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# Electroencephalogram Signal Processing For Hybrid Brain Computer Interface Systems

Md. Ali Haider

# ELECTROENCEPHALOGRAM SIGNAL PROCESSING FOR HYBRID BRAIN COMPUTER INTERFACE SYSTEMS

by

Md. Ali Haider
Bachelor of Science, Bangladesh University of Engineering & Technology
Master of Science, South Dakota State University

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This dissertation, submitted by Md. Ali Haider in partial fulfillment of the requirements for the Degree of Doctor of Philosophy from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Reza Fazel-Rezai

Dr. Reza Fazel-Rezai, Chairperson

S. Noghanian

Dr. Sima Noghanian

Dr. Kurt Zhang

Kathy Smart

Dr. Kathy Smart

This dissertation is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Grant McGimpsey
Dean of the School of Graduate Studies

May 4, 2018

Date

PERMISSION

| | |
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Md. Ali Haider
April 20, 2018

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To my Mother, for her unconditional love, care & affection.

To my lovely wife Rahena Haider, my loving daughter Ramisa and my loving son Zaiyan.

## ABSTRACT

The goal of this research was to evaluate and compare three types of brain computer interface (BCI) systems, P300, steady state visually evoked potentials (SSVEP) and Hybrid as virtual spelling paradigms. Hybrid BCI is an innovative approach to combine the P300 and SSVEP. However, it is challenging to process the resulting hybrid signals to extract both information simultaneously and effectively. The major step executed toward the advancement to modern BCI system was to move the BCI techniques from traditional LED system to electronic LCD monitor. Such a transition allows not only to develop the graphics of interest but also to generate objects flickering at different frequencies. There were pilot experiments performed for designing and tuning the parameters of the spelling paradigms including peak detection for different range of frequencies of SSVEP BCI, placement of objects on LCD monitor, design of the spelling keyboard, and window time for the SSVEP peak detection processing. All the experiments were devised to evaluate the performance in terms of the spelling accuracy, region error, and adjacency error among all of the paradigms: P300, SSVEP and Hybrid. Due to the different nature of P300 and SSVEP, designing a hybrid P300-SSVEP signal processing scheme demands significant amount of research work in this area. Eventually, two critical questions in hybrid BCl are: (1) which signal processing strategy can best measure the user's intent and (2) what a suitable paradigm is to fuse these two techniques in a simple but effective way. In order to answer these questions, this project focused mainly on developing signal processing and classification technique for hybrid BCI. Hybrid BCI was implemented by extracting the specific information from brain signals, selecting optimum features which contain maximum discrimination information about the speller characters of our interest and by efficiently classifying the hybrid signals. The designed spellers were developed with the aim to improve quality of life of patients with disability by utilizing visually controlled BCI paradigms. The paradigms consist of electrodes to record electroencephalogram signal (EEG) during stimulation, a software to analyze the collected data, and a computing device where the subject's EEG is the input to estimate the spelled character. Signal processing phase included preliminary tasks as preprocessing, feature extraction, and feature selection. Captured EEG data are usually a superposition of the signals of interest with other unwanted signals from muscles, and from non-biological artifacts. The accuracy of each trial and average accuracy for subjects were computed. Overall, the average accuracy of the P300 and SSVEP spelling paradigm was about 84% and 68.5 %. P300 spelling paradigms have better accuracy than both the SSVEP and hybrid paradigm. Hybrid paradigm has the average accuracy of 79 %. However, hybrid system is faster in time and more soothing to look than other paradigms. This work is significant because it has great potential for improving the BCI research in design and application of clinically suitable speller paradigm.

# CHAPTER I: INTRODUCTION AND BACKGROUND

## 1.1 Introduction

In every society, people with disabilities need to communicate with others. However, their economic and educational status are predominantly limited by the unavailability of tools and technologies to satisfy their special needs. There is a necessity for technological solutions to constantly increase to overcome their difficulties with everyday activities. A hands-free speller is such a tool which can help motion impaired people to express their opinions and ideas, and communicate with others[1].

In fact, the evolution of brain technology has offered limitless opportunities and possibilities for impaired as well as healthy members to contribute and participate in the society. Brain Computer Interface (BCI) systems enable the human brain to communicate with an external device bypassing the explicit pathways formed by a natural nervous system [2]. With the help of human brain signals or an electroencephalogram (EEG), brain activity in the neocortex is measured as voltage differences over the scalp. Information on subjects' intentions and thoughts is encompassed by EEG electrical patterns, which is decoded as important signatures of brain activity. The status quo BCI technology and associated signal processing schemes are advancing fast with an exciting promise to conquer disabilities through neuroprosthetics and rehabilitation. It will also improve control of devices in space, people's lives in e-home, or communication in novel ways [3].

