focus was on analyzing HRV using complexity and correlation dimension to identify stress levels. The results showed that these non-linear measures effectively distinguished between stressed and non-stressed conditions, presenting a reliable method for

monitoring stress in real time. It highlights the importance of non-linear HRV analysis in practical stress detection.

Moving on to another research [65], attention was on non-linear HRV analysis in understanding emotional regulation. Their discoveries suggest that metrics like fractal dimension and Lyapunov exponents are responsive to shifts in emotional states, providing insights into how the autonomic nervous system reacts to emotional triggers. This study backs the use of non-linear HRV metrics in psychological and emotional evaluations.

Emotional responses to audio-visual stimuli have attracted significant interest in recent years, especially with the use of HRV analysis. Traditional studies on HRV mostly looked at time or frequency domain features separately, with some recent works exploring non-linear aspects. However, there's research in integrating these three feature extraction techniques effectively.

Measures from the time domain's Standard Deviation of NN interval, RMSSD, and pNN50 give an understanding of heart rate dynamics overall. Frequency domain analysis, including VLF, low-frequency, HF power, and LF/HF ratio sheds light on autonomic nervous system activities balance. Non-linear features like Poincare plots & entropy measures capture heart rate pattern complexity and unpredictability.

The current literature lacks a unified approach considering these three, time domains, frequency domain, and non-linear features together give a more accurate interpretation of emotional responses. This comprehensive analysis could lead to more reliable results and better stress management.

This study aims to show that using all three types of features in HRV analysis can offer a full understanding of emotional responses to audio-visual stimuli. This holistic approach has promising implications for improving stress management methods in various situations.

CHAPTER- III

3. Methodology

The ECG experiment methodology is thoroughly depicted in a block diagram, illustrating the integration of advanced signal processing techniques to ensure precise and accurate HRV analysis.

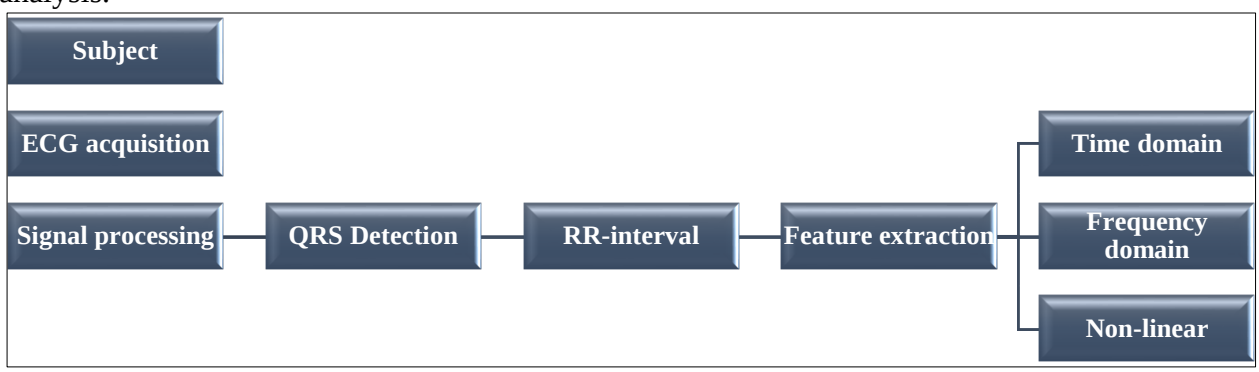


Figure 3. 1 Overall Block diagram of Experimental setup

3.1. SIGNAL ACQUISITION

This experiment was an extensive study in which ECG data was collected from seven subjects in our Biomedical instrumentation laboratory using the advanced RMS Vesta ECG machine. Each participant was systematically exposed to three distinct audiovisual stimuli, with each session precisely structured to last 12 minutes. A 60-second resting period established a baseline at the beginning of each session, followed by a 10-minute video presentation, and then another 60-second rest period. To ensure data integrity, a deliberate 2-minute gap was included between each stimulus session. The three videos administered included a comedy segment, a suspenseful clip, and a visually captivating presentation of natural scenery.

For ECG acquisition, I used three leads, focusing specifically on lead II for deriving HRV data. The sampling frequency is 500 Hz means the ECG signals were sampled at a frequency of 500 Hz to ensure high-quality data capture. The significant goal of this study is to discover the emotional states triggered by various audiovisual stimuli, aiming to enhance our understanding of

human emotional responses in different contexts. The Standard three bipolar Einthoven leads used as the Standard Limb Leads, were obtained by placing negative (-) and positive (+) electrodes on the human right arm or RA, left arm or LA, and left foot or LF of the subject [66]. The potential differences of the heart were measured in the directions shown in Figure 3.2.

Lead I can be expressed by RA as a negative (-) → LA as a positive (+). For Lead II determination also, RA is a negative (-) → LF is a positive (+), and for Lead III, LA is connected negative (-) → LF is connected with a positive (+).

ECG Lead II is preferred for signal acquisition because it aligns with the heart's electrical axis, producing clear and distinct P waves, QRS complexes, and T waves. This leads to high-quality, easily interpretable signals [67]. The setup is simple, using just three limb electrodes, which makes it less intrusive and more comfortable for subjects. Being a widely used standard in both clinical and research settings, Lead II ensures consistency and comparability across various applications [68]. Its dependability and user-friendliness also make it suitable for consumer health products like wearable ECG monitors [69].

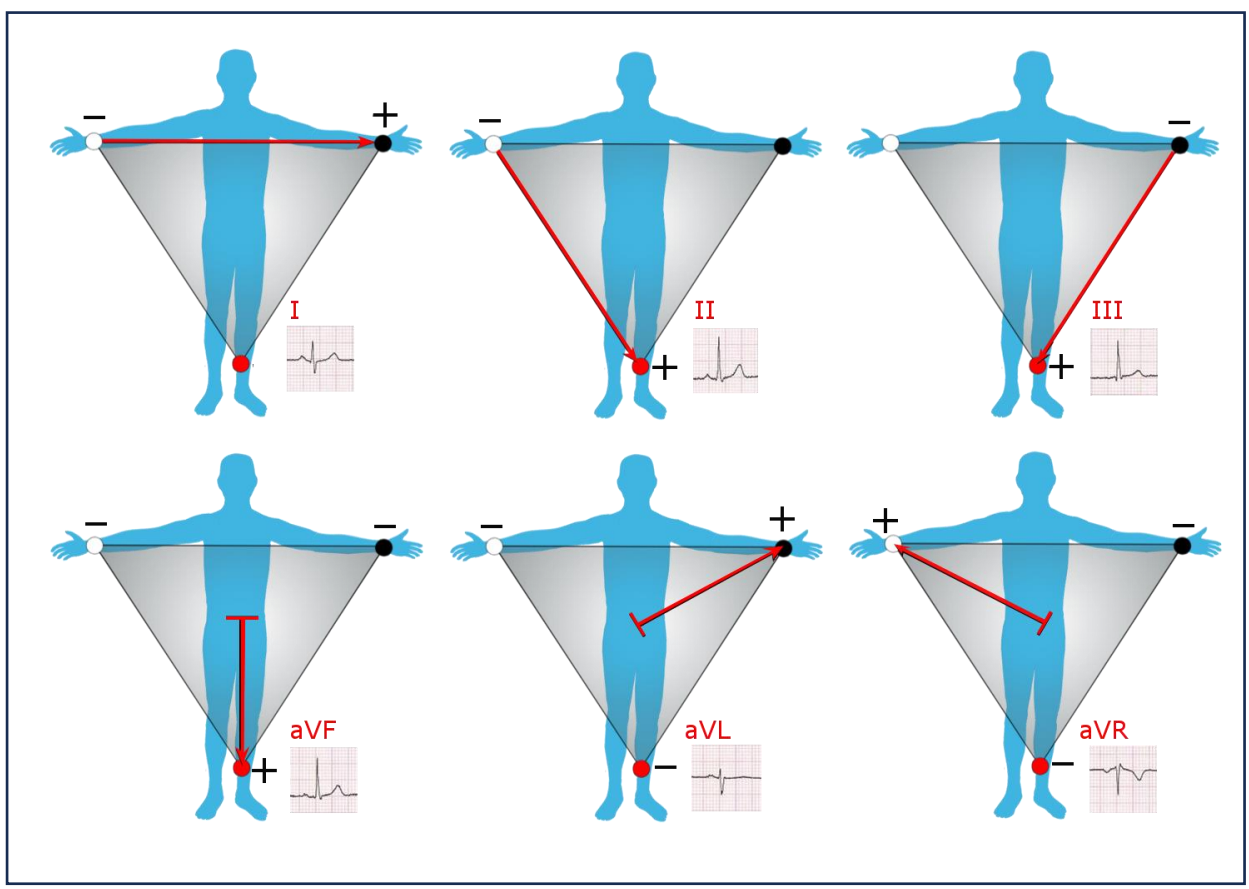


Figure 3. 2 Representation of ECG's electrode placement for the Einthoven Leads system [69]

3.2. SIGNAL PROCESSING

The signal processing for heart rate variability (HRV) feature extraction involves several methods and techniques. Some of the relevant methodologies and tools for HRV signal processing and feature extraction including HRV parameters were computed using the MATLAB Online and Python toolbox- pyHRV [70]. For python's computations were performed in the Google Colaboratory platform.

3.3. ANALYSIS ECG SIGNAL WITH STIMULI

3.3.1. QRS RECOGNITION USING PAN TOMKINS ALGORITHM

The Pan-Tompkins algorithm is a widely recognized and efficient method for detecting the QRS complex in ECG signals. This algorithm systematically processes that highlight the QRS complex of the ECG signal through a series of steps designed while minimizing noise and other irrelevant components [71].

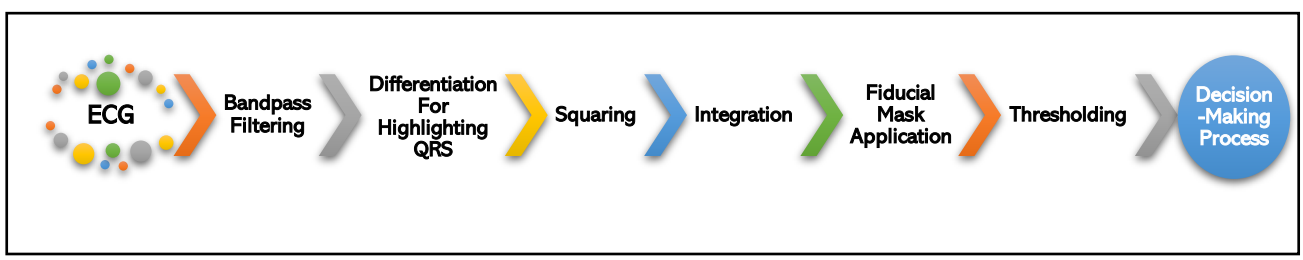


Figure 3. 3 Pan Tompkins QRS detection algorithm flowchart

The process begins with **bandpass filtering**, where the ECG signals are filtered to extract the QRS complex frequency band, typically between 5 to 15 Hz. This step effectively removes unwanted noise such as power line or baseline wander and high-frequency noise, ensuring a cleaner signal for further analysis [72].

Once the signal is filtered, it undergoes **differentiation**. This step is crucial for detecting the significant slopes in the ECG signal, corresponding to the rapid changes associated with the

QRS complex. Differentiation enhances these steep changes, making the QRS complex more distinguishable.

Following differentiation, the signal is **squared**. Squaring the signal amplifies the higher frequency components, particularly those of the QRS complex while suppressing lower frequency components like the P and T waves. This results in a positive time series, highlighting the QRS complex more effectively.

Next, the squared signal is **integrated** using a moving window. The integration process smooths the squared signal, aiding in the isolation of the QRS complex from surrounding noise. By calculating the area under the signal over specific intervals, this step ensures a clear delineation of the QRS complex.

A critical component of the Pan-Tompkins algorithm is the **fiducial mask**. This mask helps pinpoint the precise moment of the QRS complex by integrating the signal and generating weighted unit samples at the points of maximum weighted integration (MWI) maxima. This process accommodates abnormally extended QRS complexes within the window width, preventing overlap with subsequent complexes.

After applying the fiducial mask, the algorithm employs **thresholding**. This step is a continuous computing estimate of maximum peak signal and noise levels, allowing for dynamic adjustment of the threshold. Peaks that exceed this adaptive threshold are identified as QRS complexes, ensuring accurate detection despite variations in signal amplitude.

In the final step, the algorithm implements a **decision-making process** to independently determine if the found feature satisfies the standards for a QRS complex. This process ensures reliability and accuracy by filtering out any false positives or noise-induced peaks.

By systematically applying these steps, the Pan-Tompkins algorithm [73] effectively enhances the QRS complex while reducing the impact of noise and other signal components. Its robustness and efficiency make it a popular choice for real-time QRS detection in various applications, including wearable devices and continuous cardiac monitoring systems. This reliable detection method is crucial for further steps.

3.3.2. IDENTIFY R-R & NN INTERVALS

Once the QRS complexes are identified, the next important step is to identify the R-R interval, which denotes the time duration in the ECG wave between successive R-waves. For HRV calculation this interval is crucial [74]. To ensure accuracy, filters are applied to the signal to remove noise, ectopic heartbeats, baseline wandering (using techniques like the Pan-Tompkins algorithm and high-pass filters), and motion artifacts before using R-peak detection algorithms. This helps prevent the detection of false R-peaks.

After detecting the R peaks, which are mainly within the QRS wave, and each R peak is assigned a specific timestamp corresponding to its occurrence in the ECG signal. These timestamps (t_1, t_2, t_3, etc.., up to t_n) which is provide precise time points for each R-peak. After that, the R-R intervals are calculated by measurement of the time difference or interval between successive R-peaks using the formula: $R - R_i = t_{i+1} - t_i$, where $R\text{-}R_i$ is the interval between the i^{th} and $(i+1)^{th}$ R-peaks [75].

This method ensures accurate calculation of HRV and aids in the comprehensive analysis of cardiac function, which is important for clinical diagnosis and monitoring of cardiovascular health. The normal-to-normal interval (NNI) also measures intervals between detected R-peaks, emphasizing that signal preprocessing techniques have been applied to the ECG signal before R-peak detection. This ensures intervals are measured between real R-peaks without the influence of false peaks or ectopic heartbeats [76].

3.3.3. ANALYSIS of HRV

HRV defines the differences in inter-beat intervals (IBI), from which time, frequency, and nonlinear components can be extracted, calculated, and analyzed to assess cardiac and overall health[10]. Heart rate (HR) helps the body respond to sensory inputs such as physical or emotional stress and relaxation by adjusting the HR and, consequently, the IBI. A simple example is the difference in HR when a person is at rest compared to during or after physical activity, where an increase in HR occurs. Savonen et al. [77] observed increases in HR with higher intensities of physical training. In these situations, the heart regulates its performance by increasing the HR, confirming that freshly oxygenated blood is distributed throughout the human body to meet the increased oxygen demand which is essential during physical or emotional stress.

3.4. HRV'S FEATURES EXTRACTION

3.4.1. TIME DOMAIN PARAMETERS

The Time Domain parameters provide statistical information from three categories as recommended by HRV guidelines: (a) geometrical parameters derived from the NNI histogram like heart rate distribution, (b) parameters directly derived from NNI or instantaneous HR (e.g., SDNN), and (c) parameters calculated from the variances between consecutive NNI (e.g., RMSSD, pNN50) [10][54]. This section will cover the commonly used time domain parameters, including details on their computation and physiological relevance.

Heart Rate:

Pulse Rate or Heart Rate determines the number of heart's pulses or beats per minute (bpm) and is calculated using a standard equation as shown in the equation 3.1. It is a user-friendly metric for monitoring overall cardiac activity and the heart's response to physical or emotional stress [78].

$$HR = \frac{6000\ (ms)}{NNI\ (ms)} = \frac{60\ (s)}{NNI\ (s)} \qquad 3.1$$

Heart rate in [bpm] and NNI: NN interval in [ms] or [s]

Heart rate (HR) is known to adapt to a subject's physical and emotional conditions. Research by Tolg et al. observed that subjects experiencing performance anxiety in virtual reality environments showed an increase in HR with rising emotional stress [79].

Mean RR Interval (MeanNN):

Mean RR Interval (MeanNN) denotes the average duration of over a specific time period between successive normal heartbeats (NN intervals) [80].

$$MeanNN = \frac{\sum NN\ intervals}{N} \qquad 3.2$$

Standard Deviation of NN Intervals:

SDNN determines the NN interval variability, representing the dispersion of heartbeats. It offers insights into overall HRV by accounting for long-term & short-term fluctuations. It is

expected that SDNN primarily reflects the effect of the ANS on HRV, as it correlates with the Low-Frequency (LF) spectral components, which represent ANS activity [81].

$$SDNN = \sqrt{\frac{\sum(NN\ interval - MeanNN)^2}{N}} \quad 3.3$$

Root Mean Square of Successive Differences:

RMSSD mainly determines the extent of variations in successive NN intervals, capturing short-term heart rate changes that reflect PNS activity. It is a key indicator in rehabilitation and health assessments. High RMSSD indicates an ability for rapid heart rate adjustments, while low RMSSD indicates a reduced capacity for heart rate adjustments, typically due to physical or mental stress or illness. For instance, patients with diabetes mellitus often show significantly lower RMSSD results compared to healthy individuals [82].

$$RMSSD = \sqrt{\frac{\sum(NN_{i-1} - NN_i)^2}{N-1}} \quad 3.4$$

Percentage of RR Intervals with Differences > 50ms:

The percentage of consecutive NN intervals that differ by more than 50 milliseconds is determined by the equation: pNN50. pNN50 emphasizes rapid heart rate fluctuations and reflects parasympathetic nervous system modulation [71].

$$pNN50 = \frac{Number\ of\ NN\ interval\ pairs\ differing\ by\ 50\ ms}{Total\ NN\ interval} \times 100 \quad 3.5$$

These time domain features provide a valuable understanding of the ANS's activity and overall cardiac health.

