EEG based Brain Computer Interfacing For Color Perception

A thesis submitted in fulfilment of the requirements for the degree of

Master of Engineering
in
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Submitted by

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It is certified that the work contained in this thesis entitled **"EEG based Brain Computer Interfacing for Color Perception"** by **"Priti Hazra"** has been carried out under our supervision and be accepted in fulfilment of the requirement for the Degree of Master of Engineering in Biomedical Engineering. The research results presented in the thesis has not been submitted elsewhere for a degree.

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The forgoing thesis is hereby approve as a creditable study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it is submitted.

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I hereby declare that this thesis contains literature survey and original research work by the undersigned candidate, as part of his Master of Engineering in Biomedical Engineering studies during academic session 2018-2019.

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

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Abstract

Cognitive science, being enriched with different ideas from computer science, neuroscience, linguistic, philosophy and psychology, deals with perception, learning, memory, attention, decision making etc. for studying and understanding the information processing pathways of human brain/mind leading to more effective and efficient Human-Computer Interaction. Perception can be defined as a process which helps us to organize and interpret different sensory informations collected from the environment. As each individual perceives the environment differently, perception is considered as one of the most important features to understand human behaviour. It is an open area of research to predict the biological basis of perception. Human brain perceives three basic primary colors (Red, Blue and Green) differently. So, the corresponding brain signalling pathways for three monochromatic colors is also different. This work provides a non-invasive neuroimaging technique to find out the color signalling pathways of human brain. A probability estimate of signal transition from one brain region to other is determined from repetitive trial. With the help of Dempster Shafer Theory, we fused the graphs obtained from different individuals. These predicted pathways are unique and time-invariant. This method is useful for the diagnosis in abnormal color pathways for people with psychological disorder.

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Contents

List of Figures:

List of Tables:

Abbreviations:

BCI	Brain computer interfacing
EEG	Electroencephalography
MEG	Magnetoencephalography
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near infrared spectroscopy
ECoG	Electrocorticography
PCA	Principle component analysis
ICA	Independent component analysis
PSD	Power spectral density

Dedicated to my parents and my respected teachers

CHAPTER 1:

INTRODUCTION

1.1. Evolution of BCI

1.2. Types to BCI

1.3. Perception

1.4. Brain Regions responsible for Visual and Color Perception

1.5. Importance of Visual and Color Perception

1.6. Scope of the Thesis

1.1. Evolution of BCI

A Brain Computer Interface (BCI) is a communication channel that allows for direct control of a computer by the power of thoughts. In 1924, Hans Berger's [1] discovery of the electrical activity of the human brain and the development of electroencephalography (EEG) was one of the most remarkable and momentous development in the history of clinical neurology. The idea of BCI was first proposed by Jacques Vidal in 1973 in an article entitled "Toward Direct Brain-Computer Communications" [2] at the University of California, Los Angles. In this article we have found the computer processing and interpretation of EEG data in order to implement BCI. In early BCI experiments, invasive BCIs were performed in animals and electrodes were permanently implanted over the pre-central cortex which helped us to understand the non-invasive analysis of the human brain due to technological advancement of neuroimaging [3]-[4]. In 1971, Eberhard Fetz had shown that we can provide visual information to train a monkey to voluntarily control cortical motor activity [6]. Giorgio Ganis had found the brain regions activated for visual perception and the relation between visual imagery and perception [7]. Lingling Yang had investigated how different color stimuli are helpful for BCI applications [8]. Laura Dugue had examined relations between two different brain regions during visual perception [9]. Alumit Ishai had found out the distribution of neural networks that participated in formation of a visual image stored in long term memory [10]. There are some evidences of works in color perception. According to Cajochen, human alertness level can be affected by different colors [11]. Viola stated that subjective alertness and fatigue can be improved in the presence of blue color [12]. Frankline found that colored light helps to improve memory in autistic children [13]. Olurinola proved that in early teen children, retention rate can be increased with the help of colors [14]. Sur stated the role of Posterial Parietal Cortex (PPC) takes an important part in maintaining sensory modality in decision making task [15]. We have tried to re-establish these properties in our experiments.

A BCI is a system that records the changes in brain activity, then process those signals through software that extract some features, then translate those features into a message or command. We mainly perform non-invasive BCIs like EEG, MRI, fNIRs, MEG etc. BCI has six basic steps:

i) **Signal Acquisition:** Here the raw brain signals are recorded which measures the Brain activity [16].

ii) **Preprocessing:** The raw signals are needed to be processed to remove irrelevant Artifacts and Noise [17].

iii) **Feature Extraction:** In this step, we extract the relevant information from the pre-processed signal. Features are like relevant information [17]. For example, Auto-regression of an EEG signal is considered as a feature of that EEG signal.

iv) **Classification:** It is a set of particular feature extracted from the signal. We can get the brain activity pattern for different experiments from these classes.

v) **Translation:** After classification, the result is passed to the translation algorithm. Here, we execute the commands when the given pattern is identified in the brain signal.

vi) **Feedback:** After translating into command, a feedback is given to the subject for recognizing brain activity pattern. According to Neuper et. al.“ Controlling BCI is a skill that must often be learned”[18].

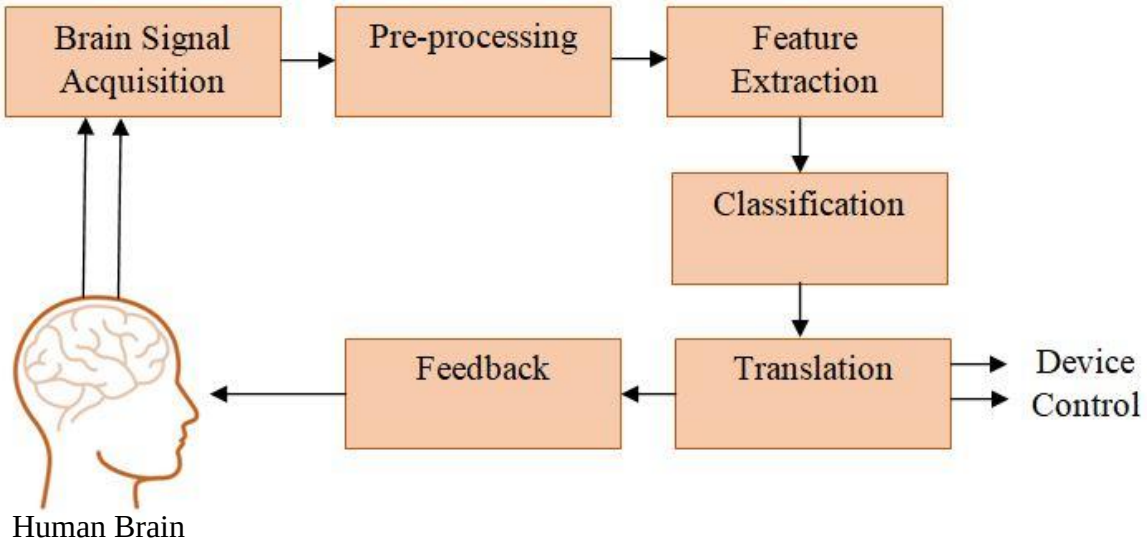

Fig.1: Schematic of a conventional BCI system

A BCI is needed to record and decode brain activity. Human brain is filled with neurons where each Nerve cell is connected to each other by axons and dendrites. Nerve cells communicate with each other by the means of electrical signals. We need an accurate communication between the brain cells and muscles for all kind of communication.

EEG is the most commonly used non invasive signal acquisition techniques used for BCI. We place the electrodes on the scalp by which we can acquire the brain waves. In EEG, we use non invasive sensors by which we can record brain waves. In invasive BCI, the electrodes are needed to implant under the scalp for which we have to undergo a neurosurgery. This is the main drawback for invasive BCI.

In BCI different stages need to be implanted. First, we acquire brain signals with the help of electrodes placed on the scalp. The recorded raw data is then preprocessed and filtered as per the requirement. Different filtering techniques are used to remove noise and unwanted artifacts from the signals acquired from different electrodes and to improve the signal activity. Different additional algorithms are also used to remove unnecessary information. Again, the software must be about the meaningful information according to the task the subject is going to perform. Then the output signal is feed to an external device that is any prosthetic device or monitor or any other application based device. If the subject performs any kind of task, then we can see the brain waves in the computer screen. Prosthetic Limbs are helpful for any kind of movement of the subject. Prosthetic devices are also helpful for differently-able persons. It is a very important part of BCI which transforms the output signal into an action.

Every BCI does not need a feedback. If we want to find out how human brain reacts to certain stimuli (visual, auditory, tactile, olfactory), we can replace a feedback by a stimulus presentation. BCI cannot be used to translate thoughts. It is not a mind reading device. BCI system can detect and classify certain brain activity patterns produced by the subject.

1.2. Types of BCI

Depending upon Different properties, BCIs can be categorized in the following sets. The main purpose of BCI is to interpret electrical signals generated by neurons in the brain.

i. ***Active, Reactive and Passive:*** When the user can control and direct the brain activity consciously then it is known as an active BCI. When an external stimulation is provided to the user and its corresponding brain activity is being recorded then it is

referred to as reactive BCI. Passive BCI relies on the recording of arbitrary brain activity and analyzing brain parameters in real time [19].

ii. ***Invasive, Non-invasive:*** In Invasive BCI, the data is collected from inside the body. To place the electrodes weed in human brain, the subject has to undergo some kind of surgery. In non invasive BCI, we measure the surface data, mainly collected from the scalp [20].

iii. ***Dependent, Independent:*** In dependent BCI, the user can control the system with the help of EEG signals acquired from the scalp. In independent BCI, user is not able to control the BCI system with the help of brain signals [21].

iv. ***Synchronous, Asynchronous:*** If the phase of the BCI signal is governed by the system, then it is known as synchronous BCI. At specific time interval, the user can control the BCI. In asynchronous BCI, the brain system interaction can be performed at any time [22].

v. ***Hybrid:*** In hybrid BCI, we combine two different interfaces. A Hybrid BCI either relies on two different brain signals or one brain signal for two different tasks or one brain signal and one external stimulus [23].

1.3. Perception

Different Sensory organ of human body constantly collect information from the surroundings and we always interpret those information that affects our interaction with the outside world. Perception refers to the process by which we can organize, interpret and experience those sensory information. Perception can be divided into two steps.

- Collection and processing of sensory input
- Processing connected with the person's knowledge or past experience or memory.

We can gain Information about the environment through the perceptual process. Perception does not only help us to gain experience, it permits us to act within the surroundings. But perception is different from sensation. Scintillation is a process by which we come to know about the environment through different sensory organs. Sensation is the uninterpreted signal collected from the surroundings. Perception is the process by which we can interpret those raw signals.

Perception is an arrangement, recognition and explanation of the sensory information collected from the environment in order to express and realize the surroundings. Perception consists of five major senses semicolon visual, hearing, test, smell and touch. Each observation involves different kind of signals acquired by our sensory organs and the result from different physical and chemical process of sensory system. Visual perception initiates when the light waves reflected from the object falls on the retina visual perception is related to different color, line length and intensity of light and motion of the object. Hearing is the capability to identify sound and by detecting vibration. It includes sound and speech perception. Those two are the process by which we can perceive sound from different sources. Taste perception is the ability to discriminate different flavors of food. We receive different tastes through taste buds, concentrated on the upper surface of the tongue. Perception is the ability to perceive different fragrances through the nose. A little touch moving across the skin produces tickle sensations is known as touch perception. The process of recognizing object from touch perception is known as Haptic perception. This is concentrated on visual and color perception.

1.3.1. Visual Perception

Visual perception is the ability to understand the surrounding using the light waves reflected back from different objects present in the environment. Light waves must be in the visible spectrum. Visual perception is the ability to understand the surrounding using the light waves reflected back from different object present in the environment. The light waves must be in the visible spectrum. Cornea is known as the window of the eye which helps the light rays to enter the eye. By controlling the diameter and size of the Pupil, Iris determines the amount of light entering the retina. Then the clear crystalline lens helps to focus on the light rays. Light

sensitive photoreceptors are present in the retina which has two different kinds of cells; rods and cones. Rod cells help in the vision in low light while cone cells are sensitive to color and responsible for detection of fine details. When light falls on the retina rod cells transform the light waves into electrical signal. With the help of optic nerve, the electrical signal then goes to the occipital lobe and different parts of cortex through side pathways of human brain (Fig. 2).

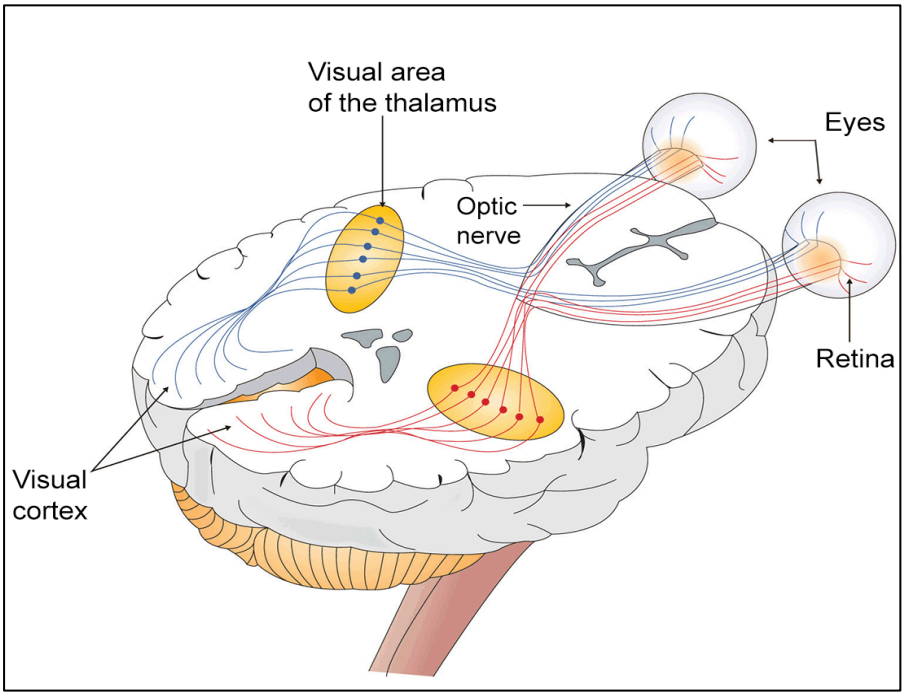

Fig. 2: Acquisition and propagation of visual information

An example of visual perception could be given as a sound of fire alarm. The sound of the alarm is the distal stimulus. This sound then stimulates a person's auditory receptors, then it is known as proximal stimulus and human brain interpret this sound. The ability to recognize the sound as the fire alarm is known as percept. There are two types of processes in perception:

- **Bottom-up processing:** In bottom up processing, section initiate as the external stimulus is given. It is a data-driven process. What we perceive is solely based on what information is coming in. It is a unidirectional process. It takes the raw information and constructs the perception necessarily [24].

- **Top-down processing:** In this processing, perception is based on knowledge and previous experiences. It is based on the use of contextual information. This kind of

perception is conducted by cognition. To construct a particular image, first brain applies its knowledge and then we need to fill the blanks with the help of perception [24].

Bottom Up Processing	**Top Down Processing**
Sense-driven	Schema-driven
Rely on collected information	Rely on knowledge and experiences
Lower level cognition	High level cognition
Organizes information	Interprets information

Table 1: Bottom-Up and Top-Down processing for visual perception

1.3.2. Color Perception

Newton stated that color is not ingredient in different object. The surface of a particular object reflects some colors and absorbs all other colors. We can see only the reflected colors. If two persons look at the same object and the same wavelength coming from that object hit their eyes, they see different colors. Different persons perceive colors differently. Human retina consists of rod cells and cone cells. Cone cells are sensitive to color. For three different primary colors, we have three types of cone cells which are responsible for producing one particular type of electrical responses to fundamental colors: red, green and blue [25]. The cones are labeled according to their order of the wavelength of the peak (Fig.3) in visible spectrum. Peak wavelength for blue color is 424-440nm, it is known as short (S) cone; Peak wavelength for green 434 color is 534-555nm, it is known as medium (M) cone and Peak wavelength for red color is 564-580nm and it is known as long (L) cone [26][27]. The value of peak wavelengths of different cone cells varies, even among persons with normal color vision [28].