To obtain a better understanding, a brief description of the human brain structure which leads to EEG generation will be useful. This work is mainly divided with two major steps: System design where paradigm is one of the major components to evoke the BCI potential. Another step is to collect and analyze the data for system evaluation. However, BCI systems usually suffers from unexpected behavior in some situations due mainly to loss of user concentration, interference from electromagnetic waves, noises from power lines or measuring electronics which poses challenges to BCI development. Sometimes the systems come with the eye fatigue caused during the training stage, the occurrence of tearful eyes, dizziness and postural discomfort.

## 1.2 Research Objectives of This Study

An injury or a disease may severely damage certain neuron pathways, what once were simple tasks may become impossible or very cumbersome to complete. Such a tragic event causes a loss of any natural way communication with the environment. Under such circumstances, recovery of neuronal becomes very difficult. The motor pathway can't be re-established to its full strength. BCI is the only alternative to this disconnected communication. This manuscript presents the BCI research which focuses on the study of EEG signal processing and classification techniques to design a speller suitable for the users in need as a tool to communicate with others. BCI research arena have observed significant achievements. However, the BCI research field is still growing and cherishes a promising future ahead. In order to make it a mature technology, still room for numerous possible improvements. Among these, few important aspects have been addressed in this work. First of all, design of a speller paradigm to lessen the fatigue and discomfort of the users. To satisfy this aspect, speller paradigms were designed for the real-time use.

Secondly, develop the associated signal processing algorithm to improve the information transfer rate. Signal processing algorithm was realized to conduct BCI experiments in real time with the following offline analysis. Finally, constitute a hybrid paradigm by the fusion of two different BCI techniques and study the response of the users to this hybrid BCI speller.

Keeping these existing limitations in mind, the motive to perform this research study was to develop an efficient BCI system with following characteristics:

- High mobility, flexibility
- Meet user’s comfort
- High accuracy and speed
- Ready to be employed in clinical premise
- To expand the group of BCI users

The contributions, to this study, to accomplish these goals can be categorized into two major themes: design of better speller paradigm, and better EEG signal processing and classification. In fact, both of these tasks need to consider the subject specific variation based on the spectral or spatial components of one’s brain activity. Therefore, such study requires developing an algorithm which mathematically can interpret the EEG features as well as discard the subject bias so that the physiological information can be conveyed to the classifier in an interpretable fashion [2]. In summary, the research goals were

- to eliminate some of the BCI limitations by implementing BCI paradigms on **LCD monitor,** and
- to develop a hybrid BCI to increase the **accuracy** and **speed** of the system.

## 1.3 EEG Signal

An EEG is a noninvasive medical imaging process that detects the electrical activity in human brain using small, flat metal discs (electrodes) attached to the scalp top surface and records this activity with the help of a conducting medium. Brain cells communicate via electrical impulses and are active all the time, even someone is asleep. This neurological activity appears as wavy lines on an EEG recording. EEG is graphically displayed along time axis as a difference in the generated voltages over two sites of brain. EEG is traditionally used for diagnostic purpose in clinics and hospitals such as for detecting epilepsy or other brain disorders, brain tumor, head injury, brain stroke, sleep disorders, dementia, to name a few. The most unique benefit of EEG is that it is risk free, safe and painless.

The local current flow is generated in the brain is due to the sodium potassium pumps at the neuronal level. The pumping of the positive ions Na+ (Sodium), K+ (Potassium), Ca++ (Calcium), and the negative ions of Cl- (Chlorine) through the channels in neuron membranes generate current in the brain as governed by membrane potential. Such activities create recordable but weak (just a few millionths of a volt) EEG signals between electrode and neuronal layers that can be amplified and stored in computer memory in digitized form. EEG was first recorded by Hans Berger in 1924 [4]. Berger first announced the term “electroencephalogram” for describing the weak electric currents recorded as human brain signal. He used his ordinary radio equipment as an electric signal amplifier and found that EEG changes following the physiological state of human. For example, the transition from relaxation to alertness will imprint a consistent and recognizable alteration in brain signal. In addition, sleep, anaesthesia, lack of oxygen and certain neural diseases, such as in epilepsy changes the functional status of brain. Hans Berger depicted that EEG can be recorded non-invasively without opening the skull.