3.4.2. FEATURES of FREQUENCY DOMAIN

Frequency domain features analysis of HRV is a crucial method for understanding the ANS's regulation of the heart. Introduced in the 1970s, this technique reveals periodic patterns in NN intervals by estimating the HRV signal's Power Spectral Density (PSD), showing how power is circulated across different frequency components [83]. Two common methods for PSD estimation are Welch's periodogram and the Lomb-Scargle periodogram.

The method starts with calculating the PSD, followed by separating it into different frequency bands and deriving parameters related to these specific bands. To prepare data for this analysis, noise and artifacts must be filtered from the ECG signal using band-pass filters, typically between 0.5 and 45 Hz [84]. The NN intervals are then resampled to create a uniformly spaced time series, which is necessary for most frequency domain analysis techniques [10].

Welch's Periodogram

Welch's periodogram is an enhanced version of the periodogram method, designed to provide a more stable estimate of the PSD with reduced variance. The process involves dividing the time series into overlapping segments [85] . Each segment is windowed with a function like Hamming or Hanning to minimize spectral leakage. However, since HRV signals are unevenly sampled, FFT cannot be applied directly. Therefore first, the HRV signal is resampled at a fixed frequency of 4 Hz. Then the Fast Fourier Transform (FFT) is applied to each windowed segment, and the gained squared magnitude of the FFT is calculated to obtain the power spectrum of each segment [86]. To get the final PSD estimate, [87] the power spectra from all segments are averaged. Mathematically, Welch's method can be expressed as in the equation 3.6:

$$P_{xx}(f) \sum_{k=0}^{K-1} |x_k(f)|^2 \qquad 3.6$$

where $P_{xx}(f)$ is the estimated PSD, L defines the length of each segment, K denotes the number of segments, and $x_k(f)$ is the Fourier Transform of the k[th] segment.

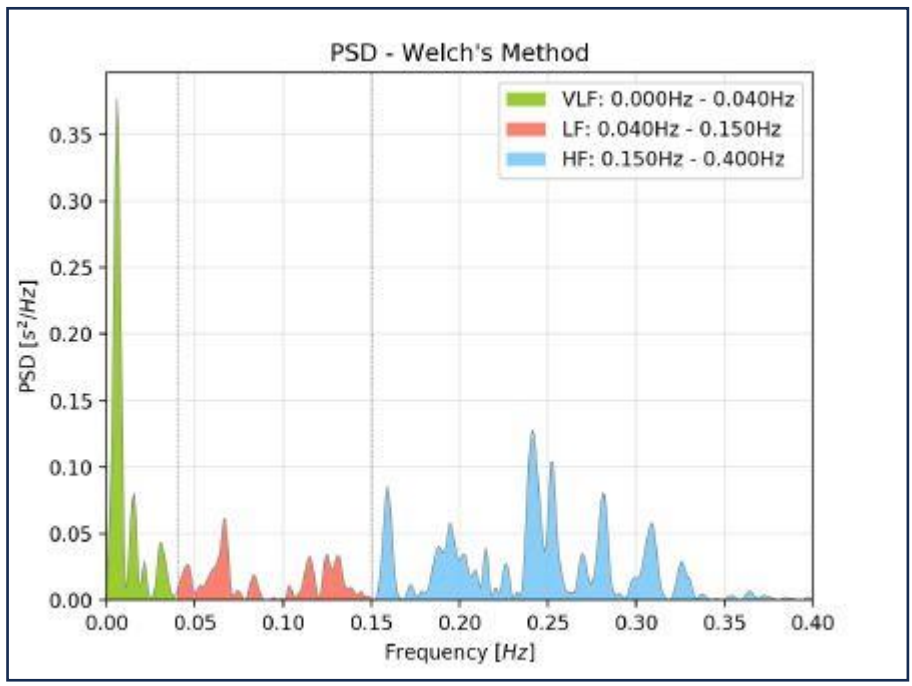


Figure 3. 4 Sample PSD computed using the Welch's method [87]

Lomb-Scargle Periodogram

To analyze unevenly spaced data the Lomb-Scargle periodogram is particularly very useful, such as HRV signals derived from NN intervals [88]. This method does not require resampling the time series, making it advantageous for non-uniform data [89]. The Lomb-Scargle periodogram estimates the PSD by fitting sinusoids to the data and accounting for the time of each data point [90]. The mathematical formulation for the Lomb-Scargle periodogram is:

$$P_{LS}(f) = \frac{1}{2\sigma^2}\left[\frac{\left(\Sigma_i\left((x_i - \bar{x})\right) cos(2\pi f t_i)\right)^2}{\Sigma_i\, cos^2(2\pi f t_i)} + \frac{\left(\sum_i (x_i - \bar{x})\, sin(2\pi f t_i)^2\right.}{\Sigma_i\, sin^2(2\pi f t_i)}\right] \qquad 3.7$$

where $P_{LS}(f)$ is the power at frequency f, x_i denotes the i-th data point, t_i states the time of the i[th] data point, $\bar{x}$ is the mean of the data points, and σ^2 is the variance of the data points [91], [92].

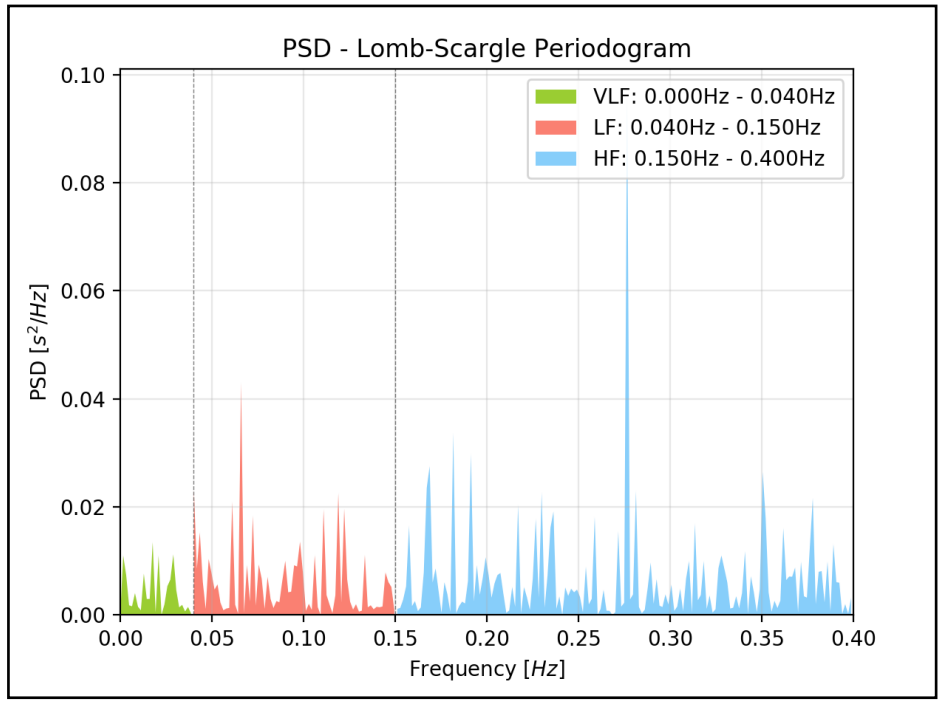


Figure 3. 5 Sample PSD computed using the Lomb-Scargle periodogram [89]

Frequency Bands and Feature Extraction

Once the PSD is estimated using either Welch's or Lomb-Scargle's periodogram, the next step is to extract relevant frequency domain features. Analyzing HRV in this way delivers a valuable understanding of the ANS regulation of cardiac function. The ANS, which includes the SNS & PNS, plays distinct roles in heart rate modulation [93].

The primary frequency domain parameters of HRV are Very Low Frequency, Low Frequency, and High Frequency bands, each reflecting different aspects of autonomic control. To obtain the power within each band, the PSD is integrated over specific frequency ranges [94]. The commonly defined frequency bands for HRV analysis are:

- **Very Low Frequency**: 0.0033 to 0.04 Hz
- **Low Frequency**: 0.04 to 0.15 Hz
- **High Frequency**: 0.15 to 0.4 Hz

The band power of these bands is calculated by integrating the PSD over the respective frequency ranges. Additionally, the total power within the frequency range between 0.0033 to 0.4

Hz is calculated. From this spectrum, crucial features are Power Spectral Density (PSD), VLF, LF, and HF, and from LF and HF get the LF/HF Ratio, and Total Power [95].

These parameters provide valuable information about the autonomic regulation of heart rate and are essential for various clinical and research applications. Literature indicates that the SNS & PNS impact the LF component, while the HF component is predominantly influenced by the PNS. The notable LF/HF ratio is highlighted as an indicator of the balance between the SNS and PNS, offering insights into sympathetic activity [96]. An increased LF/HF ratio suggests heightened SNS activity, indicative of stress, while an increase in the HF component indicates increased vagal activity which is shows stress reduction.

By utilizing both the method for frequency domain analysis Welch's and Lomb-Scargle periodograms, a comprehensive and precise analysis of HRV can be achieved, accommodating both uniformly and non-uniformly spaced data [97]. This thorough understanding of frequency domain features enhances our ability to decipher the physiological intricacies of HRV and its reflection of the autonomic nervous system.

3.4.3. NON-LINEAR FEATURES

Nonlinear parameters aim to capture the nonlinear characteristics and unpredictability of successive R-R intervals, which arise from the complex physiological variation of the human body that contribute to HRV [98].

Poincare Plot

It is a representation of a scatter plot where each RR_i is plotted against its successor RR_{i-1}. This graphical tool for HRV analysis provides a quick assessment of a subject's health conditions, as the different shapes of the scatter plot visually represent overall HRV. In the Poincare plot,

every RR interval, x(i), is plotted as a function of the former RR interval, x(i-1). This quantitative-visual technique gives a piece of summary information on heart dynamic behavior based on the plot's specific shape [99]. For a healthy heart, the points generate a shape like a comet which is oriented along the line of identity, while various cardiac dynamics or abnormalities are shown by a stretched elliptical shape along the line of identity [100].

So basically, the points are spread around the identity line and they converge into an ellipsoid configuration which is the representation [101]. The Poincare plot typically appears as an RR interval an elongated various cloud's points oriented which is basically along with the line of identity. The short-term variability reflects the dispersion of points perpendicular to the line of identity [102]. Long-term variability indicates thought to the dispersion's points along with the line of identity. Mathematically describe the plot shape, most of the researchers have adopted the technique of fitting an ellipse to the Poincare plot [102] [103].

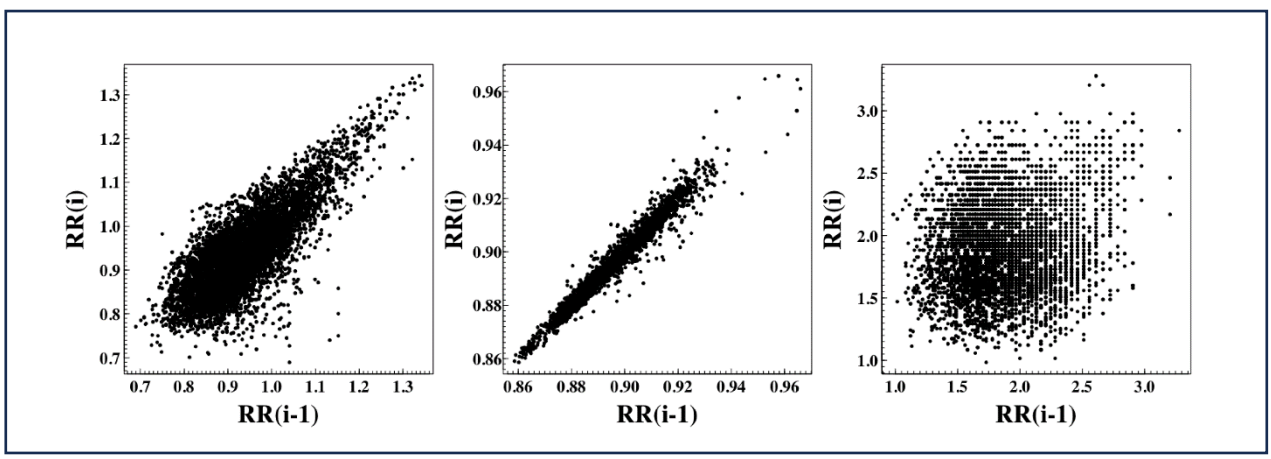


Figure 3. 6 Poincare plot for three Different RR intervals: Fig: (a) Poincare plots demonstrative of a healthy subject with a comet pattern, (b) a heartbeat irregularity in a subject with a torpedo pattern, and (c) another heartbeat irregularity in a subject with a complex pattern [103]

In the novel axis reference system, the dispersion's points around the axis are calculated by the standard deviation which is labeled as x_1. So, this standard deviation evolute the width of the Poincare cloud, which represents the level of short-term HRV. Then the long-term HRV reflects the cloud's length along the line of identity which is represented by the standard deviation (SD) around axis x_2. Specifically, the standard deviation of points perpendicular to the identity line which is called SD1, corresponds to RMSSD, which demonstrates also short-term NN variability. Meanwhile, SD2 is another parameter that is the standard deviation of points parallel to the identity line, corresponding to SDNN, which represents long-term NN variability [104].

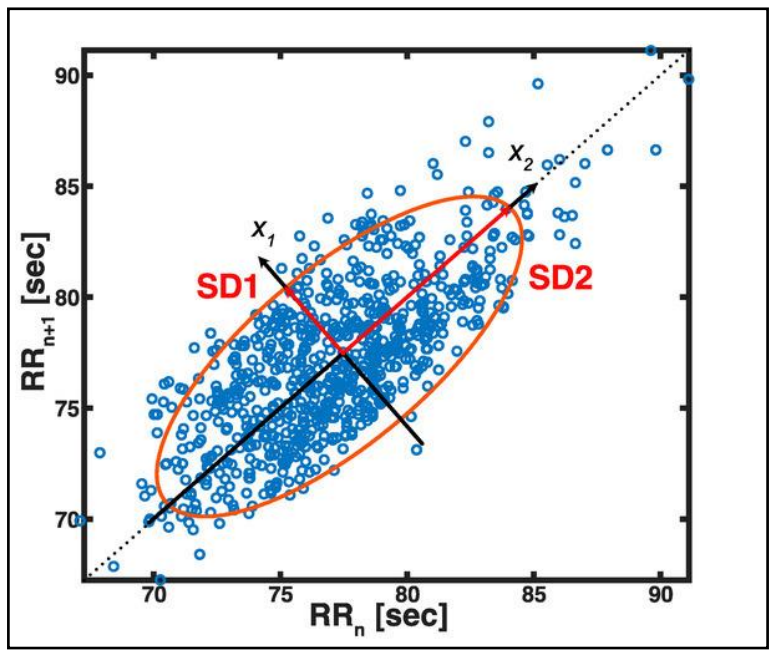


Figure 3. 7 Poincare plot of a coordinate plane [104]

A novel set of the coordinate plane, x_1, and x_2, is the intersection of the ellipse center.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} cos\,\theta & -sin\,\theta \\ sin\,\theta & cos\,\theta \end{bmatrix} \begin{bmatrix} RR_n \\ RR_{n+1} \end{bmatrix} \qquad 3.8$$

$SD1$ and $SD2$ denote the short- and long-term variability of distribution points perpendicular and parallel to the line of the identity of the fitted ellipse [102] [104]. Scientifically, the standard deviations around x_1 and x_2 are $SD1$ and $SD2$, respectively which are computed by using HRV's linear measures [105] [104]:

$$SD1^2 = Var(x_1) = Var\left(\frac{1}{\sqrt{2}}RR_n - \frac{1}{\sqrt{2}}RR_{n+1}\right)$$

$$SD1^2 = \frac{1}{2}\,Var\,(RR_n - RR_{n+1}) = \frac{1}{2}SDSD^2 \qquad 3.9$$

$$SD2^2 = SDNN^2 - \frac{1}{2}SDSD^2 \qquad 3.10$$

Short-term vagal activity is indicated by one measure, while sympathetic modulation is indicated by another. The ratio SD1/SD2 defines the relationship between short-term and long-term variations in NN interval variations, which reflects the activity of balance between SNS & PNS. This ratio also captures the complexity of heart rate patterns, with healthy hearts displaying a "comet" shaped representation and irregular heart activity showing a "fan" or "complex" representation [101][104].

Sample Entropy

SampEn describes or measures the irregularity or complexity of an NN time series by evaluating the specific length patterns that will recur within a set tolerance [106]. The SampEn function (sometimes written as SampEn (m; r; N)) depends on the embedding dimension which denotes **m**, the tolerance denotes **r**, and the number of successive NNI data points. [107] For a N is the length of NN time series x, and consider $U_m^r(i)$ represents the count of template vectors of length m+1 that are similar (i.e., distance < r) to the m which is the template vector of length starting at position i.

The conditional probability $C_m^r(i)$ is the ratio $\frac{U_m^r(i)}{U_{m+1}^r(i)}$

SampEn is given by the conditional probability of negative natural logarithm:

$$SampEn(m, r, N) = -ln\frac{C_m^r}{C_{m+1}^r} \qquad 3.11$$

Nonlinear parameters offer valuable insights into the complexity, regularity, and long-term correlations present in HRV time series data, contributing to a comprehensive understanding of autonomic nervous system dynamics [108].