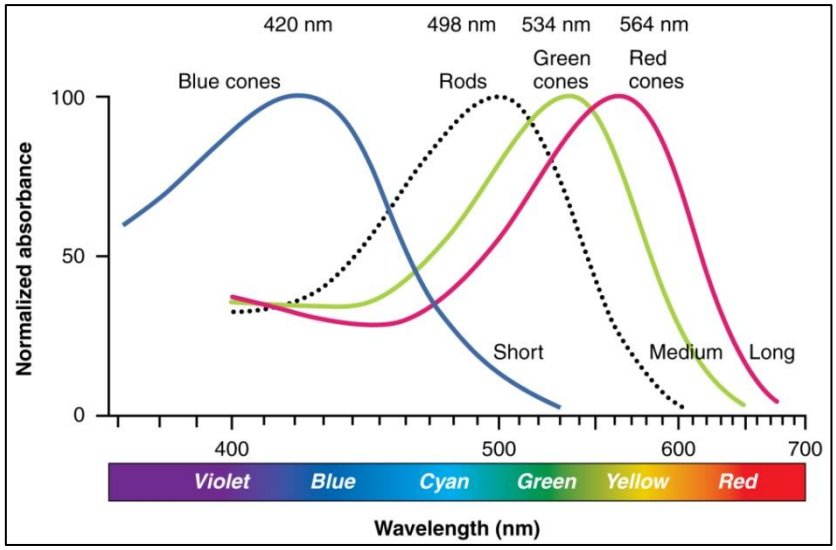

Fig. 3: Absorbance peak for different colors

Different evolutionary factors highly dominant color perception. Color perception helps herbivorous primate to find immature leaves. In nocturnal mammals, color vision is not well developed because they have to see properly in low light. Ultraviolet light has an important role in color perception in animal Kingdom, especially in the insects. Some animals have the ability to differentiate colors in the ultraviolet spectrum.

Two or more primary color or mixed together which forms a new color. Each primary color excites the cone cells responsible for that particular color. Depending on the wavelength, the light can excite two or more cone cells which help to perceive a completely new color, a mixer of primary colors. The perception of yellow color is produced by the concurrent stimulation of green and red. The perception of cyan is generated by the synchronous of blue and green cones. Parallel stimulation of red, green and blue cones bring the perception of white (Fig.4).

The concept of color subtraction is based on the selective absorption of particular wavelength. If we see a white light through a yellow filter, it will absorb blue and transmit red and green color. So we can call yellow a -B filter. A magenta filter subtracts green, so it is a -G filter and a cyan filter can be called as -R filter (Fig.4) [29].

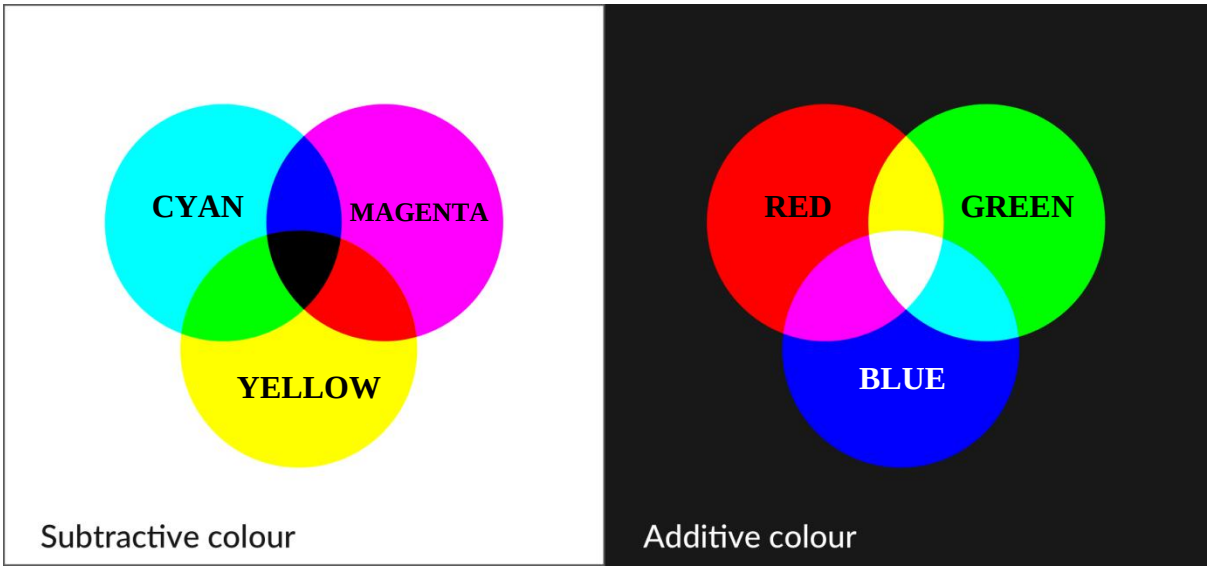

Fig. 4: Additive and Subtractive color mixture

1.4. Brain regions responsible for visual and color perception

Human Brain is the main Processing Unit of nervous system. It receives signals from organs and commands the responsible body parts to work accordingly. Brain is the most complicated organ of human body. It consists of more than 100 billion single cellular neurons that communicate with the help of trillion synapses. Fig. 5 shows different lobes of human brain.

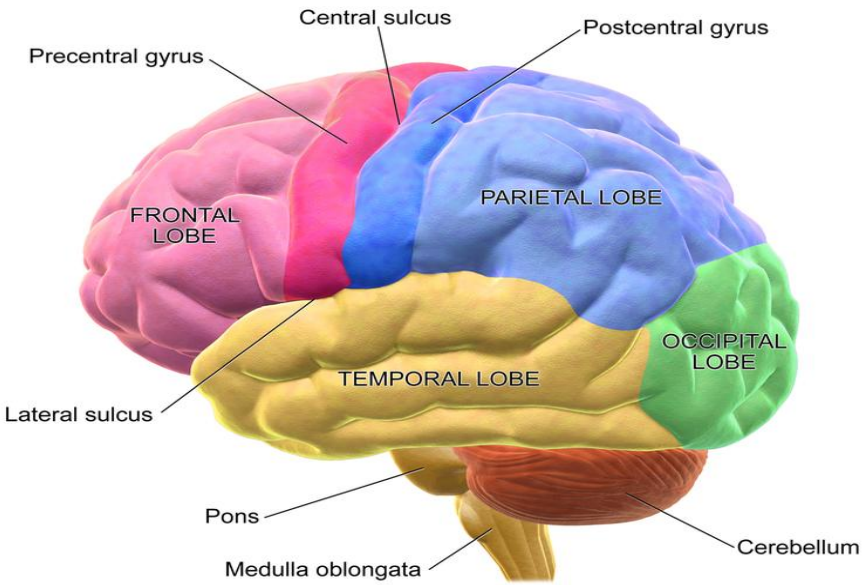

Fig. 5: Lateral view of human brain

- The **Frontal Lobe** is situated at the front of the brain responsible for motor skills, higher level cognition [30], problem solving and judgment. Motor cortex is located at the back of the frontal lobe, near the central sulcus. This area of the brain collects information from different lobes of brain and utilizes those information to conduct body movements.

- The **Parietal Lobe** is located at the middle section of the brain and helps to process tactile sensory information such as pressure, pain and touch [31]. Somatosensory cortex is located in this lobe which plays an important role for the processing of acquired different senses.

- The **Temporal Lobe** is located on the bottom section of the brain and involved in the interpretation of sound and languages [32]. This is the location of primary cortex. Hippocampus is also located in temporal lobe which is associated with the formation of memories.

- The **Occipital Lobe** is located at the back portion of the brain and helps to interpret visual stimuli and information [33]. Damage to this lobe can cause visual problems such as difficulty recognizing objects, an inability to identify colors, and trouble recognizing words.

Occipital lobe is one of the four main parts of cerebral cortex. The occipital lobe is located at the posterior part of the cerebral cortex. Occipital lobe is responsible for visual processing. Posterior region of the parietal lobe and temporal lobe also help in visual perception [34]. The main Functional area of occipital lobe is the primary visual cortex. It contains the occipital areas of the ventral stream (V2 and V4) and the occipital areas of the dorsal stream (V3 and V5) and the Dorsomedial area. Visual cortex is situated in the occipital lobe. Optic nerves go directly to the primary visual cortex from the retina. Visual stimulus coming from retina propagates through the lateral Geniculate nucleus in the thalamus and then reaches the primary visual cortex, known as visual area 1 (V1, Broadman area 17) and the striate cortex. The extrastriate regions consist of visual area 2 (V2, Broadman area 18), 3, 4 and 5 (V3, V4, V5, Broadman area 19) (Shown in Fig. 6) [35].

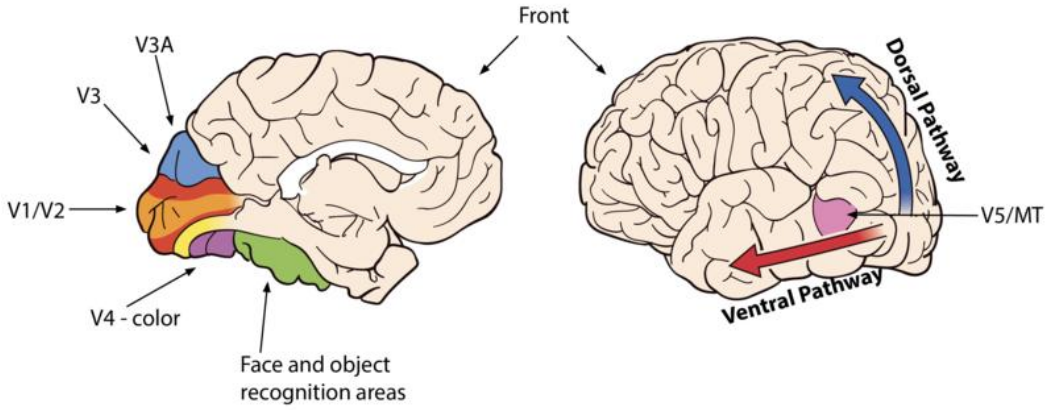

Fig. 6: Brain regions responsible for visual and color perception

Ventral stream is responsible for what or which thing is present in vision and the dorsal stream is responsible for where and how. The ventral stream helps to retrieve information for the particular stimuli that is stored in memory. With the help of the information in memory, the dorsal stream concentrates on motor action to make an output response for the stimuli. Ventral and dorsal system does not depend on each other. There is evidence that both are important for perception of complex stimuli.

Color centre is the region of human brain responsible for the processing of color signals. The color centre is located in the ventral stream of occipital lobe. Multiple brain areas including Fusiform Gyrus and the lingual Gyrus are activated when cholesterol falls on retina. These areas are labeled as visual area 4 (V4). Multiple areas of V1 are colour sensitive, which suggest that interpretation of colour stimuli is not restricted in one particular region [36]. V1 consists of two different kinds of colour sensitive neurons: single opponent and double opponent cells. Single opponent neurons respond to huge portion of colour. Double opponent neurons respond to textures, colour boundaries, edge, and shape [37] [38]. Three different cone cells, small (S) , medium (M) and long (L) perceive different wavelengths in the visible spectrum. Single opponent neurons are divided into two class: L-M neurons and S/(L+M) neurons. L-M neurons perceive information from long wavelength cones and opposed by the medium wavelength cones. S/(L+M) neurons accept input from S cones and is opposed by the addition of L and M cones [39].

1.5. Importance of Visual and Color Perception

Paying attention, differentiation, numbering things, interpretation of knowledge these are the common cognitive processes. Cognitive processes are the activities that influence our mental health. Visual perception is very important thing in cognitive processing. It helps to collect information from the environment, organize dose information in the human brain and interpret it. Graphical section defines the potential of people how they can express and explain the visual graph send evaluate the contents of the graph [40]. Graphical perception plays an important role in data visualization. It helps to increase the quality of the graph and quantity of the visualized information. If a low level system can be utilized during visual perception, it helps people to concentrate more on possible concern [41].

Visual perception plays an important role in different cognitive processes, such as attention, learning, discrimination and memory.

- **Attention:** Attention helps us to focus on certain things and it is the pillar of learning. Visual perception helps us to avoid disturbances in the surroundings in order to concentrate on certain things.

- **Learning:** Visual perception conduct crucial role in learning new things. Learning helps us to acquire knowledge. Poor visual perception makes it difficult. Difficulties in visual perception mix it tough to distinguish between foreground and background.

- **Discrimination:** Visual Perception helps us to discriminate certain things we observe. The performance of visually impaired patients discriminate certain objects is relatively low [42].

- **Memory:** The introduction memory and visual perception plays a crucial role in acquiring knowledge from the environment. When the external visual stimulus is disappeared, visuospatial working memory is accomplished buy extended activation occipital and parietal lob, via attention [43].

Researcher David Hubel stated that " It translates light into Nerve cells, allows us to see under conditions that range from starlight to sunlight, discriminates wavelength so that we can see colors, and provides a precision sufficient for us to detect the human hair or speak of dust a few yards away" [44]. Color conducts a crucial part in visual memories. Light provides an important role in color perception. It is the light reflected back from the object which is perceived by human brain. Perception of color fades with increasing age. Color perception is not inherent, we learn it time. Human color memory is also very poor. When we recall color memories, we can have a strong significance on simultaneous recognition of color [45] [46]. The effect of color memory can be accomplished if different objects are uniformly colored in a frame or one object is given in isolation [47]. Previous researches establish that the color memories stored in human brain can dominate color perception. Functional imaging methods of human brain show identical activity for color imagery and color perception. But the results are highly uncertain. Researchers have found that color imagery and color perception affect same neural areas [48]. Color perception and color imagery engage similar mental processing [49].

1.6. Scope of the Thesis

This thesis attempts to realize a BCI model which acquires EEG signals for visualizing three monochromatic colors as input, removes noises and unwanted artifacts present the signal and extracts significant EEG features from the filtered data and finally determines the brain signaling pathways of those basic colors and provide a biological basis of color perception.

CHAPTER 2:

EEG based BCI

2.1. Generation of Action Potential

2.2. Different Brain Signal Acquisition Techniques

2.3. Merits and Demerits of EEG

2.4. Working Principle of EEG

2.5. Different EEG waveforms

2.6. Application of EEG based BCI

2.1. Generation of Action Potential

The main component of brain is the neurons or nerve cells, which are also known as brain cells. It conveys information by electro - chemical signaling. Neurons can never be divided; neither can be replaced by new one. Human brain consists of about 100 billion neurons and 10 times neuroglia. It passes signals trough 1000 trillion synapses, which is equivalent to a 1 trillion bit per second processor. Memory capacity of human brain berries from 1 to 1000 terabytes. A typical neuron consists of a Soma (cell body), dendrites and a single axon. The Soma or cell body contains the cell nucleus; in order to make the cell active, dendrites receive information from the neighboring neurons and a single long action carries electrical impulses away from the cell body. Synapses are the intermediate space that allows a nerve cell to convey an electrical or chemical message to the other nerve cell. Every nerve cell is surrounded by a plasma membrane. It is a bi-layer of lipids molecules. Plasma membranes are formed of two classes of molecules - proteins and lipids. Different types of proteins are embedded in this bi-layer membrane. A lipid bi-layer acts as an electrical insulator but some protein structures embedded in the membrane is electrically active. Ion channels permits electrically charged ions to move across the membrane. Some channels can be opened or closed by adjusting the potential difference across the membrane [50].

Membrane potential refers to the electrical potential difference between the inner and the outer part of a cell. Ions can drive the signals within Nerve cells. Sodium (Na^+) and potassium (K^+) ions are the most responsible cations for action potential. Ion move across the cell membrane under two conditions: Diffusion and electric field.

Because of the presence of lipid molecules, plasma membrane acts as an electrical insulator. There are some molecules present in the membrane which are electrically active and they help in transporting ions from one side of the membrane to the other [51]. The plasma membrane has a thickness of about 7-8 nanometers. So it does not require a huge transmembrane voltage to make a strong electric field within it. Dielectric breakdown could be caused by voltage difference greater than 200 milli volts.

