# A BRAIN COMPUTER INTERFACE APPROACH TO INVESTIGATE BRAIN ACTIVATION PATTERN DURING ANALYSIS OF VISUAL AESTHETICS

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

OF

**MASTER OF TECHNOLOGY IN**
**ELECTRONICS & TELE-COMMUNICATION ENGINEERING**
**IN SPECIALIZATION OF INTELLIGENT AUTOMATION AND ROBOTICS 2016-19**

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## CERTIFICATE OF RECOMMENDATION

This is to certify that the dissertation entitled **"A BRAIN COMPUTER INTERFACE APPROACH TO INVESTIGATE BRAIN ACTIVATION PATTERN DURING ANALYSIS OF VISUAL AESTHETICS"** submitted by **SUPARNA BASU (Examination Roll No.: M6IAR19003, University Registration No.: 137293 of 2016-2017)** to Jadavpur University, Kolkata, is a record of bonafide research work under my supervision and be accepted in partial fulfilment of the requirement for the degree of **Master of Technology in Electronics and Telecommunication Engineering** of the institute. The research results presented in this thesis are not included in any other paper submitted for the award of any Degree or Diploma to any other University or Institute. The project in my opinion, is worthy for its acceptance.

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**<u>DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS</u>**

I the undersigned do hereby declare that this thesis contains literature survey and original work done by means a part of my MASTER OF TECHNOLOGY IN ELECTRONICS AND TELECOMMUNICATION ENGINEERING. All information in this document have been obtained and presented in accordance with academic rules and ethical conduct. I also declare that as required by these rules and conduct I have fully cited and referenced all materials and results that are not original with this work.

<u>Project Title</u>

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# ACKNOWLEDGEMENT

The success and final outcome of my thesis required a lot of guidance and assistance from many people and I am extremely fortunate to have got this all along the completion of my thesis work. Whatever I have done is only due to such guidance and assistance and I would not forget to thank them.

First and foremost, I owe my immense gratitude to my project supervisor **Prof. Amit konar,** department of Electronics abd Telecommunication Engineering, Jadavpur University, for his invaluable help and guidance during my dissertation work. I am highly indebted to him for constantly encouraging me by giving his critics on my work. I attribute my master degree to his encouragement and effort, and without him this thesis would not have been completed.No words will suffice in describing his contribution towards the completion of my thesis work.

I sincerely thank Prof. Sheli Sinha Chaudhuri, Head of the Department of Electronic & Telecommunication Engineering, Jadavpur University and all the authorities of the institute for providing nice academic environment and adequate infrastructure to carry out the present investigations.

I would like to acknowledge the assistance and co-operation from all my seniors Mousumi laha and Lidia Ghosh and my friend Anusri Patra. I would also like to express my heartfelt thankfulnessto all my batch mates who have directly or indirectly helped me in my project work and shared the moments of joy and sorrow throughout the period of project work finally yet importantly.

Last but not the list, I would like to thank all those who are directly or indirectly associated in completion of this thesis work.

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# ABSTRACT

The introduction of Brain computer Interfacing (BCI) has fundamentally changed the traditional standards of control and communication. The engrossing idea of "mind-controlled control" has captivated a large number of research admirers to the study of various areas of this discipline. The introduction of BCI has made revolutionary changes in the traditional standards of control and communication. Over the past few decades, computers have become an integral part of the BCI infrastructure. BCI not only provides healthy people with an easier and better life, but also offers help and rehabilitation to disabled people. The fundamental objective of this thesis is the study of brain activity during a visual aesthetic task in the context of beauty. Analyzing of the activity of the human brain on aesthetics and apply of these methods in constructive and innovative application areas of neuronal activities of brain. A basic computational intelligence and machine learning technique e.g. fuzzy logic, pattern recognition etc. have been taken into account. Several computational techniques such as AAR, Wavelet Coefficient, PSD, Horjth parameter have been taken into account for the completion of our objective mentioned above.

The thesis work is divided into four chapters. Chapter 1 discusses the main objective of this work and an introductory concept o Brain Computer Interface (BCI) along with a brief background of the development. It also discusses the signal processing steps and two promising BCI techniques: EEG and fNIRS in brief. Chapter 2 defines brains understandings of BCI, mechanism of the brain while a visual aesthetic task is going on and way to detect those brain signals and some recent research works on the cognitive aesthetics. Chapter 3 proposes a General type-II fuzzy approach for single trial P300 detection, EEG based analysis to investigate the brain reactions while a visual aesthetic task is performed. It consists all the experimental codes and graph works. Chapter 4 concludes the remarks on the entire thesis work and discusses the future directions of the research. All the chapters are provided with necessary bibliography.

# CONTENTS

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# CHAPTER 1

# INTRODUCTION

## 1. PREFACE

This chapter concentrates on the primary objectives of this thesis work and discusses about the motivation behind this work along with the methodologies used. In last decade, brain-computer interface (BCI) research has shown enormous amount of potential about direct communication of human brain to the external environment. The non-invasive BCI (EEG, fNIRS) has the potential of using the neuronal or hemodynamic brain response from the scalp for interplay with the environment. This is advantage of BCI as it minimizes the risks of surgical procedures in the invasive BCI. Several neuroimaging techniques are being used in studies now-a-days, such as Electroencephalography(EEG), magneto Encephalography(MEG), functional near-infrared spectroscopy(fNIRS), functional magnetic resonance imaging(fMRI). In our study, we used EEG and fNIRS techniques for acquisition of brain signal.

Section 1.1: Brain Computer Interfacing

1. Concept of BCI
2. History of evolutions

Section 1.2: Techniques of brain activity measurement and processing

Section 1.3: EEG based BCI

Section 1.4: fNIRS based BCI

Section 1.5: Applications of BCI

Section 1.6: Advantages and Disadvantages of BCI

### 1.1.1 BRAIN-COMPUTER INTERFACING (BCI)

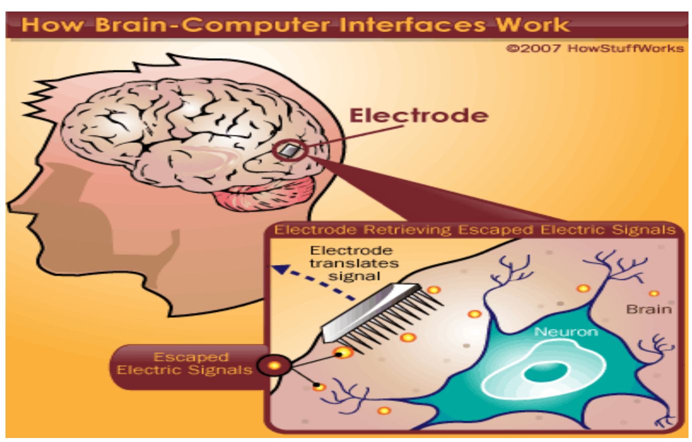
Brain-Computer Interfacing is a communication pathway between an wired brain and an external device. BCI differs from neuro modulation as the later allows bidirectional information exchange.[1] The research and development of BCI focuses mainly on neuroprosthetic applications whose objective is to restore damaged hearing, sight and movement. This technology has now developed to the point that it is being used by individuals. BCI refer to an interface which takes signals from the brain and pass it to an external hardware, or a technology which sends signals to the brain. A brain-computer interface also known as brain-machine. [2]

The most commonly used BCI technique is electroencephalography (EEG), which is a direct but non-invasive measure, but recently the focus has been on Functional Near-Infrared Spectroscopy (fNIRS).

- **BCI WORKING PRINCIPLE**

For critically disabled people, **brain-computer interface** (BCI) is one of the most important technological revolutions in decades.

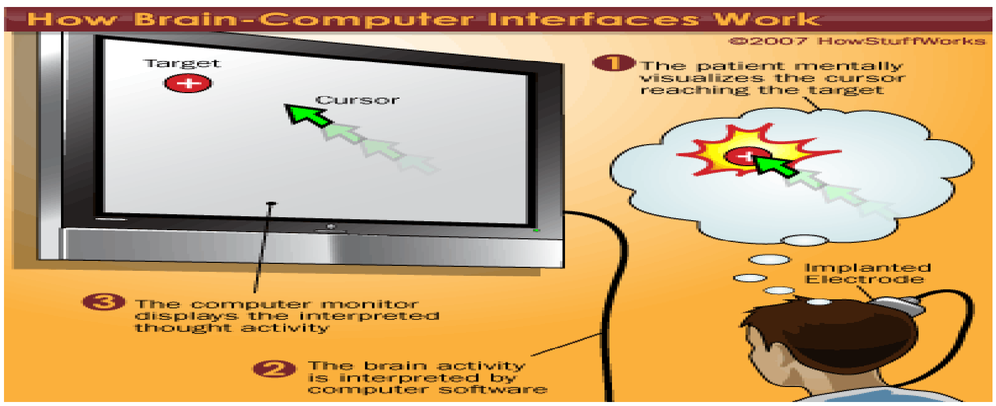
The reason that the BCI works is because of the way our brains function. Our brain is filled with neurons, and individual nerve cells are connected to one another by dendrites and axons. Every time we do tasks like thinking, moving, feeling or remembering something, our neurons start working. That work is carrying through small electric signals that zip from neuron to neuron. A difference in electric potential fetched from ions on the membrane of each neuron generates the signals. The paths used by the signals are insulated by myelin, some of the electric signal escapes. Scientists detect those signals, illuminate the meaning and use them to direct some kind of devices.



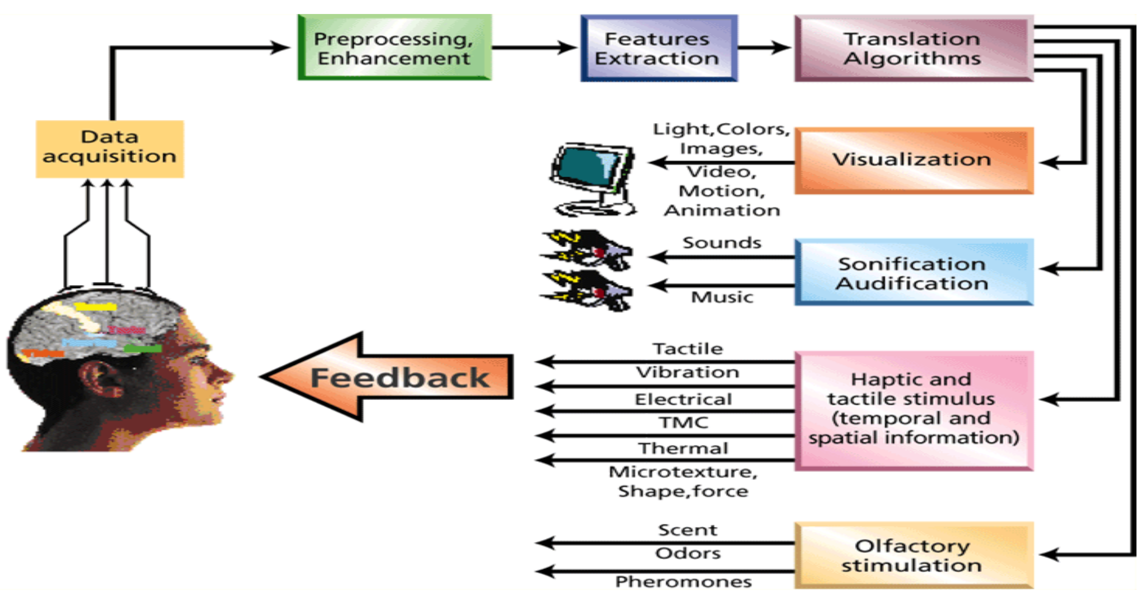

The easiest and least invasive method is a set of electrodes attached to the scalp as a device known as an electroencephalograph (EEG). The electrodes are placed to read brain signals. However, the skull blocks a lot of the electrical signal, and it disfigure what does get through.[3]

To get a higher-resolution signal, Scientists implant electrodes directly into the gray matter of the brain, or on the surface of the brain, to get a higher-resolution signal. This enables more direct reception of electric signals from where the required signals are generated and also license electrode placement in the specific area of the brain. It requires surgery to implant the electrodes, and if devices are left in the brain for a long-term, it tend to cause the origination of scar tissue in the gray matter. Those scar tissues blocks signals lately.

Despite of the position of the electrodes, the basic mechanism is the same: Minute differences in the voltage are measured by the electrodes between neurons. The signal is then amplified and filtered. In current BCI systems, it is then interpreted by a computer program.




One of the most promising areas of BCI research is the evolution of devices that can be controlled by our thoughts.



BCI can be classified into 3 segments:

**Active BCI:** An active BCI is a BCI that derives its results from brain activity that is directly and consciously controlled by the user, independently of external events or controlled by an application.

**Passive BCI:** A passive BCI is a BCI system which receives its outputs from arbitrary brain activity without the purpose of voluntary control, for enriching a human-computer interaction with implicit information.

**Reactive BCI:** A reactive BCI is a BCI that derives its outputs from brain activity that arises as a reaction to external stimulation, which is indirectly modulated by the user or controls an application.

### 1.1.2 HISTORY OF EVOLUTION

In 1969, Fetz and his colleagues, from the Regional Center for Primate Research and the Department of Physiology and Biophysics at the Washinton School of Medicine in Seattle, presented that monkeys can learn to control the deflection of a feedback arm with activity neuronal for the first time. Similar work in the 1970s showed that monkeys could easily learn to voluntarily control firing rates of individual and multiple neurons in the primary motor cortex if they were recognized for generating adequate patterns of neuronal activity.

Studies that blossomed algorithm to rebuild movements from motor cortex neurons, which control movement, back to the 1970s.

In the 1980s, Apostolos Georgopoulos at Johns Hopkings Unversity develop a mathematical relationship between the electrical responses of motor cortex neurons and the direction in which they moved their arms in case of rhesus macaque monkeys. He also found that overall distributed groups of neurons from different areas of the monkey's brains, controlled motor commands, but he was able to record the shoots of neurons in only one area per time frame, due to the technical restrictions imposed by the equipment.

There has been swift development in BCIs since the mid-1990s. different groups have been able to record complex motor cortex signals by capturing from neural ensembles (groups of neurons) and using those to control external devices.

Phillip Kennedy (who founded Neural Signals in 1987) and colleagues constructed the first intracortical BCI by implanting neurotrophic-cone electrodes into monkeys.

In 1999, research fellows led by Yang Dan at the University of California, Berkele interpreted neuronal firings to regenerate images seen by cats. The team used an arrangement of electrodes embedded in the thalamus of sharp-eyed cats. Researchers selected 177 brain cells in the thalamus lateral geniculate nucleus area, which interprets signals from the retina. Eight short movies were presented to the cats, and their neuron shoots were recorded. Using filters, the researchers interpreted the signals to develop movies of what the cats saw and were able to rebuild recognizable scenes and moving objects. Similar results in humans have achieved by researchers in Japan.

Miguel Nicolelis, a professor at Duke University, in Durham, North Carolina has been a prominent supporter of using multiple electrodes expanded over a wider area of the brain to generate neuronal signals to drive a BCI.

After governing initial studies in rats during the 1990s, Nicolelis and his colleagues developed BCIs that interpreted brain activity in owl monkeys and used the devices to regenerate monkey movements in robotic arms. Monkeys have advanced reaching and grasping abilities and good hand manipulation skills, which makes them ideal subjects for this kind of work.

By 2000 the group successfully build a BCI that regenerated owl monkey movements while the monkey controlled a joystick or reached for food. It operated in real time and was also able to control a separate robot remotely over IP. But the monkeys was unable to see the arm movements and did not receive any feedback, a so-called Open-loop BCI.

Subsequent research conducted by Nicolelis using rhesus monkeys managed to close the feedback loop and regenerate the movements of the monkeys in a robot arm. With their brains split and deeply cleft, they are considered better models for human neurophysiology than owl monkeys. The monkeys were trained to reach and grasp objects on a computer screen by manipulating a joystick, while the corresponding movements of a robot were hidden. Later, the monkeys were shown the robot directly and learned to control it by observing their movements. The BCI used speed predictions to control range movements and, at the same time, predicted grip strength. In 2011, O'Doherty and his colleagues showed a BCI with sensory feedback with rhesus monkeys. The monkey was a brain that controlled the position of an avatar arm while receiving sensory feedback through direct Intracortical Stimulation (ICMS) in the representation area of the arm of the sensory cortex.

Other laboratories that have developed BCI and algorithms that decode neural signals append those led by John Donoghue at Brown University, Andrew Schwartz at the University of Pittsburgh and Richard Andersen at Caltech. These researchers were able to generate functional BCIs, using registered signals from that are far fewer neurons than Nicolelis (16-30 neurons versus 60-200 neurons).

Donoghue's group announced training rhesus monkeys for the use of a BCI to track visual targets on a computer screen (closed circuit BCI) with or without the aid of a joystick.

Schwartz's group designed a BCI for three-dimensional tracking in virtual reality and also regenerated BCI control in a robotic arm. The same group also became headlines when they showed that a monkey could feed on pieces of fruit and marshmallows using a robotic arm controlled by the animal's own brain signals.

Andersen's group used recordings of activity prior to movement of the posterior parietal cortex in his BCI, including signals generated when experimental animals expected receiving a reward.

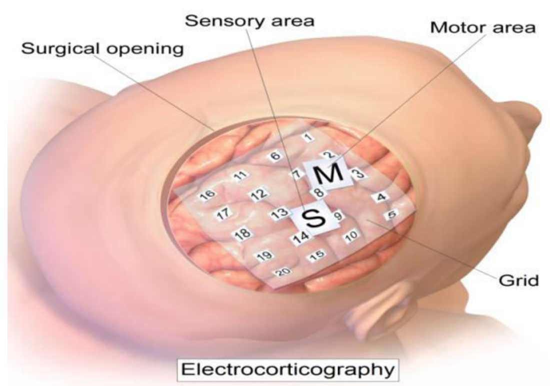
## 1.2 TECHNIQUES OF BRAIN ACTIVITY MEASUREMENT AND PROCESSING

There are various techniques available for the measurement of brain signals.

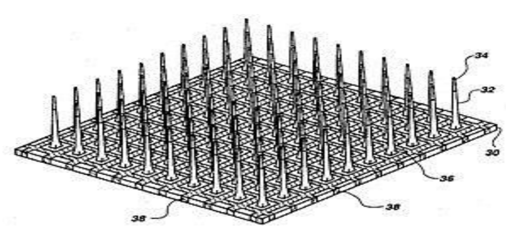
We can group them into **Non-Invasive**, **Semi-invasive** and **Invasive**.

1. **NON-INVASIVE :** Sensors are positioned on the scalp for the measurement of the electrical potentials generated by the brain (EEG) or the magnetic field (MEG).

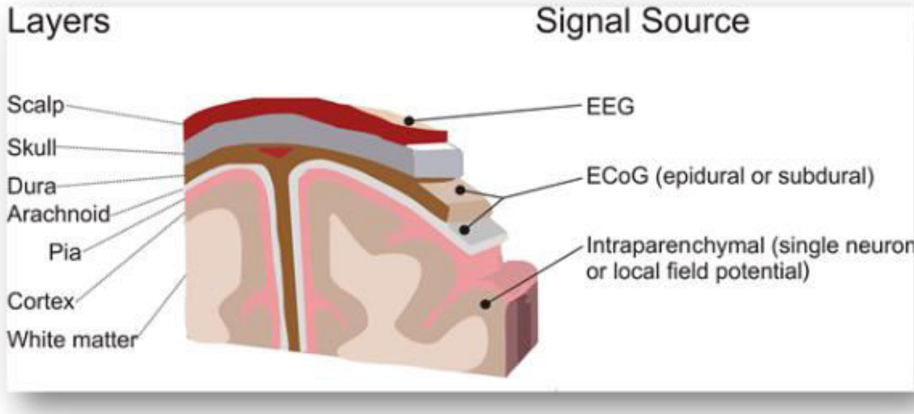
2. **SEMI-INVASIVE :** The electrodes are positioned on the open surface of the brain(ECoG).