Physiologically, low heart rate variability (HRV) in the NNI series occurs due to minimal fluctuations between successive NNIs. In this scenario, the predictability of a vector of length m+1 is similar to that of length m, meaning the m+1 data point remains within the specified tolerance levels, leading to low Sample Entropy (SampEn) values [109]. For example, if A = B = 1, then SampEn = -log(1/1) = -log(1) = 0. Conversely, high HRV results in lower predictability for an additional m+1 point due to greater fluctuations between successive NNI durations, causing more m+1 data points to fall outside the specified tolerance levels. This reduced predictability for m+1 points lead to smaller A values, thereby increasing the overall SampEn. For instance (e.g. A = 0.1; B = 1) SampEn = -log(0.1=1) = 1).

Detrended fluctuation analysis or DFA

DFA determines the correlation within the signal. So, the correlation is mainly extracted for various time scales as shown in equation 3.12 [110]. Initial, the time series of RR interval is integrated [111].

$$y(k) = \sum_{j=1}^{k} \left(RR_j - \overline{RR}\right), \qquad k = 1, \dots \dots, N \tag{3.12}$$

where $\overline{RR}$ is the RR interval's average. Following, the integrated series is divided into different segments of equal length n. A least squares line is fitted into the data within each segment. Let $y_n(k)$ is denotes these regression lines [112]. After that, the root-mean-square fluctuation of this integrated and detrended time series is calculated as shown in the equation 3.13. after the integrated series $y(k)$ as shown in the equation 3.12 is detrended by removing the local trend inside each segment.

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(y(k) - y_n(k)\right)^2} \tag{3.13}$$

The results are plotted in a double logarithmic plot containing the fluctuation results, with individual linear functions of slopes α_1 and another one is α_2 which are fitted to the short and long-term fluctuations [113][114].

An example [115] of the DFA results plot is presented in below Figure 3.8.

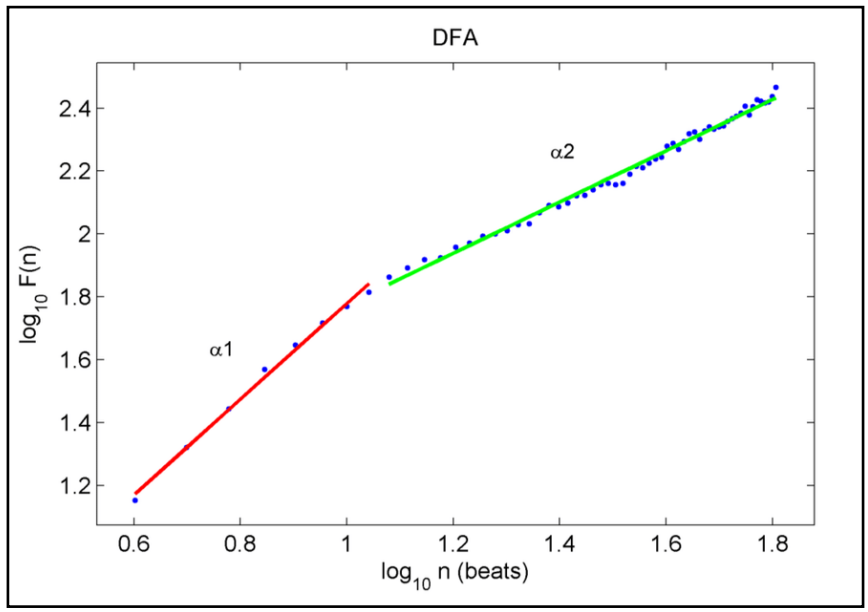


Figure 3. 8 DFA representation of the short (Red) & long (green) term fluctuations [115]

CHAPTER-IV

4. Result

In this study, the impact of various audio-visual stimuli on ECG signals was examined to understand their effects on cardiac activity. After recording the ECG signals from the subjects, the first step of this analysis involved the Pan-Tompkins algorithm for detecting of QRS complexes. This initial step allowed us to accurately identify and analyze the heartbeats, forming the basis for further investigation into the physiological responses elicited by the stimuli.

4.1. PAN TOMKINS ALGORITHM FOR QRS DETECTION

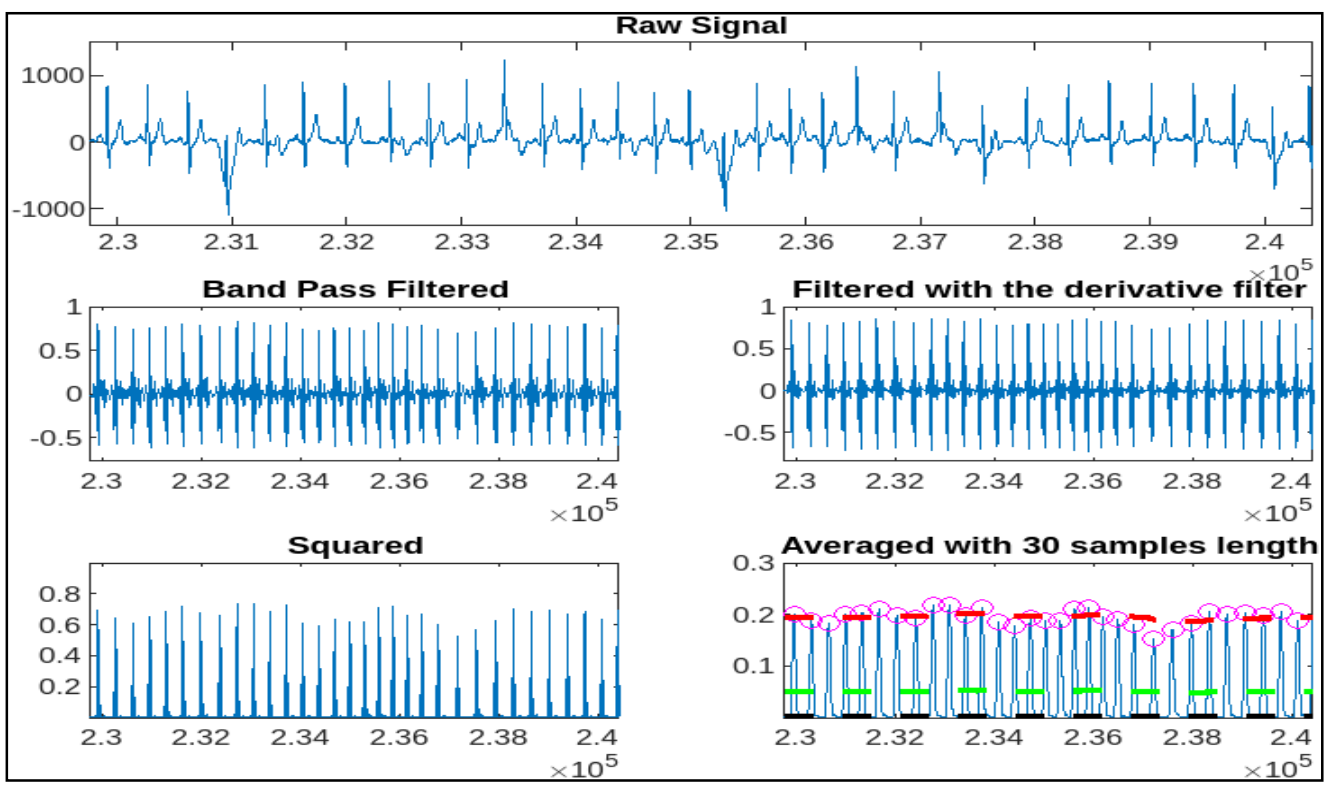


Figure 4.1. 1 Pan-Tomkins Algorithm for QRS Detection

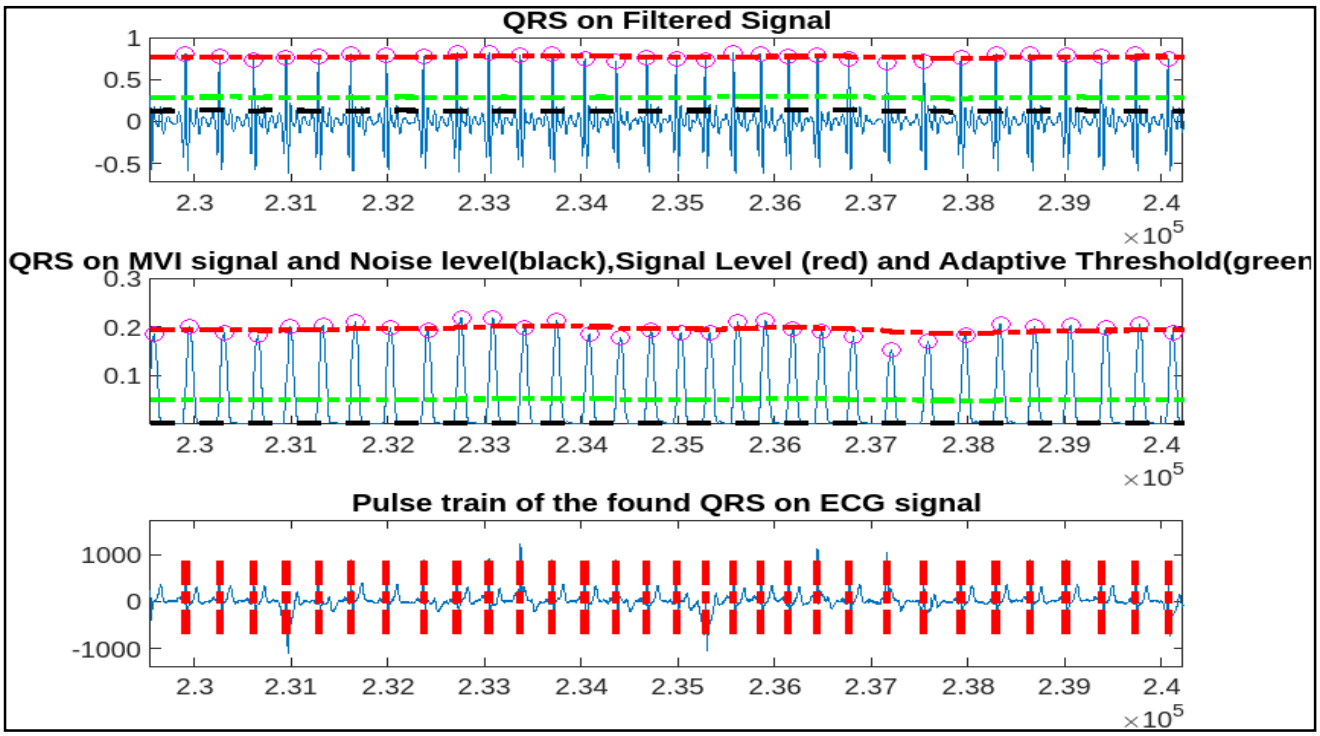


Figure 4.1. 2 Pan-Tomkins Algorithm for QRS Detection

In this computation, conducted through MATLAB Online, I demonstrate a small duration of the ECG signal for one subject; Figure 4.1.1 shows the progression from the raw signal to the squared signal, including the bandpass filtering and filtered with the derivative filter and squared ECG signal steps. Figure 4.1.2 illustrates the QRS detection on the filtered signal, the QRS detection on the MVI signal, and finally, the pulse train of the detected QRS complexes on the ECG signal.

4.2. Heart rate

To give a comprehensive view of the heart rate changes observed during the 10-minute stimulus session, Fig. 4.2.1 displays a histogram of heart rate distribution throughout the audio-visual experience.

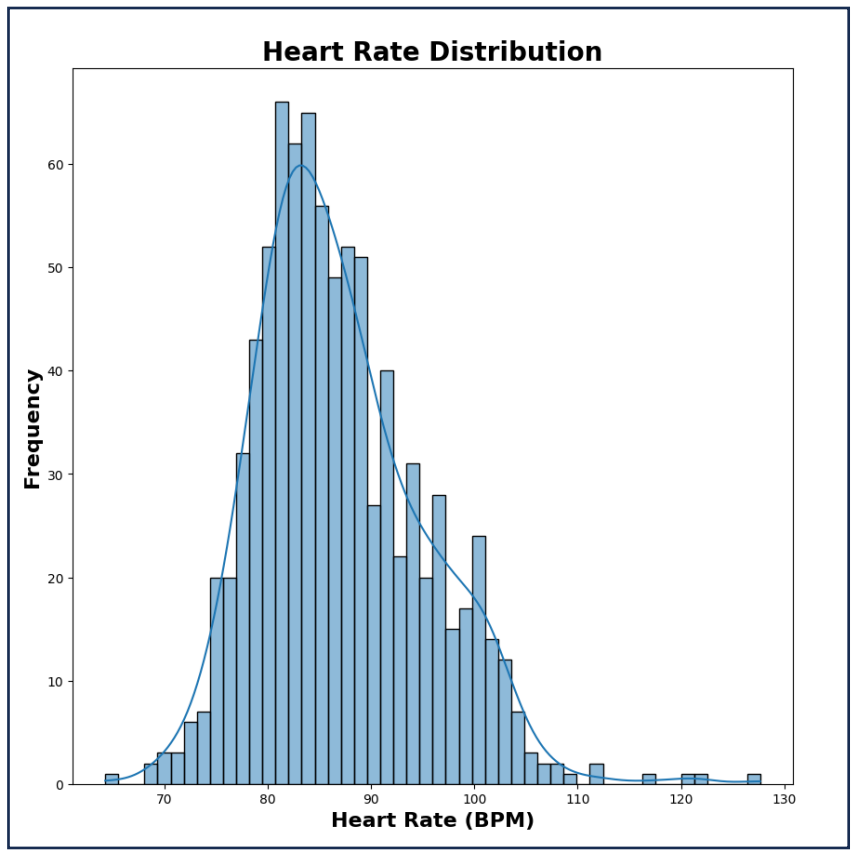


Figure 4.2. 1 Heart Rate Distribution

This visual representation is a dynamic heart rate response, laying the groundwork for a detailed analysis of specific HRV parameters in the following sections.

4.2.1. Heat Plot of The Heart Rate

It is a visual representation of heart rate data over a period of time or across different conditions. It uses color to represent the intensity or value of the dynamic nature of heart rate, which makes it easy to identify patterns and variations at a glance. In the context of analyzing heart rate responses to different types of videos, the heat plot can reveal how heart rates vary in response to different stimuli.

Nature Video

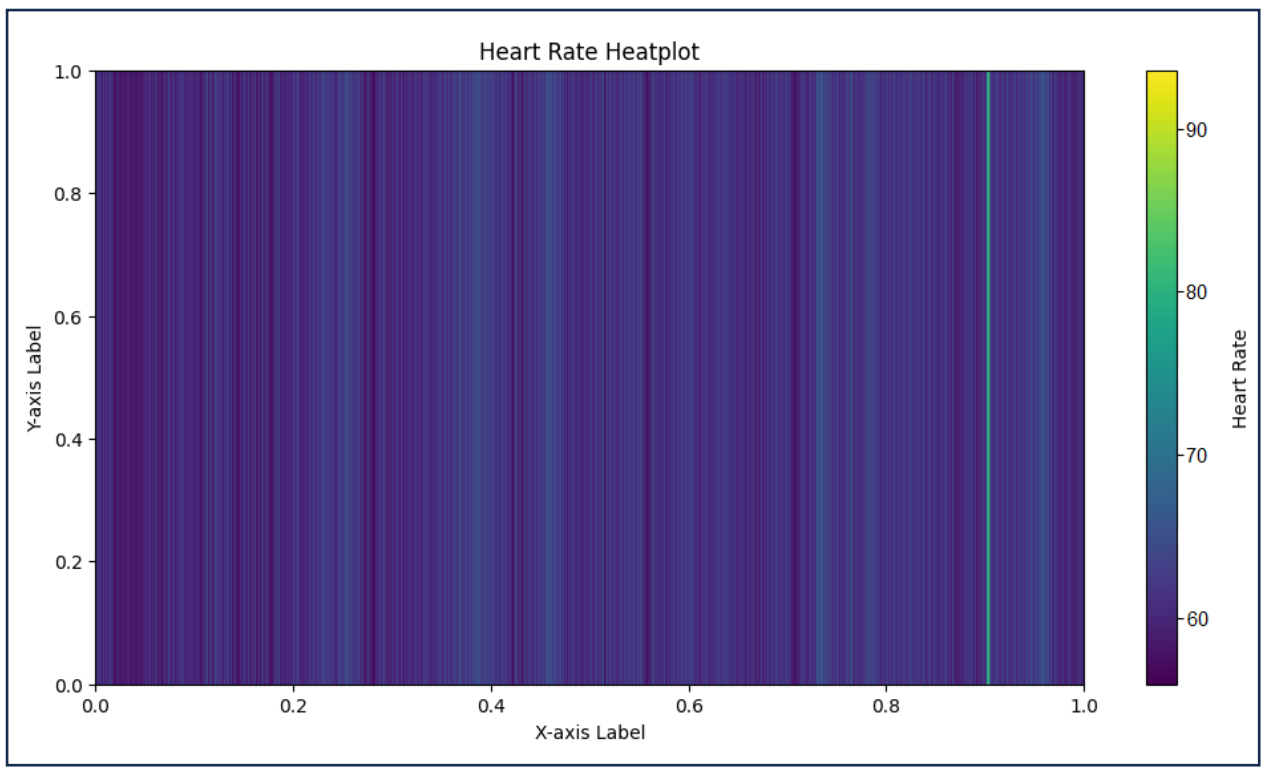


Figure 4.2. 2 Heart Rate Heat plot while watching Nature Video

During Nature Video The heart rate heat plot typically shows relatively stable and consistent heart rates. The calming and soothing nature of such videos usually results in minimal fluctuations in heart rate. Also Observed is that the heat plot displayed a uniform color range, indicating steady heart rates. This suggests that viewers are relaxed and their heart rates do not vary significantly.