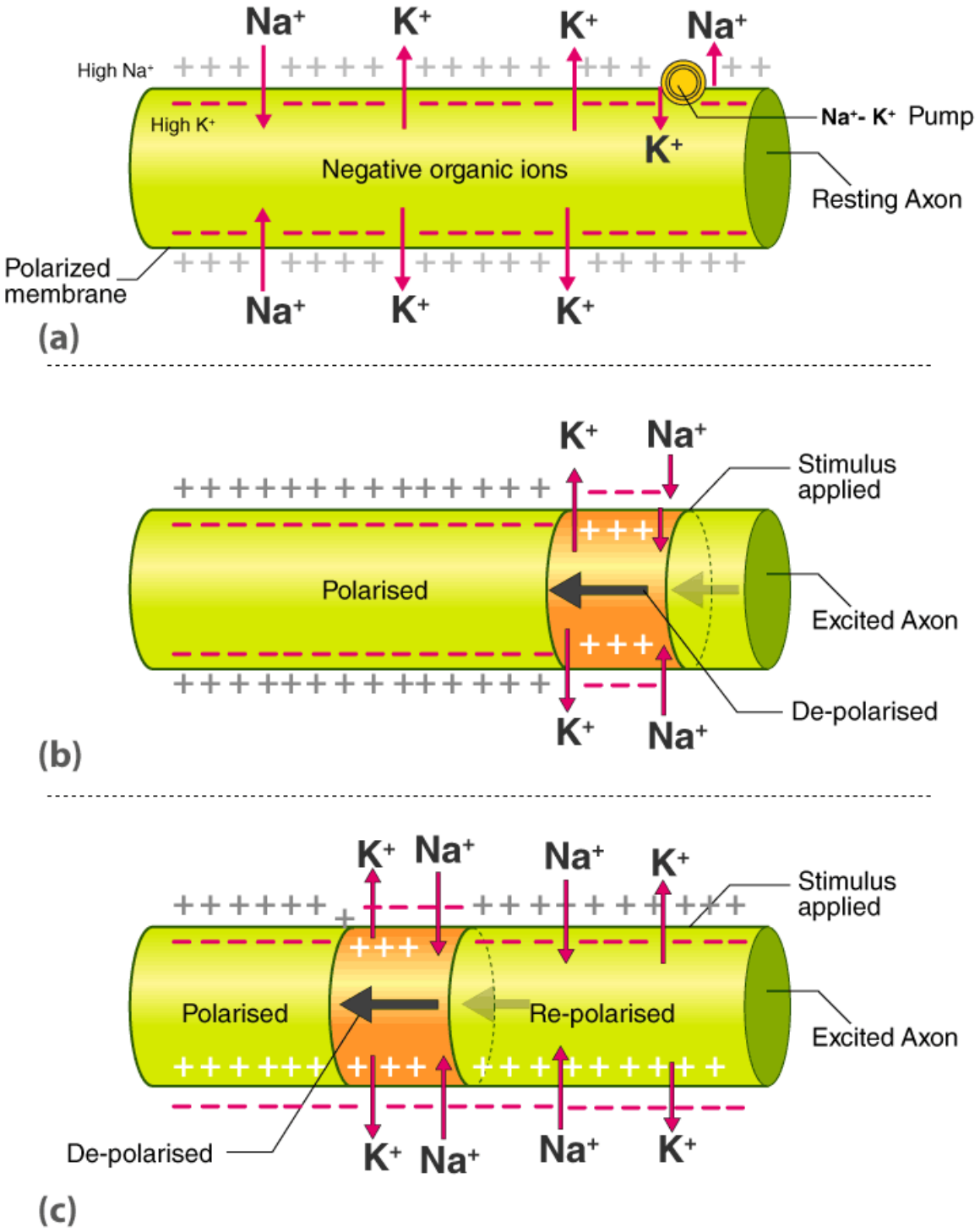

Fig.7: Propagation of action potential

Ion pumps are the essential part of cell membrane. They use cellular energy ion against the concentration gradient [52]. The most relevant on pumps responsible for the generation of action potential is known as Sodium-Potassium pump.

Protein structure embedded in the bi-layer membrane has a pore, which helps the ions to move from outside to inside of the cell. These ion channels are selectively permeable. Voltage sensitive channels are responsible for action potential; ligand-gated channels are responsible for binding of ligand molecules (neurotransmitter). Fig. 7 shows the propagation of action potential.

2.1.1. Resting Potential:

The static membrane potential of an inactive cell is known as resting potential. If we provide an external stimulus to the non-excitable cells, the resting membrane potential can be changed. When a nerve cell is at rest, the inside of the cell is relatively negative compared to the outside of the cell. The concentration of different ions tries to balance the potential on the both sides, but they cannot because the cell membrane is selectively permeable to different ions. Different ions present in the system influence the formation of resting potential. For most cells the dominating ion is potassium. Potassium has the most negative equilibrium potential. The resting potential cannot be more negative than the equilibrium potential of potassium.

For different cells, the resting membrane potential is also different (Table 2).

Cell Type	Resting Potential
Skeletal Muscle Cell	-95 mV
Nerve Cell	**-60 to -70 mV**
Smooth Muscle Cell	-60 mV
Hair cell	-15 to -40 Mv
Photoreceptor Cell	**-40mV**

Table 2: Value of resting potential for different cell type

2.1.2. Action Potential:

An action potential is generated due to the prompt increase or decrease of membrane potential of a particular axon [53]. In resting state, the membrane potential increases due to the selective permeability of the membrane to potassium ion (K^+). When

dendrites receive an external stimulus, the Na^+ channels open and an increase in membrane potential takes place. The threshold value is -60mV (Fig. 8). The charge inside the cell rises from negative to positive as the sodium ions flow back in the cell. This is known as depolarization. Due to this, the inner cell potential rises upto +30mV. The action potential takes place only if the threshold is reached. Once the depolarization takes place, the sodium ion channels are closed. The increased potential inside the cell causes the potassium channels to open. Potassium ions now flow back to the outside due to electrochemical gradient. The membrane potential repolarizes toward resting potential. This is known as repolarization. The membrane potential decreases upto -90mV which is known as hyper-polarization. The action potential propagates through the axon via depolarizing current. The action potential travels only in one direction.

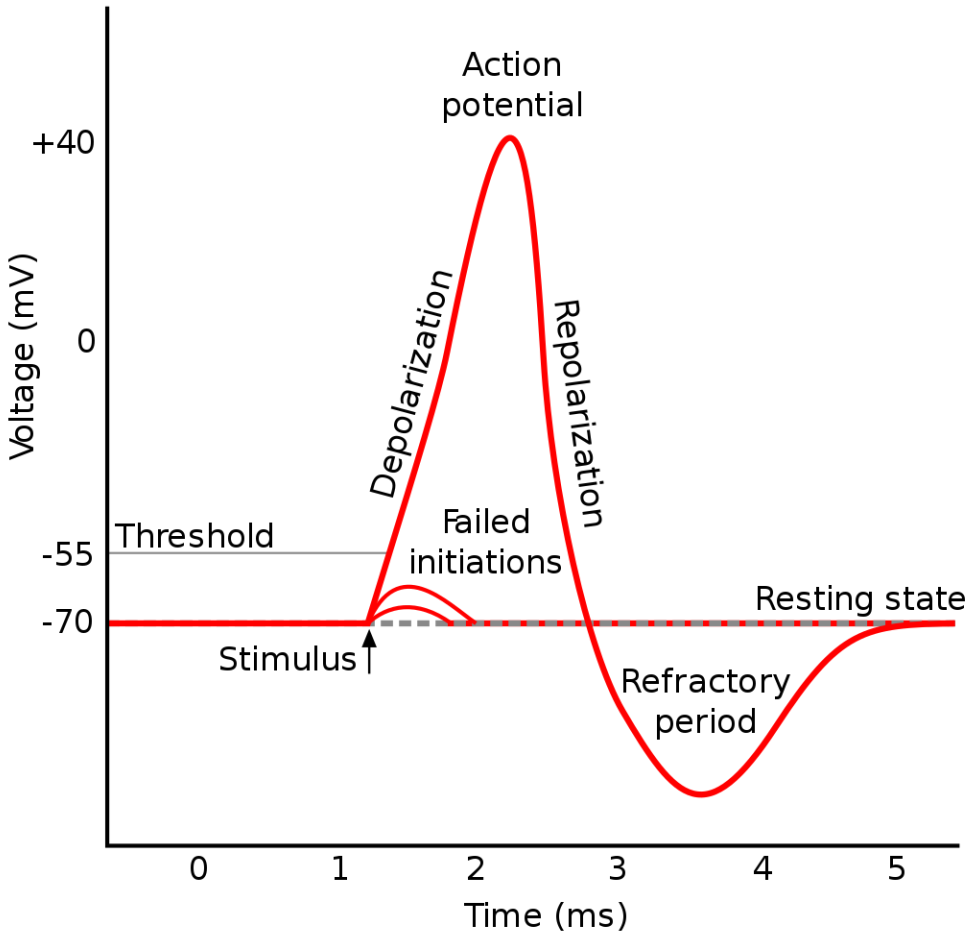

Fig.8: Different stages of action potential

2.2. Different Brain Signal Acquisition Techniques

In Brain Computer Interfacing, an external device can be controlled with the help of brain signals acquired from different electrodes. It allows movement of data [54]. Research on BCIs started at the University of California, Los Angeles in the 1970s [2]. There are non-invasive and invasive ways of acquiring brain signals.

- In non-invasive techniques, the signals are collected from the outer surface of the body. To acquire brain signal, we place the electrodes on the scalp to record the brain's electrical activity. We don't need to perform any kind of surgery to place the electrodes. But here we have to record the brain signals away from the source. So, the amplitude of the picked signal gets reduced and the signal can be easily affected by unwanted artifacts.

- In invasive BCI, the electrodes are placed inside the body and near to its location of initiation. So, the signal quality is much better than non-invasive techniques. To place the electrodes, the subject has to undergo some kind of surgery.

    - In Electrocorticogram, the skull of the subject is opened and an array of electrodes is being placed on the exposed skull. But it does not affect the brain cells. The signal quality is more improved.

    - In Deep Brain Recording, microelectrodes are being placed deep inside the brain. This is the most invasive technique to record brain signals. The microelectrodes destroy the neurons, coming in its way. The advantage of this technique it that the brain signals can be recorded from well defined spatial locations.

2.2.1. Electroencephalography (EEG):

Electroencephalography (EEG) is a non-invasive method to record brain's electrical activity. The neurons in human brain forms ionic current which leads to difference in potentials [55]. EEG measures those voltage fluctuations to record brain activity. BCI

system does not depend on the performance of peripheral nervous system and also independent of evoked potentials [56]. EEG is mainly used to diagnose epilepsy, which can be predicted with the abnormality is present in EEG recordings [57]. EEG is also helpful to diagnose brain tumor, stroke, inflammation of the brain, internal brain damage due to head injury, sleep disorders etc. It is also used to confirm brain death.

2.2.2. Magnetoencephalography (MEG):

Magnetoencephalography (MEG) is a direct measurement of brain signal which measures the magnetic fields formed by electrical currents. MEG measures the accumulated effect of ionic currents, generated in human brain, passing through the dendrites at the time of synaptic transmission. Approximately 50000 neurons are needed deactivated at the same time produce a measurable signal [58]. Action potentials are unable to produce a measurable magnetic field the currents produced by action potentials flow in the reverse direction and it cancels out the magnetic fields. The action fields are measured from the peripheral nerves. It is used to detect locations of abnormalities in the brain and also to measure brain activity [59].

2.2.3. Electrocorticography (ECoG):

In Electrocorticography (ECoG), we have to place the electrodes on the surface of exposed brain to record electrical activity of the cerebral cortex. We have to perform craniotomy for the implementation of the electrode grid inside the skull. ECoG signals measures the synchronized value of postsynaptic potential. The sources of the signal are pyramidal cells, cerebrospinal fluid, pia mater and arachnoid mater. It allows a direct stimulation of the brain which helps to identify critical regions of the cortex. It is also helpful to implement brain computer interfaces. But ECoG does not cross the blood brain barrier like other invasive recording devices. It has high Signal to Noise ratio and high spatial resolution [60].

2.2.4. Functional Magnetic Resonance Imaging (fMRI):

Functional Magnetic resonance imaging (fMRI) records brain activity by measuring the changes linked with blood flow [61] [62]. When a region of the brain is activated, blood flow increases in that particular brain area [63]. fMRI uses the principle of blood oxygen level dependent (BOLD) contrast, invented by Seiji Ogawa 64. This method is helpful to map neural activity of brain or spinal cord by measuring the change in blood flow. Hemoglobin is present in red blood cells, which carry oxygen. Deoxygenated hemoglobin is paramagnetic and oxygenated hemoglobin is diamagnetic. This difference to form an improved Magnetic resonance signal [62]. fMRI helps to map the brain anatomically to detect alzheimer's, Autism and different kind of head injury [64].

2.2.5. Functional Near-Infrared Spectroscopy (f-NIRS):

Near infrared Spectroscopy (NIRS) is approach to diagnose blood sugar, pulse-oximetry, functional neuroimaging, and rehabilitation, to implement brain computer interface with the help of near infrared region of the electromagnetic spectrum (780-2500nm) [65]. Functional near infrared spectroscopy (fNIRS) is used in the purpose of functional neuroimaging to measure the brain activity through hemodynamic responses. Skin, tissue, and bone are mostly transparent to NIR light but haemoglobin and deoxygenated haemoglobin can observe this light. This difference in absorption spectra deoxygenated haemoglobin and oxygenated haemoglobin helps to measure the present in haemoglobin concentration level. NIRS is a non invasive technique to measure brain function. It is portable device.

Neuroimaging method	Activity Measured	Direct/indirect Measurement	Temporal Resolution	Spatial Resolution	Portability
EEG	Electrical	Direct	~0.05s	~10mm	Portable
MEG	Magnetic	Direct	~0.05s	~5mm	Non-Portable
ECoG	Electrical	Direct	~.003s	~1mm	Portable
fMRI	Metabolic	Indirect	~1s	~1mm	Non-Portable
fNIRS	Metabolic	Indirect	~1s	~5mm	Portable

Table 3: Comparative study of different brain signal acquisition techniques

2.3. Merits and Demerits of EEG

❖ **Merits**

- Hardware cost is relatively lower than other commonly available techniques [66].
- EEG sensors can be reused in fMRI, ECG, MEG etc.
- Temporal resolution of EEG is very high, in the order of milliseconds. EEG has the ability to record data at sampling rate higher than 20,000 Hz [67].
- EEG is comparatively unbiased of subject movement. Different methods are there to eliminate or remove movement artifacts from EEG data [67].
- EEG does not produce any kind of sound. So, it is helpful to study auditory stimuli [68].
- EEG does not require exposure to high intensity (>1 Tesla) magnetic field [69].
- EEG does not need a feedback from the subject [70].
- EEG is completely non-invasive. The subject does not require to undergo any kind of surgery.

❖ **Demerits**

- Spatial resolution on the scalp is very low. Spatial resolution refers to the no. of pixels utilized in construction of an image [71].

- EEG measures the signal away from the source. The amplitude of the signal is very low (in microvolt range).
- Signal to Noise Ratio (SNR) is low. For sensitive data analysis, we have to extract different information separately [72].
- Source location is not EEG.
- EEG data can easily be contaminated with different unwanted muscle artifacts.

2.4. Working principle of EEG

The basic block diagram of an ECG machine is shown below. The operation of each unit is described.

I. Montage Selector:

Montages are the connection recording channels and the electrodes. Montage selector helps to select a particular channel which collects information from a particular area. EEG electrodes are placed all over the brain by following 10-20 electrode placement system. The odd numbers of electrodes are present in the left side of the brain and the even numbers of electrodes are present in the right side of the brain. EEG electrodes collect the EEG waveform from the scalp and transmit it through the montage selector panel. It helps to permit the user to select the desired electrode pair.

II. Pre-amplifiers:

As we are collecting EEG waves away from the source, the amplitude of ECG signal is very low (in microvolt range). So it is necessary to amplify signal before further processing. High gain, high CMRR operational amplifiers are generally used as preamplifiers.

III. Filters and Amplifiers:

There is a bank of filters and amplifiers present in the system. EEG waves can easily be contaminated with different unwanted muscle artifacts, eye blinking etc.

To eliminate those unwanted information and noise, we have to filter out the EEG way from. We have to select a particular filter as per our requirement.

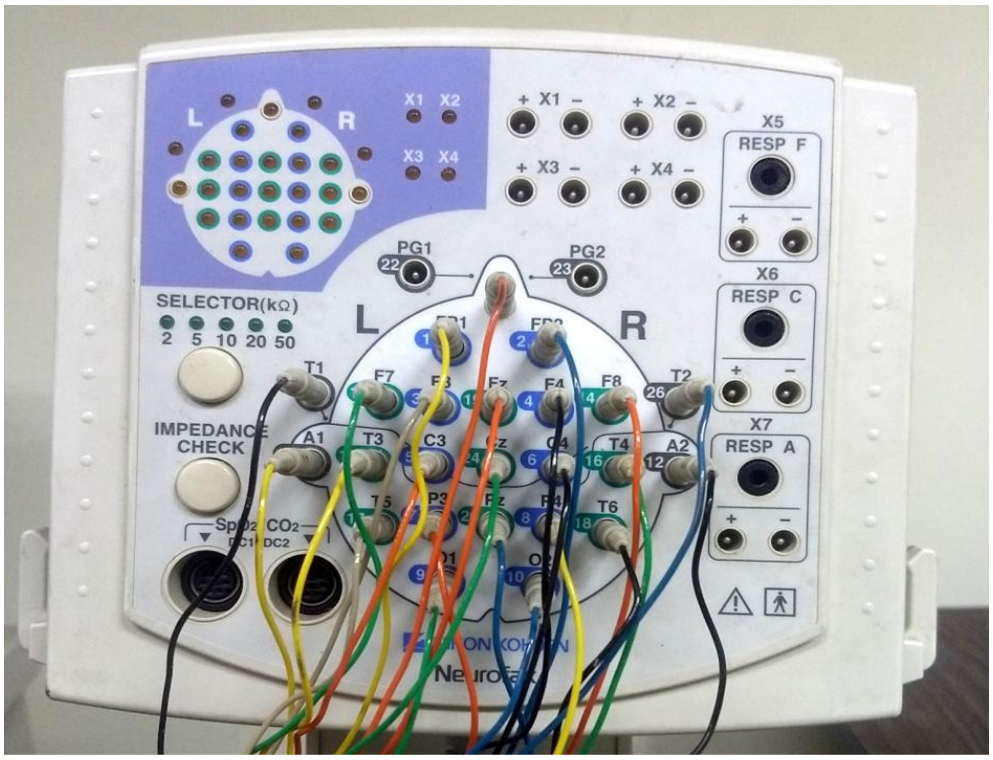

Fig. 9: Channel for different EEG electrodes

IV. Analog to digital converter:

For further analysis of EEG waveform, we use oscilloscope sand computers. But EEG wave is analog in nature and computers work in a digital domain. So, we have to convert the analog EEG data to digital form for further processing.