3. **INVASIVE :** The micro-electrodes are positioned directly into the cortex, for the measurement of the activity of a single neuron



The image below shows the different layers of the brain and from where the signal is taken.




**Invasive**

During a neurosurgery invasive types of BCI are installed directly into the brain. There are **single unit** BCIs, that distinguish the signal from a particular area of brain cells, and **multiunit** BCIs that spot from multiple areas.

Although the procedure has many possible problems, such as formation of scar tissue, but it generates the highest quality signals. The body reacts to the foreign object and forms scar around the electrodes, which results in generating poor signal. Because neurosurgery can be costly and risky, mainly blind and paralyzed patients are the targets of invasive BCI.

**Semi-Invasive**

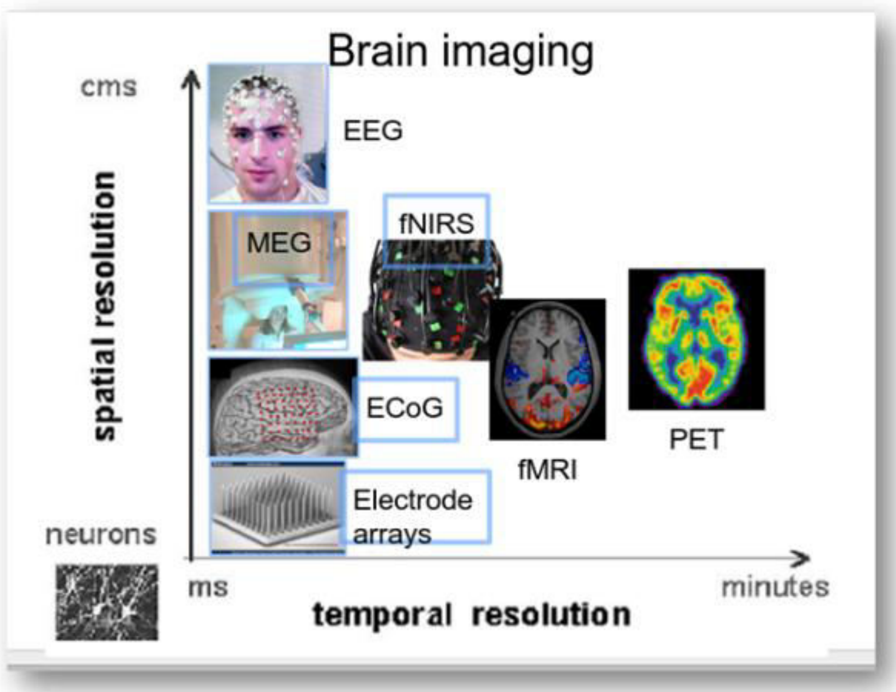
ECoG: Electrocorticography uses electrodes positioned on the open surface of the brain for the measurement of electrical activity from the cerebral cortex. It requires a surgical procedure to place the electrodes. This is why it is used only when surgery is compulsory for medical reasons (ex: epilepsy).

The electrodes may be positioned outside the dura mater (epidural) or under the dura mater (subdural). The strip or grid electrodes covers a large area of the cortex (from 5 to 255 electrodes), which allows a the study of multiple cognitive tasks.

**Non-Invasive**

There are various non-invasive techniques that are used in the study of the brain, where EEG (Electroencephalography) is the most commonly used technique because of its cost effectiveness and hardware portability. Other techniques are:

MEG (magnetoencephalography), PET (positron emission tomography), fMRI (functional magnetic resonance imaging), fNIRS (near-infrared spectroscopy)




**MEG:** a functional neuroimaging technology for the mapping of brain activity by making a record of magnetic fields which is generated by electrical currents that occur naturally in the brain, with the use of very sensitive magnetometers. MEG calculates the magnetic field generated by currents from the brain and offers a much better spatial resolution in comparison to the EEG, since magnetic fields suffer much less than electric fields due to the spatial blurring of the skull and intracerebral fluid.

**PET:** a nuclear imaging technology used in medicine to notice different processes, such as neurotransmitters, blood flow, and metabolism that happen in the body. A little amount of radioactive material, known as radiotracer, is introduced into the bloodstream which reaches the brain. Within the brain, the radiotracer bonds with glucose and generate a radionuclide named fluoro deoxy glucose (FDG). The brain utilizes the glucose and will show various levels which depends on the activity level of the different regions. Images generated by PET scanning are multicolored, warmer colors areas are considered as more active areas such as yellow and red. PET scans are generally used to detect diseases like cancer or others.

**fMRI:** a functional neuroimaging process that uses the MRI technology which calculates brain activity by evaluating changes connected with blood flow. This technology counts on the fact that there is a coupling between cerebral blood flow and neuronal activation. When any brain cell is used, blood flow to that cell increases. Within the brain, hemoglobin in capillary red blood cells carries oxygen to the neurons. Any kind of activity demands more oxygen, which increases the blood flow. If it is or not oxygenated, the magnetic properties of hemoglobin change. This disagreement allows the MRI machine to determine the areas of the brain which are active in a specific moment. MRI machine is a cylindrical tube with a powerful electro-magnet.

**fNIR:** It uses NIRS (near-infrared spectroscopy) for the motive of functional neuroimaging. Using fNIR, hemodynamic responses of the brain I calculated which are associated with neuron behavior. fNIRS calculates the changes in blood flow just like fMRI, but using another technology, infrared light vs magnetic. In the beginning of the task, oxygen consumption takes place, with the increasing complexity, the requirement of oxygen also increases. fMRI calculates the amount consumed oxygen. It also measures the amount of oxygen available in the area (overshot).

**EEG :** EEG provides the recording of electrical activity of the brain from the surface of the scalp. Electrodes are placed on the scalp to pick-up the electrical current generated by the brain.

## General scheme of pattern recognition for BCI :-

**Pattern recognition** is the process of classifying input data into objects or classes based on key features.

Basic steps for Pattern Recognition are as follows:

## 1. **Data Acquisition** :-

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer.

Example: In EEG, the electric signals could be recorded from the scalp, the surface of the brain, or from the neural activity.

## 2. **Preprocessing :-**

Preprocessing includes all the concurrent steps that let us de-noise, smooth, and de-trend signals and thus prepare them for further analysis. It removes noise, outliers, and spurious content from data. Enhance signals to visualize them and discover patterns. Change the sample rate of a signal or make the sample rate constant for irregularly sampled signals or signals with missing data. Some filtering techniques could be used in the preprocessing operation.

## 3. **Artifact Removal:-**

Artifacts may be defined as "those artificial devices that maintain, display, or operate upon information in order to serve a representational function and that affect human cognitive performance. A problem arises if the artifacts generated by the subject are used to control the BCI system, because this violates the definition of a BCI as a non-muscular communication channel.

The artifacts are disturbance that can occur during the signal acquisition and that can alter the analysis of the signals themselves. Detecting artifacts produced in electroencephalography data by muscle activity, eye blinks and electrical noise is a common and important problem in electroencephalography research.

Example:-Eye blink, heart bit etc. specially in EEG in BCI

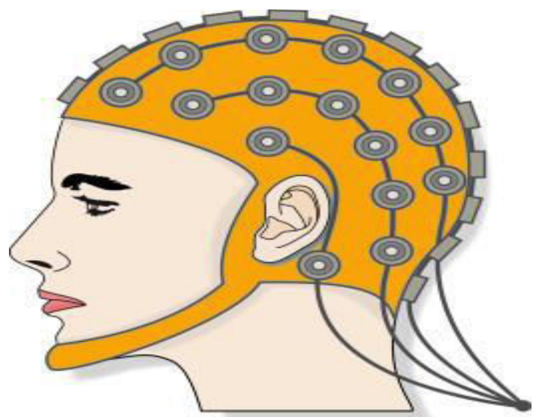
## 4. **Feature Extraction:-**

A pattern is physical or abstract structure of objects. It is distinguished from others by a collective set of attributes called features. The process of collecting features from data is called feature extraction.

## 5. Classification :-

Mapping an unknown pattern to one or more known pattern classes is referred to as classification.

# 1.3 ELECTROENCHEPHALOGRAPHY (EEG)



Electroencephalography (EEG) is an electrophysiological method to record the unprompted electrical activity of the brain over a period of time. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. It is a noninvasive process, which is done using the electrodes positioned along the scalp, although sometimes these invasive electrodes are used for particular applications. The EEG signal amplitude is about 100 μV when calculated on the scalp, and about 1-2 mV when calculated on the surface of the brain.

**Electrical activity of the brain**

The brain is made of thousands of cells, named as neurons, closely interconnected by synapses, which act as entrance of inhibitory or excitatory activity. In other words: synapses cultivate information with the help of neurons (excitatory) or intercept the movement of information from one neuron to other (inhibitory).

Any synaptic activity creates a subtle electrical impulse referred to as *post-synaptic potential* (post = behind). Definitely, the breach of a single neuron is not notable as it is too tiny. Although, whenever a minor group of neurons (about 1000 or more) shoots in sync, they creates an electrical field which is strong enough to escalate through tissue, bone, and skull. Eventually, it can be calculated on the head surface.

**How does it work**

Electroencephalography (encephalon = brain), or EEG, is the anatomical method to record all of the electrical activity from electrodes positioned on the scalp surface, initiated by the brain. Electrodes are arranged in elastic caps similar to the bathing caps from electrodes placed on the scalp surface, it ensures that the data can be collected from identical scalp positions across all respondents.

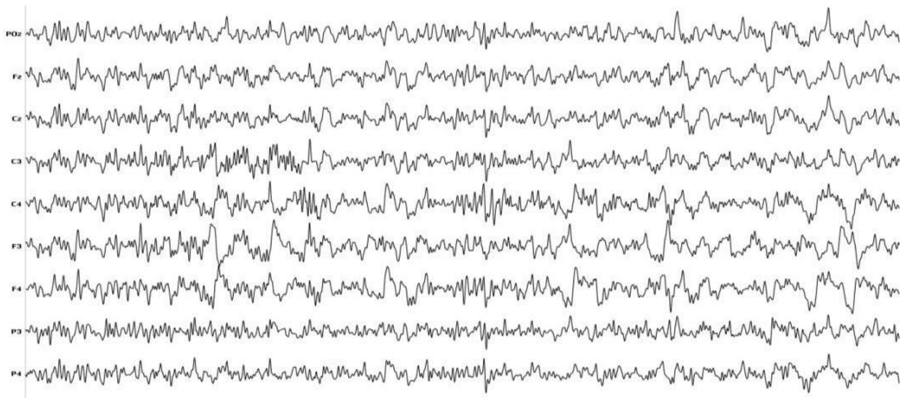
EEG

- calculates electrical activity initiated by the synchronized activity of thousands of neurons (in voltage)
- provides brilliant time resolution, which allows you to determine active brain areas at a particular time – even at sub-second timescales

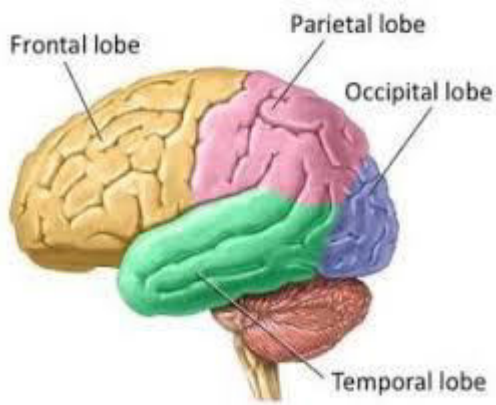
Since the voltage variation is calculated at the electrodes are very small, the noted data is digitized and then amplified. The amplified data can then be owcased as a sequence of voltage values.

Price variation in EEG systems are mainly due to the number of electrodes, digitization quality, the amplification quality, and the number of snapshots the device can take per second (this is the sampling rate in Hz).

EEG is one of the fastest imaging technologies available because it can generate thousands of snapshots per second (256 Hz or higher). Current systems present the data as continuous flow of voltages on a screen.



**How can EEG data be interpreted**




**1. Occipital cortex**: This area of the brain is mainly responsible for the processing of visual information. EEG experiments with visual stimuli (videos, images) focus on effects in occipital regions.

**2. Parietal cortex**: Parietal cortex is mainly responsible for utilizing various bodily reference frames (eye-centered, head-centered, hand-centered, body-centered). Also, parietal cortex is active during auto-referential tasks – when we are experiencing objects or information that is important to us, for example.

**3. Temporal cortex**: Temporal cortex is responsible for language production and speech processing. Medial (=inner) regions are more active during spatial navigation. In this brain region in temporal cortex we store spatial and autobiographical memories from childhood days (hippocampus)

**4. Frontal cortex**: The frontal part of the human brain is broader than other mammals. Technically, the frontal cortex does the cognitive control: it stops us from running after the blinking lights; it permits us to do postgraduate studies and pursue our careers, and sums up different memories and experiences in a consistent combination. Apart from the regional characteristics from which some electrical activity originates, it can also survey which frequencies mainly responsible for the activity in progress. When your brain is in a certain state, the frequency patterns change, your brain starts moving.

| Frequency band | Frequency range (Hz) | Biological Implication |
|---|---|---|
| Delta | <4 | Sleep, continuous attention tasks |
| Theta | 4-8 | Drowsiness, idling, dream sleep , inhibition of elicited response |
| Alpha | 8-13 | Relaxation , eye closing, inhibition control |
| Mu | 8-13 | Motor planning |
| Beta | 13-30 | Alertness, anxious thinking, active concentration, motor planning |
| Gamma | >30 | Cross modal sensory processing, short term memory matching of recognized entities. |

**EEG Electrodes and Brain Lobes**

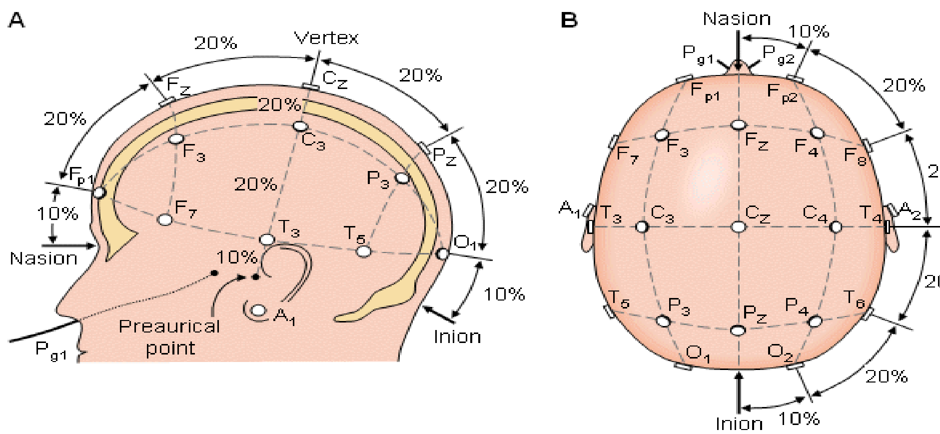
The EEG channels (electrodes), its associated brain lobes/regions and cognitive functionalities are presented in the table below:

| **EEG Channels** | **Brain Lobes/Regions** | **Cognitive Functionalities** |
|---|---|---|
| Fp1, Fp2 | Pre-frontal | Emotion, olfactory recognition |
| F3, F4, Fz, F7, F8 | Frontal | Thinking, problem solving, |

| | | |
|---|---|---|
| | | reasoning, planning, higher level cognition |
| P3, P4, Pz | Parietal | Understanding spatial relationship, verbal memory, processing tactile and sensory Information |
| O1, O2 | Occipital | Vision |
| C3, C4, Cz | Motor cortex | Motor imagery and motor-Execution |
| T1, T2, T3, T4, T5, T6 | Temporal | Language skills, speech perception, behavior, memory, hearing |

**10-20 Electrode Placement System**

The placement of EEG electrodes at the corresponding brain regions/lobes (as referred to the Table) is followed by internationally standardized 10-20 electrode placement system. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The “10” and “20” refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total nasion-inion distance of the skull. Nasion and inion are two anatomical landmarks that are used for the essential positioning of the EEG electrodes. Nasion is the intersection between the forehead and the nose and second, the inion is the lowest point of the skull on the back just above the neck. Next fig shows the International 10-20 electrode placement system on the cerebral cortex, where the first letter of each brain region refers to identify the lobe of electrode placement and a number to identify the hemisphere location. The “C” letter is only used for identification purposes only, since no central lobe exists.




## 1.3.1: SIGNALS RELATED TO EEG

Depending on the type of cognitive task performed by the brain, the EEG signals are found with different patterns. So, cognitive performance can be comprehended to a significant extend by identifying presence or absence of those signal modalities.

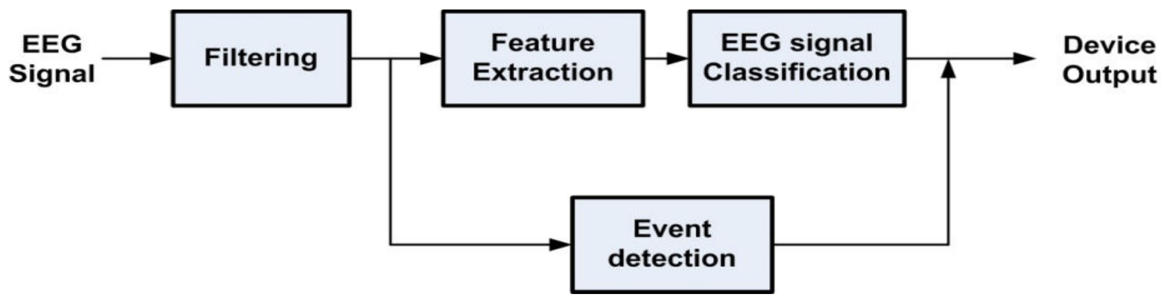
I. **Event Relate Potential (ERP):** is the measured brain response that is the direct result of a specific sensory, cognitive, or motor event.

II. **P300:** It is a potential component related to the event generated in the decision-making process. It is considered to be an endogenous potential, since its appearance is not related to the physical attributes of the stimulus, but to the reaction of a person to it. More especially, it is thought that the P300 reflects processes involved in the evaluation or categorization of stimuli. It is generally obtained using the oddball paradigm, in which the low probability objective elements are mixed with non-objective high probability elements. [4]–[6]

III. **N400:** is a component of time-locked ERP. It is a negative-going deflection that peaks around 400 milliseconds post-stimulus onset, although it can extend from 250-500ms, and is typically maximal over Centro-parietal electrode sites. The N400 is part of the normal brain response to meaningful stimuli, including visual and auditory words, sign language, pictures, faces, environmental sounds and smells. [7]–[9]

IV. **Event Related De-Synchronization/Synchronization (ERD/S)**: refers to the relative decrease or increase in the power of specific frequency band(s) of the EEG signal during dynamic cognitive processing with respect to the resting condition.

## 1.3.2 : SIGNAL ANALYSIS




### 1.3.2.1 SIGNAL ACQUISITION

In EEG-BCI, the electric potential of a brain activity is calculated through electrodes positioned on the scalp. Electrodes are metal discs that are positioned on the scalp using International 10/20 system.

There are two main types of electrodes:

**Wet** - Using saline gel. the conductivity increases as the electrical distance gets minimized. Most o them are made of stainless steel, tin, gold or silver and are covered with a silver chloride coating.