Comedy Video

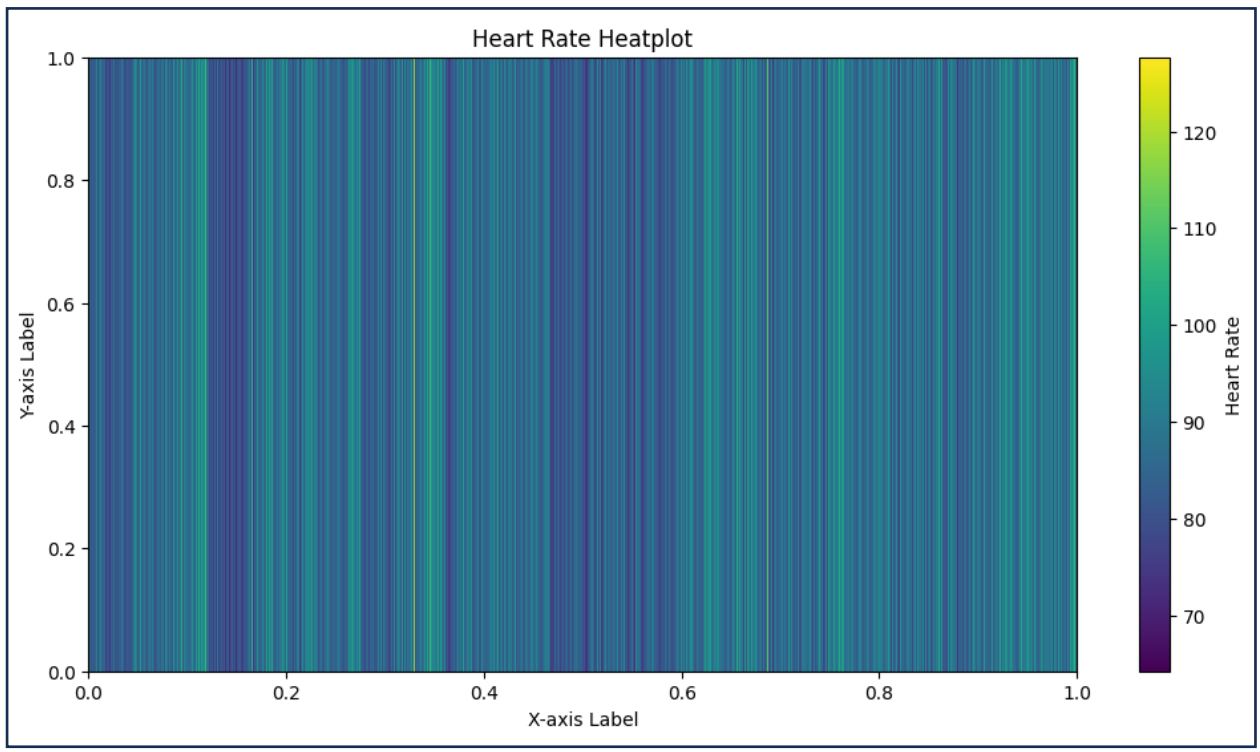


Figure 4.2. 3 Heart Rate Heat plot while watching a Comedy Video

In contrast, the heart rate heat plot for a comedy video often exhibits more variation. The humorous content can cause periodic spikes in heart rate due to laughter or heightened emotional responses. Observed is that the heat plot shows a more diverse color pattern, with noticeable peaks and valleys. This indicates that viewers' heart rates fluctuate more as they react to the comedic elements of the video.

Suspense Video

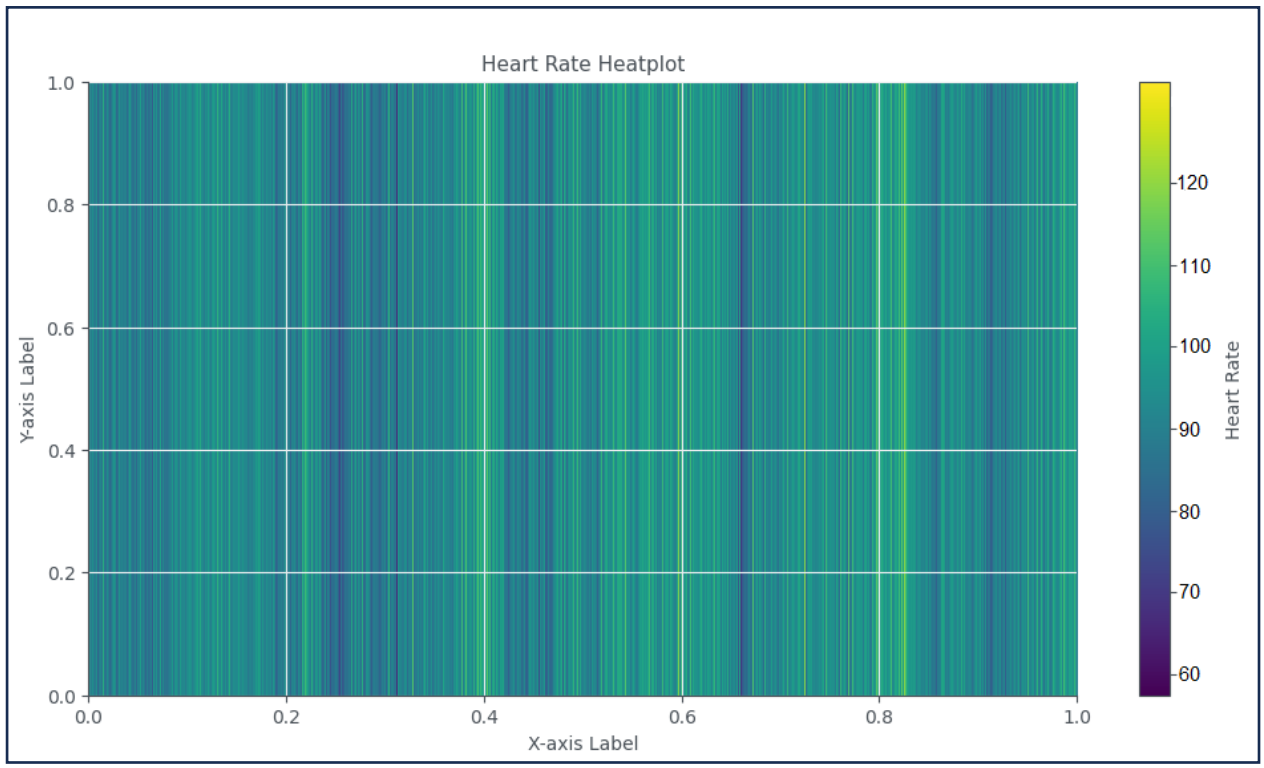


Figure 4.2. 4 Heart Rate Heat plot while watching Suspense Video

The suspense video, designed to induce stress or fear, results in significant fluctuations in heart rate. The intense and alarming nature of such videos can cause sharp increases in heart rate, followed by rapid drops. The heat plot for a suspense video displayed a highly varied color pattern, with extreme highs and lows. This suggests that viewers are experiencing strong emotional responses, leading to considerable heart rate variability.

4.3. HRV Features

4.3.1. Time domain

Conducted an extensive analysis of time-domain characteristics to gain a deeper understanding of the ANS's regulation during the demonstration of audio-visual stimulus. Our findings include SDNN, which reflects overall heartbeat variability; RMSSD, which measures rapid heart rate changes; and pNN50, which indicates the frequency of significant gaps between

heartbeats. These variations in time-domain parameters enhance our comprehension of the complex relationship between stimuli and the autonomic regulation of emotional recognition.

SDNN

TABLE 1 - SDNN VALUES OF ALL SUBJECTS

SDNN			
Subject	**Video**		
	Suspense	**Nature**	**Comedy**
Subject-01	73.03	70.5	62.27
Subject-02	52.74	37.07	54.48
Subject-03	75.79	123.84	80.98
Subject-04	36.41	30.83	41.237
Subject-05	39.24	34.83	46.67
Subject-06	38.5	41.31	65.86
Subject-07	94.33	41.31	92.19

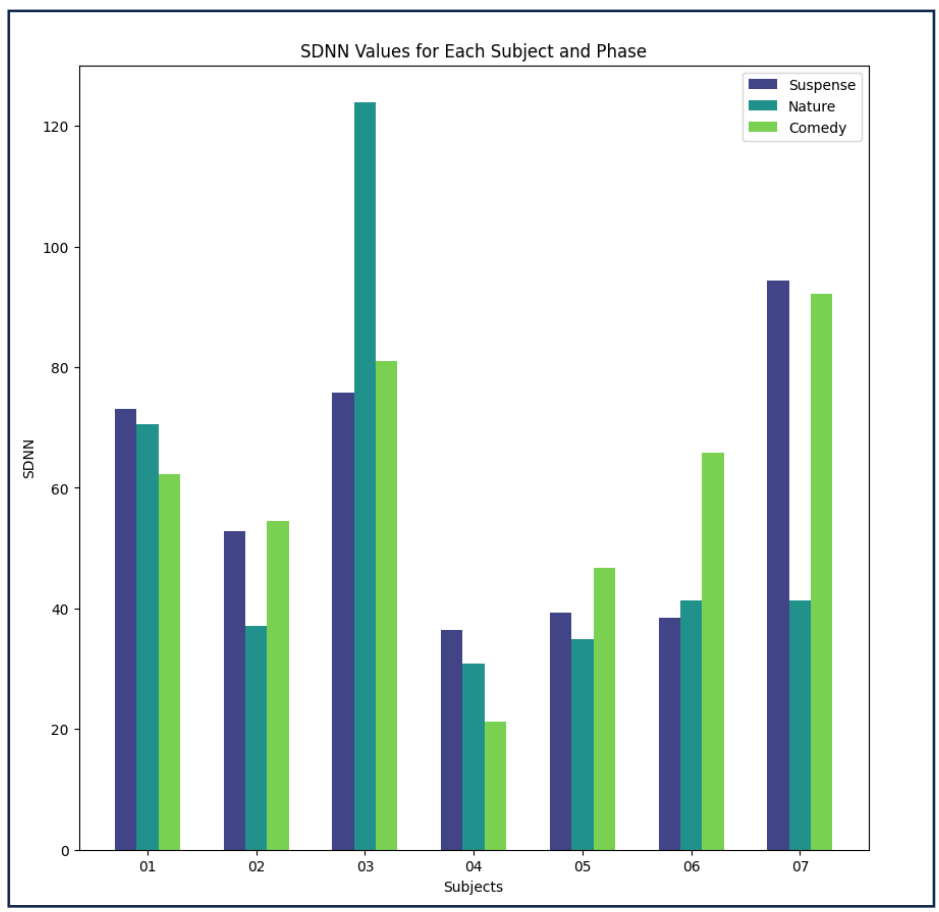


Figure 4.3. 1 SDNN values for each subject and phase

- **Suspense Videos:** SDNN values for suspense videos vary significantly among subjects, ranging from 36.41 to 94.33. This indicates a high variability in heart rate during suspense videos, suggesting that suspenseful content can elicit a strong autonomic response, likely due to increased sympathetic activity.
- **Nature Videos:** The SDNN values for nature videos are generally lower compared to suspense and comedy videos, with values ranging from 30.83 to 123.84. The higher value for Subject-03 suggests a significant parasympathetic response, indicating a state of relaxation and reduced stress.
- **Comedy Videos:** SDNN values for comedy videos also show variation, ranging from 41.237 to 92.19. This indicates a moderate autonomic response, potentially due to the mixed emotional states elicited by humor, which can include both relaxation and excitement.

RMSSD

Table 2 - RMSSD values of all Subjects

RMSSD			
Subject	**Video**		
	Suspense	**Nature**	**Comedy**
Subject-01	103.45	93.96	93.43
Subject-02	62.72	48.45	74.52
Subject-03	90.75	186.58	90.4
Subject-04	32.83	28.65	33.87
Subject-05	40.91	34.07	26.94
Subject-06	21.59	35.31	41.45
Subject-07	106.21	35.31	113.63

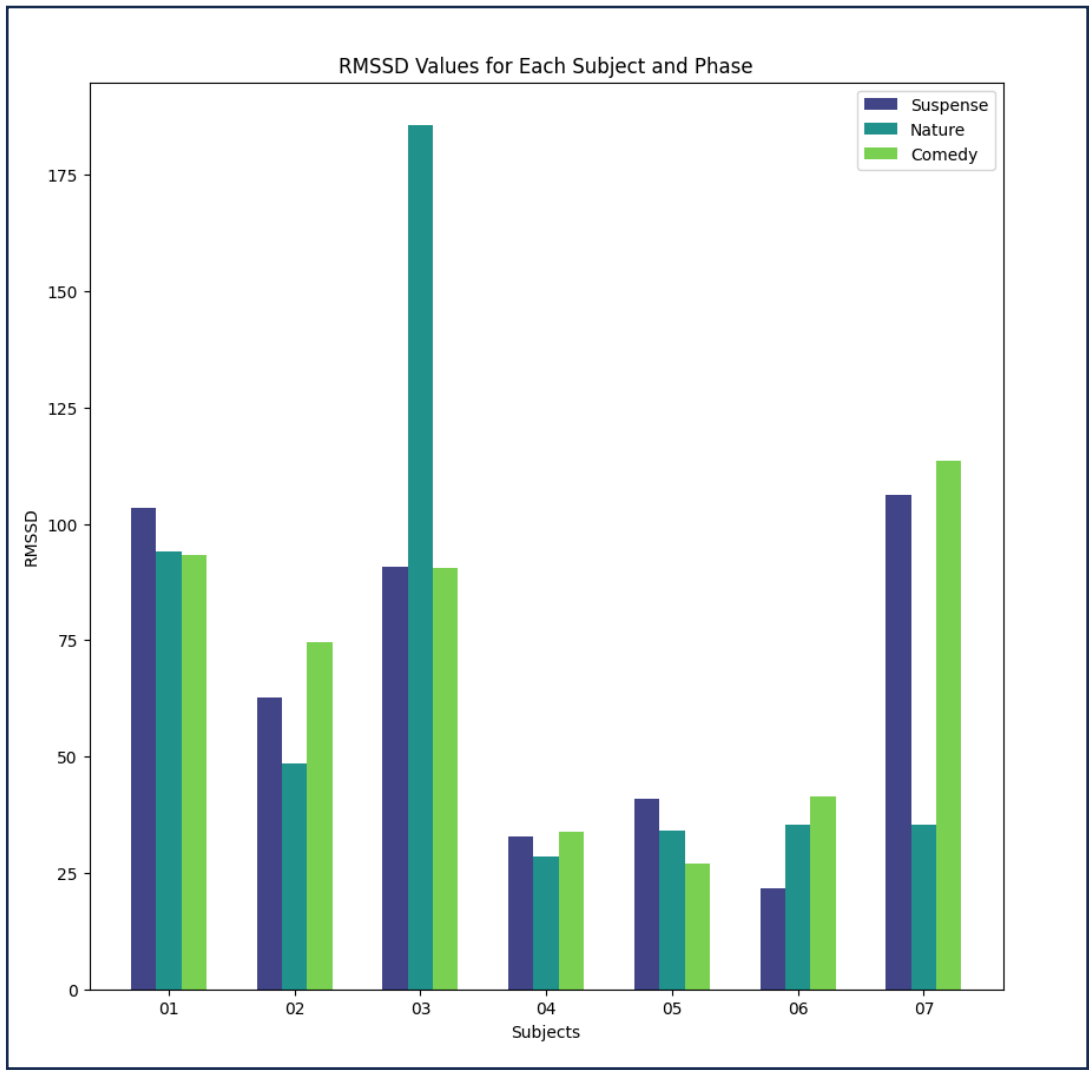


Figure 4.3. 2 RMSSD values for each subject and phase

- **Suspense Videos:** RMSSD values for suspense videos range from 21.59 to 106.21. Higher RMSSD values indicate increased vagal tone and parasympathetic activity, which may be a result of anticipatory relaxation phases interspersed with stress responses.
- **Nature Videos:** RMSSD values for nature videos range from 28.65 to 186.58. Higher values suggest a strong parasympathetic response, indicative of relaxation and stress reduction.
- **Comedy Videos:** RMSSD values for comedy videos range from 26.94 to 113.63. These values indicate a varied autonomic response, potentially due to the mixed emotional effects of humor.

pNN50

TABLE 3 – PNN50 VALUES OF ALL SUBJECTS

pNN50			
Subject	**Video**		
	Suspense	**Nature**	**Comedy**
Subject-01	482	497	489
Subject-02	217	175	231
Subject-03	449	479	401
Subject-04	107	68	93
Subject-05	127	120	48
Subject-06	15	57	92
Subject-07	463	57	446