V. Writing unit:

This path consists of a synchronized motor, chart paper and an ink type direct writing recorder. The motor helps to move the paper and the ink draw the corresponding EEG waveform on the paper.

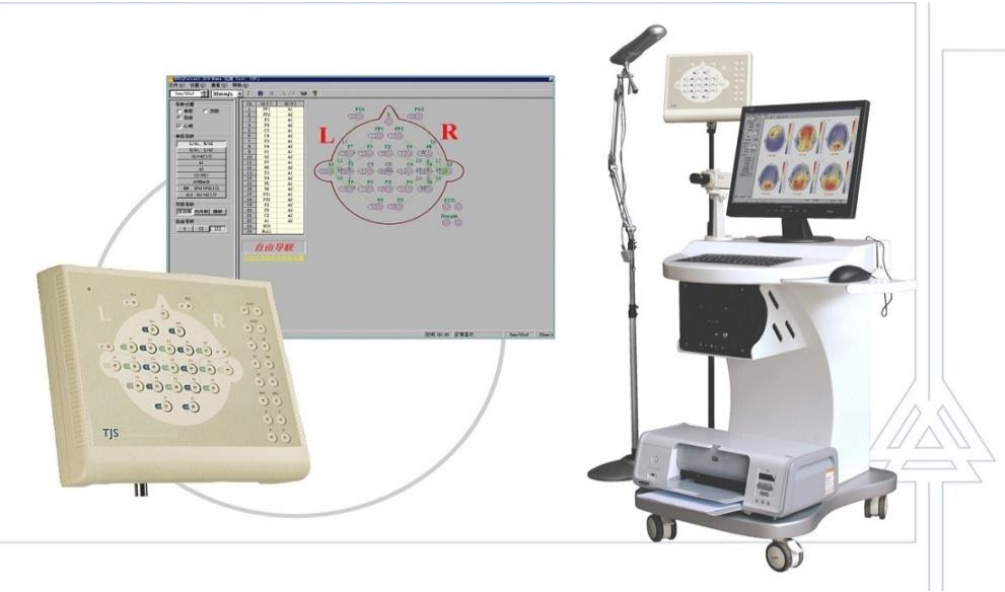

Fig.10: EEG device

2.5. Different EEG waveforms

We have different EEG waves with different frequencies (Fig. 11). The frequency band of EEG signal is 0.5 to 50 Hz.

1. **Infra-low waves:**

   The frequency of the signal is less than 0.5 Hz. These are the basic cortical rhythms responsible for higher brain function. This is the slowest brain wave. The low frequency makes them difficult to measure. It is mainly responsible for network function.

2. **Delta waves:**

   The frequency of delta wave is 0.5 to 3 Hz. These are slow and loud brain waves. The source of these signals non REM sleep and deep meditation. Regeneration and fixing is accelerated in this condition. These waves eliminate exterior attention. That is why uninterrupted deep sleep is necessary for healing process.

3. **Theta waves:**

The frequency band theta wave is 3 to 8 Hz. This wave produces mostly in sleep. This is the entrance of memory and learning. In this state, our external sensed are pulled back and concentrates on signals coming from inside. This is known as twilight state. In theta, we perceive dreams. This is the place where we put our nightmares, fears.

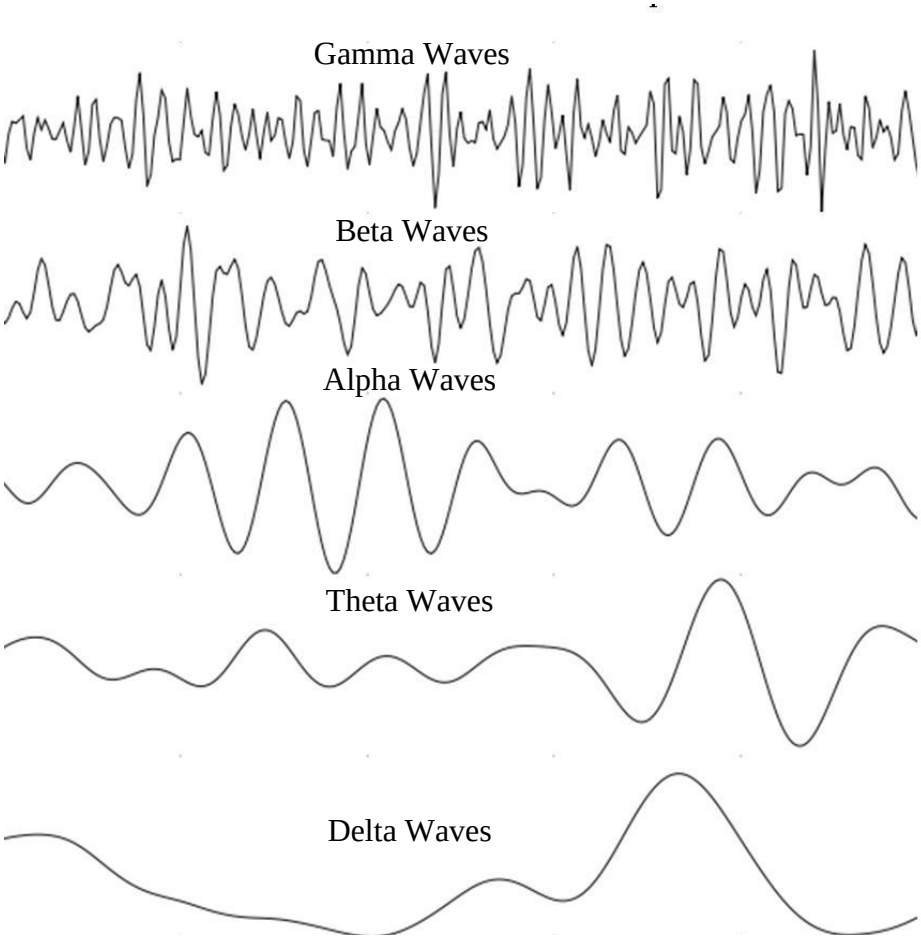

Fig.11: Different EEG waves

4. **Alpha waves:**

The frequency band of alpha wave is 8 to 12 Hz. Alpha waves are responsible for the learning state. It also helps in alertness, calmness and mental coordination.

5. **Beta waves:**

   The frequency band of beta wave is 12-38 Hz. Beta waves denotes consciousness, waking state when we are performing any kind of cognitive task. This is the fast activity of human brain. Beta waves are also responsible for decision making, problem solving, judgment etc.

6. **Gamma waves:**

   The frequency range of gamma wave is 38-42 Hz. This is the fastest brain wave and it is responsible for parallel processing of information in different brain lobes. These brain waves pass data quickly and silently.

2.6. Application of EEG based BCI

EEG is the most commonly used brain signal acquisition technique to implement Brain Computer Interfacing. The main advantage of EEG base BCI is it is portable and EEG is completely non-invasive. No pre-experimental training is required to participate in EEG based BCI. The participant does not have to give any response back, there is no feedback. EEG based BCI is mainly used for controlling any prosthetic device and study of brain signals during any cognitive task. But the main drawback of EEG based BCI is poor spatial resolution and its tendency to pick unwanted artifacts in EEG data. The performance of concentration dependent cognitive task is comparatively more difficult.

Due to high temporal resolution, the real time data analysis of EEG based BCI is widely performed. In EEG based BCI, the brain activity can be studied to find the pathway of any mental task and with the help of acquired brain signal, we target to control an external device without the need for rehabilitation. In neuro-rehabilitation, a close loop control system is present to utilize feedback mechanism which can be used to control prosthetic limbs [73]. One of the most important areas in BCI is to find and analyze the connection between acquired brain signal activities and human models, cognitive processing and biomechanics. This helps to study the relationship between brain activity and real or imagery upper limb movement [74] [75].

Persons with severe motor disabilities need a substitution for communication and control because they are unable to perform the traditional neuro-mascular ways of communication. Systems based on sensorimotor rhythms (SMR) and slow cortical potentials (SCP) use frequency and time components (real-time data) because they do not depend on any specific motor task. Alternatively, systems based on P300 event related potentials (ERP) use time domain components generated by specific stimuli. Amyotropic Lateral Sclerosis (ALS) leads to complete loss of almost all voluntary muscle control. BCI system based on Event-related desynchronization/ synchronization (ERD/ERS) helps to achieve some sort of movements after several training procedures. BCI system helps to control their brain activity. Patients suffering from traumatic spinal cord injury can control electrostimulation devices after extensive training. SMR based BCI helps to control an orthosis and a prosthetic device which can be used in stroke rehabilitation.

CHAPTER 3:

PRINCIPLE AND METHODOLOGY

3.1. System Overview

3.2. Artifact Removal and Filtering of EEG

3.3. Feature Extraction and Feature Reduction

3.4. e-LORETA

3.5. Representation of Color Pathways

3.6. Dempster Shafer Theory

3.7. Calculation of Probability Values of each edge

3.8. Normalization of BPA values

3.9. Computation of Orthogonal Summation

3.1. System Overview

A Short framework of the overall system (Fig. 12) is provided here. First, we record the signals of brain activity from 21 surface electrodes placed all over the brain. Next the unprocessed EEG data is feed to eLORETA software brain activation regions at different time points [76]. Three different color stimuli are responsible for the activation of different brain regions which is provided by eLORETA [77]. Then we collect signals from different stimulated brain regions and signals are filtered with the help of a fourth order elliptical band pass filter. Has good attenuation in the stop band and smooth round off characteristics from pass band to stop band and vice versa [78]. Next, the removal of artifacts is performed independent component analysis (ICA) [79]. Then feature extraction is done, in the theta upper band and alpha lower bands, to determine the color stimuli by power spectral density (PSD) [80]. Principal component analysis is performed to reduce the number of features [81]. Finally we represent the color Pathways multi subjective fusion was done with the help of Dempster Shafer theory [82].

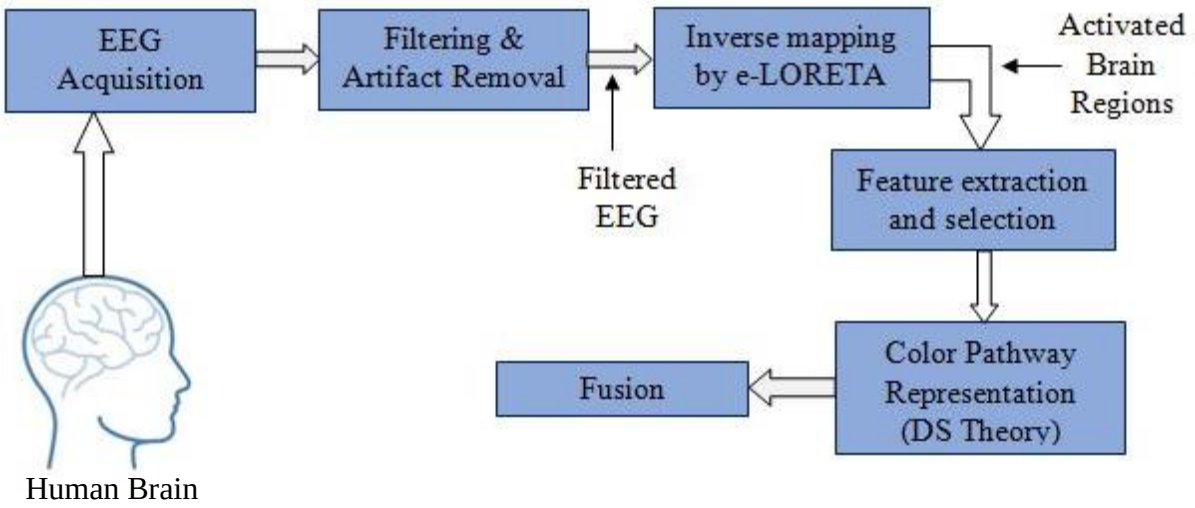

Fig.12: System overview

3.2. Artifact Removal and Filtering of EEG data

Acquired EEG data contains mainly three types of artifacts: instrumental artifacts, experimental artifacts and physiological artifacts. These artifacts are needed to be eliminated from the EEG data with the help of different filters.

3.2.1. Elimination of Artifacts

3.2.1.1. Instrumental Artifact Removal

Instrumental noise is present in the system due to the surrounding condition or the presence of abnormalities in the EEG machine. This kind of noise has high frequencies. So, a low-pass filter is needed to eliminate those frequencies.

3.2.1.2. Experimental Error Removal

Movement artifacts are present due to head movement or body movement, which is responsible for the generation of experimental error. This can bring a sudden change in the amplitude of the EEG signal. A few principles are there to remove these artifacts, like Principle Component Analysis based filtering, Wiener filtering strategies, Savitzkey-Golay filters etc.

3.2.1.3. Removal of Physiological Artifacts

Physiological noises can be generated due to heart beat or pulse, breathing, eye-blinking, Mayer waves etc, which can be distinguished in blood pressure changes. Band pass filtering, Principle Component Analysis, Independent Component Analysis can be used to remove these noises.

3.2.2. Filtering of EEG data

There are 4 types of filters normally used for EEG data analysis. They are Butterworth Filter, Chebyshev Filter, Elliptic Filter and Bessel filter.

3.2.2.1. Butterworth Filter:

Butterworth filter is best known for its maximum flat response. It produces an approximately flat pass band with no ripple. The low-pass or high-pass roll-off rate is 20dB/decade for every pole. The phase response is comparatively good.

3.2.2.2. Chebyshev Filter:

Chebyshev filter helps to achieve a faster roll-off and allows ripple in the frequency response. As the number of ripples increases, the role of becomes sharper. In Type 1 Chebyshev filter, ripples are present only in the pass band and in Type 2 filter, ripples are present in stop band. When the filter order is low, Chebyshev filter can achieve faster transition from the pass band to stop band.

3.2.2.3. Elliptic Filter:

The cut off slope of elliptic filter is steeper than other filters, but it has ripple in pass band and stop band. The phase response is non-linear. It provides the steepest transition between pass band and stop band.

3.2.2.4. Bessel Filter:

Bessel filter provides maximum flat response in magnitude and phase. The phase response of pass band is nearly linear.

Digital filtering is a basic preprocessing step for analyzing EEG data. The main goal in EEG signal processing is to implement high pass filter how to remove slow frequencies (< 0.1 Hz) low pass filter to remove frequencies above 40 or 50 Hz. Filtering techniques is also important for separating noise from the signal. Here we are using an elliptical band pass filter of order 4. This filter has a faster transition in gain from the pass and to stop band. The number of ripples present in each band is alterable. As the stop band ripple comes near to zero, and then it becomes Chebyshev filter of type I. If the pass band ripple approaches zero, it turns into Chebyshev filter of Type II.