**Dry** – these more appropriate and easier to use, but can lose higher frequencies

EEG is the most trustworthy technology for real-time applications, since it can make calculation every thousandths of a second. The problem with EEG is noise. As the electrodes are placed on the scalp, there are intermediate layers, more background noise and muscles.

EEG calculates the electrical activity that occurs in the brain. The voltage difference between at least 2 electrodes is recorded for analysis. The EEG must be recorded simultaneously from several electrodes to interpret the ERP. During the synaptic excitation of the dendrites in the neurons, the electric currents are created and collected by the EEG.

The minimum arrangement consists of three electrodes: active electrode, reference electrode and ground electrode. The EEG records the potential difference over the time between the signal or the active electrode and the reference electrode. It is very tough to obtain a reference where there is no electrical activity in the brain. It is generally found in the mastoid, the ear lobes or the tip of the nose. The ground electrode is used to calculate the differential voltage between the active point and the reference point.

The signal picked up by the electrodes is far away and attenuated by the different layers it has to travel. For this reason an amplifier is needed to bring the microvolts to a range that can be digitized.

The A/D converter then converts the amplified signal from analog to digital form. The bandwidth for EEG signals is limited to approximately 100Hz, making 200Hz enough for sampling EEG signals.

#### 1.3.2.2 PRE-PROCESSING

The first step of EEG signal processing is called pre-processing. Pre-processing of EEG signals is two-fold. First fold involves a) filtering of EEG signals and second fold includes b) artifact removal.

a) **Filtering**: Filtering is performed either by using finite impulse response (FIR) or infinite impulse response (IIR) bandpass filters. IIR filters can be any of four realizations: Butterworth, Chebyshev-I, Chebyshev-II and Elliptic. Pass bands of the filters are selected based on the association of the significant EEG frequency bands (delta, theta, alpha, mu, beta and gamma) for a particular cognitive task.

- Filtered output by **Butterworth filter** of a given (input) signal:

[N, Wn] = buttord(Wp, Ws, Rp, Rs) returns the order N of the lowest order digital Butterworth filter which has a passband ripple of no more than Rp dB and a stopband attenuation of at least Rs dB. Wp and Ws are the passband and stopband edge frequencies, normalized from 0 to 1 (where 1 corresponds to pi radians/sample). buttord also returns Wn, the Butterworth natural frequency (or,the "3 dB frequency") to use with BUTTER to achieve the specifications.

[N,Wn] = buttord(Wp, Ws, Rp, Rs, 's') does the computation for an analog filter, in which case Wp and Ws are in radians/second.

- Filtered output by **Chebyshev-I filter** of a given (input) signal:

`[b,a] = cheby1(n,Rp, Wp)` returns the transfer function coefficients of an `n`th-order lowpass digital Chebyshev Type I filter with normalized passband edge frequency `Wp` and `Rp` decibels of peak-to-peak passband ripple.

`[b,a] = cheby1(n,Rp, Wp,ftype)` designs a lowpass, highpass, bandpass, or bandstop Chebyshev Type I filter, depending on the value of `ftype` and the number of elements of `Wp`. The resulting bandpass and bandstop designs are of order 2`n`.

`[z,p,k]= cheby1(___)` designs a lowpass, highpass, bandpass, or bandstop digital Chebyshev Type I filter and returns its zeros, poles, and gain. This syntax can include any of the input arguments in previous syntaxes.

`[A,B,C,D] = cheby1(___)` designs a lowpass, highpass, bandpass, or bandstop digital Chebyshev Type I filter and returns the matrices that specify its state-space representation. [10]

b) **Artifact removal**: Artifact may appear in the EEG signal as unwanted noise either due to spurious pick-ups of line signal or due to undesired movement of muscle/eye-blinking.

Artifact removal is chiefly performed by EEGLAB software, which is compatible with all latest MATLAB versions.

It is done by Independent Component Analysis (ICA)

**ICA:** is a computational method for separating a multivariate signal into additive subcomponents. This is done by assuming that the subcomponents are non-Gaussian signals and that they are statistically independent from each other. ICA is a special case of blind source separation.

#### 1.3.2.3 FEATURE EXTRACTION

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set.

When the input data to an algrithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features. Determining a subset of the initial features is called feature Selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

The properly used EEG signal features include time-domain features like Autoregressive Parameter(AR), Adaptive Autoregressive Parameter(AAG), Hjorth Parameter; frequency-domain eatures like Power Spectral Density(PSD), Band Power Estimate(BPE);time-doimain correlated featres like Wavelet Coefficients etc. [11]

A. **Autoregressive Yule Parameters :** The defining characteristic of an autoregressive model is that it attempts to fit signal samples to their time delayed versions. The Yule – Walker set of equations can be employed to solve for the parameters which define such a regression. These regression coefficients are called autoregressive Yule parameters and may be employed for the purpose of feature extraction.

Mathematically, the model can be illustrated using,

$$y_k = a_1{}^*y_{k-1} + \dots + a_p{}^*y_{k-p} + x_k$$

Where $x_k$ denotes a zero mean Gaussian noise process calculated as N{0,□ $\frac{2}{x}$ }, $p$ is the order of the AR model, $y_{k-i}$ denotes the previous samples, $a_i$ signifies the coefficients and $i$ is an integer that can vary [0, $p$], and $y_k$ is the estimated output while index $k$ is used to refer to distinct equidistant time instances. In the present works, we have used sixth order AR model, that is $p$=6. Usually, AR model is employed to represent any wide sense stationary stochastic time series that is characterized as,

$$< x_k > = \text{constant and} < x_k\, x_{k+d} > = r_d$$

- **Yule-Walker Method**

  For an AR model of order *p,* can be expressed as,

$$y_k = \sum_{i=1}^{p} a_i y_{k-i} + x_k$$

By convention, $y_k$ is assumed to have zero mean too. The estimation method includes multiplying both sides by $x_{k-d}$ where $d$ signifies a time delay, averaging and normalizing the obtained outcome. Since $d$ can vary from 1 to $p$, repeating the above mentioned steps for $p$ number of times yields a set of equations, known as Yule- Walker equations, which can be presented as matrix form as,

$$\begin{bmatrix} 1 & & r1 & \cdots & r(p-1) \\ \vdots & \vdots & & \square & \vdots \\ r(p-1) & & r(p-2) & \cdots & 1 \end{bmatrix} \begin{bmatrix} a1 & \square \\ a(p) & \square \end{bmatrix} = \begin{matrix} r1 \\ r2 \\ r(p) \end{matrix}$$

B. **Hjorth Parameters :** In 1970, B. Hjorth defined three parameters to perform time domain analysis of signals. These parameters measured the variance and rate of change of variance of a signal over a period of time and are enlisted as follows

$$Activity = \mathrm{var}(\, x(t))$$

$$Mobility = \sqrt{\frac{\mathrm{var}(\, y'\,(t))}{\mathrm{var}(\, y(t))}}$$

$$Complexity = \frac{Mobility(\, y'\,(t))}{Mobility(\, y(t))}$$

Activity is a simple measure of the variance of the signal over time and has been found to be proportional to cortical idling; it can be used to represent the frequency of the signal. Mobility indicates the normalized variance of the first derivative of the signal or the mean frequency. Complexity denotes the change in frequency as it deals with the second derivative of the signal.

C. **Power Spectral Density:** It is a measurement of the power distribution across different frequencies. It is calculated by Welch‟s method by the command pwelch() . The steps of Welch‟s method is listed as follows.

i) The data is windowed into overlapping segments.

ii) Fast Fourier Transform of each of the windows is calculated.

iii) The squared magnitude is calculated and the result is averaged.

Thus, the power spectral density $S(f)$ of the ith signal $Xi$ of can be expressed as follows.

$$S(f)=\frac{1}{n}\sum_{k=1}^{n}\frac{\Delta t}{L}|f(X_k W)|^2$$

Where $X_k$ is the kth data segment, W is a data window of length $\Delta t$, L is the squared average of the window contents and $f(.)$ represents the Fourier transform.

### 1.3.2.4 FEATURE SELECTION

Feature selection, also known as **variable selection**, **attribute selection** or **variable subset selection**, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Feature selection techniques are used for four reasons:

- simplification of models to make them easier to interpret by researchers/users
- shorter training times
- to avoid the curse of dimensionality (refers to various phenomena that arise when analyzing and organizing data in high-dimensional spaces [often with hundreds or thousands of dimensions] that do not occur in low-dimensional settings such as the 3D physical space of everyday experience)
- enhanced generalization by reducing over-filtering (formally, reduction of Variance)

The central premise when using a feature selection technique is that the data contains some features that are either *redundant* or *irrelevant*, and can thus be removed without incurring much loss of information. *Redundant* and *irrelevant* are two distinct notions, since one relevant feature may be redundant in the presence of another relevant feature with which it is strongly correlated.

Feature selection techniques should be distinguished from Feature Extraction. Feature extraction creates new features from functions of the original features, whereas feature selection returns a subset of the features. Feature selection techniques are often used in domains where there are many features and comparatively few samples (or data points).

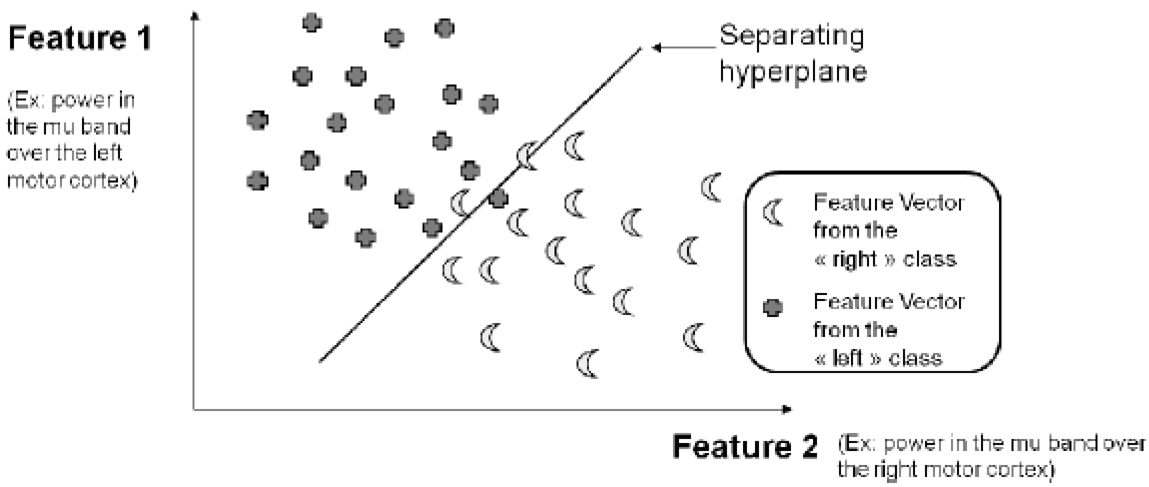
Varieties of Feature Selection techniques are available: Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Evolutionary Optimization based techniques etc.

- **Principal component analysis** (**PCA**)**:** is a statistical process to convert a bunch of mostly correlated considerations of variables (each of them takes various numerical values) into a bunch of uncorrelated variables consecutively using the orthogonal transformation is called principal components. If there exists "n" no. of observations along with "p" no. of variables, then the different main component number is minimal (n-1, p). The transformation is calculated in a way so that the first principal component receives the greatest possible variance and each component afterwards has the highest possible variance only if it is orthogonal to the antedate components. The output vectors are an uncorrelated orthogonal set. PCA is responsive to the relative values of the original variables.

## 1.3.2.5 CLASSIFICATION

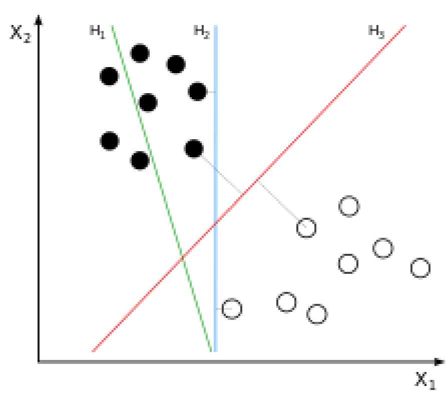
The classification step in a BCI aims at translating the features into commands. To do so, one can use either regression algorithms or classification algorithms, the classification algorithms being by far the most used in the BCI community. Classifiers are able to learn how to identify the class of a feature vector, thanks to training sets, i.e., labeled feature vectors extracted from the training EEG examples. Typically, in order to learn which kind of feature vector correspond to which class (or mental state), classifiers try either to model which area of the feature space is covered by the training feature vectors from each class - in this case the classifier is a generative classifier - or they try to model the boundary between the areas covered by the training feature vectors of each class - in which case the classifier is a discriminant classifier. [12]

For BCI, the most used classifiers so far are discriminant classifiers, and notably **Linear Discriminant Analysis (LDA) classifiers**. The **aim of LDA** (also known as Fisher's LDA) is to use hyperplanes to separate the training feature vectors representing the different classes. The location and orientation of this hyperplane is determined from training data. Then, for a two-class problem, the class of an unseen (a.k.a., test) feature vector depends on which side of the hyperplane the feature vector is. LDA has a very low computational requirement which makes it suitable for online BCI system. Moreover this classifier is simple which makes it naturally good at generalizing to unseen data, hence generally providing good results in practice. LDA is probably the most used classifier for BCI design.




Discriminating two types of motor imagery with a linear hyperplane using a Linear Discriminant Analysis (LDA) classifier.

Another very popular classifier for BCI is the **Support Vector Machine (SVM)**. An SVM also uses a discriminant hyperplane to identify classes. However, with SVM, the selected hyperplane is the one that maximizes the margins, i.e., the distance from the nearest training points, which has been found to increase the generalization capabilities.

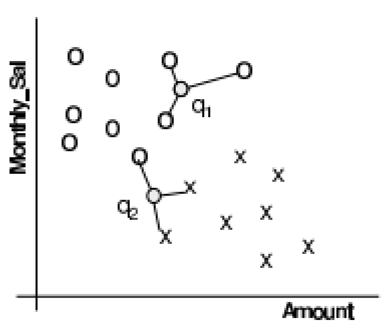


**H1 does not separate the classes; H2 does, but only a small margin; H3 separates them with a maximal margin.**

Generally, regarding classification algorithms, it seems that very good recognition performances can be obtained using appropriate off-the-shelf classifiers such as LDA or SVM. What seems to be really important is the design and selection of appropriate features to describe EEG signals. With this purpose, specific EEG signal processing tools have been proposed to design BCI.

- **k-Nearest Neighbour classifier :**

The intuition underlying Nearest Neighbour Classification is quite straightforward, examples are classified based on the class of their nearest neighbours. It is often useful to take more than one neighbour into account so the technique is more commonly referred to as k-Nearest Neighbour (k-NN) Classification where k nearest neighbours are used in determining the class. Since the training examples are needed at run-time, i.e. they need to be in memory at run-time, it is sometimes also called Memory-Based Classification. Because induction is delayed to run time, it is considered a Lazy Learning technique. Because classification is based directly on the training examples it is also called Example-Based Classification or Case-Based Classification. The basic idea is as shown in Figure below, which depicts a 3-Nearest Neighbour Classifier on a two-class problem in a two-dimensional feature space. In this example the decision for q1 is straightforward - all three of its nearest neighbours are of class O, so it is classified as an O. The situation for q2 is a bit more complicated at it has two neighbours of class X and one of class O. This can be resolved by simple majority voting or by distance weighted voting (see below). So k−NN classification has two stages; the first is the determination of the nearest neighbours and the second is the determination of the class using those neighbours.



Let us assume that we have a training dataset D made up of (xi)i∈[1,|D|] training samples. The examples are described by a set of features F and any numeric features have been normalised to the range [0,1]. Each training example is labelled with a class label yj ∈ Y . Our objective is to classify an unknown example q. For each xi ∈ D we can calculate the distance between q and xi as follows:

$$d(\mathbf{q}, \mathbf{x}_i) = \sum_{f \in F} w_f \delta(\mathbf{q}_f, \mathbf{x}_{if}) \quad \ldots\ldots (1)$$

There are a large range of possibilities for this distance metric; a basic version for continuous and discrete attributes would be:

$$\delta(\mathbf{q}_f, \mathbf{x}_{if}) = \begin{cases} 0 & f \text{ discrete and } \mathbf{q}_f = \mathbf{x}_{if} \\ 1 & f \text{ discrete and } \mathbf{q}_f \neq \mathbf{x}_{if} \\ |\mathbf{q}_f - \mathbf{x}_{if}| & f \text{ continuous} \end{cases} \quad \ldots\ldots\ldots (2)$$

The k nearest neighbours are selected based on this distance metric. Then there are a variety of ways in which the k nearest neighbours can be used to determine the class of q. The most straightforward approach is to assign the majority class among the nearest neighbours to the query. It will often make sense to assign more weight to the nearer neighbours in deciding the class of the query. A fairly general technique to achieve this is distance weighted voting where the neighbours get to vote on the class of the query case with votes weighted by the inverse of their distance to the query.

$$Vote(y_j) = \sum_{c=1}^{k} \frac{1}{d(\mathbf{q}, \mathbf{x}_c)^n} 1(y_j, y_c) \quad \ldots\ldots\ldots (3)$$

Thus the vote assigned to class yj by neighbour xc is 1 divided by the distance to that neighbour, i.e. 1(yj , yc) returns 1 if the class labels match and 0 otherwise. In equation 3 n would normally be 1 but values greater than 1 can be used to further reduce the influence of more distant neighbours.

#### 1.3.2.6 CLUSTERING

Alternative to classification, one may perform clustering, if class/ group labels are not known. One example of a clustering algorithm is fuzzy C-means clustering may be implemented in MATLAB using the command fcm(). It is described as follows.

[center, U, obj_fcn] = fcm(data, cluster_n) applies the fuzzy c-means clustering method

to a given data set.

The input arguments of this function are

data: data set to be clustered; each row is a sample data point

cluster_n: number of clusters (greater than one)

The output arguments of this function are

center: matrix of final cluster centers where each row provides the center coordinates

U: final fuzzy partition matrix (or membership function matrix)

obj_fcn: values of the objective function during iteration.

## 1.4 FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (fNIRS)

Functional Near-Infrared Spectroscopy is the use of near-infrared spectroscopy (NIRS) for the purpose of functional neuroimaging.

**Functional Neuroimaging:** The use of fNIRS as functional imaging method based on the principle of neuro-vascular coupling also known as Hemodynamic response or Blood Oxygen-Level Dependent (BOLD) response. Through neuro-vascular coupling, neuronal activity is linked to related crashes in localized cerebral blood flow.

**Spectroscopy:** It is the study of the interaction between matter and electromagnetic radiation. Spectroscopy data are often represented by an emission spectrum, a plot of the response of interest as a function of wavelength or frequency. One of the central concepts in spectroscopy is a resonance and its corresponding resonant frequency.

**Near-Infrared Spectroscopy:** it is a spectroscopic method that utilizes the near-infrared region of the electromagnetic spectrum (from 770mm to 2600mm). Near-infrared spectroscopy relies on molecular overtone and combination vibrations. Such transitions are prohibited by the selection rules of quantum mechanics. Thus, the molar obsorptivity in the NR region is typically very small. One advantage is that NIR can typically penetrate much further into a sample than mid-infrared radiation.

Using fNIRS, brain activity is measured through hemodynamic response (it allows the rapid delivery of blood to active neuronal issues) associated with neuronal behavior. It is a non-invasive imaging method involving the quantification of chromophore concentration resolved from the measurement of NIR light attenuation or temporal or phasic changes. NIR spectrum light takes advantage of optial window in which skin, tissue, and bone are mostly transparent to NIR light in the spectrum of 700-900mm, while Oxygenated Hb and Deoxygenated Hb are stronger obsorbers of light.