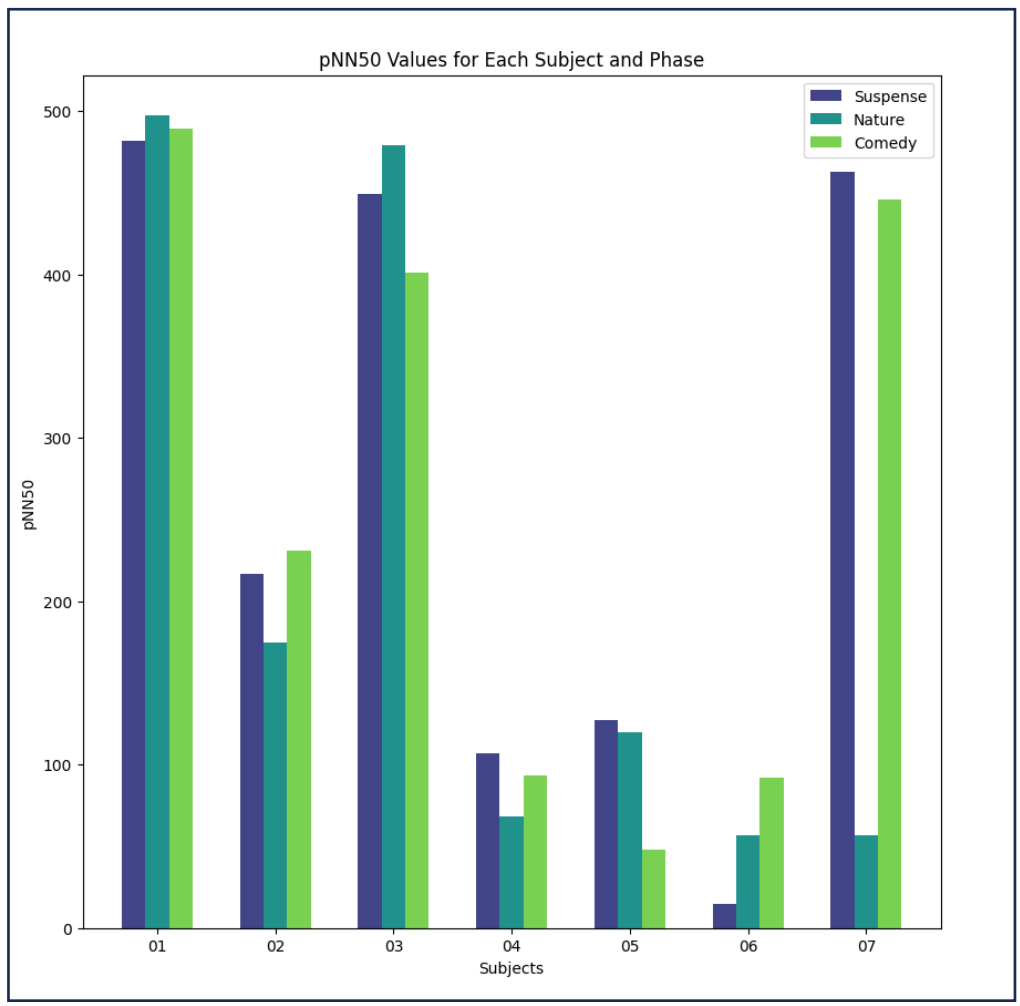


Figure 4.3. 3 pNN50 values for each subject and phase

- **Suspense Videos:** pNN50 values for suspense videos vary significantly among subjects, ranging from 15 to 482. Higher pNN50 values suggest a greater proportion of successive heartbeats with significant variability, indicating increased parasympathetic activity.
- **Nature Videos:** The pNN50 values for nature videos are generally high for some subjects, ranging from 57 to 497, indicating a relaxation response with increased parasympathetic activity.
- **Comedy Videos:** pNN50 values for comedy videos also show considerable variation, ranging from 48 to 489, suggesting mixed autonomic responses due to the emotional variability induced by humor.

4.3.2. Analysis of Frequency Domain

Next, the frequency domain features analysis was explored to unravel another layer of the physiological response to the audio-visual stimuli. Presented the Welch periodogram and Lomb-Scargle periodogram a visual representation of how our heart rate variability distributes across different frequencies and the Power Spectral Density (PSD) comparison plot using Welch and Lomb-Scargle periodograms provides a visual representation of the HRV signal's frequency components estimated in different segment by these two methods. This analysis demonstrates how different types of stimuli (Nature, Comedy, and Suspense videos) can distinctly affect the HRV frequency components in a single subject.

PSD Plot and PSD Comparison Plot

A. Welch Periodogram

The Welch periodogram provided a window into the specific spectral characteristics of our HRV, highlighting dominant frequencies that shed light on the interplay between SNS & PNS influences during the audio-visual experience.

Nature video

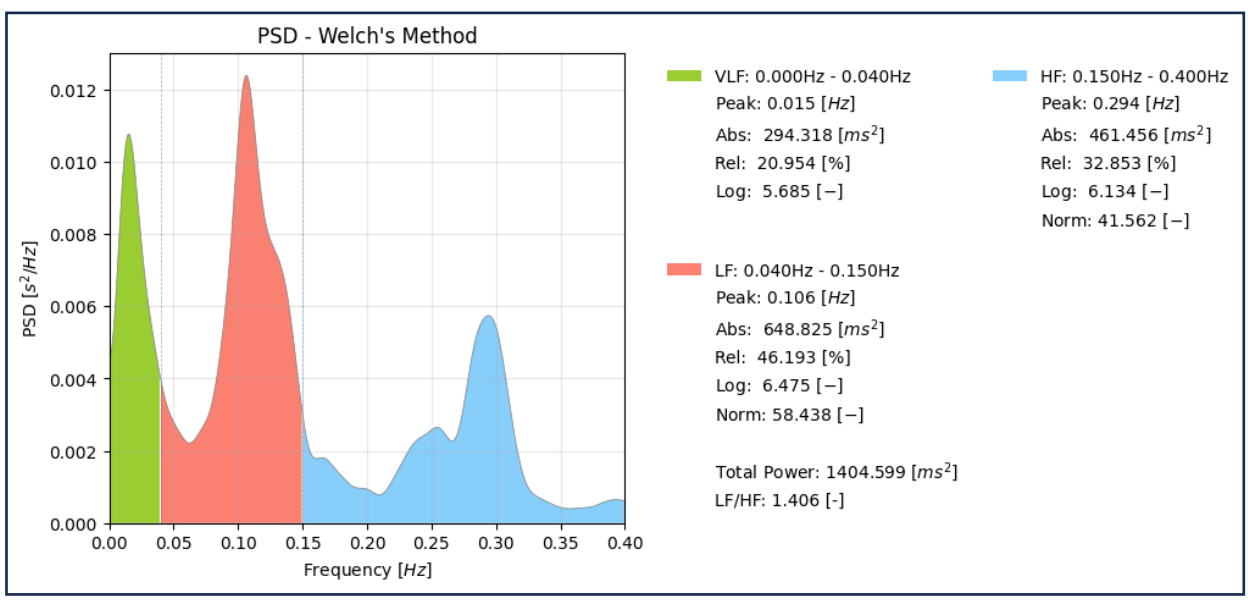


Figure 4.3. 4 PSD estimation using Welch's method while watching a Nature video

Physiological Significance:

- **VLF**: The moderate value indicates some sympathetic activity but not high-stress levels.
- **LF**: Higher than VLF and HF, suggesting balanced sympathetic and parasympathetic activity with a slight tilt towards sympathetic.
- **HF**: Reflects parasympathetic activity (vagal tone). The significant value here indicates relaxation and recovery.

PSD Comparison Plot Using Welch Periodogram

The PSD comparison plot using Welch's method effectively highlights the frequency component in signal's different segments. The legend is divided into segments and shows different colors representing each segment (from Segment 1 to Segment 9). The plot represents the PSD of nine different segments of a signal, with each segment spanning 60 seconds (or 1 minute). Each segment is analyzed separately to capture its unique frequency characteristics. Each colored line represents the PSD for a specific segment and the curves illustrate how the power distribution varies across different frequency bands for each segment.

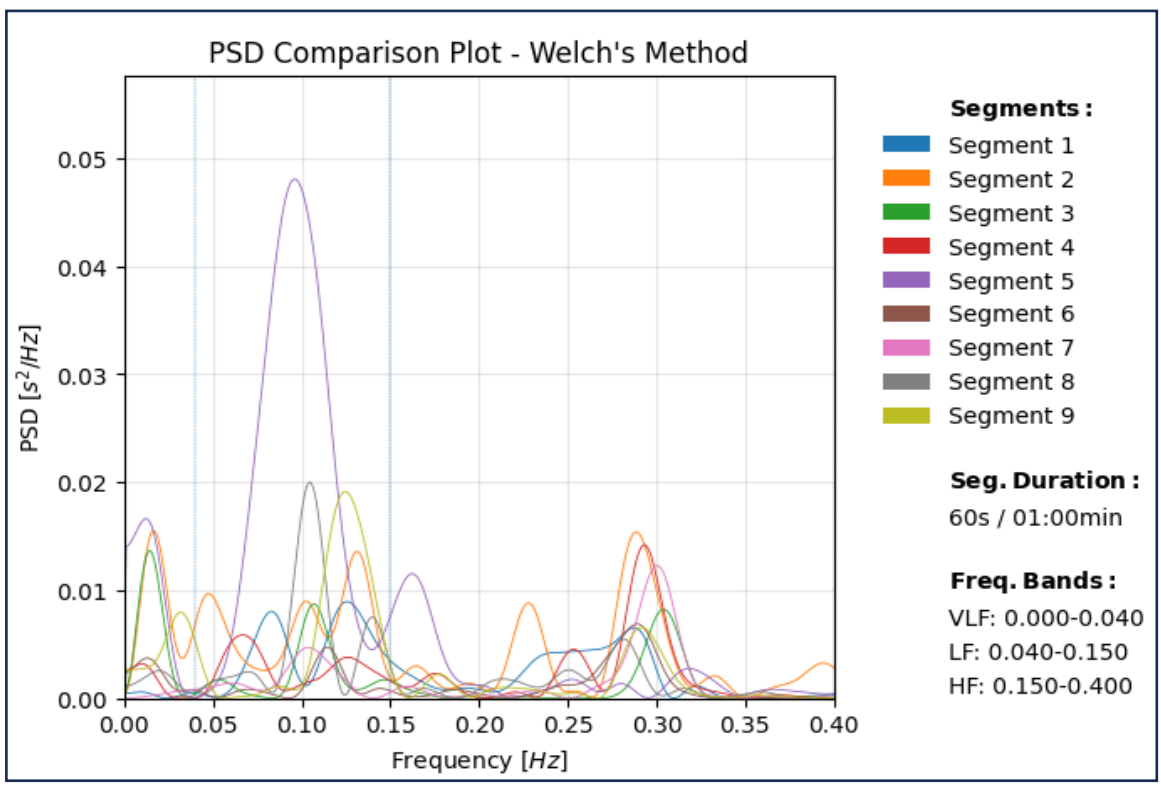


Figure 4.3. 5 PSD Comparisons estimation using Welch's method while watching a Nature video

Comedy video

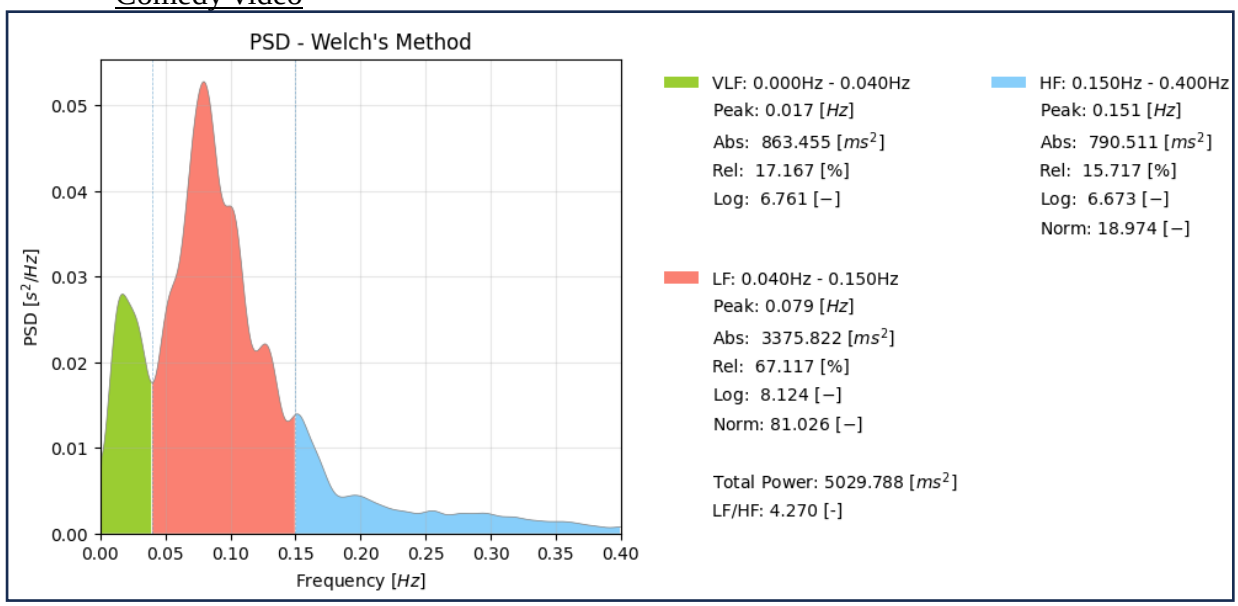


Figure 4.3. 6 PSD estimation using Welch's method while watching a Comedy video

Physiological Significance:

- **VLF**: Lower than LF, increased arousal and alertness during comedy video.
- **LF**: Indicating strong sympathetic activity due to comedy's stimulating and engaging nature.
- **HF**: Lower, reflecting less parasympathetic activity compared to the nature video.
- **LF/HF Ratio**: High, indicating significant sympathetic dominance.

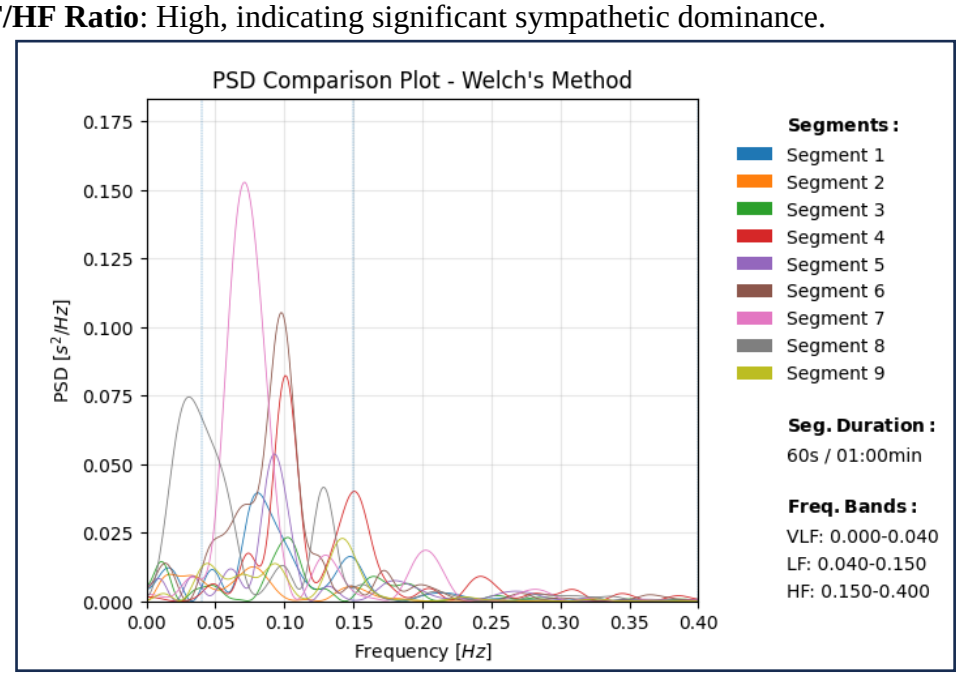


Figure 4.3. 7 PSD comparison estimation using Welch's method while watching a Comedy video

Suspense video

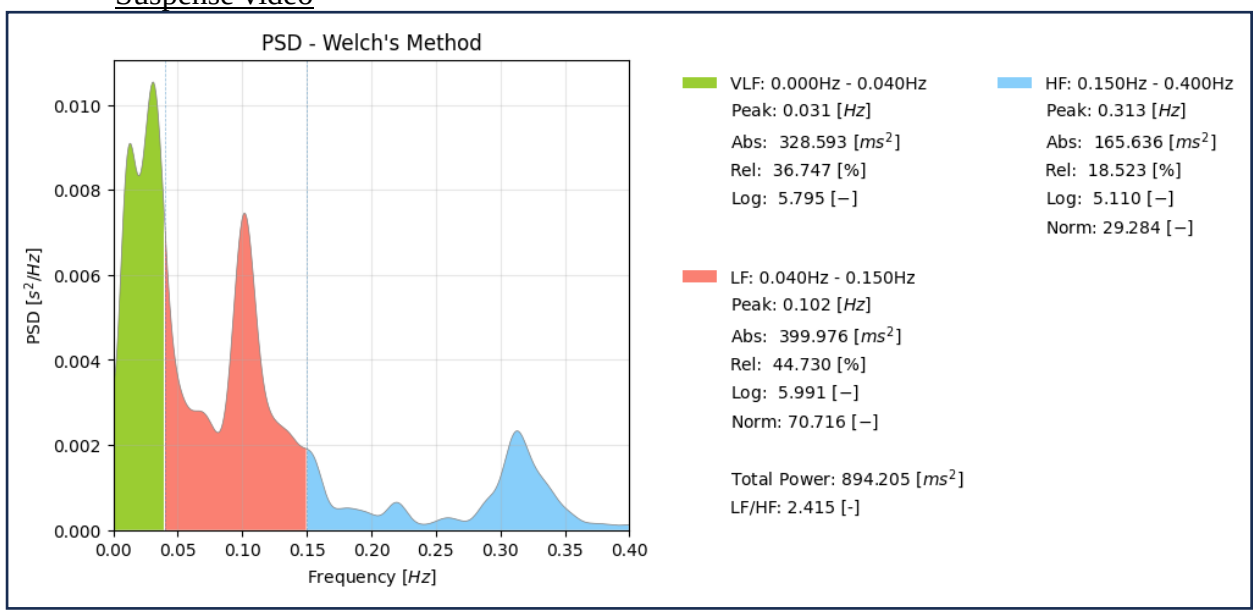


Figure 4.3. 8 PSD estimation using Welch's method while watching a Suspense video

Physiological Significance:

- **VLF**: Elevated, might indicate higher stress levels or sympathetic activation due to suspense.
- **LF**: Slightly high, suggesting sympathetic dominance but not as much as the comedy video.
- **HF**: Reduced, indicating low parasympathetic activity which aligns with stress or suspense.
- **LF/HF Ratio**: Elevated, indicating the sympathetic nervous system's predominance.