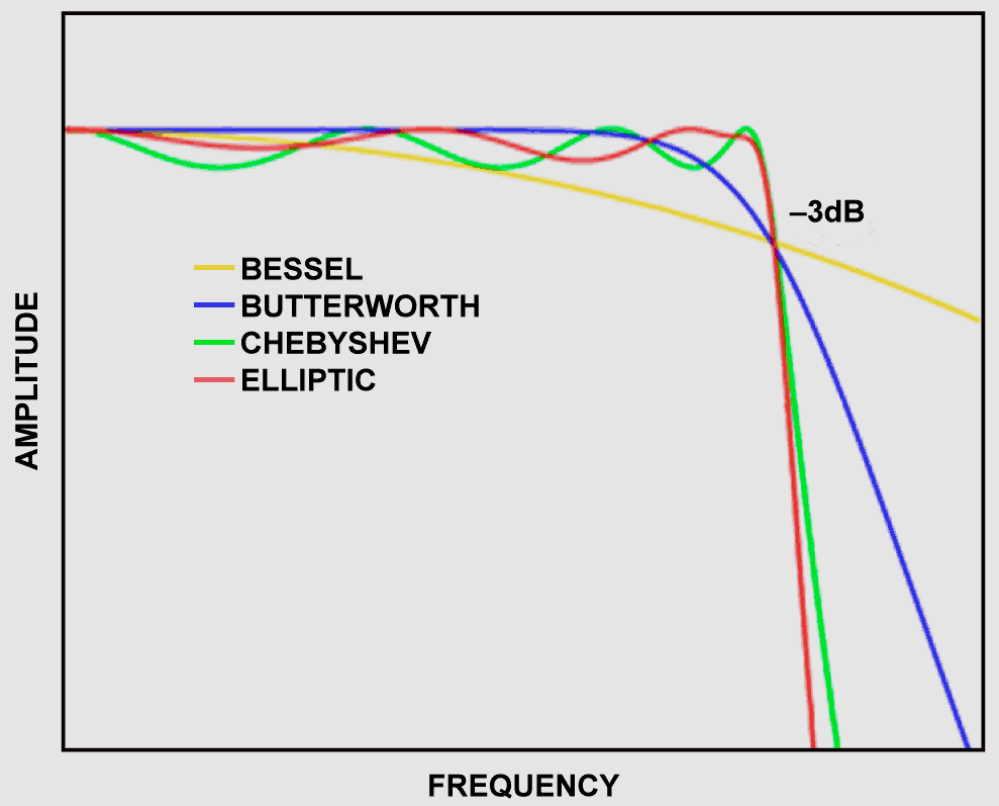

Fig. 13: Frequency response of different filters

Chebyshev filter has steeper transition from pass band to stop band and it produce more pass band ripple in type I filter and more stop band in type II filter. Chebyshev filter can minimize the error between the ideal and actual characteristics.

The Gain response *($G_n(\omega)$)* of n-th order low pass Chebyshev filter is given below:

$$Gn(\omega) = |Hn(j\omega)| = \frac{1}{\sqrt{(1 + \varepsilon^2 Tn^2 \frac{\omega}{\omega 0})}}$$

$|Hn(j\omega)|$= $|Hn(s)|$= Absolute value of Transfer Function [$s=j\omega$]

ω= Angular Frequency

$\omega 0$= Cut-off Frequency

T_n= Chebyshev polynomial of n-th order

ε= Ripple Factor

Filter gain attains a maximum value at G=1 and minimum value at $G= {}^{1}/_{\sqrt{(1+\varepsilon^2)}}$

3.2.3. Independent Component Analysis (ICA):

In signal processing, Independent Component Analysis is a statistical and computational approach for differentiating a mixed signal into sub-components. These sub-components are non-gaussian signals and they are independent from each other.

It illustrates a constructive model for the recognized multivariate data, which is given as a large set of data. In this model, the variables are granted to be linearly dependent of some unrecognized variables and the mixing system is also unidentified. These unrecognized variables are mutually independent and their distribution is non-gaussian and they are known as the independent component of the collected data. By performing ICA, these independent components are found. ICA is related to principle component analysis and factor analysis. ICA is more impressive technique to find independent factors or sources when other conventional methods fail to accomplish.

Independent Component Analysis gives the best result under the consideration of two assumptions:

- The source signals are independent of each other.
- The source signal's values have non-gaussian distribution.

There are some effects of mixed source signals:

1. The source signals are independent but the mixture of those signals is not independent. They share some of other source signals.
2. According to central limit theory, the addition of two independent random variable approaches to a Gaussian distribution.
3. The temporal complexity of a mixed signal larger than that of a single source.

Suppose we have a mixture of n independent signal sources $(S) = [S1, S2, S3 \dots \dots \dots . Sn]T$
These source signals are statistically independent and collected from n electrodes with or without the presence of noise or artifacts.
These signals are modeled with a nonsingular matrix (A) of (n*n) order such that

$$X = AS$$

$X = [X1, X2, X3 \dots \dots \dots Xn]T$ = collection of observed signals

From the given observed signal, we have to determine a de-mixing matrix B by implementing Independent Component Analysis (ICA).

$$Y = BX$$

Y is the set of recovered signals. $Y = [Y1, Y2, Y3 \ldots \ldots Yn]T$

Y is far more similar to S [83].

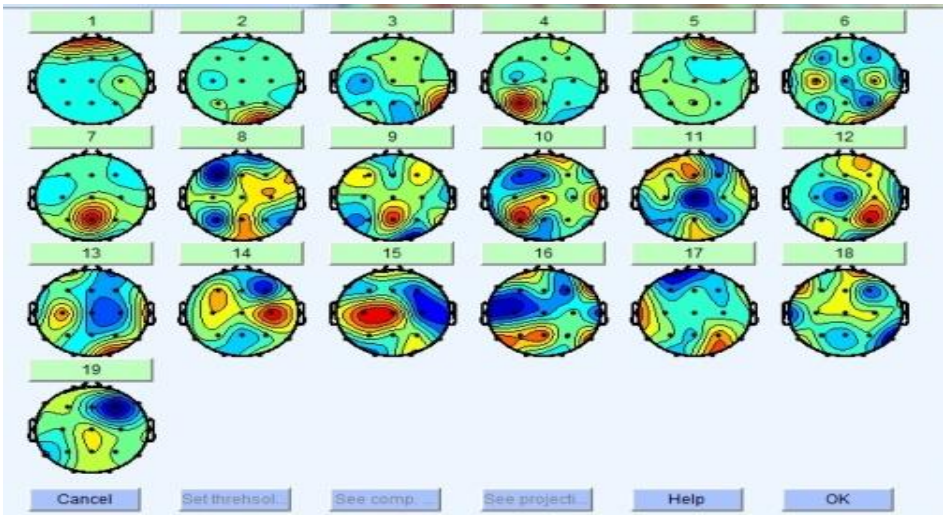

Fig.14: Scalp maps obtained from ICA

3.3. e-LORETA

Different neuro-imaging techniques target to represent the functioning of the brain. EEG is a non-invasive scalp potential measurement technique to estimate the electric neural activity distribution on the cortex. In 1994 LORETA was first introduced. It helps to localize electrical activity of the brain based on scalp potential collected from different channels during the EEG recording. LORETA stands for low resolution brain electromagnetic tomography analysis. LORETA computes 3D distribution of 2394 voxels. It evaluates Fourier transform co-efficient at different frequencies. This method identifies all forms of amplitude-amplitude, phase-phase and phase-amplitude coupling of information flow. There is an method to use Hilbert transformation and calculate Granger causality measures of connectivity between spontaneous amplitude signal and phase signal.

- **s-LORETA** stand for standardized low resolution brain electromagnetic tomography. It does not have any localization property in the presence of biological noise.

- **e-LORETA** stands for exact low resolution brain electromagnetic tomography. It is the first 3D distributed linear solution for the inverse mapping problem of EEG with zero localization error.

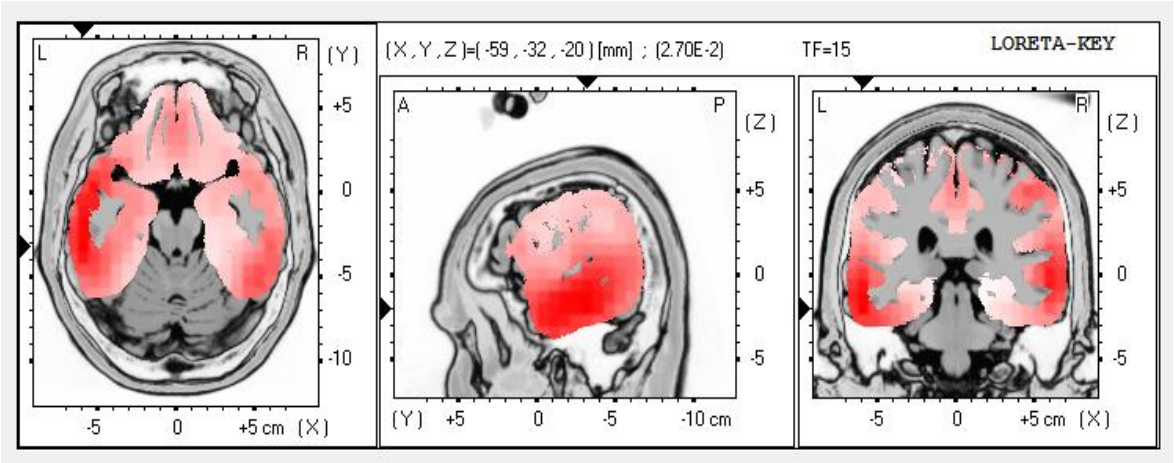

Fig. 15 (a): Axial, Sagittal and Coronal view of human brain

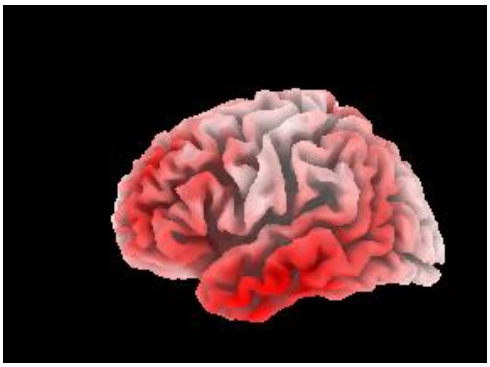

Fig. 15 (b): 3D representation of human brain using e-LORETA

e-LORETA analysis for particular frequency bands is helpful to determine the brain activation region any kind of mental task and helps to discover the brain. The simultaneous process of acquiring scalp potential measured from the EEG electrons and 3D distribution responsible for neural activity is a very useful analysis tool for our research.

3.4. Feature Extraction and Feature Reduction

Here we have calculated Power Spectral Density (PSD) to extract EEG features. The power spectrum is obtained by the amount of power stored in different frequency of signals. We have performed Short-Term Fourier Transform (STFT) to get the PSD spectrum. The statistical average of the signal with the corresponding frequency is known as spectrum. When the signal exists over a long period of time then we use Power Spectral Density. It describes the spectral energy distribution per unit time. We have also performed Skewness, Kurtosis, Mean, Standard Deviation but none of these have produced any significant result which can be helpful for the discrimination of three basic colors. But, in Power Spectral Density, the difference in feature values was prominent for three basic color stimuli.

Principle Component Analysis (PCA) is dimension-reduction method which is used to reduce a large set of data to a small set which contains the maximum uncorrelated information of the large set, known as principle components. PCA is far more similar to Factor Analysis. PCA is performed only on a square symmetric matrix. Different steps of PCA are shown in the following block diagram.

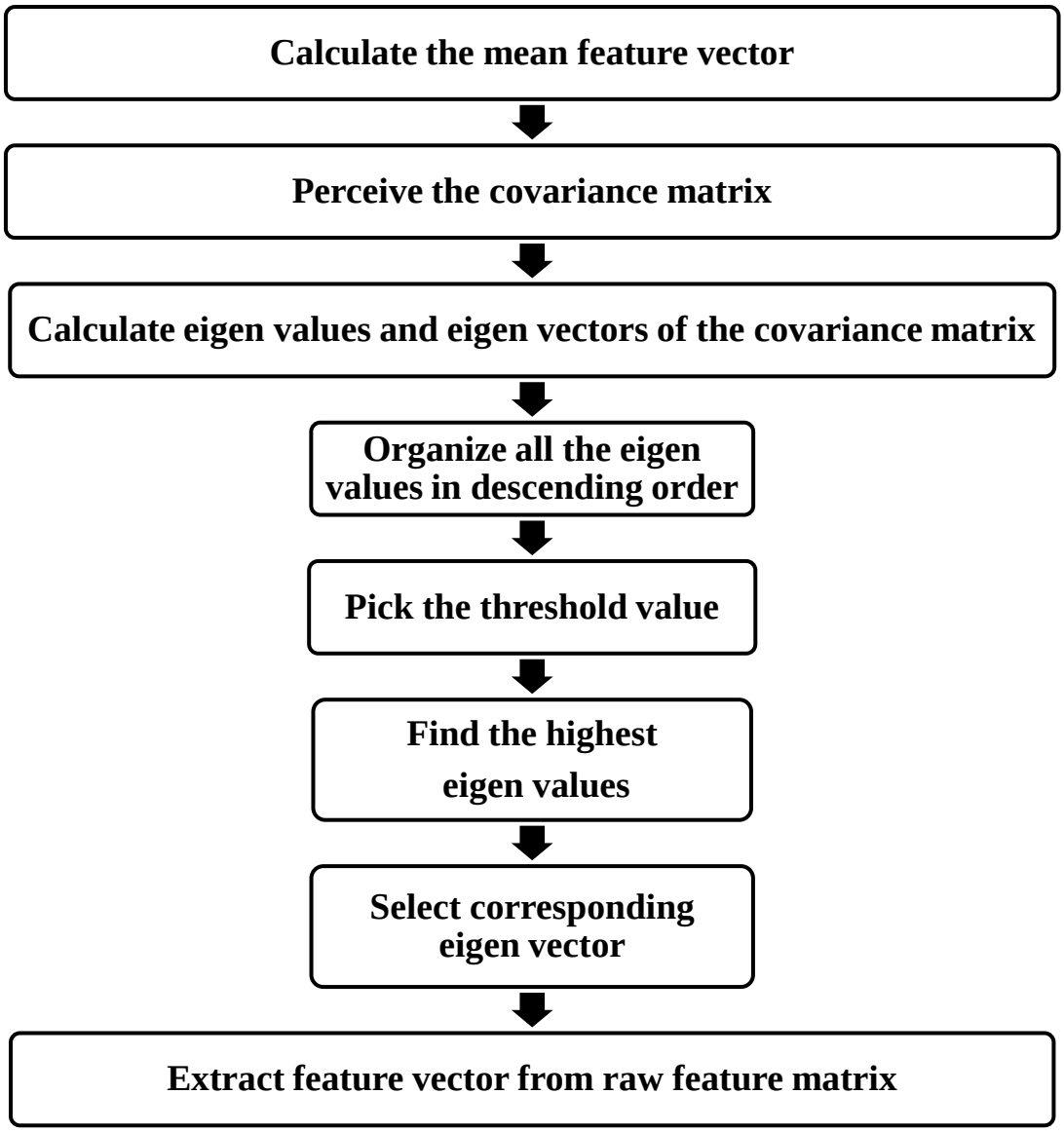

Fig. 16: Flow chart of PCA

3.5. Representation of Color Pathways

When a monochromatic light falls on the retina, human brain produces a specific signaling pathway in the brain responsible for particular light. We have done the determination of color Pathways in two steps. First, we performed Short Term Fourier Transform to detect the time points, when the scalp EEG electrodes reach the highest value of signal power. STFT is done on small Windows of the signal and it helps to identify the window which contains large average power produced in EEG drawn from a particular brain lobe [84]. Secondly, we have constructed a graph which contains the lobe name and the time point when that lobe's signal power is maximum. It helps us to identify the sequence of brain lobes through which the

brain signal is travelling with the increase of time. The acquired pathway is known as Brain Pathway due to Colored stimuli (BPC), or simply a color pathway. To obtain each graph, the same experiments are performed on the same subject under same experimental condition. To generate the probability values attached to each edge of the color pathways, multiple experiments are needed to be performed.

The color pathways are represented by a BPC graph. Each BPC graph contains three tuples i.e. $$BPC =< N, E, P >$$

Where,

N= set of nodes present in a BPC graph, where each node represent single brain lobe. The initial node contains an arrow which helps to differentiate it from other nodes.
E= set of arcs or edges which connects two different brain lobes
P= Represent the probability values assigned to each edge which connects a pair of nodes. It is a association function to E in [0,1].

Here,

N= {retina (*r*), occipital lobe (*occ*), parietal lobe (*par*) and temporal lobe (*temp*) and pre-frontal lobe (*pf*)},

$$E = \{ er, o, eo, p, ep, t, et, pf \}$$

Where, $e_{i,j}$ denotes the interconnection between a pair of nodes.

Each edge is assigned with a specific probability mass value. These probability mass values are determined by the number of instances an edge is picked out of 100 experimental instances on the same subject under the same experimental condition.

3.6. Dempster Shafer Theory

The Dempster Shafer theory is an approach for dealing with unpredictability; it also helps to connect with other frameworks like probabilities and possibilities. It is an approach to obtain degrees of belief for individual values from subjective probabilities for a related query and to combine those degrees of belief based on independent values. Value of subjective probability varies with the difference of the connected queries. Each query has a degree of support whose value lies between 0 and 1.

- 0 for not supporting the query
- 1 for completely supporting the query

θ is a set of all possible outcomes to be made.

Each θ_i is mutually exclusive. Value of at least one θ_i has to be true. Theta is also known as Frame of Discernment.

Suppose we have three queries such as θ_1 , θ_2 and θ_3 .

Then the Frame of Discernment

$$\theta = \{\Phi, \theta 1 , \theta 2 , \theta 3 , (\theta 1 , \theta 2), (\theta 2 , \theta 3), (\theta 1 , \theta 3), (\theta 1 , \theta 2 , \theta 3)\}$$

Φ is the empty set with a probability value of 0, since one of the outcomes has to be true.