The or more wavelengths are selected, with one wavelength above and one below the isosbetic point (In spectroscpy, an isostropic point is a specific wavelength, wave number or frequency at which the total absobance of a sample does not change during a chemical reaction or physical change of the sample) of 810mm at which deoxy-Hb and Oxy-Hb have identical absorption co-efficient. Using modified Beer-Lambart Law(mBLL), relative concentration can be calculated as a function of total photon path length. Once the HbR and HbO levels are processed, they are utilized to compute the levels of oxygenation (in /µM), and values that might be roughly regarded as percent changes in blood volume. The formulae can be written as:

$$\mathrm{HbR} = C_{\mathrm{emperical}} \frac{OD_{850} \cdot \epsilon_{HbO,730} - OD_{730} \cdot \epsilon_{HbO,850}}{\epsilon_{HbO,730} \cdot \epsilon_{HbR,850} - \epsilon_{HbO,850} \cdot \epsilon_{HbR,730}}$$

$$\mathrm{HbO} = C_{\mathrm{emperical}} \frac{OD_{730} \cdot \epsilon_{HbR,850} - OD_{850} \cdot \epsilon_{HbR,730}}{\epsilon_{HbO,730} \cdot \epsilon_{HbR,850} - \epsilon_{HbO,850} \cdot \epsilon_{HbR,730}}$$

Where OD is optical density, $C_{\mathrm{emperical}}$ means empirical adjustment value of the machine, and $\xi$ is extinction coefficient. Blood volume and oxygenation can be computed as HbO+HbR and HbO-HbR respectively.

**Modified Beer-Lambart Law (mBLL):** It is readily derived from the first order taylor expansion of the optical density : $OD \approx OD^0 + (\partial OD^0/\partial \mu_a)\Delta\mu_a + (\partial OD^0/\partial \mu's)\Delta \mu's$, wherein the partial derivatives are evaluated in the "baseline" state ( $\mu_a=\mu^0{}_a$, $\mu'_s=\mu'^0{}_s$), $OD^0 \equiv -\log[I^0/I_s]$ is the baseline optical density, and the differential changes in absorption and scattering are denoted by :

$$\Delta\mu_a \equiv \mu_a(t) - \mu^0{}_a$$

$\Delta\mu'_s \equiv \mu'_s(t) - \mu'^0{}_s$, respectively

Note that the superscipt "O" indicates the baselie within this approximation, the changes in optical density from baseline is :

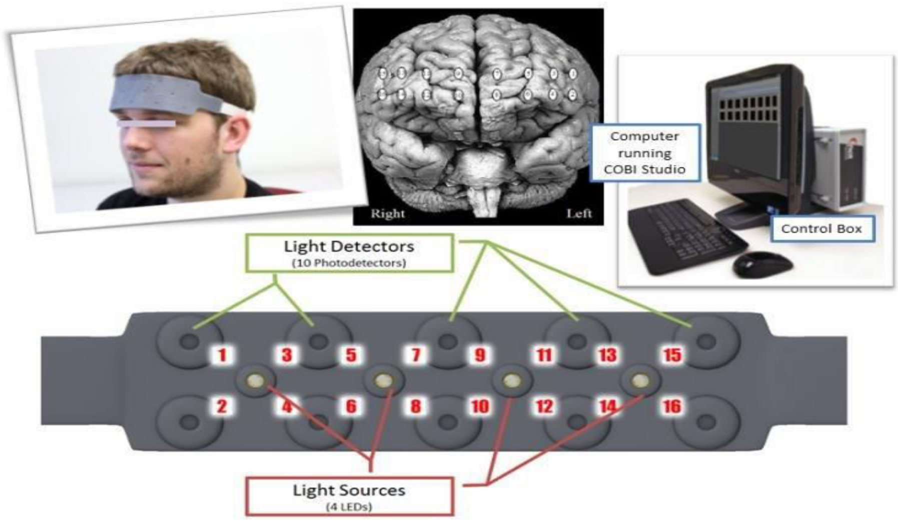
$$\Delta OD = -\log(I(t)/I_0) \approx \langle L\rangle\Delta\mu_a(t) + (\mu^0{}_a/\mu'^0{}_s)\langle L\rangle\Delta\mu'_s(t) \approx \langle L\rangle\Delta\mu_a(t).$$

Here, $\langle L\rangle \equiv \partial OD^0/\partial\mu_a$ is the so-called differential pathlength, which is approximately the mean pathlength that diffusing photons travel through the medium from source to detector.

whereas the traditional Beer-Lambert law relates *absolute* optical densities to *absolute* absorption coefficients, the Modified Beer-Lambert law relates *differential changes* in the optical density to *differential changes* in the absorption coefficient.

fNIRS uses near-infrared(NI) light emitter-detector pairs. The NI light discharged into scalp spread through the brain tissues which results in multiple scattering of photons. Some of the photons leave the head after going through the central area of the brain, where the chromophors (i.e. HbO and HbR) are still there in time. These excited photons are then detected by using strategically positioned detector. [13]

## 1.4.1 BRAIN-SIGNAL ACQUISITION




Signals that are responsible for motor execution and motor imagery tasks are collected from the Motor cortex. Those signals, which are related to mental arithmetic, mental counting, music imaginary, landscape imaginary etc. are collected from Pre-frontal cortex.

Various emitter-detector pairs are used in these two areas. Generally, the emitter-detector distance is kept within a certain range, as it plays an important role in calculation. Increasing emitter-detector distance produces an increased imaging depth. For the calculation of hemodynamic response from the cortical area, a 3cm distance between an emitter-detector was suggested. (A distance of less than 1cm might generate only skin layer responses, whereas that of more than 5cm might produce weak and useless signals.)

For the Pre-frontal cortex, 3 emitters and 8 detectors are enough to fairly generate most brain signals. For motor cortex tasks, 6 emitters and 6 detectors are required to record brain activity.

## 1.4.2 PRE-PROCESSING

The resulting fNIRS signal might contain various noises, like instrumental noise, experimental errors, and physiological noise. Since the instrumental noise and experimental errors are associated to the brain activities, the need to be moved for the conversion of the raw optical density signals to the concentration changes of HbO and HbR through the mBLL.

**Instrumental Noise:** It is the noise that might present in hardware or caused due to the surrounding environment. It generally involves high frequencies. Such high frequencies can be easily dismised by Low-Pass Filters (LPF). Furthermore, by minimizing the variation of the external light, instrumental noise can be reduced.

**Experimental Noise**: It includes motion artifacts like head motions, which causes the movement of opcodes from the assigned position. This can cause a sudden change in light intensity resulting in a spike-like noise.

Several methods for motion artifact correction have been proposed:

- The Wiener filtering-based method
- Eigen Vector-based spatial filtering (Principle Component Analysis[PCA] based filtering)
- Wavelet Analysis-based methods
- Savitzky-Golay type filters

**Physological Noise:** It includes those due to heartbeat(1~1.5Hz), respiration(0.2~0.5Hz), Mayer waves(~0.1Hz), which are related to blood pressure fluctuations.

Several methods have been used to remove them:

- Band Pass Filters (BPF)
- Adaptive Filtering
- Principle Component Analysis (PCA)
- Independent Component Analysis (ICA)

## BAND-PASS FILTERING

BPF is a device that passes frequencies within a certain range and rejects (attenuates) frequencies outside that range. Since the frequency range of afore mentioned physiological signals are usually known, a BPF can be an efficient means. In general, the band of 0.1~0.4Hz can effectively remove a large portion of physiological noise without eliminating the fNIRS signals elicited by a task of 10s period.

The types of BPF include:

- Butterworth filters
- Elliptical filters
- Chebyshev filters

## ADAPTIVE FILTERING

To take physiological noise into account, additional elements related to noise can be added in the regression model. While modeling the conical functional response, simultaneously a series with adaptive amplitudes and phase components can be included to model the contribution of specific physiological noise to the heartbeat, respiration and blood pressure.

The automatic regressive moving average with exogenous signals (ARMAX) based on the model that incorporates physiological signals as exogenous signals can be used to predict the state of the brain during a particular cognitive task. The signal fNIRS in each channel can be considered as an output of a linear combination of several components. The components consists the dynamic properties of changes in HbO and HbR in a specific region of the brain (the influence of current / previous stimuli), physiological signals, fluctuation of the baseline and other noises.

## ICA and PCA

ICA is a computational method for separating a multivariate signal into additive subcomponents. This is done by assuming that the subcomponents are non-Gaussian signals and that they are statistically independent from each other. ICA is a special case of blind source separation. ICA associated with the physiological noise signals can be identified by their spectral densities. Isolating the main IC associated with the original hemodynamic response results in a physiological-noise-free signals and the original hemodynamic response was reconstructed using all ICs (with weights derived from their t-values) as well as primary IC. [14]

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components. If there are ‘n’ observations with ‘p’ variables, then the number of distinct principal component is min (n-1,p). The transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors (each being a linear combination of the variables and containing *n* observations) are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables. Te performance of PCA is greatly dependent on the number f channels and the number of Eigen Vectors to be removed and therefore, PCA is not suggested when the number of channels is less. [15]–[18]

The fNIRS signals are also affected by te skin blood flow and other contributions from the surfacical tissues. It has been shown that the removal of thee artifacts from cerebral signal are possible by employing several methods:

Additional Short-distance detector(s), Adaptive filtering, Statistical parametric mapping (SPM)[in which artifacts are included as aggressors into the model], ICA

The spatial distribution of one of the ICs was directly related to the skin blood flow, which was again verified by a laser doppler tissue blood flow meter.

## 1.4.3 FEATURE EXTRACTION and SELECTION

After data pre-processing, the different brain activities are classified on basis of certain features. In FNIRS-BCI, although some feature are extracted directly from detected light-intensity signals, most are extracted from hemodynamic signals. The reason for this is that Hbo, HbR, total Hb(HbT) and cerebral oxygen exchange(COE=HbO-HbR) provide more option for selection of appropriate features.

Selection of an optimal feature set for classification is essential for good classification. It is necessary to select such features that have similarities with a certain class and different from other classes. Different combinations of such features provide the necessary discrimination information for classification.

- **Heuristic method**

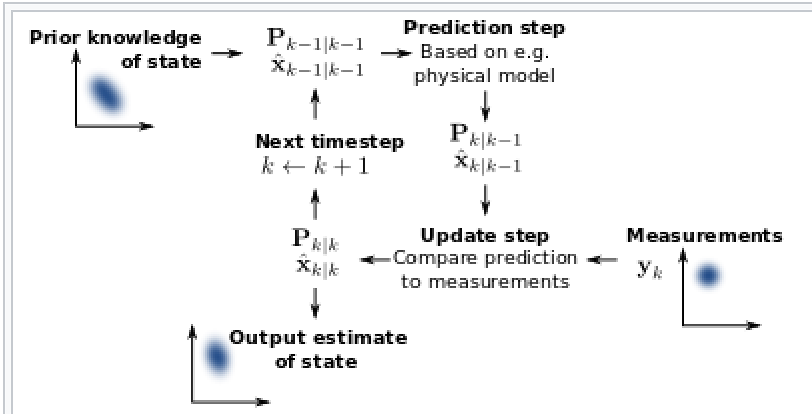
After noise removal, the shape of the hemodynamic signal is usually clear. By observing the hemodynamic signals arising from different activities, one can determine the difference in signals : pea amplitude, mean value, variance, slope, skewness, kurtosis. The most commonly used features or discrimination of different activities for fNIRS-BCI are signal mean, slope, signal variance, amplitude, skewness, kurtosis and zero crossing.

- **Filter co-efficients**

Some fNIRS-BCI studies have proposed the use of filter co-efficient obtained by Kalman filtering, Recursive Least Square estimation, and Wavelet Transformation.

**Kalman filtering**:

In statistics and control theory, Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe. [19][20], [21]




The Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. $\hat{x}_{k|k-1}$ denotes the estimate of the system's state at time step *k* before the *k*-th measurement $y_k$ has been taken into account; $P_{k|k-1}$ is the corresponding uncertainty.

## Recursive least squares (RLS) filtering:

It is an adaptive filter algorithm that recursively finds the coefficients that minimize a weighted linear least squares cost function relating to the input signals. This approach is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity.

## Wavelet Transformation:

The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^{*}_{(a,b)}(x)\, \mathrm{d}x$$

Where the * is the complex conjugate symbol and function $\psi$ is some function. This function can be chosen arbitrarily provided that it obeys certain rules. [22]

They assume that different brain activities will produce different filter co-efficient, in which different signals can be classified. This method has been shown to work well, even though significant classification-accuracy improvement over the heuristic method has been demonstrated.

- **Generic Algorithm**

Generic Algorithm is an optimization technique that is used t select the most efficient feature from a set. Although feature selection is also dependent on individual activities, the mean value and slope values of HbO, HbR, or HbT frequently have been used in fNIRS-BCI. It has been shown that HbO performs more robustly than HbR and HbT for assessing task-related cortical activation.

## 1.4.4 CLASSIFICATION TECHNIQUES

Classification techniques are used to identify the different brain signals that are generated by the user. These identified signals are then translated into control commands for application interface purposes. Classification algorithms, as calibrated by the users through supervised learning during the training phase, are able to detect brain-signal patterns during the testing stage. Some of the commonly used classification methods in fNIRS-BCI are SVM, LDA, HMM, and ANN.

- **Support Vector Machine (SVM)**

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data is unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The support-vector clustering algorithm, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely used clustering algorithms in industrial applications. [23]–[25]

The SVM classifier tries to maximize the distance between the separating hyperplane and the nearest training point(s) (the so-called support vectors). The separating hyperplane in the 2D feature space is given by the equation:

$$\boldsymbol{f(x) = r.x + b,}$$

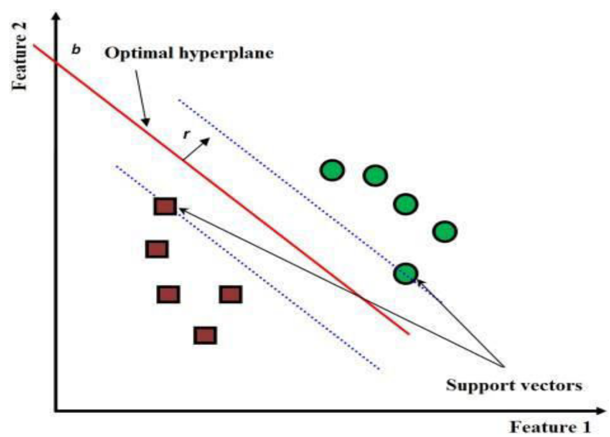
Where $r, x \in R^2$ and $b \in R^1$. The optimal solution $r^*$ that maximizes the distance between the hyperplane and the nearest training point(s) can be obtained by minimizing the cost function.

$$J(r, \xi) = \frac{1}{2} \| r \|^2 + C. \sum_{n=1}^{z} \xi_n,$$

While satisfying the constraints:

$$(x_n . r + b) \geq 1 - \xi_n \text{ for } y_n = +1,$$
$$(x_n . r + b) \geq -1 + \xi_n \text{ for } y_n = -1,$$
$$\xi_n \geq 0 \, \forall \, n,$$

where $\|r\|^2 = r^T r$, $C$ is the positive regularization parameter chosen by the user (a large value of $C$ corresponds to a higher penalty for classification errors), $\xi_n$ is the measure of training error, $z$ is the number of misclassified samples, and $y_n$ is the class label (+1 or −1 in the case of binary classification) for the $n$-th sample.




Since SVM maximizes the distance from the nearest training point(s), it is known to enhance the generalization capabilities. Also, the regularization parameter $C$ allows for accommodating the outliers and therefore reduces errors on the training sets.

- **<u>Linear Discriminant Analysis (LDA)</u>**

Linear discriminant analysis (LDA), is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier or, more commonly, for dimensionality reduction before later classification.

LDA is the most commonly used classification in fNIRS-BCI studies. It utilizes discriminant hyperplane (s) to separate data representing two or more classes. Because of its simplicity and low computational requirements, it is highly suitable for online BCI systems.

In LDA, the separating hyperplane is found by seeking such data projection by maximizing the distance between the two classes' means and minimizing the interclass variances. LDA assumes a normal data distribution along with an equal covariance matrix for both classes. An LDA algorithm tries to find a vector $v$ in the feature space such that two projected classes 1 and 2 in the $v$-direction can be well separated from each other while maintaining a small variance for each. This can be accomplished by maximizing the Fisher's criterion given by:

$J(v)=(v^T S_b v)/(v^T S_w v)$

where $S_b$ and $S_w$ are the between-class and within-class scatter matrices defined as:

$S_b = (m_1 - m_2)(m_1 - m_2)^T$,

$Sw = \sum_{xn\in C1}(x_n - m_1)(x_n - m_2)^T + \sum_{xn\in C2}(x_n - m_1)(x_n - m_2)^T$

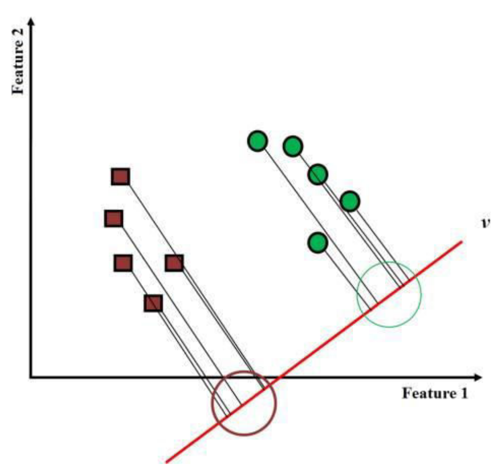
where $m_1$ and $m_2$ represent the group means of classes $C_1$ and $C_2$, respectively, and, $x_n$ denotes samples. It can be seen that a vector $v$ that satisfies (eqn 1) can be reformulated as a generalized eigenvalue problem as:

$S^{-1}{}_w S_b v=\lambda v$.

The optimal $v$ is then the eigenvector corresponding to the largest eigenvalue of $S^{-1}{}_w S_b$ or is directly obtained as:

$v=S^{-1}{}_w(m_1 - m_2)$

provided that $S_w$ is non-singular.




LDA is also closely related to Principle Component Analysis (PCA) and factor analysis in that they both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities. [26]

- ## Hidden Markov Model (HMM)

The HMM is based on augmenting the Markov chain. A Markov chain is a model that tells us something about the probabilities of sequences of random variables, states, each of which can take on values from some set. These sets can be words, or tags, or symbols representing anything, like the weather. A Markov chain makes a very strong assumption that if we want to predict the future in the sequence, all which matters is the current state. The states before the current state have no impact on the future except via the current state. [27]

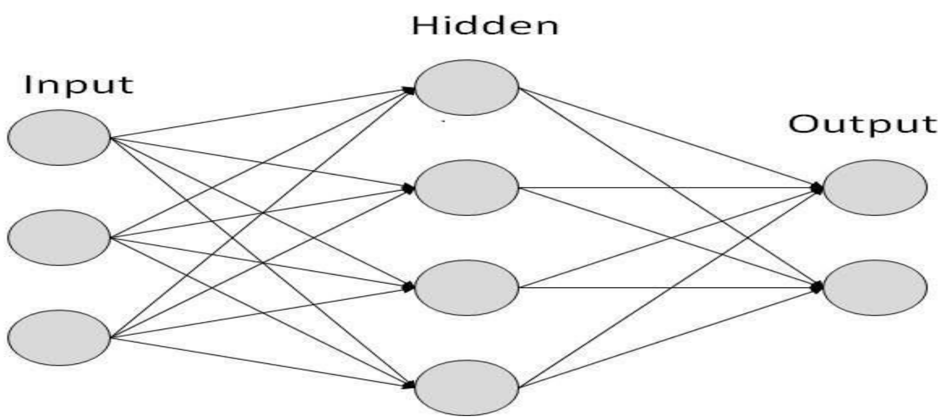
HMM is a non-linear probabilistic classifier that provides the probability of observing a given set of features that are suitable primarily for classification of time series. Some fNIRS studies have successfully demonstrated the feasibility of using HMM for BCI.