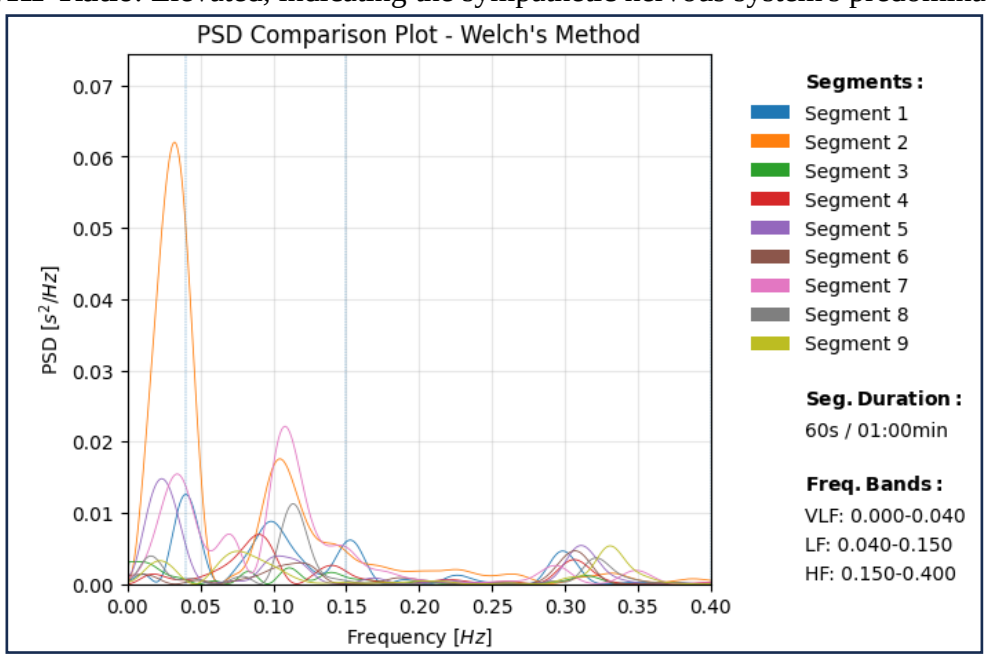


Figure 4.3. 9 PSD Comparisons estimation using Welch's method while watching a Suspense video

B. Lomb-Scargle

Next, introduce the Lomb-Scargle method which was our next analytical tool in unraveling the intricacies of the heartbeat narrative, providing the clarification of the frequency components of HRV. In the context of HRV, it offers insights into autonomic nervous system regulation through the VLF, LF, and HF frequency bands.

Nature Video

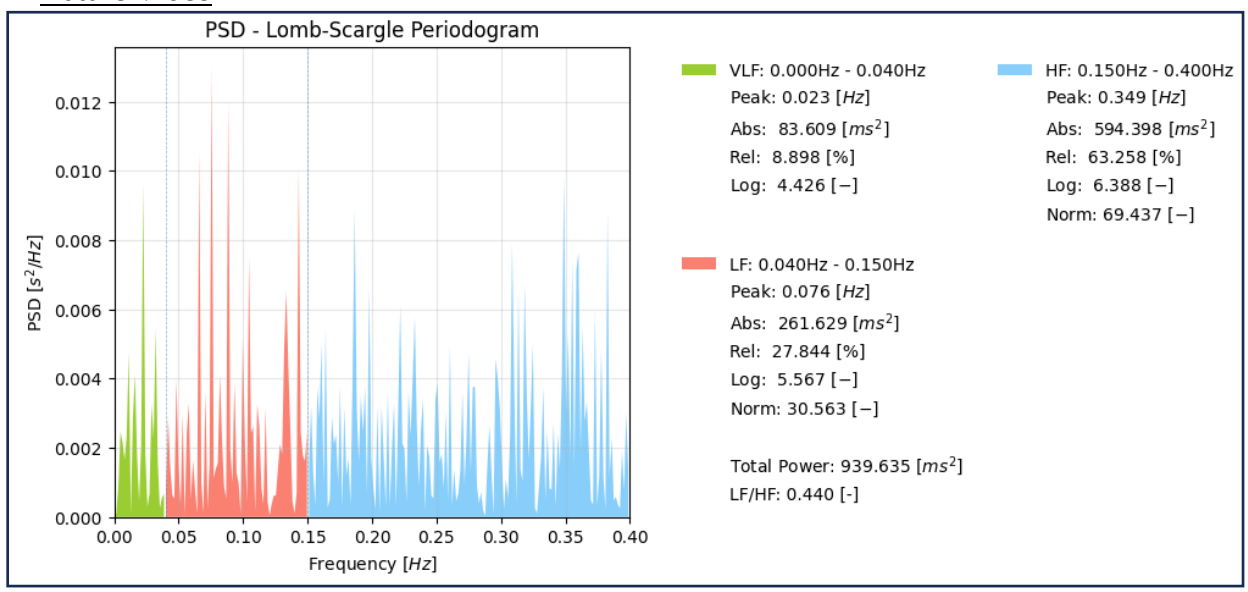


Figure 4.3. 10 PSD estimation using Lomb Scargle's method while watching a Nature video

Physiological Significance:

- **VLF**: Low, indicating minimal stress and low sympathetic activation.
- **LF**: Moderate, suggesting balanced sympathetic and parasympathetic activity.
- **HF**: High, reflecting strong parasympathetic (vagal) activity, indicative of a relaxing effect.
- **LF/HF Ratio**: Low, reinforcing the dominance of parasympathetic activity.

PSD Comparison Plot Using Lomb-Scargle Periodogram

Here the Lomb-Scargle periodogram of Power Spectral Density (PSD) comparison plot provides a detailed visualization of the HRV signal's frequency components across multiple segments. The Lomb-Scargle periodogram is particularly useful in this method which is beneficial for its ability to handle irregularly spaced data points and is robust in capturing the frequency domain characteristics of Heart Rate Variability.

In the provided plot, the PSD is estimated using the Lomb-Scargle periodogram across nine different segments of the HRV signal. The x-axis represents the frequency in Hertz (Hz) (range from 0.00 to 0.40 Hz), covering the standard frequency bands of HRV analysis and the y-axis denotes the PSD in squared seconds per Hertz[s^2/Hz]. The plot includes nine segments, each represented by a different color. The segments have a duration of 60 seconds (1 minute), which is typical for short-term HRV analysis. The PSD values vary across the different segments, as depicted by the multiple-colored lines. This variability indicates that the HRV signal's frequency components are not constant over time but fluctuate, which could be due to changes in ANS activity, physiological conditions, or external stimuli.

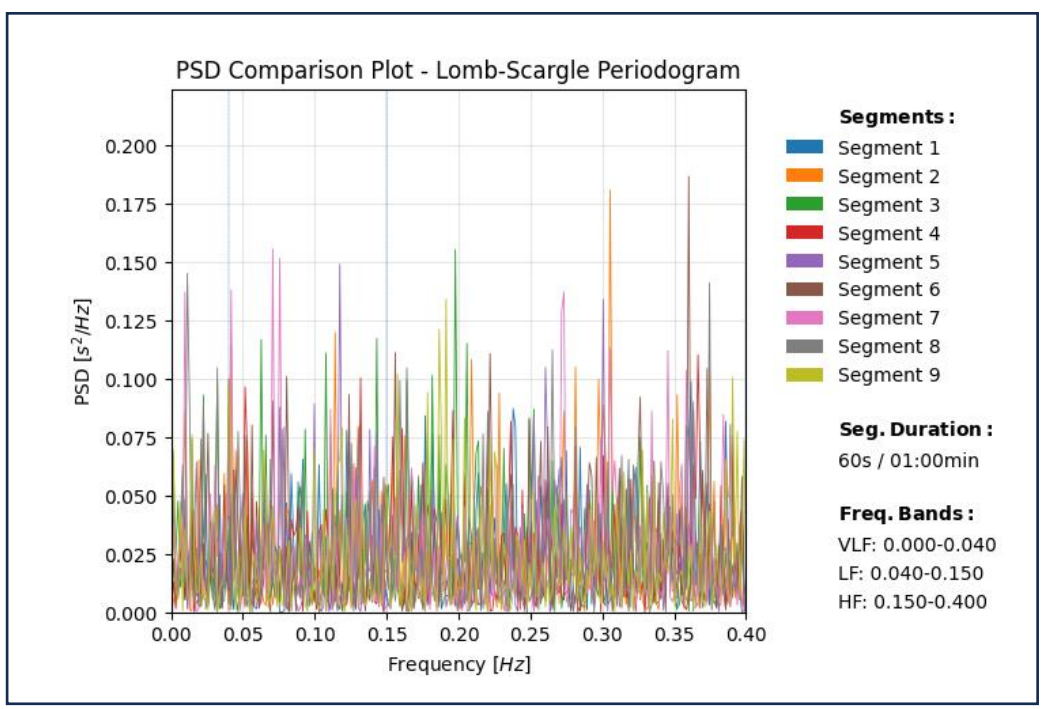


Figure 4.3. 11 PSD Comparisons estimation using Lomb Scargle's method while watching a Nature video

Comedy video

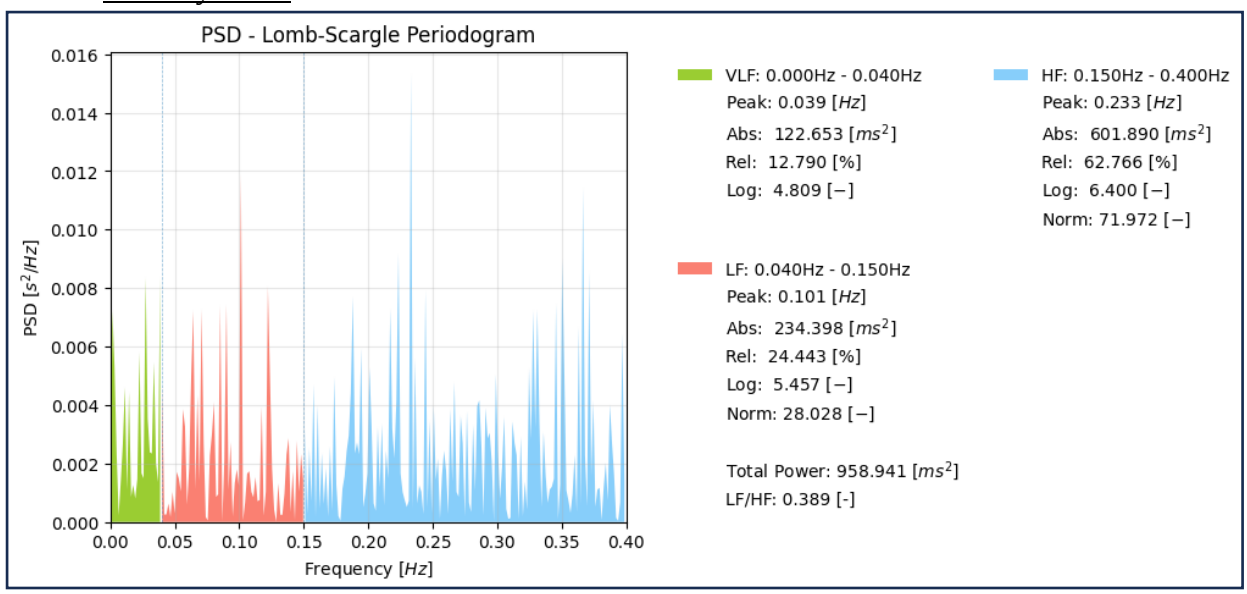


Figure 4.3. 12 PSD estimation using Lomb Scargle's method while watching a Comedy video

Physiological Significance:

- **VLF**: Slightly higher than in the nature video, indicating increased arousal.
- **LF**: Lower relative power, but still significant, suggesting sympathetic engagement.
- **HF**: High, reflecting strong parasympathetic activity, but less than the nature video.
- **LF/HF Ratio**: Low, indicating predominant parasympathetic activity with some sympathetic engagement.

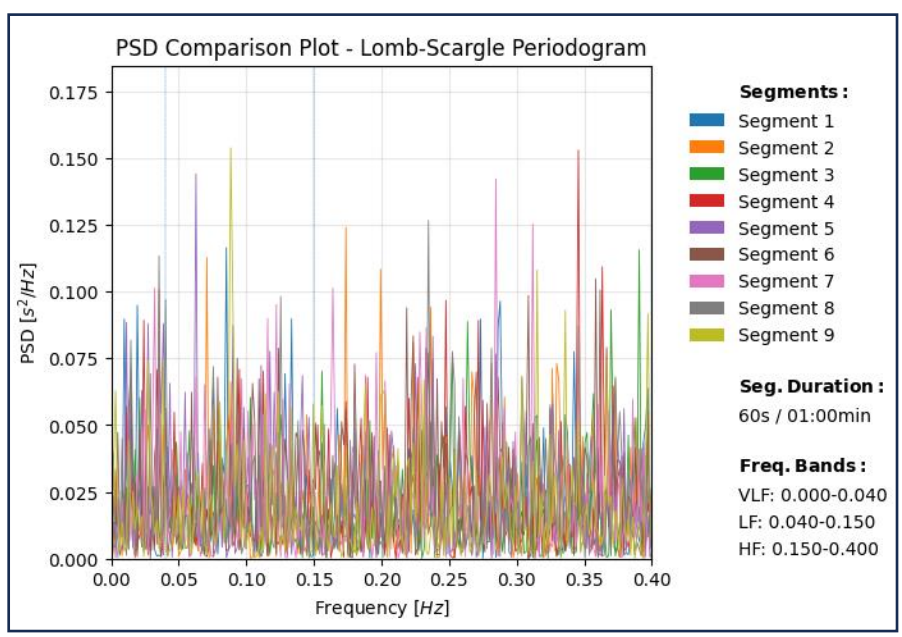


Figure 4.3. 13 PSD Comparisons estimation using Lomb Scargle's method while watching a Comedy video

Suspense video

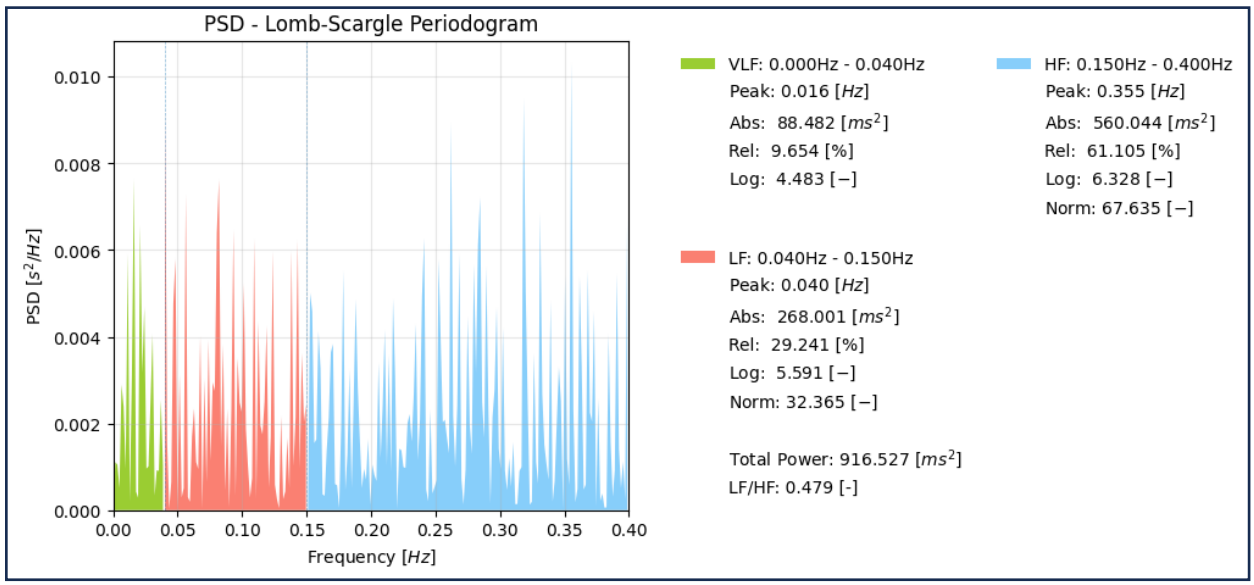


Figure 4.3. 14 PSD estimation using Lomb Scargle's method while watching a Suspense video

Physiological Significance: **LF**: Higher relative power compared to the other videos, suggesting increased sympathetic activity due to suspense. **HF**: High, but lower than in nature and comedy videos, indicating a balance between activities of sympathetic and parasympathetic. **LF/HF Ratio**: Slightly higher than the comedy video, showing a modest increase in sympathetic engagement.