Each element has a probability value between 0 and 1.

The mass function is a subset of of theta with all relevant and available proofs that supports the query. The summation of all mass function is always 1.

The combination is obtained from the two sets of mass function m_1 and m_2 by calculating product probabilities.

$$m1,2(\Phi) = 0$$

And,

$$m1,2(A) = m1 \oplus m2\ (A)$$

3.7. Calculation of Probability Values of each edge

θ is the Frame of Discernments (FOD) [82] which holds the edges of a specific BPC graph. If K subjects have taken part in this experiment, then we have *K* FODs. Let $m_1(e)$, $m_2(e)$,…$m_K(e)$ be the basic probability values assigned at each edge *e* in *K BPC*s which is obtained from *K* subjects. Basic probability values are calculated by estimating the number of occurrences (*q*) of each edge of a BPC graph out of total number of *Q* experiments performed on the same subject. The basic probability value for the *i*-th subject is $m_i(e)= q/Q$. Similarly, we can determine $m_i(e_k)$ for i=1 to *N* and for any feasible edge in the *BPC* graphs. Let X_1 and X_2 be two focal elements, comprising one or two members, in two FODs θ_1 and θ_2 respectively. Then, we according to Dempster-Shafer theory obtain the orthogonal

summation of $m_i(X_1)$ and $m_j(X_2)$ for any feasible *i*, *j* in [1, *N*] and call it $m_{i,j}(X)$ where $X = X_1 \cap X_2$.

$$m_{i,j}(X) = K^{-1} \sum_{X = X_1 \cap X_2} m_i(X_1).\, m_j(X_2) \quad \text{..... (1)}$$

And

$$K = 1 - \sum_{X_r \cap X_s \neq \varphi} m_i(X_r).\, m_j(X_s) \quad \text{..... (2)}$$

Where, X_r and X_s are feasible groups of objects, such that $m_i(X_r)$ and $m_j(X_s)$ are known.

In this application, we consider a given edge in different FODs (*BPC*s obtained for *N* subjects) as X_1 and X_2. So, instead of group of objects, $X = X_1 = X_2$ here denotes a particular edge, and $X = X_r = X_s$ denotes the set of common edges in all the *BPC*s.

In Fig. 17, we obtain 3 *BPC*s as the 3 FODs acquired from 3 subjects by allowing blue light to be incident on the retina of three experimental subjects in the same experimental conditions.

Suppose, we want to obtain $m_{12}(e_{r,p})$ from the known measurements of $m_1(e_{i,j})$ and $m_2(e_{i,j})$ for all valid *i*, *j*. We take help of Fig. 17 (b) and 17 (c) first to compute $m_{12}(e_{r,p})$, and then use Fig, 17 (a) later to obtain $m_{1,2,3}(e_{r,p})$.

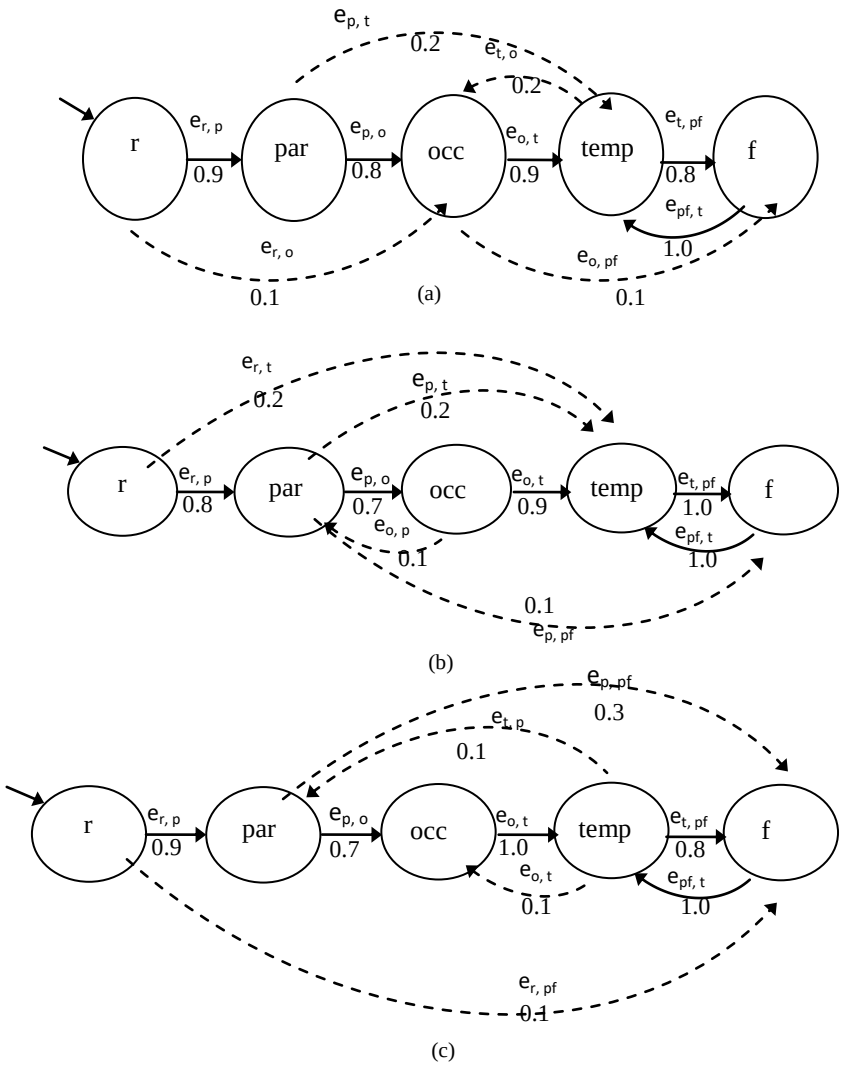

Fig. 17 , (a), (b), (c) BPC graphs obtained for three experimental subjects

It is noted from Fig. 17 (a), (b) and (c) that most of the common edges in these figures have values equal to 1. So, we do not need to perform orthogonal summation of those edges. However edges $e_{r,p}$, $e_{r,t}$, $e_{r,o}$, and $e_{r,pf}$ have different basic probability values. So, we need to keep them in a table for orthogonal summation of the said parameters from 3 subjects. This is done in two steps. In the first step, we compute the orthogonal summation of the above edges from Fig. 17 (b) and 17 (c) and in the second step we again compute the orthogonal summation of the resulting edges indicated from the BPA shown in Fig. 17 (a).

3.8. Normalization of BPA values

Now to compute the orthogonal summation of the edges, we require BPA of the two frames of discernments θ_1 and θ_2. The values of θ_1 and θ_2 are unknown. We assign a probability mass of 0.5. So, the value of probability masses of edges obtained for two subjects are given in Table 4.

$m_1(e_{r,p}) = 0.8$	$m_1(e_{r,t}) = 0.2$	$m_1(e_{r,o}) = 0$	$m_1(e_{r,f}) = 0$	$m_1(\theta_1) = 0.5$
$m_2(e_{r,p}) = 0.9$	$m_2(e_{r,t}) = 0$	$m_2(e_{r,o}) = 0$	$m_2(e_{r,f}) = 0.1$	$m_2(\theta_1) = 0.5$

Table 4: BPAs obtained from Fig. 17 (b) and 17 (c)

$m_1(e_{r,p}) = 0.53$	$m_1(e_{r,t}) = 0.13$	$m_1(e_{r,o}) = 0$	$m_1(e_{r,f}) = 0$	$m_1(\theta_1) = 0.34$
$m_1(e_{r,p}) = 0.6$	$m_2(e_{r,t}) = 0$	$m_2(e_{r,o}) = 0$	$m_2(e_{r,f}) = 0.06$	$m_2(\theta_1) = 0.35$

Table 5: Normalization of the BPAs obtained from Table 4

To keep the sum of the basic probability values acquired from one subject =1, we divide each value by the sum obtained from the subject present in one row. So, we have to perform normalization to obtain the Table 5.

3.9. Computation of Orthogonal Summation

Suppose X_1=X_2= $e_{r,p}$. We have to compute orthogonal summation of $m_1(e_{r,p})$ and $m_2(e_{r,p})$ with the help of product probabilities: $m_1(.).m_2(.)$ in Table . We compute the common probability of θ_1 with all possible edges of M2 and common probability of θ_2 with all possible edges of M1. This is shown in the last row and the last column of the Table 6. The diagonal entities represent the commonality between two subjects. From the equation (1), we have to calculate the numerator of $m_{1,2}(e_{r,p})$ by the sum of the product of $m_1(e_{r,p}).m_2(e_{r,p}) + m_1(\theta_1).m_2(e_{r,p}) + m_1(e_{r,p}).m_2(\theta_2)$. The value of $m_{1,2}(e_{r,p})$ = (0.53 × 0.6) + (0.34 × 0.6) + (0.53 × 0.35) =0.318 + 0.204 + 0.185 = 0.707 as indicated in Table 6. We also obtain the denominator of $m_{1,2}(e_{r,p})$ by the sum of the diagonal elements, last column sum and last

row sums as shaded in Table 6, where each entry in the shaded region has to be considered once only.

M1 / M2	$e_{(r,pf)}$ (0.53)	$e_{(r,o)}$ (0.13)	$e_{(r,t)}$ (0)	θ_1 (0.35)
$e_{(r,pf)}$ (0.6)	0.318	0.078	0	0.204
$e_{(r,o)}$ (0)	0	0	0	0
$e_{(r,t)}$ (0.06)	0.0318	0.007	0	0.0204
θ_1 (0.34)	0.185	0.045	0	0.119

Table 6: Product probabilities to compute orthogonal summation

The value of the denominator appears to be 0.891. The value of orthogonal summation of $m_{1,2}(e_{r,p})$ is calculated as (0.707/0.891)=0.793, which is larger than their original values $m_1(e_{r,p})$= 0.53 and $m_{1,2}(e_{r,p})$=0.6. So, we can say that the edge $e_{r,p}$, from Fig. 17 (b) and (c), is made stronger by the orthogonal summation of the previously assigned values.

The result of orthogonal summation calculated for 2 subjects is shown in the Table 7.

X=	$e_{r,p}$	$e_{r,t}$	$e_{r,f}$	θ
$m_{1,2}(X)$	0.793	0.051	0.082	0.667

Table 7: Results of orthogonal summation

Now we have to perform orthogonal summation of the normalized value obtained from Fig. 16 (a) to compute the commonality between three subjects.

In case of multiple edges emerging from a node in the BPC graph, we have to choose the edge with the highest probability value.

CHAPTER 4:

EXPERIMENTS AND RESULTS

4.1. Experimental Setup

4.2. Stimulus Preparation

4.3. Preprocessing of EEG data and Removal of Artifacts

4.4. Inverse mapping using e-LORETA

4.5. Extraction of EEG features

4.6. Probability Calculation to Represent Color Pathways

4.7. Performance Analysis

4.1. Experimental Setup

The experiment is performed using a 21 channels Nihon Kohden EEG data acquisition system with a sampling rate of 500 Hz to acquire the EEG signals from the scale of the subject. We place the scalp electrodes at the FP_1, FP_2, F_3, F_4, F_7, F_8, C_3, C_4, P_3, P_4, O_1, O_2, T_3, T_4, T_5, T_6, F_Z, C_Z and P_Z locations according to the international 10-20 system of EEG electrode placement. This system provides a relationship between the location of the electrode and the specific area of cerebral cortex underneath the scalp. The number "10" and "20" refer to the exact distances between two adjacent electrodes are either 10% or 20% of total Nasion-Inion distance of the skull.

Fig.18: Experimental setup

4.2. Stimulus Preparation:

Thirty two healthy adults with normal eyesight have taken part in these experiments. The age group of all the participants was 22 to 30 years. Among the 30 subjects, 18 are men and 12 are women. A Remote controlled 15 watt RGB flood light with 110 to 220 volt power supply has been used as the light source. Each light of these three basic colors was given to each subject continuously for 2 seconds. A time gap of 20 seconds has been kept between the consecutive presentations of color stimuli. This time gap helped to exclude the residual effect the previous light. For each subject we have repeated each trials 10 times. The arrangement of colored light was selected randomly in each trial from the list: Red, Green and Blue.

Fig illustrates one sequence of color stimuli. A frication cross of 3 seconds duration was shown to the subjects as initiation of each trial.

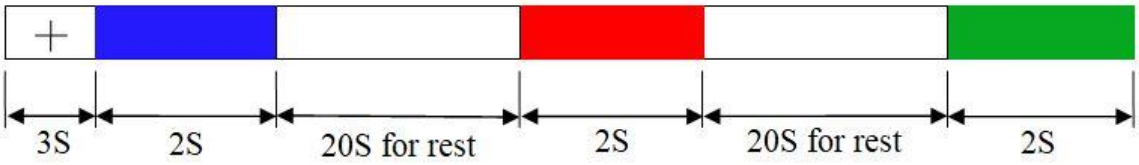

Fig. 19: Stimulus used in the experiment

4.3. Preprocessing of EEG data and Removal of Artifacts

The sampling rate of our system is 500Hz or 500 data per sec. The frication cross or the initiation cross was shown to the subject for 3 seconds whose data is not required. We have to eliminate (500*3) = 1500 corresponding data. The subject is exposed to each monochromatic color light for 2 seconds which leads to acquire 1000 data. Then we have a time gap of 20 seconds or a collection of 10,000 data which is not necessary for further processing. So, those data are removed from the datasheet. We have studied that the brain response of optical stimulation is optimum at the Alpha lower band (8-10Hz) and theta higher band (6-8 Hz) [84]. This helped us to filter the collected EEG data using an active band pass filter of pass band 6 - 10Hz. There are huge varieties of digital filter algorithms, but we select the 4th order Chebyshev filter for its smooth round off characteristics near the cut off frequencies. The presence of artifacts in the EEG data is very common. We have to remove the artifacts due to eye blinking or unwanted muscle contraction. To remove those artifacts we have performed indefinite component analysis (ICA) to demonstrate the 19 independent signal sources, out of which 12 are found to be artifact free. 19 independent scalp maps of 19 color sources have been shown in the Fig.

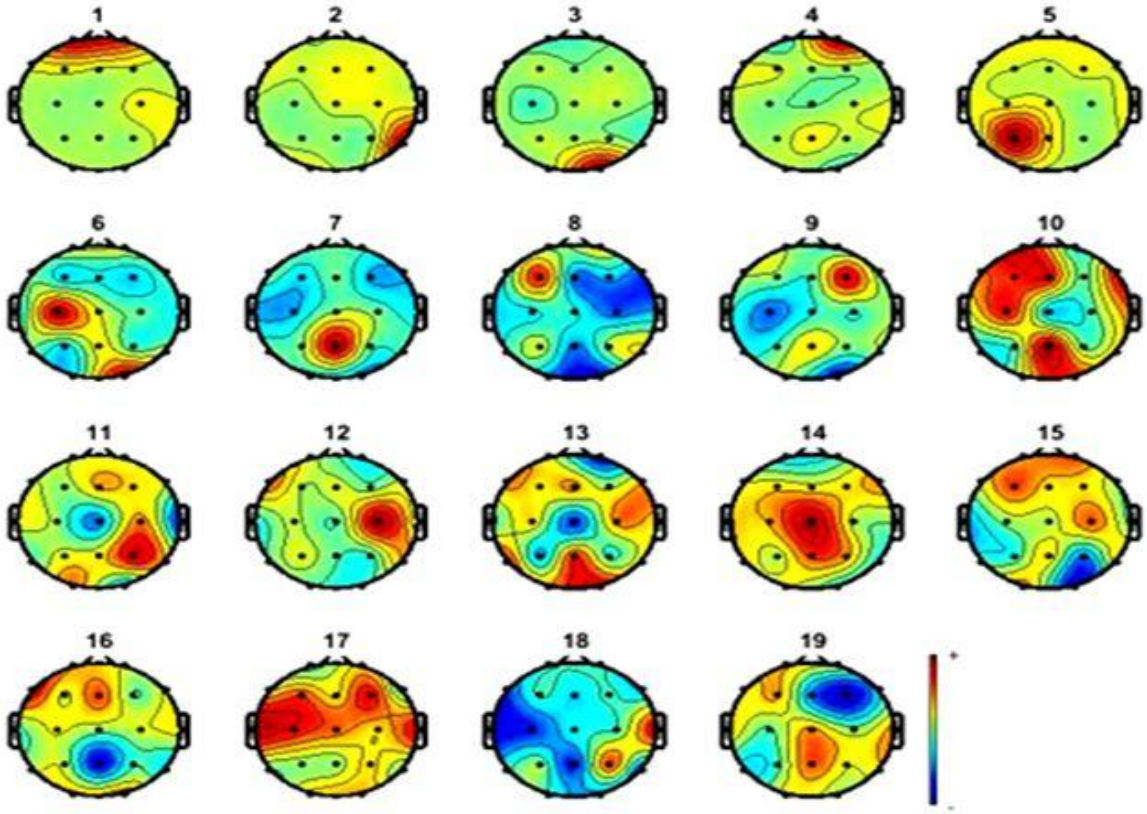

Fig. 20: Scalp maps for 19 independent sources

4.4. Inverse mapping using e-LORETA

In this experiment, we have targeted to determine highly activated brain areas using exact low resolution brain electromagnetic topographic analysis software (e-LORETA) [76]. In this experiment, we have collected EEG data for 60 seconds (=60,000 milliseconds) of each subjects which helped us to recognize basic colors. The e-LORETA software divides the whole time frame into 640 slices. Each slice has a length of 93.75 milliseconds. According to different brain activation regions at different time points, prefrontal lobe is highly activated for red color, the parietal lobe is highly activated for blue color send temporal lobe is highly activated for Red and Green colors.