- ## Artificial Neural Network (ANN)

Artificial neural networks (ANN) are computing systems vaguely inspired by the biological neural networks that constitute animal brains. The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. The idea of ANNs is based on the belief that working of human brain by making the right connections can be imitated using silicon and wires as living neurons and dendrites.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it.

In common ANN implementation, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are called 'edges'. Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times. The output at each node is called its activation or node value.

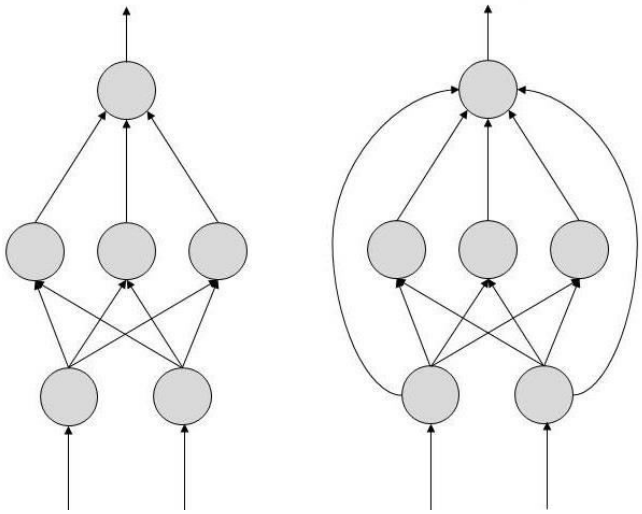



**Types of Artificial Neural Networks**

There are two Artificial Neural Network topologies − FeedForward and Feedback.

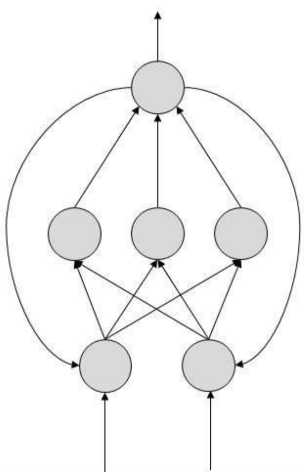
- **FeedForward ANN**

In this ANN, the information flow is unidirectional. A unit sends information to other unit from which it does not receive any information. There are no feedback loops. They are used in pattern generation/recognition/classification. They have fixed inputs and outputs.



- **FeedBack ANN**

Here, feedback loops are allowed. They are used in content addressable memories.

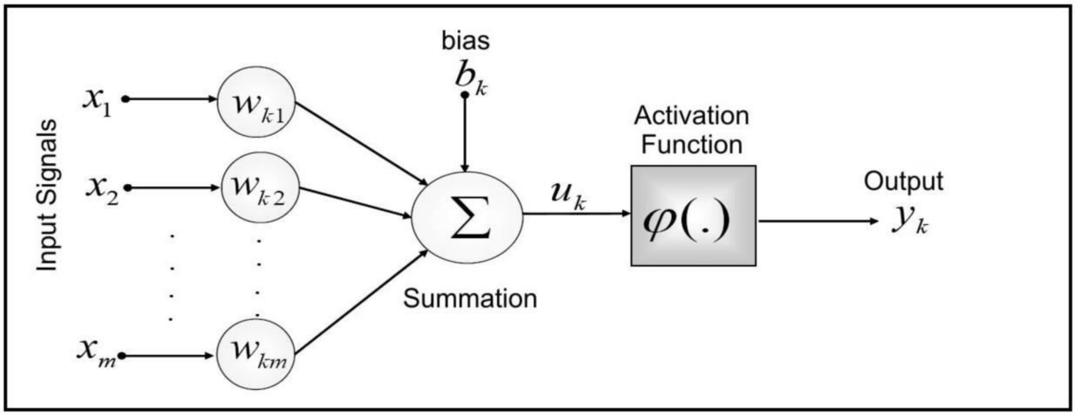


**Working of ANNs**

In the topology diagrams shown, each arrow represents a connection between two neurons and indicates the pathway for the flow of information. Each connection has a weight, an integer number that controls the signal between the two neurons.

If the network generates a "good or desired" output, there is no need to adjust the weights. However, if the network generates a "poor or undesired" output or an error, then the system alters the weights in order to improve subsequent results.

If output signal is "High", it means image is recognized and I output signal is "Low", it means image is not recognized. [28]




Net, $U_k = W_{k1}X_1 + W_{k2}X_2 + \ldots\ldots\ldots\ldots.. + W_{km}X_m + b_k$

$= W^T X + b$, where $W$ and $X$ are two vector sets

Output, $y_k = f(\text{Net})$

**Backpropagation**

While designing a Neural Network, in the beginning, we initialize weights with some random values or any variable for that fact. But it's not necessary that whatever weight values we have selected will be correct, or it fits our model the best. If the model output is way different than our actual output i.e. the error value is huge; then we need to explain the model to change the parameters (weights), such that error becomes minimum.

The Backpropagation algorithm looks for the minimum value of the error function in weight space using a technique called the delta rule or gradient descent. The weights that minimize the error function is then considered to be a solution to the learning problem. [29]

- Backpropagation Algorithm :

initialize network weights (often small random values)

**do**

**forEach** training example named ex

prediction = neural-net-output(network, ex) *// forward pass*

actual = teacher-output(ex)

compute error (prediction - actual) at the output units

compute {\displaystyle \Delta w_{h}} for all weights from hidden layer to output layer *// backward pass*

compute {\displaystyle \Delta w_{i}} for all weights from input layer to hidden layer *// backward pass continued*

update network weights *// input layer not modified by error estimate*

**until** all examples classified correctly or another stopping criterion satisfied

**return** the network

Two other classifiers that have been used in fNIRS-BCI are partial least squares discriminant analysis (PLSDA) and quadratic discriminant analysis (QDA). Although some non-linear classifiers have been shown to increase classification accuracies over those of linear classifiers, the high-speed execution of the linear classifiers has made them the preferred ones for fNIRS-BCI.

## 1.5 APPLICATIONS OF BCI

- Provide disabled people with communication, environment control, and movement restoration.

- Provide enhanced control of devices such as wheel chairs, vehicles, or assistance robots for people with disabilities.
- Provide additional channel of control in computer games.
- Monitor attention in long-distance drivers or aircraft pilots, send out alert and warning for aircraft pilots.
- Control robots that function in dangerous or inhospitable situations (e.g., underwater or in extreme heat or cold).
- Create a feedback loop to enhance the benefits of certain therapeutic methods.
- Develop passive devices for monitoring function, such as monitoring long-term drug effects, evaluating psychological state, etc.

## 1.6 ADVANTAGES and DISADVANTAGES of BCI

### Advantages:

- Allow paralyzed people to control prosthetic limbs with their mind.
- Transmit visual images to the mind of a blind person, allowing them to see.
- Transmit auditory data to the mind of a deaf person, allowing them to hear.
- Allow gamers to control video games with their minds.
- Allow a mute person to have their thoughts displayed and spoken by a computer

### Disadvantages:

- Research is still in beginning stages.
- The current technology is crude.
- Ethical issues may prevent its development.
- Electrodes outside of the skull can detect very few electric signals from the brain.
- Electrodes placed inside the skull create scar tissue in the brain. [30]

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CHAPTER 2

# CONCEPT OF AESTHETICS AND LITERATURE REVIEW

## 2.1 INTRODUCTION

In this chapter the concept of aesthetics and some important works on that particular topic are discussed to evaluate the importance of the thesis work. It also discusses the theory of how the brain really understands aesthetics. It also discusses how we can record the reactions to the visual aesthetics from brain.

## 2.2 CONCEPT OF AESTHETICS

Aesthetics is a concept of philosophy which discusses the nature of beauty, art and taste, with the innovation and admiration f beauty. From technical point of view, it is the study of sensory and subjective emotional values, which sometimes stated as judgments of taste and sentiment. Mathematically, completeness, colour, symmetry, part-whole relationship etc. are used for the study of theoretical aesthetics.

Aesthetics investigates how artists do their imagination, and the create and perform their work; how people enjoy or criticize the work of art; and what happens to people's mind when they see a painting, or read any poetry, or listen to their favorite music. It studies how brain reacts when the like or dislike any work and how it effects their attitude, mood and beliefs.

## 2.3 HOW BRAIN INTERPRET AESTHETICS

Human brains are in persistence state of aesthetic assessment. With the proper use of human senses, we captivate reality into a dialogue, apprehending external stimuli and by giving each input a proper value (consciously or unconsciously) with the help of a reward mechanism. Scientists now-a-days have begun to understand how brain understands arts by using neuromaging techniques. In this study, which is known as neuroaesthetics, we will discuss why art is so valued and will raise concerns regarding the nature and also the future of the arts.

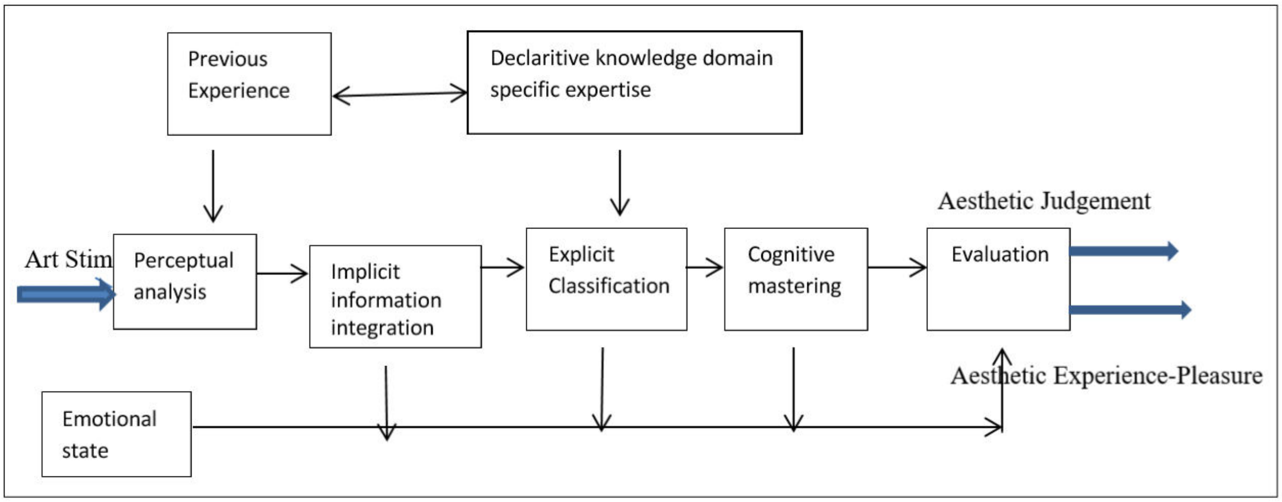


Fig : Schematic model of aesthetic experience

This model of aesthetic experience covers all the required processes in our experiment with the work of art. The model is designed by Augustine, Belke, Leder, and Oeberst in 2004. In this particular model, a participant starts with a perceptual assessment of the artwork, compares the current work with the previous references, classifies the artwork into a suitable category, and interprets and assesses the work, which results in aesthetic judgment and emotion. In the aesthetic Baumgarten sense, only the first two or three stages will be considered. Automatic stages of recognition are mostly at work and the affect of the work is generated by evaluating the degree of detection of the structures by our recognition system and also how well the novelty or familiarity of the work is assessed. At these stages we are concerned about the sensuous pleasure or displeasure, but the next stages emotional experiences and cognitive processes are taken into account.

We can conclude that neuroaesthetics is a combination of two evidently opposite human aspires: arts and science. In today's world studying different fields opens up different ways to collect the truths about our existence. This world is physically demonstrated in the harmony in the mnemonic, visual and limbic systems during aesthetic assessment. The way memories gives us idea about beauty, our creativity and the ability of appreciate any artwork is provided by neuroscience.

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## 2.4 PROCESS OF DETECTING BRAIN RESPONSE TO A VISUAL AESTHETICS

Visual art is a strong resource for mental and physical prosperity. However, we know very little about the main effects at the neural level. The critical question is whether works of visual art and the assessment of cognitive art can affect the functional interaction of the default mode network (DMN) in different ways. We used the process of fNRI to study a non-clinical DMN sample of 28 adults after retirement (62.71 years ± 3.62 SD) before (T0) and after (T1) weekly involvement in two different 10-week art interposition. Participants were randomly divided into groups broken down by sex and age. In the visual arts production group, 14 participants actively created art in an art class. In the group on the evaluation of cognitive art, 14 participants cognitively assessed the works of art in the museum. The DMNs of both groups were identified in the posterior cingulated cortex (PCC / preCUN) using the seed voxel correlation analysis (SCA). The analysis of covariance (ANCOVA) was used to associate MRI data with psychological resistance, which was calculated using a brief German counterpart of Reilience scale (RS-11). We discovered that the visual art group performed a greater spatial improvement in the functional connectivity of PCC / preCUN with the frontal and parietal cortical layers from T0 to T1 than the cognitive art assessment group. In addition, functional connectivity in the visual art group was related to psychological resilience (i.e., stress tolerance) in T1. Our results are the first to signify the neural impact of the production of visual art on psychological stability in adulthood.

| | | Visual art production | Cognitive art evaluation | Total |
|---|---|---|---|---|
| **Number of participants** | | **14** | **14** | **28** |
| **Age** | | 63.50 (±3.80 SD) | 63.93 (±3.34 SD) | 63.71 (±3.52 SD) |
| **Sex** | Female | 8 | 7 | 15 |
| | Male | 6 | 7 | 13 |
| **Handedness** | Right- handed | 11 | 13 | 24 |
| | Left- handed | 1 | 1 | 2 |
| | Ambidextrous | 2 | 0 | 2 |
| **Education** | Low | 5 | 0 | 5 |
| | Middle | 6 | 5 | 11 |
| | High | 3 | 9 | 12 |
| **Retired since** | 0–12 months | 9 | 6 | 15 |
| | 12–24 months | 2 | 3 | 5 |
| | 24–36 months | 3 | 5 | 8 |
| **Number of attendances** | 6 sessions | 0 | 1 | 1 |
| | 7 sessions | 2 | 3 | 5 |
| | 8 sessions | 1 | 3 | 4 |
| | 9 sessions | 5 | 3 | 8 |
| | 10 sessions | 6 | 4 | 10 |

doi:10.1371/journal.pone.0101035.t001

| Group | n | Pre-intervention | Post-intervention | P-value |
|---|---|---|---|---|
| Visual art production | 14 | 60.64 (±1.71 SEM) | 63.50 (±1.47 SEM) | 0.013* |
| Cognitive art evaluation | 14 | 62.57 (±2.32 SEM) | 64.79 (±1.80 SEM) | 0.195 |

Significant at 0.05

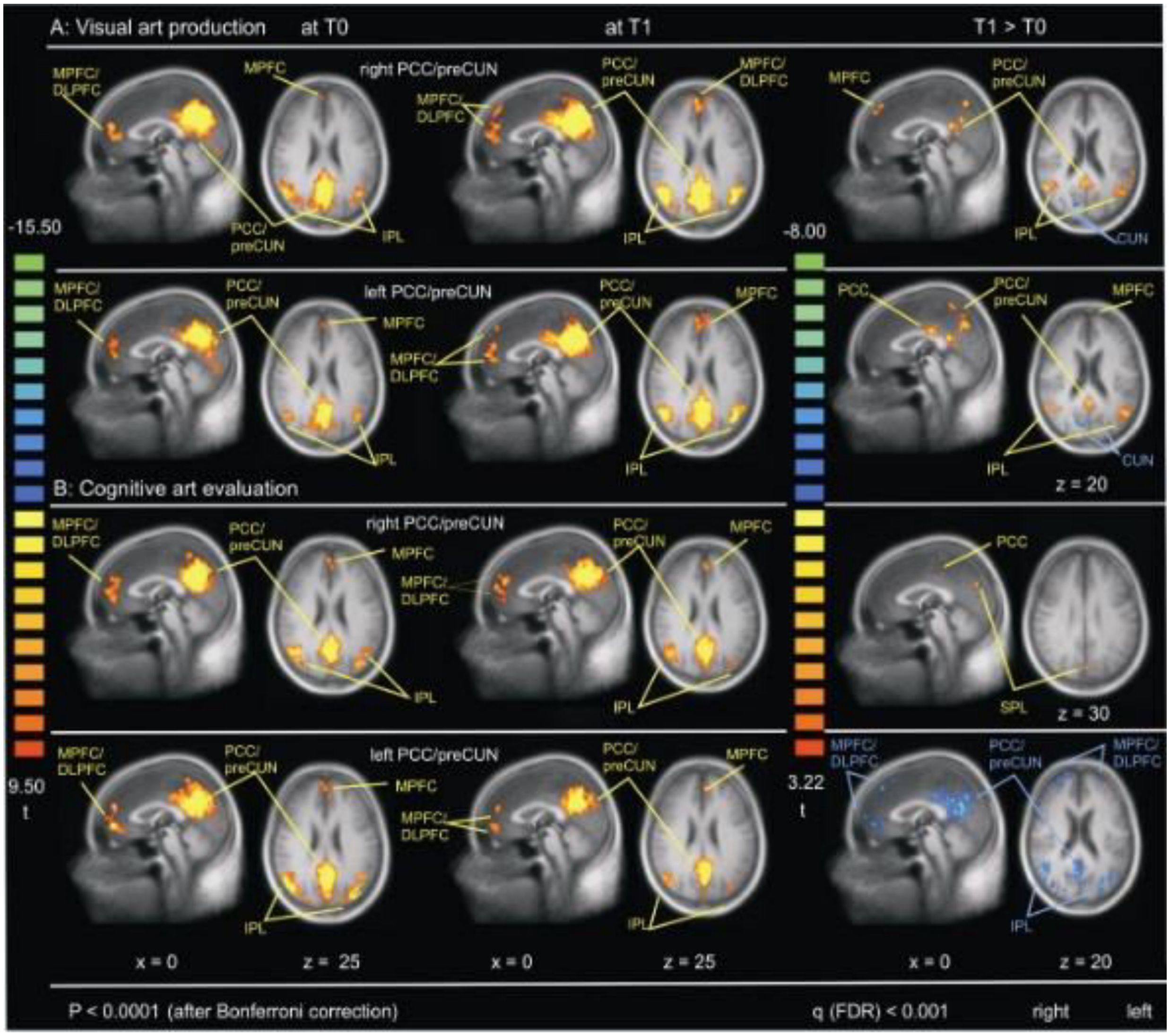


Fig: Brain regions with notable functional connectivity to the right and left PCC/preCUN at T0 and T1

## Gregory's Visual Assumption Theory

Psychologist Richard Gregory presumed that visual perception is based on top-down processing.

*Downward processing* or conceptual processing occurs when we shape our perceptions, starting with the big image. We make the best assumption about what we see, based on expectations, beliefs, prior knowledge and past experience. In other way, we make calculated assumptions. According to Gregory, we are usually right in these assumptions.

### The Hollow Face Experiment

One of the experiments that Gregory conducted to test his theory was called a hollow mask test.