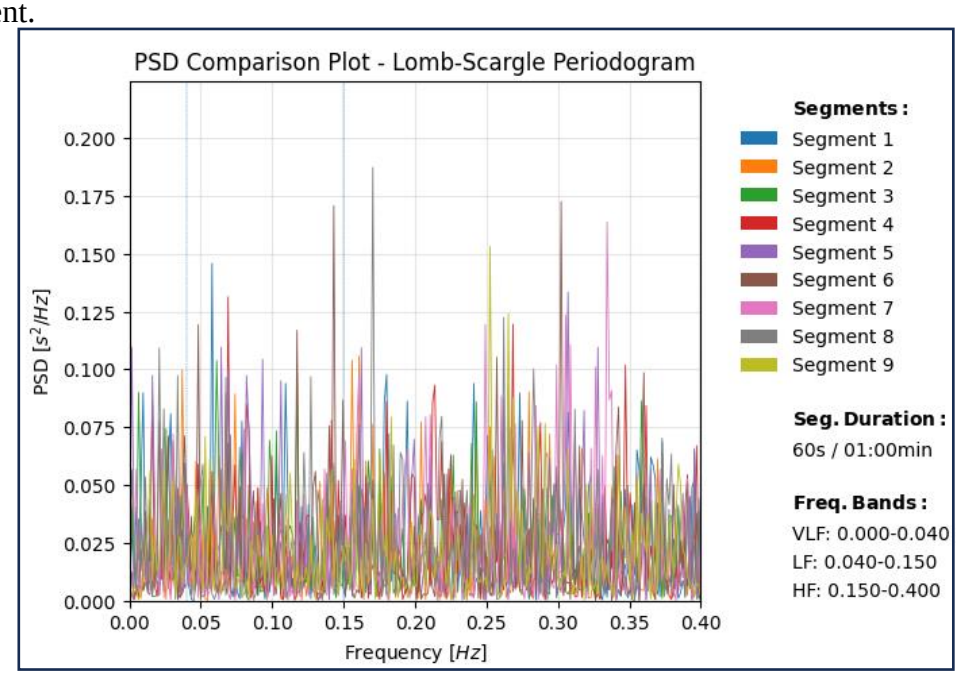


Figure 4.3. 15 PSD Comparisons estimation using Lomb Scargle's method while watching a Suspense video

LF/HF Ratio

It is a measure of the balance between SNS & PNS activity, with higher values representing sympathetic dominance and lower values demonstrating the dominance of parasympathetic. Tables represent information regarding LF/HF Ratio Values through a welch periodogram.

Table 4 – LF/HF values of all Subjects

LF/HF Ratio Values Through Welch			
Subject	**Video**		
	Suspense	**Nature**	**Comedy**
Subject-01	0.526	0.701	0.636
Subject-02	0.547	0.57	0.617
Subject-03	0.308	0.174	0.82
Subject-04	1.296	1.697	4.387
Subject-05	1.46	0.855	5.77
Subject-06	2.415	1.406	4.27
Subject-07	0.713	1.328	0.942

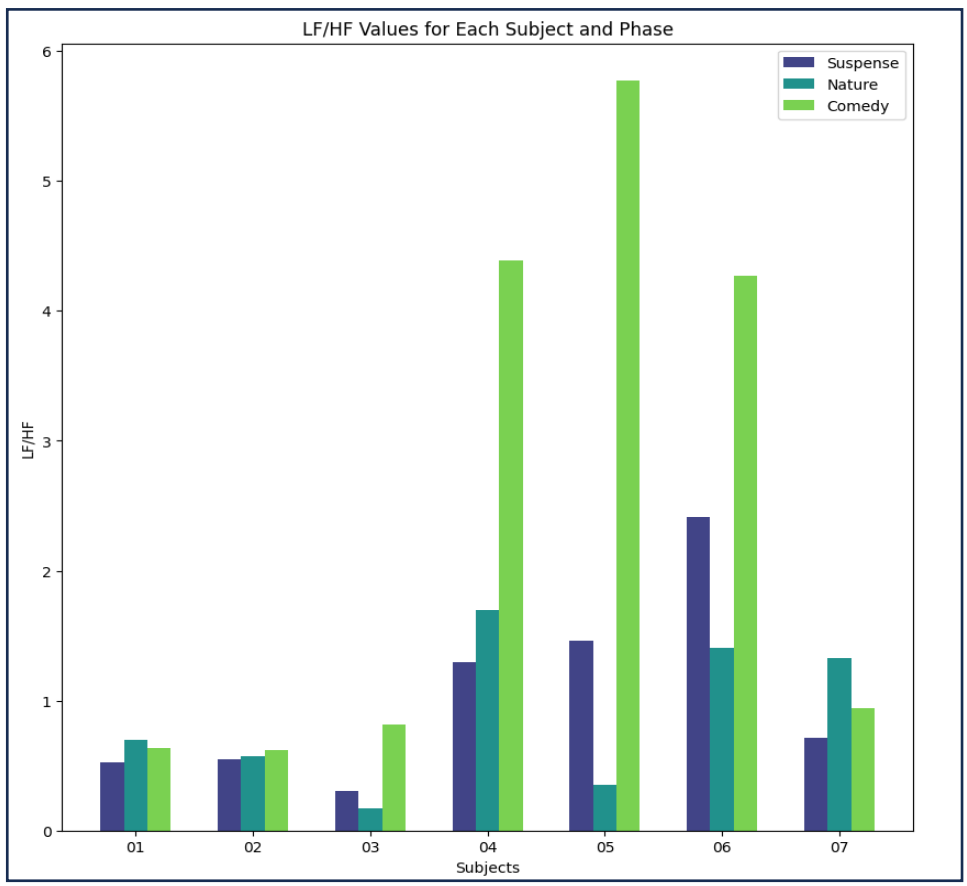


Figure 4.3. 16 LF/HF values for each subject and phase

Some facts here observed are that Subject-06 displayed sensitive sympathetic dominance during suspenseful content, Subject-03 showcased parasympathetic dominance in nature videos, and Subject-05 indicated increased sympathetic activity during comedic content. These results contribute to a deeper understanding in frequency domain HRV analysis of how individual preferences and emotional engagement shape physiological responses, setting the stage for further research in personalized interventions and stress management strategies

4.3.3. Non-Linear Features Analysis

Poincare Plot

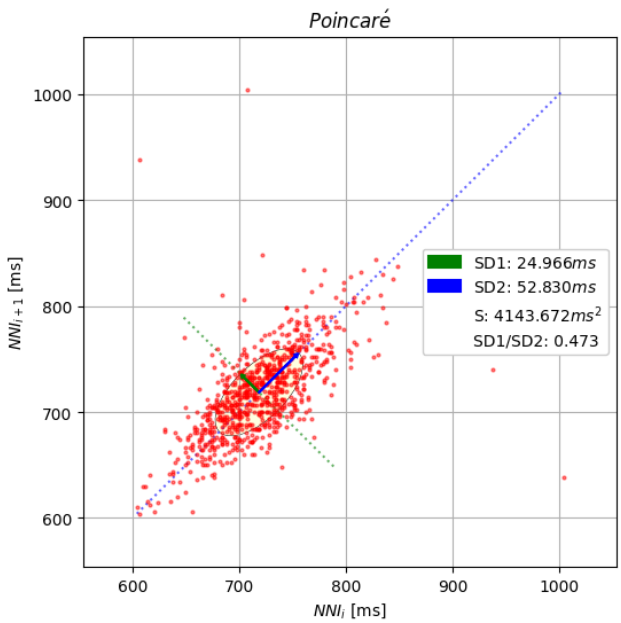


Figure 4.3. 17 Poincare Plot of Nature Video

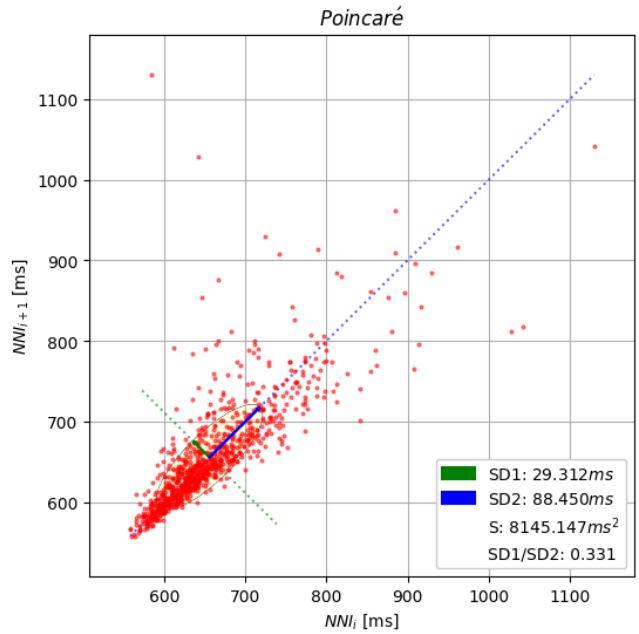


Figure 4.3. 18 Poincare Plot of Comedy Video

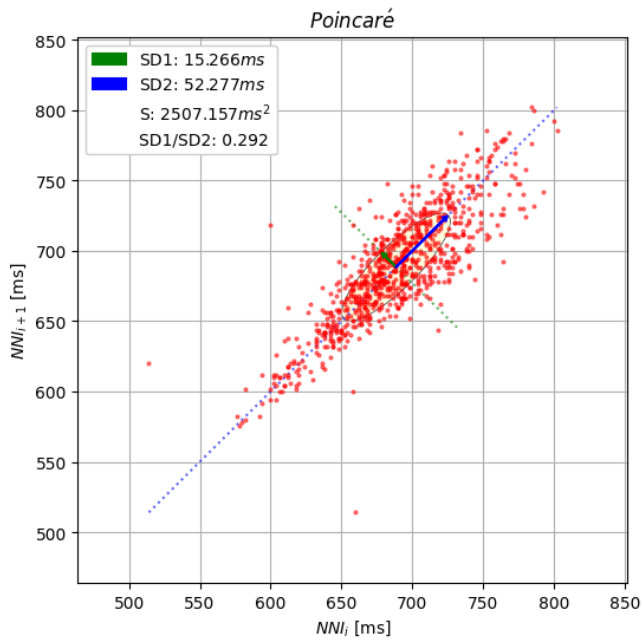


Figure 4.3. 19 Poincare Plot of Suspense Video

For the nature video, the Poincare plot exhibits a comet pattern. This pattern indicates a balanced and healthy autonomic response, characterized by moderate variability in heart rate. The comet shape suggests that the subject experienced a relaxed and stable state while watching the nature video. The distribution of points reflects a good balance between HRV's short-term and long-term, indicating a well-regulated autonomic nervous system typical of a calming and restful environment.

The comedy video resulted in a slide torpedo pattern on the Poincare plot. This pattern is indicative of increased variability in heart rate, with a greater dispersion of points along the plot. The slide torpedo shape suggests that the subject experienced a heightened autonomic response, likely due to the excitement or amusement induced by the comedic content. This pattern reflects a more dynamic and reactive state, with increased short-term variability and a broader range of heart rate fluctuations.

While watching the suspense video, the Poincare plot shows a spreaded comet pattern. This pattern indicates a stressed autonomic response, characterized by reduced variability in heart rate. The spreaded comet shape suggests that the subject experienced heightened stress or anxiety during the suspense-inducing stimulus. The distribution of points reflects lower short-term HRV and a more concentrated range of heart rate fluctuations, indicating a less flexible and more constrained autonomic response typical of a stress-induced state.

Sample Entropy

The Sample Entropy results highlight how different types of videos—Suspense, Nature, and Comedy—elicit varying levels of response complexity among viewers. This variability can be scientifically interpreted through the lens of cognitive and emotional engagement.

Table 5 – Sample Entropy values of all Subjects

Sample Entropy			
Subject	**Video**		
	Suspense	**Nature**	**Comedy**
Subject-01	2.0693	2.0166	2.1055
Subject-02	1.0326	2.0693	1.0499
Subject-03	1.9854	1.751	1.9156
Subject-04	1.2336	1.2067	1.1855
Subject-05	1.6092	1.5755	1.439
Subject-06	1.5163	1.5052	0.746
Subject-07	1.844	1.8933	2.0017

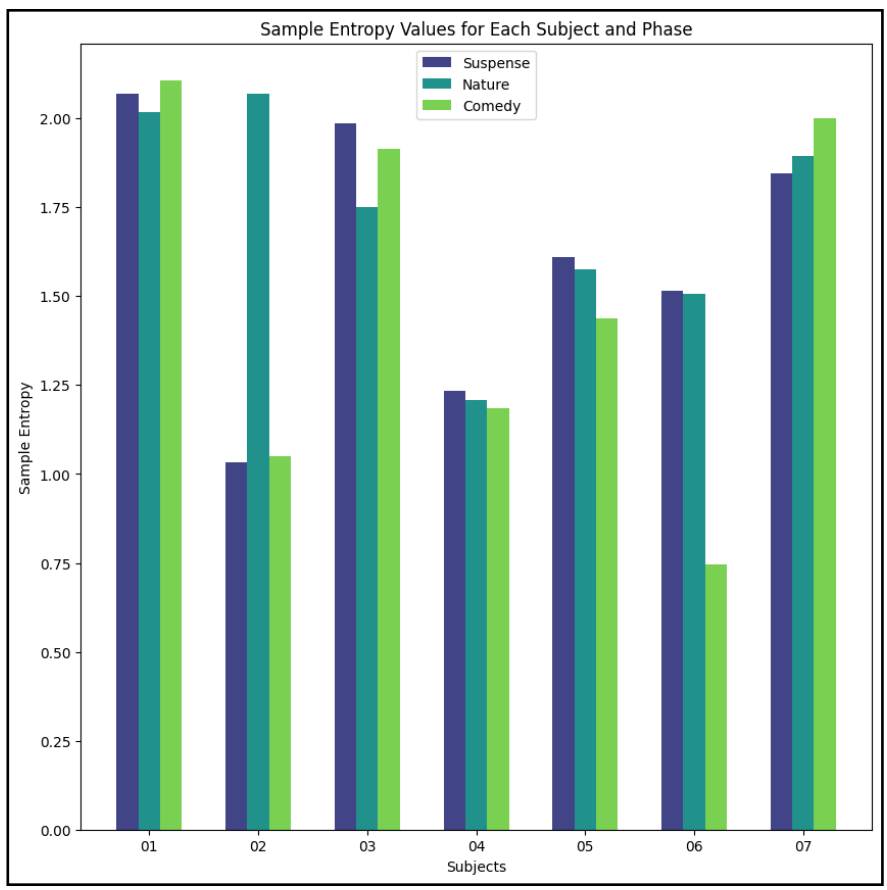


Figure 4.3. 20 Sample Entropy values for each subject and phase

The results represent information regarding Sample Entropy that is relatively higher during suspenseful content in maximum cases, suggesting more irregular and complex heart rate patterns. This could indicate increased physiological responsiveness or engagement during suspenseful videos. Individual perceptions, emotional responses, and preferences during different genres may contribute to variations in Sample Entropy. Subject-01 and Subject-07 demonstrate higher Sample Entropy during nature videos, potentially reflecting diverse responses to the calming or visually engaging nature content, and also exhibit elevated Sample Entropy during comedic content, suggesting a potential for heightened physiological complexity during moments of humor.

Detrended Fluctuation Analysis

DFA is an important parameter for analyzing HRV, particularly for time series data for evaluating long-range correlations. DFA provides particularly two scaling exponents, one α1 is short-term and another α2 is long-term, which define the fractal properties of the time series. Typically, α1 ranges from 0.5 to 1.5, where values around 1.0 suggest a balance between randomness and long-term correlations, indicating healthy autonomic function.

In this experiment, I assessed the Heart Rate Variability (HRV) of 7 subjects using Detrended Fluctuation Analysis (DFA) while they were exposed to three different types of audio-visual stimuli: nature, comedy, and suspense. For this analysis, I am presenting the DFA results from one subject to illustrate how HRV varies across these stimuli.

For Nature audio-visual stimuli

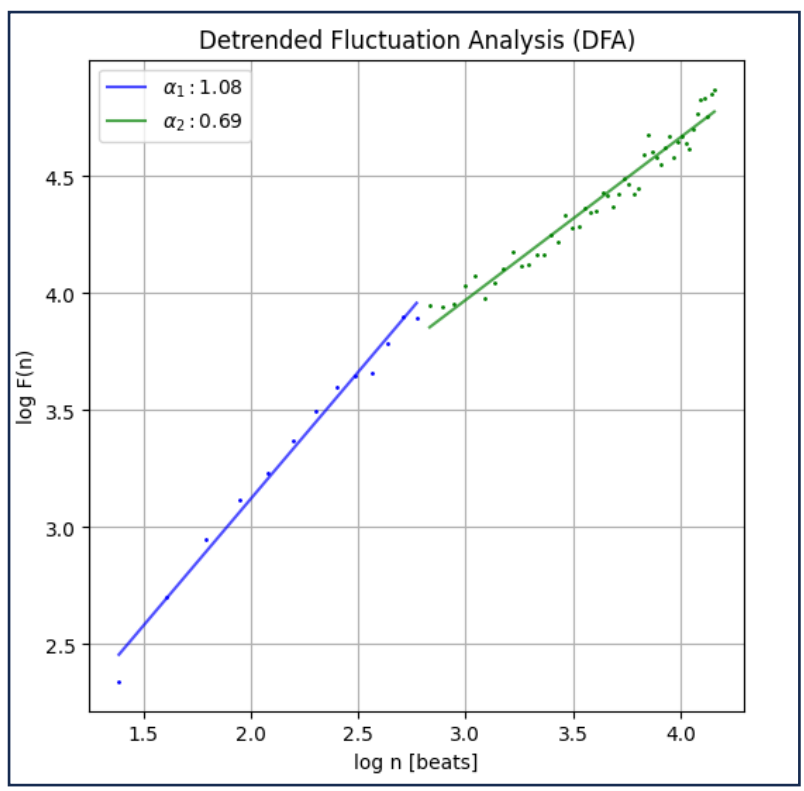


Figure 4.3. 21 DFA for Nature Video

When the subject watched the nature video, the DFA results showed an α1 value of 1.08 and an α2 value of 0.89. The α1 value of 1.08 is within the typical range (0.5 to 1.5) for short-term HRV and indicates a healthy balance between randomness and long-term correlations. This suggests a relaxed autonomic state, consistent with the calming effect expected from nature scenes.