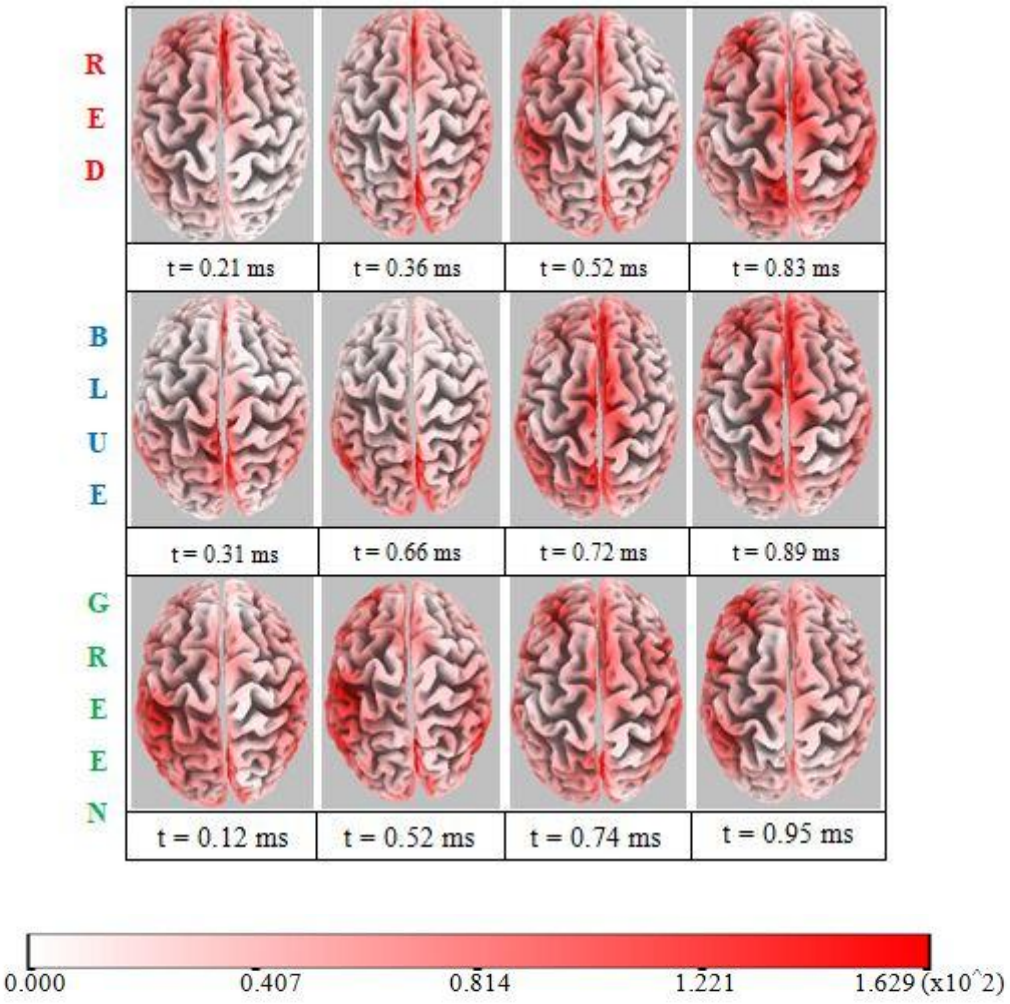

Fig. 21: Representation of 3D surface plot of whole brain for three basic colors averaged over 30 subjects at different tome points

In Fig 21, different brain regions activated for different colors at different time points has been shown.

4.5. Extraction of EEG features

In this experiment, we have performed power spectral density for the important EEG features. We have performed STFT response of the filtered EEG data to obtain the power spectral density (PSD). Fig shows the plot of power spectral density [80]. For a particular subject, we took 257 PSD features by Welch method which has a hamming window of length 64 and there was 50% overlap between consecutive windows. Now we have 257*12=3084

features for 12 artifact free electrodes. We reduce the huge range of features to 100 features with the help of PCA based feature selection algorithm [85].

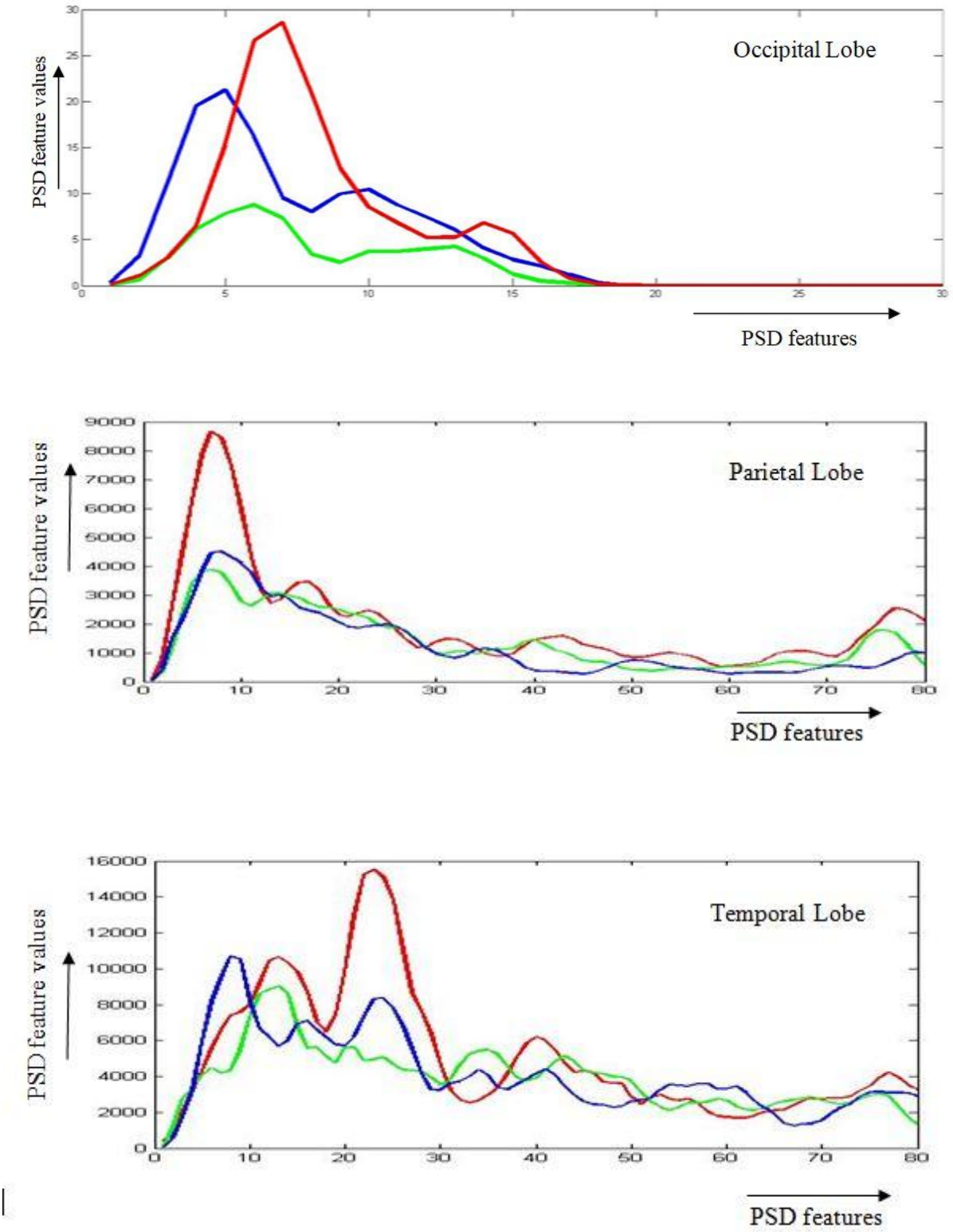

Fig. 22: PSD features extracted from occipital lobe, parietal lobe and temporal lobe for three basic colors

4.6. Probability Calculation to Represent Color Pathways

First we have to record the approximate time points when the average brain power for a particular brain lobe is maximum. At this time points, in which lobe average power is maximum is assumed to be active. The brain signal always initiates from the retinal cone cells. Everytime we begin the start point of the color signaling pathway at the retina (r). Based on the time of arrival of the signal at different brain lobes, we construct the lobes as parietal (par), temporal (temp), occipital (occ), frontal (f) and pre-frontal (pf). We form the transition of brain signal between different lobes as: r → par, par → temp, temp → occ, occ → f, f → pf.

We repeat the experimental trial 10 times on each subject for three different color stimuli and determine the probability mass value associated with each edge in the BPC graph. Table 8 gives an illustration to calculate the probability mass values from 10 experimental trials on each subject for blue colored stimuli.

We repeat the same procedure on 30 subjects to obtain 30 BPC graph and implement Dempster Shafer Theory to combine those 30 graphs into a single graph for each monochromatic light. The end results of signal transition from one lobe to the next lobe for three basic color stimuli are shown in Fig. 23.

Trial	**r → par**	**par → temp**	**temp → occ**	**occ → f**	**f → pf**	**r → f**
1	✓	✓	✓	✓	✓	✗
2	✓	✓	✓	✓	✓	✗
3	✓	✓	✓	✓	✓	✗
4	✓	✓	✓	✓	✓	✗
5	✓	✓	✓	✓	✓	✗
6	✓	✓	✓	✓	✓	✗
7	✓	✓	✓	✓	✓	✗
8	✓	✓	✓	✓	✓	✗
9	✓	✓	✓	✓	✓	✗
10	✗	✓	✓	✓	✓	✓
Prob.	0.9	1.0	1.0	1.0	1.0	0.1

Table 8: Probability analysis of one subject for blue color

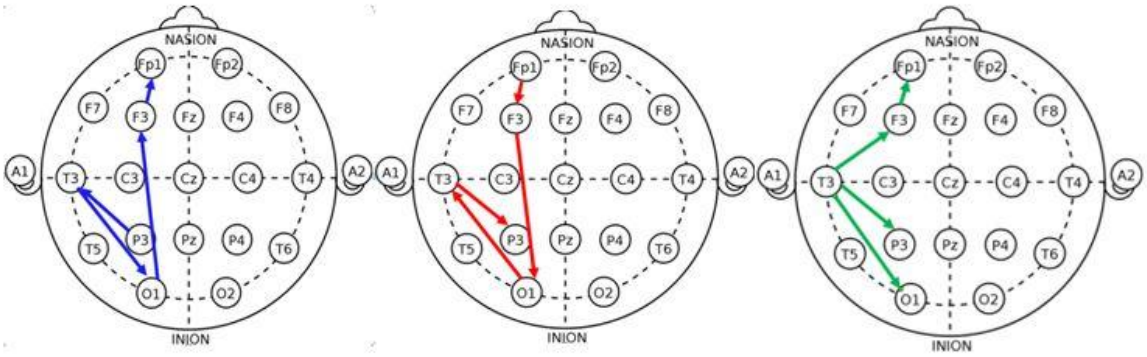

Fig. 23: Color pathways of brain for three basic colors using BPC graph

4.7. Performance Analysis:

Four other different methods for pathway detection have been found. In this experiment, the percentage score for three primary colors was calculated. Cross-correlation technique exhibits the lowest performance as mentioned in Table 9, where as the percentage score calculated by Granger Causality and Phase Synchrony technique is comparatively good. It is observed that Dempster Shafer theory outperforms all other techniques for pathway detection.

Color Stimulus	Cross-correlation technique [86]	Transfer entropy [87]	Granger Causality [88]	Phase Synchrony technique [89]	Graph Theory [90]	**Dempster Shafer Theory**
Red	74%	86%	91%	90%	89%	**96%**
Green	83%	87%	87%	89%	84%	**93%**
Blue	84%	85%	88%	91%	**81%**	**95%**

Table 9: Comparison of the percentage scores with the existing methods

CHAPTER 5:

CONCLUSION AND FUTURE SCOPE

5.1. Summary of the work

5.2. Future directions

5.1. Summary of the work

Brain computer interfacing is an important tool to communicate with external device with the help of brain signals. EEG works as an intermediate device of acquiring brain signal which is non-invasive, user friendly and cost-effective. The study of this work is concerned to indicate the signaling side pathways in the brain for different optical wavelength of different color stimuli. We have found that the signaling pathways of brain response varies considering for different wavelengths of three basic monochromatic colors. These results provide a new breakthrough in the field of cognitive neuroscience. In this work, we differentiate the brain responses of three monochromatic lights which generate EEG waves when the light falls on the retinal cone cells. EEG scalp electrodes collect those EEG signals of different frequency bands, among which alpha lower frequency band and theta higher frequency band is found most relevant in this experiment. After filtering, those EEG signals using a 4^{th} order Chebyshev filter, Power Spectral Density (PSD) analysis is performed which generates different EEG features. Power Spectral Density helps to differentiate between three primary colors. Principle Component Analysis (PCA) based feature reduction technique is used to reduce the number of features. The color side-pathways in the brain is represented by a specialized graph where the nodes represent different brain lobes, the connecting arcs represent the probability mass of signal transfer. For N subjects, we get N graphs and then using Dempster Shafer theory, the probabilities associated with N graphs are fused to get the common-signaling pathways.

The electrical response of the cone cells to the red light is found to pass through the following lobes sequentially: pre-frontal lobe, frontal lobe, occipital lobe, temporal lobe and parietal lobe. Similarly, the electrical response of blue light follows the pathway: parietal lobe, temporal lobe, occipital lobe, frontal lobe and pre-frontal lobe. The brain response to green light follows the pathway: temporal lobe, occipital lobe, parietal lobe, frontal lobe and pre-frontal lobe. Blue color is responsible to influence smart planning, red color helps in spontaneous decision-making and the green color focuses in memory activation and recalling.

5.2. Future directions

1. Further advancement in this study can be obtained by predicting pathways for simultaneous processing of different colors by human brain, from a multicolored photograph.
2. Patients suffering from any psychological disorders exhibits signal pathways different from the normal signaling sequence. So, it is very helpful to detect and diagnose the abnormality present in the color signaling pathways.
3. It can be helpful for robotic operation. To perform an operation successfully, the responsible robotic device should have the ability to perceive different colors to identify different organs. These signaling pathways can be implemented in those devices.
4. Color blind persons can be provided with suitable sensors to guide them through traffic signals while driving a car.

Bibliography

1. Haas, L.F., 2003. Hans berger (1873–1941), richard caton (1842–1926), and electroencephalography. Journal of Neurology, Neurosurgery & Psychiatry, 74(1), pp.9-9.
2. Vidal, J.J., 1973. Toward direct brain-computer communication. Annual review of Biophysics and Bioengineering, 2(1), pp.157-180.
3. Birbaumer, N., 2006. Breaking the silence: brain–computer interfaces (BCI) for communication and motor control. Psychophysiology, 43(6), pp.517-532.
4. Birbaumer, N. and Cohen, L.G., 2007. Brain–computer interfaces: communication and restoration of movement in paralysis. The Journal of physiology, 579(3), pp.621-636.
5. Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G. and Vaughan, T.M., 2002. Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6), pp.767-791.
6. Fetz, E.E. and Finocchio, D.V., 1971. Operant conditioning of specific patterns of neural and muscular activity. Science, 174(4007), pp.431-435.
7. Ganis, G., Thompson, W.L. and Kosslyn, S.M., 2004. Brain areas underlying visual mental imagery and visual perception: an fMRI study. *Cognitive Brain Research*, *20*(2), pp.226-241.
8. Yang, L. and Leung, H., 2013, July. An online BCI game based on the decoding of users' attention to color stimulus. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 5267-5270). IEEE.
9. Dugué, L., Marque, P. and VanRullen, R., 2011. The phase of ongoing oscillations mediates the causal relation between brain excitation and visual perception. *Journal of Neuroscience*, *31*(33), pp.11889-11893.
10. Ishai, A., Ungerleider, L.G. and Haxby, J.V., 2000. Distributed neural systems for the generation of visual images. *Neuron*, *28*(3), pp.979-990.
11. Cajochen, Christian. "Alerting effects of light." *Sleep medicine reviews* 11.6 (2007): 453-464.
12. Antoine U Viola,., et al. "Blue-enriched white light in the workplace improves self-reported alertness, performance and sleep quality." *Scandinavian journal of work, environment & health* (2008): 297-306.
13. Anna Franklin, et al. "Color perception in children with autism." *Journal of Autism and Developmental Disorders* 38.10 (2008): 1837-1847.
14. Oluwakemi Olurinola, and Tayo Omoniyi. "Colour in Learning: Its Effect on the Retention Rate of Graduate Students." *Journal of Education and Practice*6.14 (2015): 1-5.
15. M. J. Goard, G. N. Pho, J. Woodson, and M. Sur, “Distinct roles of visual, parietal, and frontal motor cortices in memory-guided sensorimotor decisions,” *Elife*, *5*, 2016.