Fig: Hollow mask

He used a Charlie Chaplin's rotational mask to explain how we see the hollow surface of the mask as obtruding, based on our expectations from the world. Our previous knowledge of a normal person is that the nose obtrudes. So, we subconsciously restore the hollow face to a normal face.

Based on the theories provided by Gregory, we can conclude that:

Nearly 90% of the information that we see is lost by the time it reaches our brain. Due to this, the brain must have to make its best assumption based on our past experience or previous knowledge. The visual information about what we see is merged with previously stored information about the world that we have created from our experience.

Our environment provide context for the visual information we absorb.

## 2.5 SOME RECENT WORKS ON AESTHETICS

Beautiful web page design turned out to be one of decisive factors in user satisfaction. Relations

between the design features and the aesthetics of a webpage often explained using linear regression models. Visual aesthetics on web pages are known to be crucial factor in guaranteeing the quality of customer service and significantly affects website user ratings. Linear regression model is the basic method to justify this knowledge. However, these Models cannot illustrate fuzziness and non-linearity o the human perception. To eliminate these limitations, this study recommends a model based on fuzzy rules for correlating webpage design Features on web page aesthetics with the help of user ratings. This model increases predictability on the same experimental data, with fewer variables in comparison with a linear regression model based and classifies web pages and gives more specific design knowledge.
It was found that the fuzzy model use fewer variables, but it have better predictive performance than linear regression which was created using the same experimental data while all interaction and quadratic terms were taken. Additionally, the fuzzy model gave valuable knowledge of the web page classification and different contribution of the function for each web page class. This, therefore, facilitates the extraction of special design knowledge for different web pages patterns. In addition, a large set of regression variables results in significantly increased training time.("Ying Li and Anshul Sheopuri," 2015)

| Item | Fuzzy rule-based model | Linear regression model |
|---|---|---|
| Model characteristic | Multiple local linear models | A global linear model |
| Number of variables | Small (4) | Large (10, including 4 second-order terms) |
| Training time | Short | Long |
| Predictive ability | Better | Worse |
| Interpretation | Webpage classification | Global effects of variables |
| | Local effects of variables | Hard to explain second-order variables |

Fig: Comparison between two methods

A new class of art forms appears. These "coactive" forms of art incorporate control systems whose goal is to show beauty through interaction with viewer. We will present how these systems can be interpreted through the control system, and how they enhance some important problems in intellectual management design and systems theory. Some examples of these systems are presented. Some primary knowledge and observations about coactive systems are also presented. There are many examples regarding the relationship between art and science / technology that are helpful for both parties. We will describe here a new art form that unites the latest technology in touch and computer control create interactive, dynamic, "aesthetic systems." We have named such systems coactive to highlight the fact that their aesthetic reactions comes from the viewer's interaction with art object / system. We traverse through the fact that how these systems can be judged through the control system, and how they can be identified from existing classes of control systems.

Although control theory does not usually applied for designing and creation of coactive systems, these systems, however, build and demonstrate interesting behavior. Consequently it may be helpful to retroactively examine how some of these devices work through control theory. There are also advantages for this new art form in the application of control theory more strictly to the development Coactive systems. Because the device can behave like almost anything that can be seen as a dynamic, and range of behavior it must be open to the interpretation of the viewer, the systems provide a unique basis for experiment with multiple controls and explore some of the following questions:

- The emergence of a higher level of global behavior from lower level space management.
- The value and degree of aesthetic behavior and how it can be produced.
- Mapping of low-level sensory data to higher-level constraints need to maintain the desired aesthetic behavior.

These problems are clearly same to many prospective of intellectual control, as well as "aesthetic control"(Koch & Gaw, 2002)

Previous studies have presented that automatic presumption of high quality image or aesthetics are very complex. However, if we are able to do this, it may be useful in many applications. In this article, we describe the aesthetic gap and discuss key points about the issues of aesthetics and emotion output in natural images. We present accurate, current questions that need to be answered, the impact that the target audience has a problem specification, a wide technical solutions and evaluation criteria. Then we report our efforts to create real-life data sets that provide sustainable appeals to check and compare algorithms for these tasks, providing a statistical analysis and understanding of them.

The image processing and analysis process tried to quantify and correct image quality at a low level, for a long time, taking the original image into account or may be without it. In higher levels, the level of perception often affects our emotions and mood, but little progress has been made in automatic output image quality that affects mood or emotions. What kind makes the latter problem difficult in that low-level image properties insufficiently characterize high level perception aesthetics. In addition, there is a lack of correct and specific definitions, evaluation metrics and test data for this problem even though it is sensible for many applications; for example, image search, photography, illustration of the history and improvement of photos. In this article we are trying to find solution for the problems of the natural output of image aesthetics from visual content, identifying issues of interest, the target audience and how they influence a problem, evaluate indicators and present real datasets for testing. Conclusions are taken from several previous trials in solving this type of problems. While facial attraction was a topic for many popular sites, and this lead us to an automatic facial aesthetics conclusion, which uses symmetry and proportions, here we deal in general images.


Fig: Three aesthetics issues of significance

We considered at the key features of algorithmic output of emotions that natural images triggers in people. Although very limited work has been published so far, we hope that these exposure delicacies will motivate more contributions. We created and analyzed several data sets from uncontrolled Internet sources. Still others, such as Shutter point, regularly grow online and can help generate more reference tests. Large dataset based on low noise User controlled studies will be a welcome addition.(Datta, Li, & Wang, 2008)

Deep convolution neural networks recently reached great success in solving the problem of image aesthetics assessment. In this document, we offer an efficient method that takes global, local and scene-based image information for review and uses the elements extracted from the corresponding pre-trained deep learning models for classifying derivatives functions with vector machine support. In contrast with the famous methods that demands fine tuning or learning a new model from raw data our method directly receives the features generated by off-the-shelf models for classification o image and recognition of scene. We also analyzed that this can affect performance on both sides: deep neural network architecture and input local and scene-aware information. It is proven to be a case that deep residual network can create a more aesthetic image representation and complex functions which improves overall performance. Experiments on a common scale aesthetic evaluations show that our method surpasses modern results in photo aesthetics score.

Wide distribution of photographic devices like digi-cam and smart phone allows people to take photos more convenient than ever. Great effort and time must pay for sifting piles of images stored on devices and cloud storage. Therefore, automatically choosing aesthetically nice images are very useful in such conditions. Figure 1 shows some examples of good and bad aesthetic images.

(a) (b)

Now-a-days, the researchers have turned to this complex problem by developing ways to classify images in binary categories of high quality and low quality. Early work focused mainly on the different aesthetics of handmade work functions and function representations, such as SIFT or color descriptors. With the development of deep learning, deep neural network (DNN), especially convolution neural network (CNN) has been successfully used in various fields, such as classification of image, detection of objects, recognition of scenes and so on. Modern presentation achieved deep neural network proves its powerful ability representations of functions for various visual tasks.

This article presents a productive and efficient scheme that, we can increase the image aesthetics assessment accuracy using complex features derived from convolution neural networks of deep preparation. The training we offer without the method accepts local, global and scene information images into account and uses ready deep training model in the procedure for the allocation of signs. Our experimental analysis shows that our method achieves superior performance compared to other modern approaches.(Fu, Yan, & Fan, 2018)

This article discusses the recent work on aesthetics evaluation of food dishes by surveying its appearance. In particular, we constructed the working space which is based on work in the field of color science, psychology and statistics to allow users to computationally evaluate, the image of the dish is visually appealing. In addition, we also Rate the uniqueness of the dish by comparing its color composition against image repository dish. Evaluation engine was recently integrated into the Google glass app that brings a new dimension of wearable computing for this work. Our prior experiments with the evaluation system showed brilliant outputs and initial deployment of Google Glass gained quite some interests. Maintaining, designing of the food colour is one of the most important tasks for the food industry, since the attractiveness of food is mainly determined by its appearance, as color the most visible visual aspect. Technically, the appearance of a dish that affects people's mind will affect their appetite, which includes every feeling in the whole perception mode, including various outlooks of social life. However, when people eat, they eat with their eyes first. It gives inspiration to us to evaluate the aesthetics of the food dish by surveying its appearance, color combinations to be specific. our objectives are: 1) we will try to prove that the computational method odds can be used to carry out such aesthetic evaluation tasks as people can; and 2) such an estimation will help people or cooks in advance to choose or create dishes which are more visually pleasant.

This article discusses the latest work on aesthetics and the uniqueness of food, surveying its color combinations, ensuring its visual appeal and comparison of its appearance with large storage of images of dishes. Google Glass app was developed on the basis of an evaluation mechanism that offers a natural and an interactive user interface. Previous studies have shown some interesting results. Point to be noted, that this work might be focused in the area of food technology, but the basic technology can be easily used in other areas like fashion industry, packaging, web designing and even interior decorating.(Chen, Hua, Xie, Lin, & Tang, 2016)

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# CHAPTER 3

# EEG-based EXPERIMENTAL ANALYSIS TO INVESTIGATE BRAIN REACTIONS FOR VISUAL AESTHETICS

## 3.1 INTRODUCTION:

Beauty is the ascription of a property or characteristic to an animal, idea, object, person or place that provides a perceptual experience of pleasure or satisfaction. Beauty is studied as a part o aesthetics, culture, social psychology, philosophy and sociology. Recognition of beauty in objects and/or faces and/or scenarios is a special characteristic of human beings. A limited amount of work on cognitive aesthetics in context of beauty is done till date as per our knowledge. Most of the work considers beauty as subjective, so no particular interpretation on the commonality in brain activation pattern is offered so far, when subjects are called for visual examination for the assessment of beauty. (Armstrong & Detweiler-Bedell, 2008; Brielmann & Pelli, 2017; Martin, 2007)

Result of a behavioral experiment confirmed that trend for lay people to consider as beautiful mostly abstract ones ("usual response"). Furthermore, when participants gave unusual responses, they needed longer time, especially when considering abstract stimuli as beautiful. Brain imaging studies confirm that the Pre-frontal lobe plays the most important role in the assessment of beauty by recognizing and decoding visual stimuli. The Parietal lobe, which integrates sensory information along various modalities including spatial sense and navigation, the dorsal stream of visual system, helps understanding natural scenes. The Temporal lobe is involved in processing sensory input into derived meanings for the appropriate retention of visual memory.

The purpose of this study is to investigate the cortical activation patterns during execution, observation, imagery, and passive movements to develop a generic system for the analysis of cognitive aesthetics in the context to beauty. EEG signals here are processed with E-Loreta to identify the locations which are mostly active during the experiment. During the execution phase of E-Loreta software, it is found that the Pre-frontal lobe, the Temporal lobe, the Parietal lobes are mainly activated. The signals are passed through Independent Component Analysis (ICA) to identify the main sources.

The main complication with BCI analysis is the selection of features and classifiers for proper analysis. Another important concern is removal of artifacts caused due to parallel thinking and/or motor activities like eye-blinking, movements of hands and/or any other body part, head motions, heartbeat. In addition, subjective variation sometimes adds inter-personal uncertainty which can be resolved by Type-2 fuzzy classifiers (it have the advantages to handle intra/inter-personal uncertainty).

The paper provides 2 different techniques for decision-making using z-slice and vertical-slice methods of type-2 fuzzy reasoning. The former part is represented by General type-2 fuzzy class and the later part is modeled as an Interval type-2 fuzzy class.

First, we need to identify the commonalties in the brain activation pattern for a set of beautiful stimuli. Second, we need to adjust certain parameters of the input stimuli to find their range around predefined centre points to achieve commonality. Classification is done in 2 steps.

Step 1 : a type-2 fuzzy inference is derived from the observed type-1 membership functions of the former position

Step 2 : we go for Karnik-Mendel model of defuzzification of the inference and check whether the output lies within mentioned interval of the class “beauty”.

If the result is ‘true’, the input stimuli is considered ‘Beautiful’.

If the result is ‘false, the input stimuli is considered ‘Non-Beautiful’.

The most important parameter in recognizing beauty is to extract certain EEG features from the maximum activated regions, reduce artifacts with precision and classify the data using suitable classifiers.

## 3.2 CLASSIFICATION:

During the experiment, if the human brain gets mental pleasure while watching the subject presented, it would expect to release a P-300 signal. P-300 wave is an event related potential (ERP) component elicited in the process of decision making. It is considered to e an endogenous potential, as its occurrence links not the physical attributes of a stimulus, but to a person's reaction to it. It is usually elicited using the Oddball paradigm, where low probability target items are mixed with high probability non-target items. In other words, if a 6x6 grid of characters is presented to the subject, and various columns or rows contains the character a subject desires to communicate, the P-300 response is elicited(since the character is "special" it is the target stimulus described in the typical oddball paradigm). Additionally, mental attachment to an object stimulus is often responded by a release of brain signals is the $\theta$-band, $\alpha$-band, $\beta$-band, $\gamma$-band. As a result, any properly trained classifier can easily differentiate between beautiful and non-beautiful classes.

**Detection of P300 signal:** Adaptive Autoregressive Parameter (AAR), Horzth parameter, Power spectral density are the features that is used or P300 detection.

**Activated brain lobes:** Pre-frontal lobe, frontal lobe and temporal lobe

## 3.3 CLUSTERING

The main idea is to find different groups of data that have common attributes (called clusters) in the EEG data. Those clusters are then used to determine patterns and correlation between different electrodes. This information is then used to understand the human brain reaction to the event, similar brain parts who acts similarly, etc. This research is done on the basis of Type-II fuzzy logic systems to understand the activities of different brain parts during the task. The performance of the classifier is assessed with the classification accuracy. A T2 FLS is used to classify the neuronal activities generated from visual aesthetics, based on the information extracted from te received EEG signal with Short-Time Fourier Transform (STFT).

Brief overview of Type-II Fuzzy logic :

Karnik, N. N., & Mendel, J. M. (n.d.). Introduction to type-2 fuzzy logic systems. 1998 IEEE International Conference on Fuzzy Systems Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98CH36228). doi:10.1109/fuzzy.1998.686240

Karnik, N. N., Mendel, J. M., & Qilian Liang. (1999). Type-2 fuzzy logic systems. IEEE Transactions on Fuzzy Systems, 7(6), 643–658. doi:10.1109/91.811231

## 3.4 MATERIALS AND METHODS

### A. PARTICIPANTS :

Three healthy women volunteers between 23 ~ 27 ages with no history of neurological, physical, or psychiatric illness participated in this study. All subjects understood the purpose of the study and agreed to participate willingly.

### B. TASK AND PROCEDURE :

Participants were seated comfortably on a chair in an upright position at a distance of approximately 1m from the computer screen on which stimuli was displayed and they were asked not to move. They were asked not to move from their position and stay calm throughout the experiment to avoid unwanted noise. Each experimental session commenced by fixating the subject with a fixation cross. We had used 50stimuli of image belonged to five different categories and broad range of contents to provide each participant with positive and negative aesthetic experiences through the task. The protocol for each condition was as follows: rest (3 s), Instruction set (5 s), Encoding (5 s), rest (5 s) and recall (5 s) with regard to the assignment of artistic stimuli, we used two classes i) Beautiful and ii) Not-beautiful. Task and rest were cued by beep sound at every start. In rest phase, all subjects were instructed to keep their eyes closed and to relax without performing any movements or any imaginations. The sequence of the trials for every subject was randomly assigned. Each participant was provided:

i) Ten beautiful faces

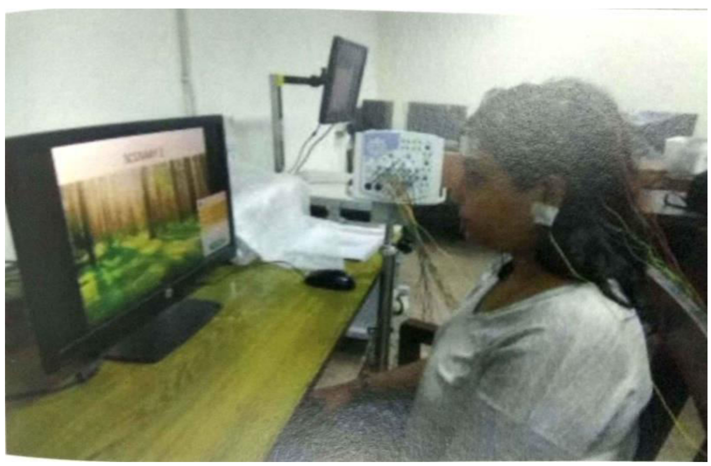
ii) Ten beautiful houses

iii) Ten beautiful sceneries

iv) Ten beautiful flowers

1. **DATA ACQUISITION :**

In this study we have used NIHON-KOHDEN (21 electrode) EEG machine or the experiment. EEG data were collected from the five denied brain region: Frontal (F), Central(C), Occipital (O), and Left-Right Temporal (LT, RT) regions. Electrodes were placed on the scalp as per standard 10-20 electrodes placement system. P300 signals appear within 5s of the target stimulus presentation. So, EEG output of 5s duration post the onset of the target was collected as a trial of P300 signal.



**Experimental Setup**

2. **PRE-PROCESSING :**

The resulting EEG signals were first band passed through the band 0.15-5Hz to eliminate the exogenous components present at stimulus presentation frequency, i.e. 5.7Hz and above. A 6$^{th}$ order elliptical filter with 1dB passband ripple and 60dB stopband attenuation was used for implementing the BPF. Since the time complexity of feature extraction from a filtered trial was significantly low(~25ms) even at 500hz sampling frequency, downsampling was not required in this case. Butterworth filter, p-welch filter were used for artifact removal.

It appears that the plots from the positive deflection of P300 occurs within 200-40ms of the target stimulus presentation. The latency and deflection of P300 varies not only over subjects but also over different trials of the same subject.