The α2value of 0.89, close to 1.0, indicates moderate long-term correlations, further supporting the relaxed state.

For Comedy audio-visual stimuli

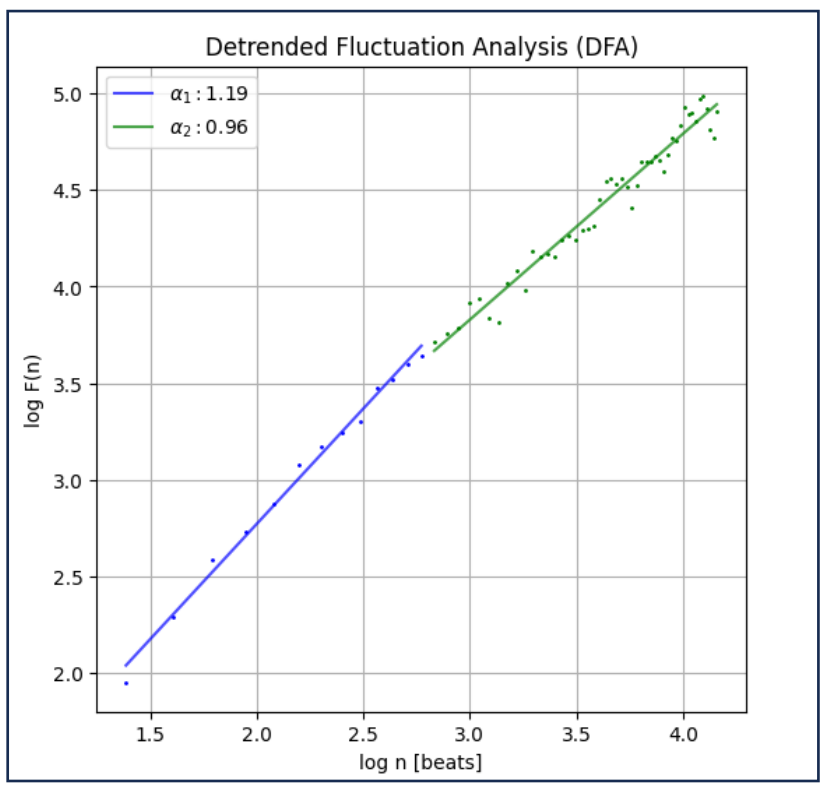


Figure 4.3. 22 DFA for Comedy Video

While watching the comedy video, the subject's α1 value was 1.19 and the α2 value was 0.96. The α1 value of 1.19 is within the typical range but slightly elevated, indicating a moderate Excitement response in short-term HRV. The α2 value of 0.96, close to 1.0, suggests maintained long-term correlations, consistent with a heightened state of excitement expected during a comedic stimulus.

For Suspense audio-visual stimuli

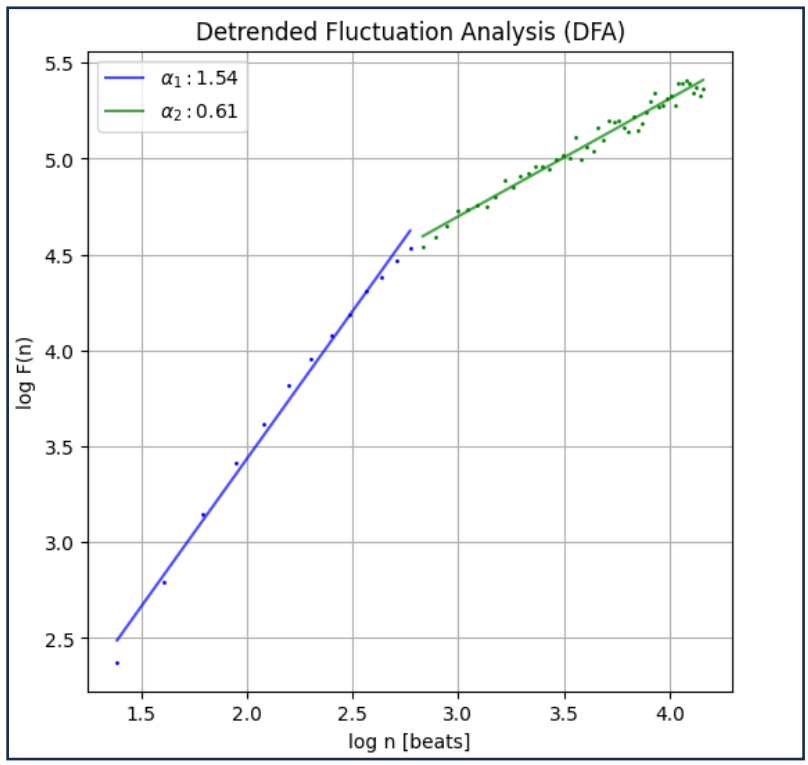


Figure 4.3. 23 DFA for Suspense Video

During the suspense-inducing video, the subject's α1 value increased to 1.54, while the α2 value decreased to 0.61. The α1 value of 1.54 is higher than the typical range, suggesting an increased complexity in short-term HRV. This could indicate a heightened autonomic response, possibly reflecting transient stress or excitement induced by the suspense content. The lower α2 value of 0.61 suggests reduced long-term stability, which might be associated with a more immediate and transient emotional response.

Considering these results of DFA in the context of audio-visual stimuli provides valuable insights into the autonomic regulation and emotional states of individuals.

CHAPTER-V

5. Discussion

In the initial step of the analysis, I mainly obtained the ECG signals from seven subjects and applied the Pan-Tompkins algorithm for R-peak detection. This algorithm, renowned for its efficiency in real-time QRS detection, allowed me to accurately identify the R-peaks within the ECG signal, which are critical for further HRV analysis. By using this method, I ensured high accuracy and reliability in analyzing the moments of various cardiac dynamics, thereby providing a novel foundation for consequent heart rate calculations.

Following the detection of R-peaks, heart rate histograms were created to visualize the distribution of heart rates over the experimental period. This visualization technique offered a clear representation of how heart rates varied among the subjects when exposed to the different audiovisual stimuli—nature, comedy, and suspense videos. By examining these histograms, I was able to discern patterns and trends in heart rate responses, which are indicative of the ANS's reaction to different types of audio-visual stimuli.

My analysis revealed distinct differences in heart rate distributions across the various stimuli categories. Subjects exposed to nature videos typically exhibited a more uniform and stable heart rate distribution, suggesting a calming response to the ANS. In contrast, the comedy videos induced moderate fluctuations in heart rates, reflecting a mix of both relaxation and excitement. The most pronounced changes were observed during the suspense videos, where heart rate histograms showed a significant shift towards higher heart rates, indicative of an increased stress response.

In the Next step, the heart rate heat plot is a powerful tool to visualize how different types of videos impact heart rate. By comparing heat plots for nature, comedy, and suspense videos, it becomes evident that: **Nature Videos**: Induce a stable heart rate with minimal fluctuations. **Comedy Videos**: Cause moderate heart rate variations due to intermittent emotional spikes. **Suspense Videos**: Lead to significant heart rate fluctuations, reflecting strong emotional

responses. These observations can be useful in various applications, including stress management, entertainment content analysis, and understanding human physiological responses to different stimuli.

In the next study of Time domain analysis for SDNN shows the variation of SDNN across subjects. Certain subjects display a decrease in SDNN while watching nature videos, and their responses to suspense and comedy videos are almost indistinguishable. The reduction in SDNN for some subjects during nature videos may indicate a shift towards sympathetic dominance. Nature videos can evoke a range of emotions. Exposure to nature scenes may cause alertness or excitement, leading to increased SNS activity and reduced HRV. On the other hand, both suspense and comedy can trigger emotional responses, such as increased heart rate and changes in autonomic balance. The similarity in SDNN patterns may reflect a shared physiological response to emotional engagement. On the contrary, the increase in SDNN for certain subjects during nature videos suggests a different response. It could indicate a shift towards parasympathetic dominance, reflecting a more relaxed and calm state. Nature scenes are often associated with relaxation and stress reduction, leading to increased parasympathetic activity and enhanced heart rate variability.

Similar inter-subject variability is observed in RMSSD and pNN50, suggesting that individuals have different baseline autonomic nervous system states and responses to emotional stimuli. Some individuals display higher RMSSD and pNN50, indicating increased parasympathetic modulation and more adaptive autonomic response, while others show reduced HRV, reflecting increased sympathetic dominance

For the Frequency Domain the PSD analysis, through Welch periodogram & Lomb Scargle is used to measure the power distribution over the signal's frequency components. In the context of HRV, it provides an understanding of the ANS’s regulation of the heart. The HRV frequency components are typically divided into three bands, first VLF ranges between 0.000 to 0.040 Hz, then LF ranges between 0.040 Hz to 0.150 Hz, and HF ranges between 0.150 Hz to 0.400 Hz. The analysis of the PSD for HRV during the viewing of nature, comedy, and suspense videos reveals distinct physiological responses. The nature video shows a balanced autonomic response with moderate VLF, higher LF, and significant HF, indicating a relaxing and calming effect due to notable parasympathetic activity. In contrast, the comedy video elicits a strong sympathetic response with low VLF, predominantly high LF, and lower HF, suggesting heightened arousal and

engagement, reflected in the high LF/HF ratio. The suspense video, meanwhile, indicates elevated stress levels with increased VLF, moderately high LF, and reduced HF, aligning with a stressed state and significant sympathetic dominance. These variations in frequency components and their respective powers align well with the expected emotional responses, illustrating how different audio-visual stimuli can impact autonomic regulation as measured through HRV.

In the Power Spectral Density (PSD) comparison plot section Welch and Lomb Scargle periodograms provide a visual representation of the HRV signal's frequency components estimated by these two methods. Welch's periodogram, known for its robustness and reduced variance, involves segmenting the signal into overlapping windows in 9 segments duration of 60s or one minute of the total video, applying a window function to minimize spectral leakage, and averaging the resulting periodograms. In contrast, the Lomb-Scargle periodogram also did 9 segments of different 60s each duration of total length. This comparison is essential for validating HRV analysis techniques of different frequency components and ensuring robust interpretation of autonomic function. The nature video shows a balanced autonomic response with low VLF, moderate LF, and high HF, indicating a relaxing and calming effect due to dominant parasympathetic activity. The comedy video elicits a slight increase in VLF, moderate LF, and high HF, suggesting a balance between activities of parasympathetic and sympathetic with some engagement and arousal. The suspense video shows low VLF, the highest LF among the three, and slightly lower HF, indicating an increased sympathetic response due to suspense and a balance between sympathetic and parasympathetic activities. These variations in frequency components and their respective powers align well with the expected emotional responses, illustrating how different audio-visual stimuli impact autonomic regulation as measured through HRV.

The LF/HF ratio indicates the balance between SNS & PNS activity, with higher values signifying dominance of SNS activity and lower values signifying dominance of PNS activity. Among the seven subjects, five exhibited the maximum LF/HF ratio during the comedy video. Four subjects showed the lowest LF/HF ratio during the suspense video, while three subjects had the lowest ratio during the nature video. Most subjects experienced that the LF/HF ratio increased during the comedy video, indicating sympathetic activity dominance. Comedy, which often induces laughter and positive emotions, can trigger an arousal response, leading to heightened sympathetic activity and an elevated LF/HF ratio. Conversely, suspenseful videos can evoke both

arousal and stress, but for these individuals, the stress or fright from the suspense video likely reduced emotional dominance, resulting in a lower LF/HF ratio. The lower LF/HF ratio observed during nature videos for certain subjects suggests a stronger parasympathetic response. Nature scenes are typically associated with relaxation and stress reduction, which enhances parasympathetic activity and lowers the LF/HF ratio. Individual differences, such as personal experiences, emotional associations with specific stimuli, and baseline autonomic nervous system states, have a significant impact on these reactions, contributing to the variability in the LF/HF ratio across subjects.

Nonlinear dynamic analysis The First Poincare plot demonstrates that for **Nature Video**: The comet pattern in the Poincare plot suggests a balanced and relaxed autonomic state. This is indicative of moderate heart rate variability, reflecting a well-regulated autonomic nervous system typical of a calming environment. **Comedy Video**: The slide torpedo pattern indicates increased heart rate variability and a heightened autonomic response. This reflects the subject's dynamic and reactive state, likely due to the excitement or amusement induced by the comedic content. **Suspense Video**: The spread comet pattern suggests a stressed autonomic state, with reduced heart rate variability. This reflects the subject's heightened stress or anxiety, indicating a less flexible autonomic response typical of a stress-induced state.

In the next analysis of non-linear parameters, Sample Entropy revealed that subjects 1, 3, 4, and 5 exhibited the highest entropy during suspense videos, moderate entropy during nature videos, and the lowest entropy during comedy videos. Subjects 2 and 6 deviated from this pattern. Subject 2 showed significantly high entropy in nature videos and low, similar values in suspense and comedy videos. In contrast, Subject 6 had the highest entropy in both suspense and nature videos, with notably low entropy in comedy videos. Subject 7 displayed the highest entropy in comedy videos, moderate levels in nature videos, and the lowest in suspense videos.

Low sample entropy in comedy videos, as seen in Subject 6, suggests a more predictable physiological response. Comedy typically follows a structured pattern, leading to a predictable and rhythmic response. The predictability of comedic content, combined with the positive emotions and relaxation it elicits, contributes to the observed low sample entropy. Conversely, high sample entropy during comedy videos, as seen in Subjects 1 and 7, indicates a more complex and irregular

physiological response. The diversity and unpredictability of comedic content led to heightened cognitive engagement and emotional variability, resulting in constantly changing physiological patterns.

Subjects 3, 4, and 5 exhibited high sample entropy during suspenseful videos, indicating a complex and irregular physiological response. The unpredictable nature of suspenseful content leads to heightened cognitive and emotional arousal, contributing to increased sample entropy. However, predictability in the storyline or heightened cognitive focus could lead to a more regulated and less complex physiological response, resulting in low entropy.

Nature videos consistently induced high sample entropy, suggesting a diverse and dynamic physiological response. The visually rich and calming nature scenes elicit complex patterns in physiological signals, reflecting the complexity of emotional and cognitive processes. Interestingly, some subjects showed relatively consistent physiological responses across different genres, with slight differences. This may suggest a more stable and uniform autonomic nervous system regulation across various emotional and cognitive stimuli.

For analyzing the Detrended Fluctuation Analysis (DFA) for short-term HRV (α1), distinct patterns emerged across the different stimuli. For the nature videos, the α1 value was 1.08, indicative of a balanced autonomic response typically associated with a relaxed state. This suggests that nature scenes foster a stable and calm autonomic nervous system reaction. Conversely, the suspense videos yielded an elevated α1 value of 1.54, reflecting increased complexity in HRV. This elevation suggests that the subjects experienced transient stress or excitement in response to these stimuli. The comedy videos resulted in an α1 value of 1.19, indicating a moderate stress response, possibly due to the mixed emotional cues of humor and surprise inherent in comedic content.

Regarding long-term HRV (α2), the nature stimuli resulted in an α2 value of 0.89. This value suggests moderate long-term correlations in heart rate variability, consistent with a relaxed state over a prolonged period. In contrast, the suspense stimuli produced a lower α2 value of 0.61, indicating reduced long-term stability and suggesting a more immediate and pronounced autonomic stress response. The comedy stimuli, with an α2 value of 0.96, showed maintained long-term correlations in HRV, typical of an alert or excited state. This indicates that while the comedy videos elicited some level of arousal, they did not significantly disrupt the long-term autonomic

balance of the subjects. Overall, these findings highlight the nuanced effects of different audiovisual stimuli on both short-term and long-term, reflecting varying degrees of ANS activity and emotional responses.

CHAPTER- VI

6. Conclusion

The research work serves as a characteristic tool for discerning emotional responses to various audio-visual stimuli through Heart Rate Variability (HRV). Results show that different time, frequency, and non-linear domains can characterize individual emotional and physiological responses to different video content. Specifically, the analysis of HRV metrics, such as Standard Deviation of NN intervals (SDNN), LF/HF ratio, and sample entropy, demonstrates the nuanced interplay between the autonomic nervous system and emotional stimuli. Similarly, the LF/HF ratio patterns during comedy, suspense, and nature videos highlight the differential activation of sympathetic and parasympathetic branches.

The observed different variability in the dynamic nature of the complexity of heart rate considering the factors, the interpretation of the Poincare plot, and DFA's results in the context of audio-visual stimuli can provide valuable insights into the autonomic regulation and emotional states of individuals in Nature, comedy and suspense audiovisual stimuli. The observed variability in sample entropy across subjects during different video genres further underscores the complexity of individualized responses, with some subjects consistently exhibiting higher entropy during suspense videos, reflecting a more complex physiological response. These findings underscore the role of individual preferences and emotional engagement in shaping physiological reactions to audio-visual stimuli, laying the groundwork for future research in personalized interventions and stress management.

CHAPTER- VII

7. Future Scope

The future scope of this work is expansive, with significant potential in various domains. Incorporating subjective ratings using the SAM scale in future work holds the promise of refining our insights into emotional responses, potentially making our studies more accurate and contributing significantly to the evolving landscape of emotion research in this field.

In clinical settings, ECG-based HRV analysis could aid in diagnosing and treating mental health conditions, as well as enable remote patient monitoring. The development of wearable devices and integration with mobile health apps could provide real-time emotional state feedback, enhancing personal stress management.

In workplaces, this technology could help monitor and reduce employee stress, while educational institutions could use it to manage student stress and improve performance.

Further research and development, including refining HRV techniques and cross-disciplinary collaboration, will drive innovations in emotional health. Overall, this work aims to contribute to better stress management, improved mental health, and enhanced well-being in everyday life.

CHAPTER-VIII

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