16. Wolpaw, J.R., Loeb, G.E., Allison, B.Z., Donchin, E., do Nascimento, O.F., Heetderks, W.J., Nijboer, F., Shain, W.G. and Turner, J.N., 2006. BCI meeting 2005-workshop on signals and recording methods. IEEE Transactions on neural systems and rehabilitation engineering, 14(2), pp.138-141.
17. Petrantonakis, P.C. and Leontios, J., 2014. EEG-based emotion recognition using advanced signal processing techniques. Emotion Recognition: A Pattern Analysis Approach, pp.269-293.
18. Neuper, C. and Pfurtscheller, G., 2009. Neurofeedback training for BCI control. In Brain-computer interfaces (pp. 65-78). Springer, Berlin, Heidelberg.
19. Zander, T.O. and Kothe, C., 2011. Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. *Journal of neural engineering*, *8*(2), p.025005.
20. Pfurtscheller, G., Allison, B.Z., Bauernfeind, G., Brunner, C., Solis Escalante, T., Scherer, R., Zander, T.O., Mueller-Putz, G., Neuper, C. and Birbaumer, N., 2010. The hybrid BCI. *Frontiers in neuroscience*, *4*, p.3.
21. Allison, B.Z., McFarland, D.J., Schalk, G., Zheng, S.D., Jackson, M.M. and Wolpaw, J.R., 2008. Towards an independent brain–computer interface using steady state visual evoked potentials. *Clinical neurophysiology*, *119*(2), pp.399-408.
22. Mason, S., Kronegg, J., Huggins, J., Fatourechi, M. and Schlögl, A., 2006. Evaluating the performance of self-paced brain computer interface technology. *Neil Squire Soc., Vancouver, BC, Canada, Tech. Rep*.
23. Pfurtscheller, G., Allison, B.Z., Bauernfeind, G., Brunner, C., Solis Escalante, T., Scherer, R., Zander, T.O., Mueller-Putz, G., Neuper, C. and Birbaumer, N., 2010. The hybrid BCI. *Frontiers in neuroscience*, *4*, p.3.
24. Delorme, A., Rousselet, G.A., Macé, M.J.M. and Fabre-Thorpe, M., 2004. Interaction of top-down and bottom-up processing in the fast visual analysis of natural scenes. Cognitive Brain Research, 19(2), pp.103-113.
25. Edwin H Land, (1983): "Recent advances in retinex theory and some implications for cortical computations: color vision and the natural image," *Proceedings of the National Academy of Sciences*, vol. 80, no. 16, pp. 5163-5169, 1983
26. Wyszecki, Günther; Stiles, W.S. (1982). *Color Science: Concepts and Methods, Quantitative Data and Formulae* (2nd ed.). New York: Wiley Series in Pure and Applied Optics. ISBN 978-0-471-02106-3
27. R. W. G. Hunt (2004). *The Reproduction of Colour* (6th ed.). Chichester UK: Wiley–IS&T Series in Imaging Science and Technology. pp. 11–2. ISBN 978-0-470-02425-6
28. Neitz, J. and Jacobs, G.H., 1986. Polymorphism of the long-wavelength cone in normal human colour vision. Nature, 323(6089), p.623.
29. Kalloniatis, M. and Luu, C., 2011. Color perception. *From: Webvision: The Organisation of the Retina and Visual System. WordPress*.
30. Daum, I., Schugens, M.M., Spieker, S., Poser, U., Schönle, P.W. and Birbaumer, N., 1995. Memory and skill acquisition in Parkinson's disease and frontal lobe dysfunction. *Cortex*, *31*(3), pp.413-432.

31. Fogassi, L., Ferrari, P.F., Gesierich, B., Rozzi, S., Chersi, F. and Rizzolatti, G., 2005. Parietal lobe: from action organization to intention understanding. *Science*, *308*(5722), pp.662-667.
32. Squire, L.R. and Zola-Morgan, S., 1991. The medial temporal lobe memory system. *Science*, *253*(5026), pp.1380-1386.
33. Kandel, E.R., Schwartz, J.H. and Jessel, T.M., 1991. Principles of Neural Science. 3rd edit. Elsevier Science Pub. Co., Chapters, 1, pp.19-20.
34. Bailey, Regina. "Occipital Lobes and Visual Perception." ThoughtCo, Feb. 1, 2019, thoughtco.com/occipital-lobes-anatomy-373224.
35. Mather, George. "The Visual Cortex". *School of Life Sciences: University of Sussex*. University of Sussex. Retrieved 6 March 2017
36. Bramão, I., Faísca, L., Forkstam, C., Reis, A. and Petersson, K.M., 2010. Cortical brain regions associated with color processing: An FMRI study. *The open neuroimaging journal*, *4*, p.164.
37. Shapley, R. and Hawken, M.J., 2011. Color in the cortex: single-and double-opponent cells. *Vision research*, *51*(7), pp.701-717.
38. Conway, B.R., 2001. Spatial structure of cone inputs to color cells in alert macaque primary visual cortex (V-1). *Journal of Neuroscience*, *21*(8), pp.2768-2783.
39. Livingstone, M.S. and Hubel, D.H., 1984. Anatomy and physiology of a color system in the primate visual cortex. *Journal of Neuroscience*, *4*(1), pp.309-356.
40. Cleveland, W.S. and McGill, R., 1984. Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American statistical association*, *79*(387), pp.531-554.
41. Healey, C. and Enns, J., 2012. Attention and visual memory in visualization and computer graphics. *IEEE transactions on visualization and computer graphics*, *18*(7), pp.1170-1188.a
42. Kim, S., Jeneson, A., van der Horst, A.S., Frascino, J.C., Hopkins, R.O. and Squire, L.R., 2011. Memory, visual discrimination performance, and the human hippocampus. *Journal of Neuroscience*, *31*(7), pp.2624-2629.
43. Druzgal, T.J. and D'Esposito, M., 2001. Activity in fusiform face area modulated as a function of working memory load. *Cognitive Brain Research*, *10*(3), pp.355-364.
44. Hubel, D.H., 1988. Eye, brain, and vision (Scientific American Library) WH Freeman. *New York*.
45. Hansen, T., Olkkonen, M., Walter, S. and Gegenfurtner, K.R., 2006. Memory modulates color appearance. *Nature neuroscience*, *9*(11), p.1367.
46. Pérez-Carpinell, J., De Fez, M.D., Baldoví, R. and Soriano, J.C., 1998. Familiar objects and memory color. *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de la Couleur*, *23*(6), pp.416-427.
47. Hering, E., 1920. *Grundzüge der Lehre vom Lichtsinn*. Springer.

48. Simmons, W.K., Ramjee, V., Beauchamp, M.S., McRae, K., Martin, A. and Barsalou, L.W., 2007. A common neural substrate for perceiving and knowing about color. *Neuropsychologia*, *45*(12), pp.2802-2810.
49. Chang, S., Lewis, D.E. and Pearson, J., 2013. The functional effects of color perception and color imagery. *Journal of Vision*, *13*(10), pp.4-4.
50. Mourek, J., Langmeier, M. and Pokorny, J., 2009. Significance of the plasma membrane for the nerve cell function, development and plasticity. *Neuro endocrinology letters*, *30*(6), pp.694-699.
51. Lieb, W.R. and Stein, W.D., 1986. Simple diffusion across the membrane bilayer. *Transport and diffusion across cell membranes*, pp.69-112.
52. Hodgkin, A.L. and Keynes, R.D., 1955. Active transport of cations in giant axons from Sepia and Loligo. *The Journal of physiology*, *128*(1), pp.28-60.
53. Hodgkin, A.L. and Huxley, A.F., 1952. A quantitative description of membrane current and its application to conduction and excitation in nerve. *The Journal of physiology*, *117*(4), pp.500-544.
54. Krucoff, M.O., Rahimpour, S., Slutzky, M.W., Edgerton, V.R. and Turner, D.A., 2016. Enhancing nervous system recovery through neurobiologics, neural interface training, and neurorehabilitation. *Frontiers in neuroscience*, *10*, p.584.
55. Niedermeyer, E. and da Silva, F.L. eds., 2005. *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins.
56. Blankertz, B., Dornhege, G., Krauledat, M., Muller, K.R., Kunzmann, V., Losch, F. and Curio, G., 2006. The Berlin Brain-Computer Interface: EEG-based communication without subject training. *IEEE transactions on neural systems and rehabilitation engineering*, *14*(2), pp.147-152.
57. Tatum IV, W.O. ed., 2014. *Handbook of EEG interpretation*. Demos Medical Publishing.
58. Okada Y (1983). "Neurogenesis of evoked magnetic fields". In Williamson SH, Romani GL, Kaufman L, Modena I (eds.). Biomagnetism: an Interdisciplinary Approach. New York: Plenum Press. pp. 399–408. ISBN 978-1-4757-1785-3.
59. Carlson, N.R., 2012. *Physiology of behavior*. Pearson Higher Ed.
60. Shenoy, P., Miller, K.J., Ojemann, J.G. and Rao, R.P., 2008. Generalized features for electrocorticographic BCIs. *IEEE Transactions on Biomedical Engineering*, *55*(1), pp.273-280.
61. Rinck, P., 2014, August. Magnetic resonance: a critical peer-reviewed introduction. In *Magnetic resonance in medicine. The basic textbook of the European magnetic resonance forum*, (pp. 21-01).
62. Huettel, S. A.; Song, A. W.; McCarthy, G. (2009), *Functional Magnetic Resonance Imaging* (2 ed.), Massachusetts: Sinauer, ISBN 978-0-87893-286-3
63. Logothetis, N.K., Pauls, J., Augath, M., Trinath, T. and Oeltermann, A., 2001. Neurophysiological investigation of the basis of the fMRI signal. *Nature*, *412*(6843), p.150.
64. Subbaraju, V., Sundaram, S. and Narasimhan, S., 2018. Identification of lateralized compensatory neural activities within the social brain due to autism spectrum disorder in adolescent males. *European Journal of Neuroscience*, *47*(6), pp.631-642.

65. Coyle, S.M., Ward, T.E. and Markham, C.M., 2007. Brain–computer interface using a simplified functional near-infrared spectroscopy system. *Journal of neural engineering*, *4*(3), p.219.
66. Vespa, P.M., Nenov, V. and Nuwer, M.R., 1999. Continuous EEG monitoring in the intensive care unit: early findings and clinical efficacy. *Journal of Clinical Neurophysiology*, *16*(1), pp.1-13.
67. Hämäläinen, M., Hari, R., Ilmoniemi, R.J., Knuutila, J. and Lounasmaa, O.V., 1993. Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. *Reviews of modern Physics*, *65*(2), p.413.
68. O'Regan, S; Faul, S; Marnane, W (2010). "Automatic detection of EEG artifacts arising from head movements". *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. pp. 6353–6.
69. Schenck, J.F., 1996. The role of magnetic susceptibility in magnetic resonance imaging: MRI magnetic compatibility of the first and second kinds. *Medical physics*, *23*(6), pp.815-850.
70. Mulholland, T., 1973. Objective EEG methods for studying covert shifts of visual attention. In *The psychophysiology of thinking* (pp. 109-151). Academic Press.
71. Srinivasan, R., 1999. Methods to improve the spatial resolution of EEG. *International Journal of Bioelectromagnetism*, *1*(1), pp.102-111.
72. Schlögl, A., Slater, M. and Pfurtscheller, G., 2002, October. Presence research and EEG. In *Proceedings of the 5th International Workshop on Presence* (Vol. 1, pp. 9-11).
73. Lebedev, M.A. and Nicolelis, M.A., 2017. Brain-machine interfaces: from basic science to neuroprostheses and neurorehabilitation. *Physiological reviews*, *97*(2), pp.767-837.
74. Contreras-Vidal, J.L., Presacco, A., Agashe, H. and Paek, A., 2012. Restoration of whole body movement: toward a noninvasive brain-machine interface system. *IEEE pulse*, *3*(1), pp.34-37.
75. Mulder, T., 2007. Motor imagery and action observation: cognitive tools for rehabilitation. *Journal of neural transmission*, *114*(10), pp.1265-1278.
76. Pascual-Marqui, R.D., Lehmann, D., Koenig, T., Kochi, K., Merlo, M.C., Hell, D. and Koukkou, M., 1999. Low resolution brain electromagnetic tomography (LORETA) functional imaging in acute, neuroleptic-naive, first-episode, productive schizophrenia. *Psychiatry Research: Neuroimaging*, *90*(3), pp.169-179.
77. Hata, M., Kazui, H., Tanaka, T., Ishii, R., Canuet, L., Pascual-Marqui, R.D., Aoki, Y., Ikeda, S., Kanemoto, H., Yoshiyama, K. and Iwase, M., 2016. Functional connectivity assessed by resting state EEG correlates with cognitive decline of Alzheimer's disease–An eLORETA study. *Clinical Neurophysiology*, *127*(2), pp.1269-1278.
78. Jiang, Y., Deng, Z., Chung, F.L., Wang, G., Qian, P., Choi, K.S. and Wang, S., 2017. Recognition of epileptic EEG signals using a novel multiview TSK fuzzy system. *IEEE Transactions on Fuzzy Systems*, *25*(1), pp.3-20.
79. Kachenoura, A., Albera, L., Senhadji, L. and Comon, P., 2008. ICA: a potential tool for BCI systems. *IEEE Signal Processing Magazine*, *25*(1), pp.57-68.

80. Herman, P., Prasad, G., McGinnity, T.M. and Coyle, D., 2008. Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*(4), pp.317-326.
81. Halder, A., Jati, A., Singh, G., Konar, A., Chakraborty, A. and Janarthanan, R., 2012. Facial action point based emotion recognition by principal component analysis. In *Proceedings of the International Conference on Soft Computing for Problem Solving (SocProS 2011) December 20-22, 2011* (pp. 721-733). Springer, New Delhi.
82. Mena, J.B. and Malpica, J.A., 2003. Color image segmentation using the Dempster-shafer theory of evidence for the fusion of texture. *INTERNATIONAL ARCHIVES OF PHOTOGRAMMETRY REMOTE SENSING AND SPATIAL INFORMATION SCIENCES*, *34*(3/W8), pp.139-144.
83. Xu, L., Cheung, C.C., Yang, H.H. and Amari, S.I., 1997, June. Independent component analysis by the information-theoretic approach with mixture of densities. In *Proceedings of International Conference on Neural Networks (ICNN'97)* (Vol. 3, pp. 1821-1826). IEEE.
84. Yoto, A., Katsuura, T., Iwanaga, K. and Shimomura, Y., 2007. Effects of object color stimuli on human brain activities in perception and attention referred to EEG alpha band response. *Journal of Physiological Anthropology*, *26*(3), pp.373-379.
85. Martin, R., 2001. Noise power spectral density estimation based on optimal smoothing and minimum statistics. *IEEE Transactions on speech and audio processing*, *9*(5), pp.504-512.
86. Li, Y., Wu, J. and Yang, J., 2011, May. Developing a logistic regression model with cross-correlation for motor imagery signal recognition. In *The 2011 IEEE/ICME International Conference on Complex Medical Engineering* (pp. 502-507). IEEE.
87. Vicente, R., Wibral, M., Lindner, M. and Pipa, G., 2011. Transfer entropy—a model-free measure of effective connectivity for the neurosciences. *Journal of computational neuroscience*, *30*(1), pp.45-67.
88. Coben, R. and Mohammad-Rezazadeh, I., 2015. Neural connectivity in epilepsy as measured by Granger causality. *Frontiers in human neuroscience*, *9*, p.194.
89. Palva, J.M., Palva, S. and Kaila, K., 2005. Phase synchrony among neuronal oscillations in the human cortex. *Journal of Neuroscience*, *25*(15), pp.3962-3972.
90. Kar, R., Konar, A., Chakraborty, A. and Nagar, A.K., 2014, July. Detection of signaling pathways in human brain during arousal of specific emotion. In *2014 International Joint Conference on Neural Networks (IJCNN)* (pp. 3950-3957). IEEE.