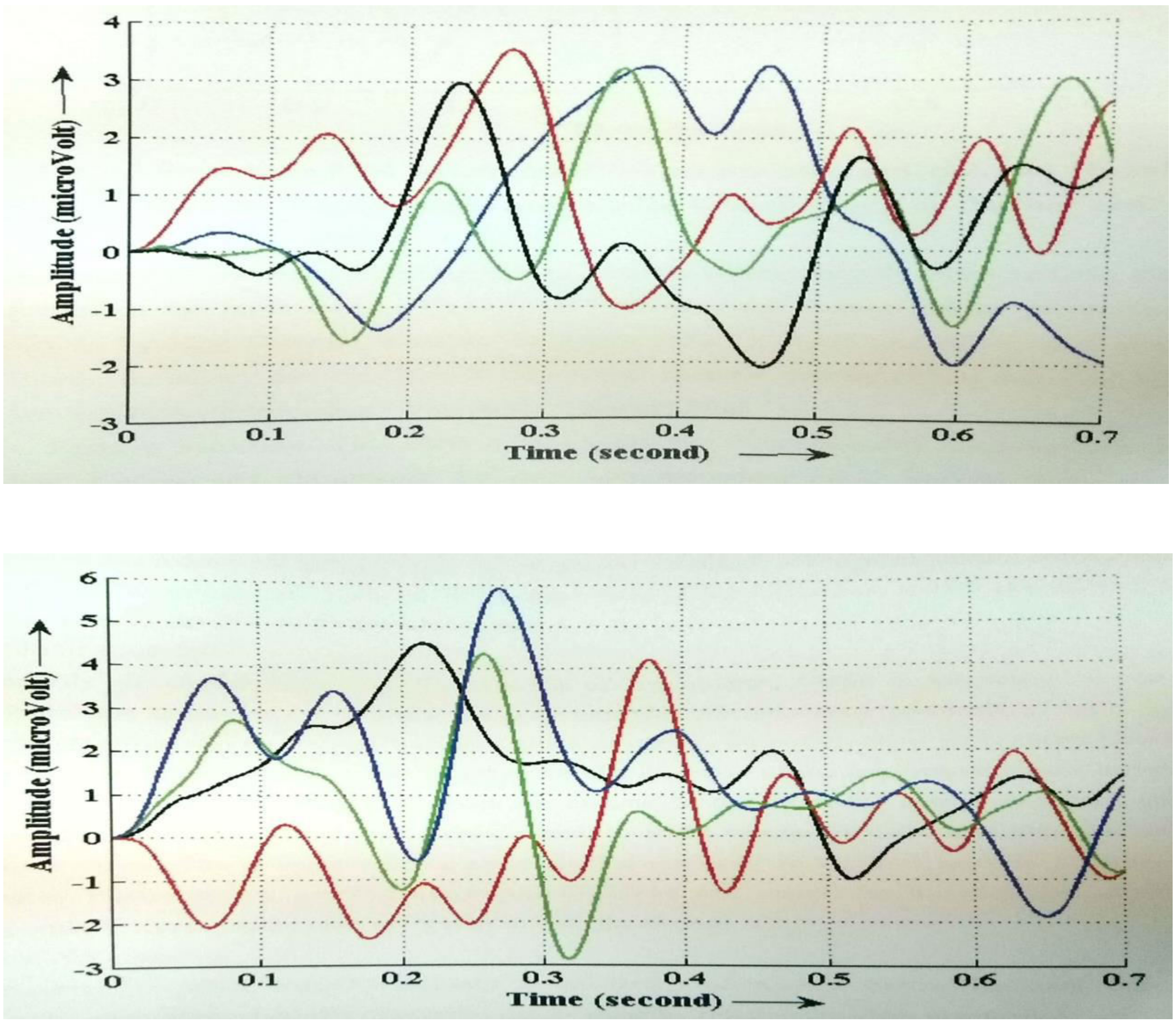



**Fig : Illustrative P300 waveforms of two subjects (a)subject 2 and (b) subject 3.**

(The target stimulus presentation is marked by 0 on the time axis)

## 3. FEATURE EXTRACTION :

For feature extraction, we have time domain features like Adaptive Auto Regressive (AAR) parameter, Hjorth parameter, Discrete Wavelet transform(DWT), and frequency domain features like Power Spectral Density(PSD), ICA(Independent Component Analysis), Wavelet ICA and time-domain correlated features like Wavelet Coefficients etc.

## 4. FEATURE SELECTION :

Feature selection is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Varieties of Feature Selection techniques are available: Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Evolutionary Optimization based techniques etc.

## 5. CLASSIFICATION :

The classification step in a BCI aims at translating the features into commands. It is basically a supervised learning process. Some well know classifier algorithm include Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Back Propagation Neural Network (BPNN), k-Nearest Neighbor classifier (k-NN), Fuzzy Classifier etc.
We have used SVM classifier, k-NN classifier and Fuzzy type-II classifier in our study.

- SVM classifier :

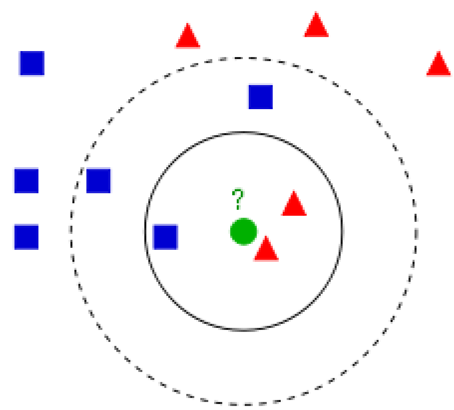
An SVM uses a discriminant N-dimensional hyperplane to identify classes. However, with SVM, the selected hyperplane is the one that maximizes the margins, i.e., the distance from the nearest training points, which has been found to increase the generalization capabilities. In this case, the complexity does not depend on te dimension of the feature space, so SVM can be used for higher dimensional feature spaces. The training data was classified in two distinct classes $W_1$(Beautiful) and $W_2$(Not-beautiful).

- k-NN classifier :

k-nearest neighbors algorithm (*k*-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the *k* closest training examples in the feature space. The output depends on whether *k*-NN is used for classification or regression:

- In *k-NN classification*, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its $k$ nearest neighbors ($k$ is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor.

- In *k-NN regression*, the output is the property value for the object. This value is the average of the values of $k$ nearest neighbors.




Example of $k$-NN classification. The test sample (green dot) should be classified either to the first class of blue squares or to the second class of red triangles. If $k = 3$ (solid line circle) it is assigned to the second class because there are 2 triangles and only 1 square inside the inner circle. If $k = 5$ (dashed line circle) it is assigned to the first class (3 squares vs. 2 triangles inside the outer circle).

**Algorithm**

Let m be the number of training data samples. Let p be an unknown point.

1. Store the training samples in an array of data points arr[]. This means each element of this array represents a tuple (x, y).
2. for i=0 to m:
3. Calculate Euclidean distance d(arr[i], p).
4. Make set S of K smallest distances obtained. Each of these distances correspond to an already classified data point.

5. Return the majority label among S. (Cunningham, Delany, & Cunningham, 2007)

- Fuzzy type –II classifier

A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership value (or membership grade) for each element of this set is a fuzzy number in [0,1]. Such sets can be used in situations where there is uncertainty about the membership grades themselves, e.g., an uncertainty in the shape of the membership function or in some of it's parameters. Consider the transition from ordinary sets to fuzzy sets. When we cannot determine the membership of an element in a set as 0 or 1, we use fuzzy sets of type-1. Similarly, when the circumstances are so fuzzy that we have trouble determining the membership grade even as a crisp number in [0,1], we use fuzzy sets of type-2.

Type-1 FLSs have been successfully used in widely different applications. While designing a type-1 FLS, the locations and spreads of fuzzy sets are decided based on the available linguistic/numeric information; however, almost always there is some uncertainty associated with the available information. If the rules are formed from linguistic information, generally, there is no information available about where the centers of the fuzzy sets should be located. In general (at least, initially), the *sets* are located somewhat arbitrarily. If the rules are formed from numerical data, again there is generally some kind of uncertainty associated with the data. The data can be noisy. There can be measurement errors. So, then this uncertainty carries over to the rules. In the case of a type-1 FLS, if there is a lot of data available to train the system, the effect of the initial arbitrary choice of membership function parameters reduces after training; but, if there is insufficient or noisy training data, this may not happen. Then, a type2 FLS, gives a more useful representation of the output. Type-2 FLSs handle a different kind of uncertainty than that handled by a *non-singleton type-1 FLS* [ *A Non-Singleton system deals with the uncertainty in the input, whereas Q type-2 system deals with the uncertainty* in *our knowledge about the system*]. Hence, type-2 systems should be *robust* to rule uncertainties. (Özbay, Ceylan, & Karlik, 2011)

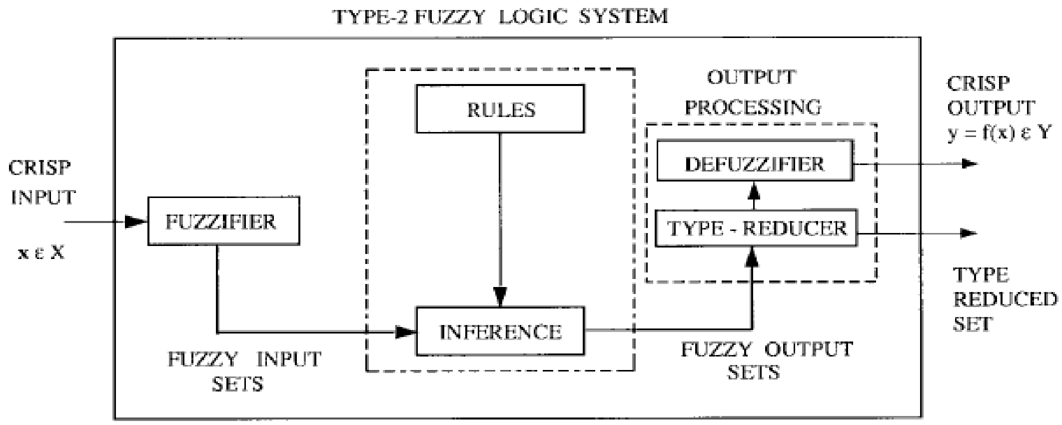



Fig : The structure of a type-2 FLS. In order to emphasize the importance of the type-reduced set we have shown two outputs for the type-2 FLS, the type-reduced set and the crisp defuzzified value.

we use the following notation and terminology: A is a type-1 fuzzy set and the membership grade (a synonym for the degree of membership) of $x \in X$ in A is $\mu_A(x)$, which is a crisp number in [0,1] ; a type-2 fuzzy set in X is $\tilde{A}$ and the membership grade of $x \in X$ in $\tilde{A}$ is $\mu_{\tilde{A}}(x)$, which is a type-1 fuzzy set in [0,1] ; the elements of the domain of are called *primary memberships* of x in $\tilde{A}$ and the memberships of the primary memberships in $\mu_{\tilde{A}}(x)$ are called *secondary memberships* of x in $\tilde{A}$; the latter defines the possibilities for the primary membership, e.g., the type-2 fuzzy set $\tilde{A} \in X$ has fuzzy grades (fuzzy sets in $J_x \subseteq [0,1]$ ), $\mu_{\tilde{A}}(x)$ that can be represented for each $x \in X$ as,

$$\mu_{\tilde{A}}(x) = f_x(u_1)/u_2 + f_x(u_2)/u_2 + \ldots\ldots\ldots + f_x(u_m)/u_m$$

$$= \Sigma_i\, f_x(u_i)/u_i\,, \qquad u_i \subseteq J_x$$

the primary membership having secondary membership equal to one is called the *principal* MF; when the secondary MF's of a type-2 fuzzy set are type-1 Gaussian MF's we call the type-2 fuzzy set a *Gaussian type-2 set* (regardless of the shape of the primary MF); when the secondary MF's are type-1 interval sets we call the type-2 set an *interval type-2 set.*

For all x, we form a 3D membership function as type-II membership functon-that characterizes a type-II fuzzy set. A type-II fuzzy set is charecterized by the membership function :

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \forall_u \in J_x \subseteq [0,1]\}$$

In which $0 \le \mu_{\tilde{A}}(x,u) \le 1$ .

Hence, a type-II membership grade can be any subset in [0,1], the primary membership and corresponding to each primary membership, there is a secondary membership that defines the possibilities for the primary membership. Uncertainty is represented by a region, which is called footprint of uncertainty (FOU). (Melin & Castillo, 2013)

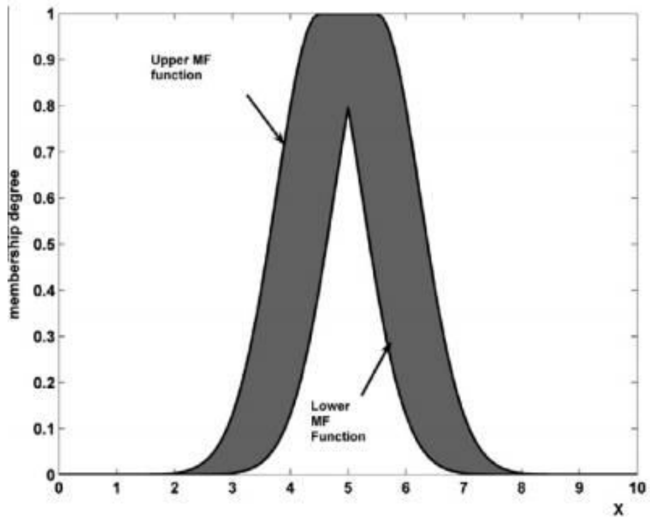



Fig : Type-II fuzzy logic

An alternative representation of T2FS, Ã, found in literature is given by,

$$\tilde{A} = \int_{x \in X} \int_{u \in Jx} \mu\tilde{A}(x,u) | (x,u) \quad , \quad J_x \subseteq [0,1]$$

$$= \int_{x \in X} \left[ \int_{u \in Jx} \frac{fx(u)}{u} \right] / x \quad , \quad J_x \subseteq [0,1]$$

Where $f_x(u) = \mu_{\tilde{A}}(x,u) \in [0,1]$

- <u>Event-Related fields (ERF)</u>

Event-related fields are triggered by sensory stimuli and appear as a series of wave extending hundreds of milliseconds after stimulus onset. They reflect the processing of the stimulus in cortex and have a highly subject specific morphology. ERFs are derived by averaging single trials. Average ERFs are calculated for each condition (beautiful, or not-beautiful), individual sensors ad participants for 100ms period of time. A period of 5s has been set to each stimuli. The sampling frequency is 500Hz. A strong positive effect appeared in right anterior temporal region within the 100-200ms window. Its corresponding negative effect appeared in the contra lateral hemisphere i.e. left anterior temporal region. This effect is sustained during the subsequent time window until 500ms. This is observed for both beautiful stimuli and not beautiful stimuli.

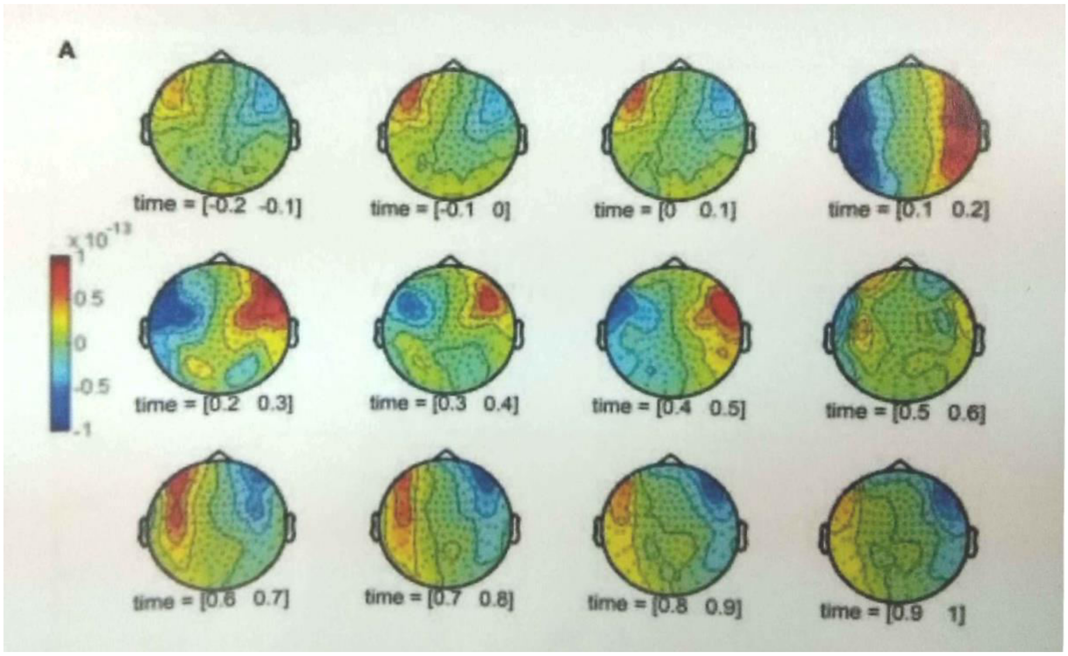



Fig : Topographic representation of the activity in 100ms window from 200ms prior to stimulus onset to 1s after stimulus onset for Beautiful stimuli.

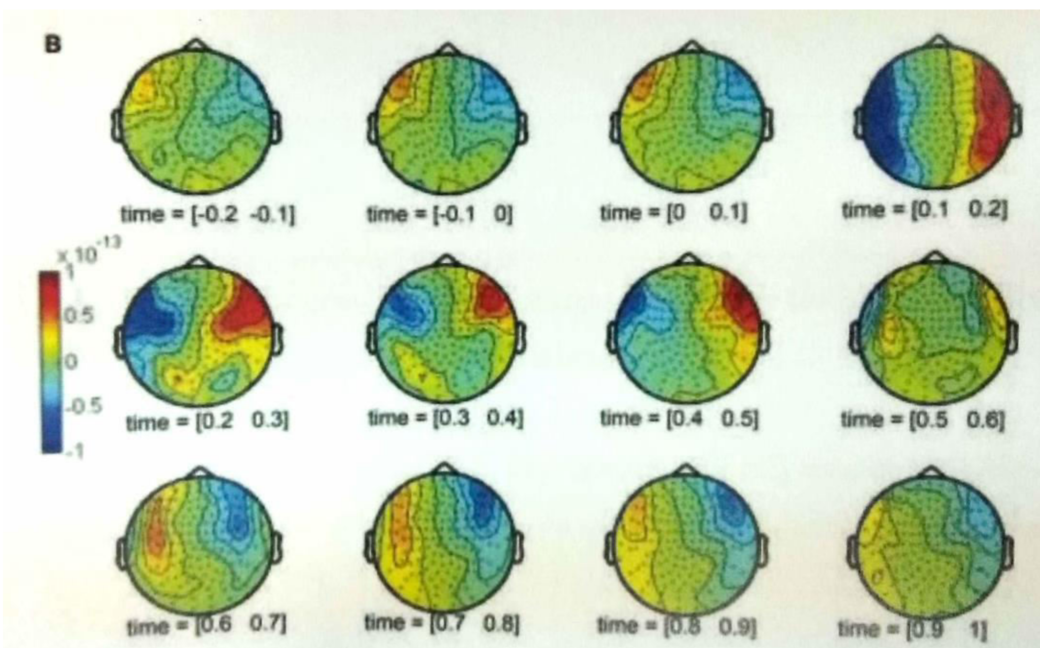



Fig : Topographic representation of the activity in 100ms window from 200ms prior to stimulus onset to 1s after stimulus onset for Not-Beautiful stimuli.

**TIME-FREQUENCY ANALYSIS:**

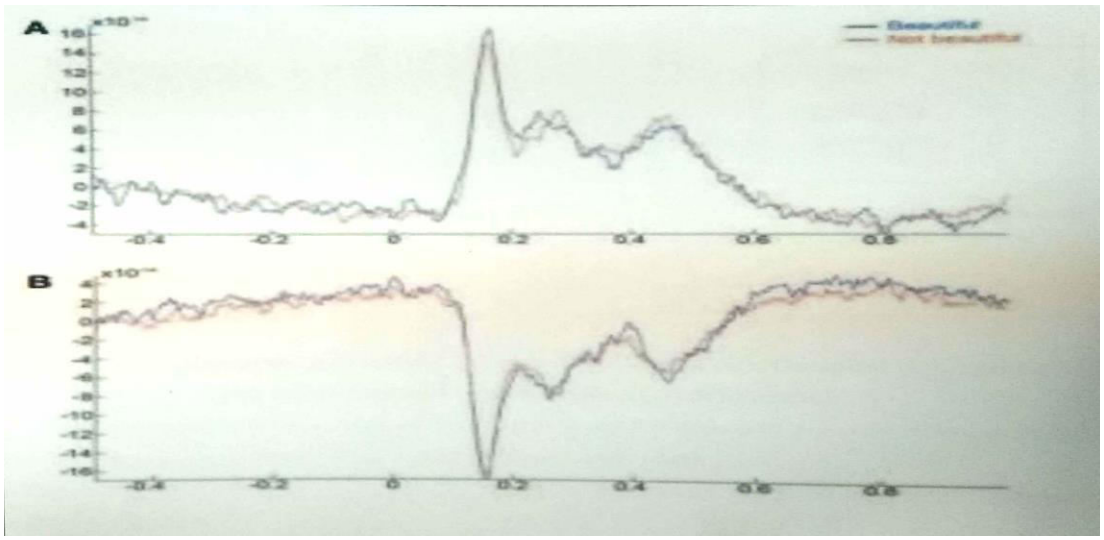



Fig : Time Courses of activity of left and right hemisphere for Beautiful and Not-Beautiful stimuli

A comparison between experimental classes, Beautiful and Not-Beautiful, has been assessed during aesthetic application.

The wavelet co-efficient, W(p,z), obtained as below :

$$X_{CWT}(s,\tau) = \frac{1}{\sqrt{|X|}} \int_{-\infty}^{\infty} \psi^{*}\left(\frac{t-\tau}{s}\right) dt$$

Where S defines the time localization, and τ the wavelet time scale representing the period of the rhythmic component.

Power spectral density of standard frequency band, theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma (30-50Hz) has been calculated. The sensors are grouped into five brain regions : Frontal, Right Temporal, Left Temporal, Occipital, and Central.

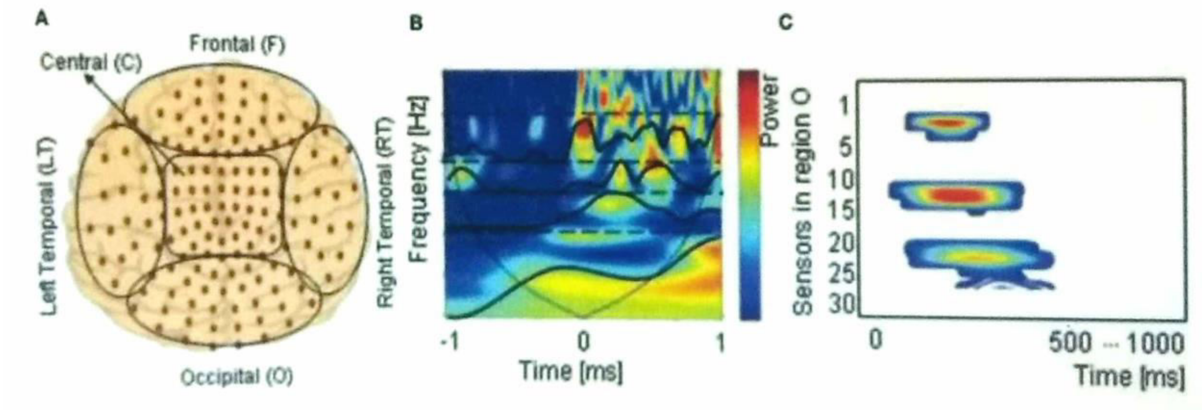
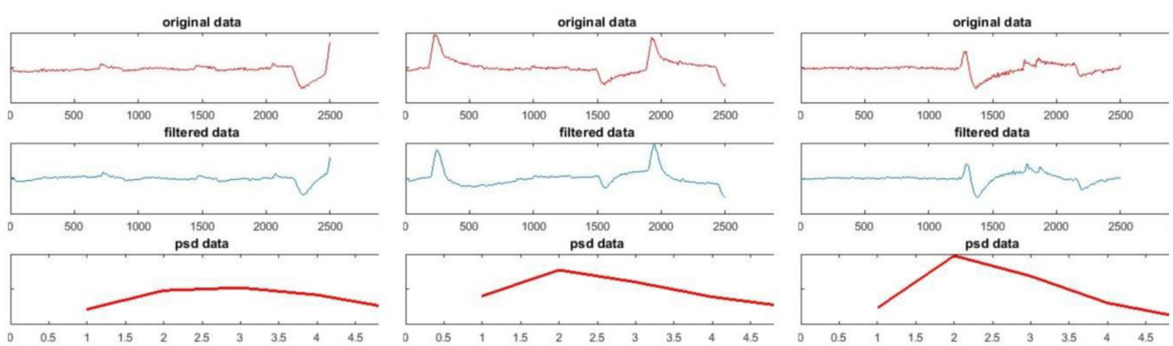



Fig : (A) Human brain's five regions : Frontal(F), Left Temporal(LT), Right Temporal(RT), Central(C), Occipital(O)

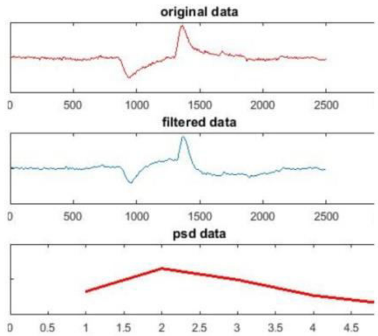
(B) Time-Frequency representation of one sensor from 1s before to 1s after stimulus onset. Frequency scales are averaged in standard spectral bands (dash lines)

(C) The brain region time-spectral band diagram represents the time dependent spectral changes for all channels.

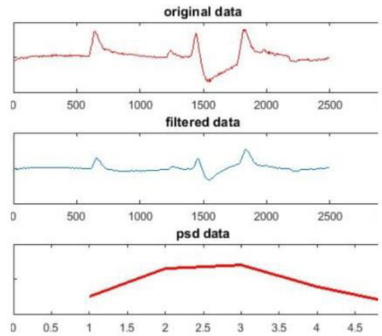
## 3.5 EXPERIMENTAL RESULTS



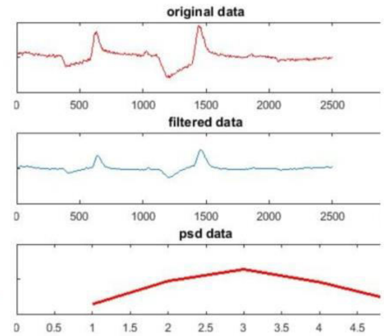

Stimuli face 1 Stimuli face 2 Stimuli face 3



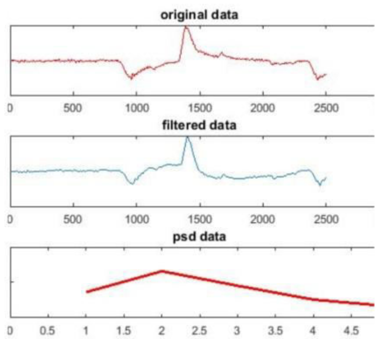

Stimuli face 4



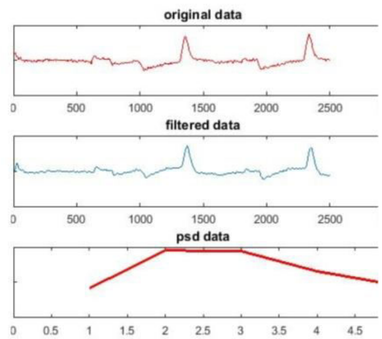

Stimuli face 5



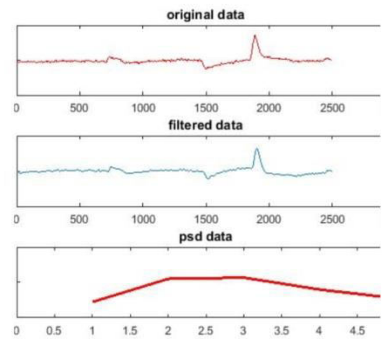

Stimuli face 6



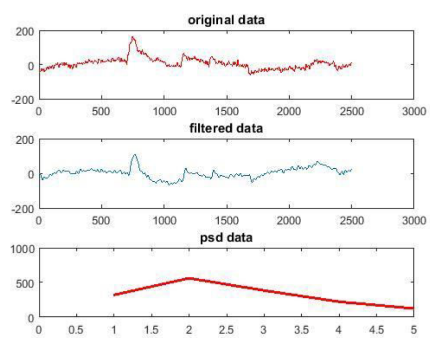

Stimuli face 7




Stimuli face 8

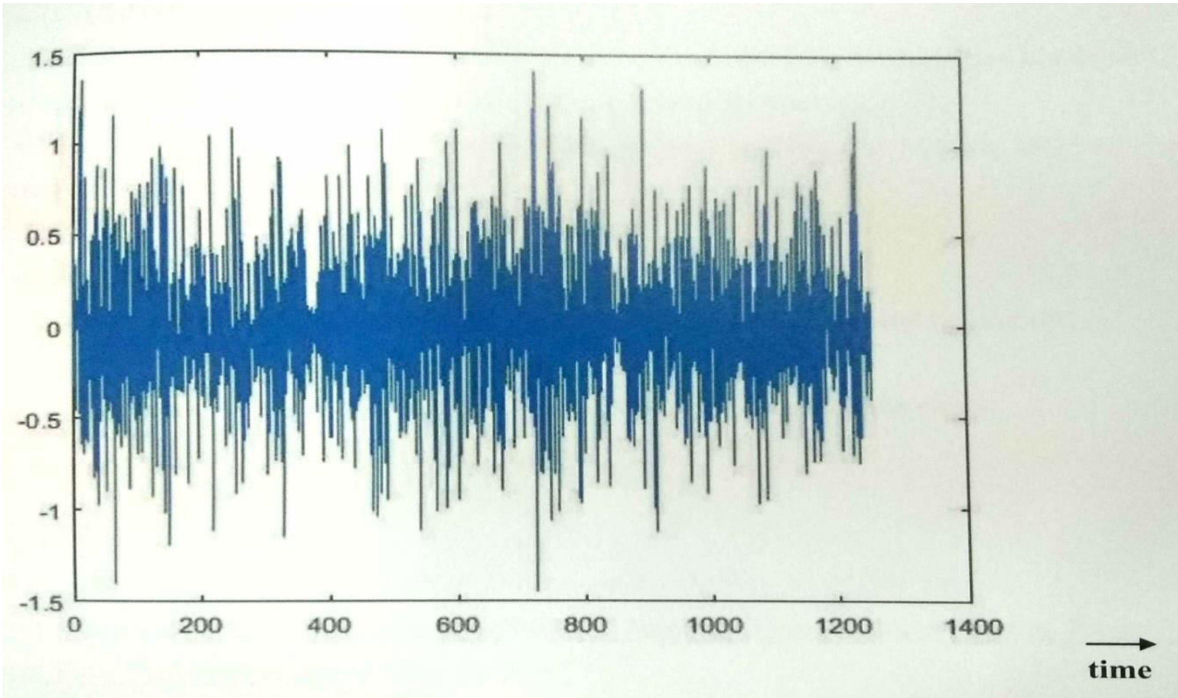



Stimuli face 9



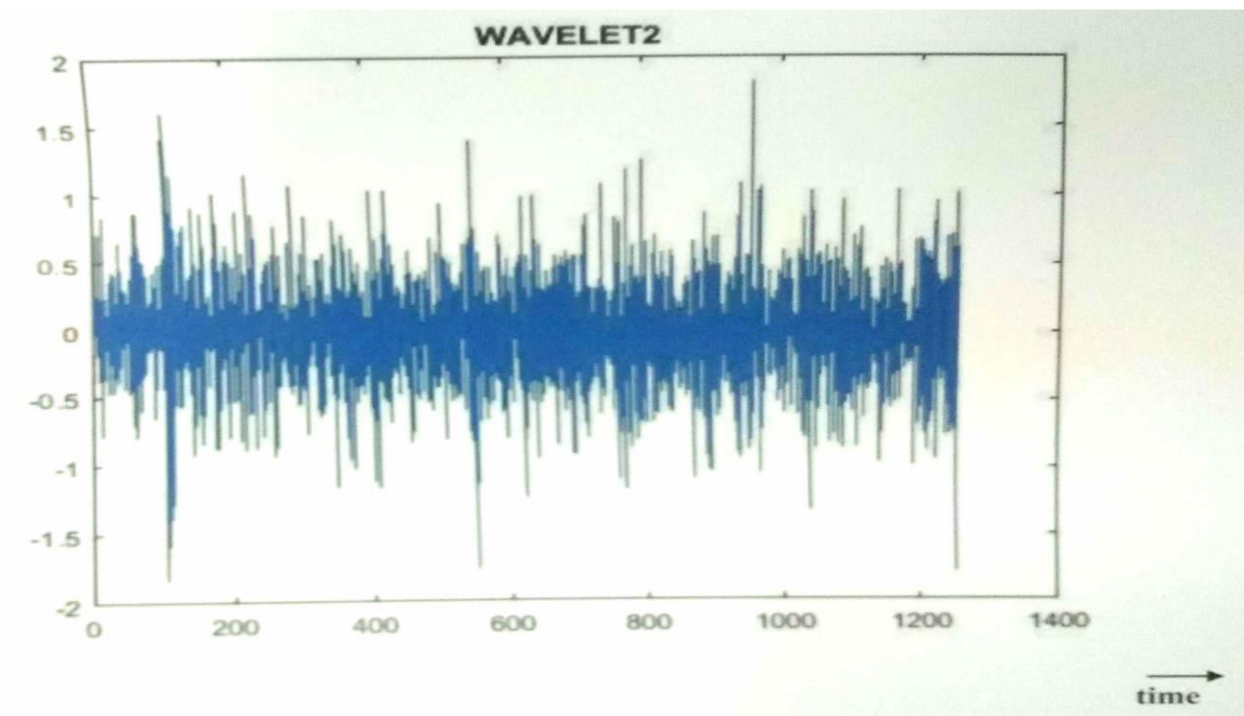

Stimuli face 10

$C_A$ ↑



1.5
1
0.5
0
-0.5
-1
-1.5
0
200
400
600
800
1000
1200
1400
time


$C_D$ ↑



WAVELET2
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
200
400
600
800
1000
1200
1400
time

## 3.6 MATLAB CODEs

- **<u>For PSD</u>**

```
clc

clear all

load('enl.mat')

subplot(2,1,1);

plot(enl(:,1),'r');

title('original data');

f1=filtering(enl(:,1));

subplot(2,1,2);

plot(f1)

title('filtered data');

% L=5000;

% Fs=500;

% [psdp3,freq3]=pwelch(f1,[],[],[],500);

% a1=smooth(psd1);

%

% plot(freq1,a1,'r','linewidth',2)

% xlim([0,5]);

% hold on;

% f2=filtering(Ap4);
```

```
% L=5000;

% Fs=500;

% [psdp4,freqp4]=pwelch(f2,[],[],[],500);

% a2=smooth(psd2);

% plot(freq2, a2,'r','linewidth',2)

% xlim([0,5]);
```

- **<u>For Hjorth Parameter</u>**

```
function c=HjorthParameter(xV)

[row col]=size(xV);

for i=1:1:col

n=row;

% n=length(xV);

dxV=diff([0;xV(:,i)]);

ddxV=diff(0;dxV);

mx2=mean(xV(:,i).^2);

mdx2=mean(dxV.^2);

mddx2=mean(ddxV.^2);

mob=mdx2/mx2;

complexity(i)=sqrt(mddx2/mdx2-mob);

mobility(i)=sqrt(mob);
```

```
end

c=[mobility',complexity'];

end
```

- **<u>For AAR(Adaptive Auto-regressive Parameter)</u>**

```
A = aryule(X,1);

Command window : [A,E]=aryule(E1,20);
```

## 3.7 CONCLUSION

The objective of this study is to determine the brain activity pattern during an aesthetic task in the context of beauty. For this, we performed a Type-II classifier analysis.
Future aspects of this work open us facilities like multi dimensional approach n medical science, neuro marketing, cognitive science etc.

## 3.8 ACKNOWLEDGEMENT

I am sincerely thankful to all the referee(s) for their important suggestions, comments, sharing their knowledge which were really very helpful and useful for the improvement of my thesis work significantly.
Author Contributions: All of the authors provided equal contributions to the work.

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# CHAPTER 4

# CONCLUSION AND FUTURE RESEARCH SCOPES

In this chapter, we reanalyze the primary objectives of the thesis work and briefly summarize the discoveries of the work to support the extent of which the goal of the thesis is achieved and also discussed the scope of future research to the concept of cognitive aesthetics.

## 4.1 SYNOPSIS OF THE THESIS WORK

This paper deals with the scope of aesthetic analysis of subjects for developing better treatments for the patients suffering from physiological/psychological disorder. This thesis provides interesting perception in the different aspects of the development of present day advance BCI system. This thesis primarily centre around the idea of exploring different ideas and advancements of neuronal cognitive of aesthetics to build more sophisticated modalities in BCI. Throughout this research we have thoroughly studied the different techniques of signal processing and observed new avenues of modern applications.

Chapter 1 thoroughly discusses the prime idea and motivation of the research work and briefly summarize the basic concepts of EEG, fNIRS to prepare the backbone of this work. It starts with a introduction to BCI and quickly outlines the history of its evolution. Then it resented the working principle of BCI. Followed by a brief details of the techniques used to measure the brain activity and different types of BCI systems. Then a survey is presented on the processing of the BCI signal. After that, there is a detailed study about the EEG signals processing technique i.e. how does it work, which brain lobes are covered, how to take EEG signals, a brief about the processing technique filters used and finally the advantages and disadvantages. And at last it discusses the fNIRS based BCI technique and the applications of BCI.

In Chapter 2, there is a brief idea about the visual aesthetics. This chapter discusses some recent research works done in this context.

Chapter 3 is focused on the algorithm for the single trial detection of P300 signal. P300 have large-scale applications in modern BCI systems as the EEG response is a unconstrained indication of the attention of the subject which requires no training. Thus, development of classification methods can be done easily. Moreover, detection of P300 in single trial is important for high speed communication of online BCI, without compromising the accuracy of classification greatly. In this chapter, this issue is addressed by taking latency and deflection in account as the main features of P300 signal. The inter-subject and intra-subject variations of the above mentioned features are exploited by utilizing the uncertainty management feature of GT2FS. The secondary membership functions of these type-II fuzzy sets are allotted by taking the density measure of primary membership function into account in the footprint Of Uncertainty. Presence/absence of P300 in the received EEG signal is identified by utilizing the constructed GT2FS. This chapter contains all the experiments and results relevant to objective the research work which confirms the efficiency of the proposed algorithm.

In chapter 4, we have concluded the entire work done throughout the research briefly. It also contains the future directions of research on this particular topic using different methods.

Although the thesis work have shown some really practical and useful results but still adequate scopes of further improvements exits which creates a vast open space of research. Some of the possible research directions are mentioned below.

And finally, the thesis considers analysis of aesthetics by human brain from the constructive perspective only.

# 4.2 FUTURE RESEARCH SCOPES

Future research scopes can be opened up if sample size is increased. Few of the research directions are mentioned below:

1. Visual perception assessment based on Regression analysis for product colour finalization:

Colours evoke the composite psychological reactions and generate relevant feeling; in this way colours play a vital role in decision making of what we like and dislike. It establishes a relationship between human responses and colour appearance characteristics, like lightness, hue and chroma.

2. Designing a 3-dimensional landscape:

Landscape such as ecology, geography, politics, planning, history, arts and designing has been a integral part of the physical characteristics of the environment. Landscape is a complicated phenomenon which continuously unfolds through time and space. Throughout the time, it is the reflection of natural processes and cultural changes. It can be a result of either human involvement in the ecosystem (Cultural Landscape) or natural processes (Natural Landscape). Since we are dependent on the natural sources, degradation of natural ecosystem has now become an important subject in maintainable development. So, natural and cultural landscapes are needed to be protected or the cause of sustainability.

### 3. Refurbishment of paintings:

Refurbishment allows the viewers to visualize a piece of art as complete. Admiration is a cognitive reaction of an individual, which manifest the response of our aesthetic senses.

### 4. Neuro-marketing:

It is an advanced concept of marketing that investigates the human cognitive reactions to stimuli to plan effective and creative commercial campaigns. In case of 90-95% customers, the decision-making process is done in the subconscious mind. In humans, the thought process in the subconscious mind is 200,000 times faster than the conscious mind which in near to 11million bits/sec.

### 5. Computational Aesthetics:

It triggers the problem of ‘aesthetic pollution’ caused by the computerized designs and gives motivations for the improvement of the recent computational methods by appending aesthetic awareness.

In short, the thesis is successfully done and it served all the proposed objectives and have made an important contribution to the research of BCI.