Contemporary views about the origin and nature of EEG signals require a broad discussion about the brain and its functionalities. the brainstem, the cerebellum, and the cerebrum are the three principal parts of a brain [5]. The cerebrum is the largest part of the brain which is further divided into various lobes and structures. The cerebrum directs the conscious or unconscious thought and action through motor functions. The brainstem is the junction to the cerebral spinal column and acts as the base of the brain. the medulla, pons, and midbrain are the structures which constructs the brainstem. As an intersection, the brainstem's primary function is to relay the cerebellum and cerebrum signals to the spinal column. Basic life functions such as breathing, heart rate, and body temperature are regulated by the brainstem. The brainstem also handles many involuntary or automatic responses, such as sneezing, coughing, and yawning. The cerebellum is located just under the cerebrum. The cerebellum's handles motor learning, posture or coordination, and balance of the body. Voluntary movements require the combined action of a variety of different muscle groups, and the cerebellum plays a key role by coordinating the timing and actions of these different muscles. On the other hand, the cerebrum itself is separated into four different lobes: the frontal lobe, the parietal lobe, the occipital lobe, and the temporal lobe. Altogether, these four parts of the brain is known as the "cerebral cortex" which is further bisected into two different halves: the right hemisphere and left hemisphere. Figure 1.1shows the lateral view of the inner parts of the human brain along its functionalities.

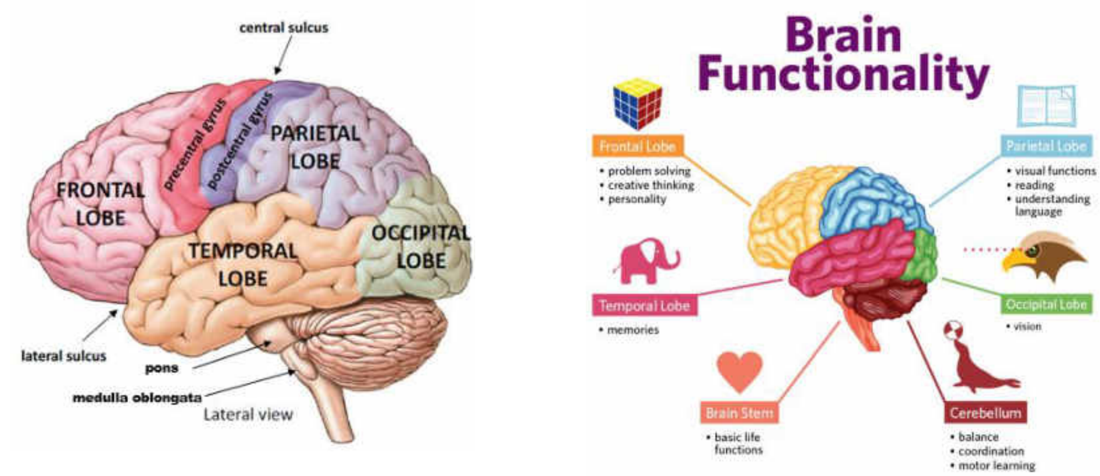



**Figure 1.1: Inner parts of human brain and its tasks [6].**

The frontal lobe of the brain regulates one's personality. In addition, planning, reasoning, emotions and problem-solving tasks are typically accomplished by the frontal lobe. Information from the other parts of the brain is received by the rear part of the frontal lobe or the motor cortex. The motor cortex also ensures that the body movement are carried out. The occipital lobe is responsible for the processing of visual information. This part of the brain receives visual information from the retinas in the eyes and then interprets that information for use. The top portion of the brain is known as parietal lobe whose main function is making visual perception of various stimuli, recognition of languages, orientation and reading. The parietal lobe is also home to the somatosensory cortex. The temporal lobe perceives speech information. The temporal lobe contains hippocampus which is associated with auditory function and memory. Any damage to temporal lobe pertains with loss of cognitive efficiencies such as memory problems and language deficiencies.

In case of clinical interpretation of EEG, sufficient understanding of normal EEG waveform is a key to identify the abnormality or any fluctuation of the normality in EEG throughout the entire lifecycle of a patient under a clinical diagnosis. However, in case of BCI study, it is not necessary to have deep clinical knowledge for EEG interpretation instead EEG measurement and waveform analyses incorporating frequency, morphology and voltage bear important aspects. Advanced analytical studies map the EEG signal attributes to measure physiological characteristics such as subject engagement, workload, fatigue and drowsiness.

### 1.3.1 EEG Measurement

It is interesting to know that EEG signal consists of oscillating waves with different characteristics which are identifiers of different brain states. Depending on the frequency, brain wave pattern gets different names which are given in Table 1.1.

**Table 1.1 Basic brain waves and their characteristics**

| Frequency Band | Frequency Range | Brain States |
|---|---|---|
| Gamma (γ) | >35 Hz (mainly up to 45 Hz) | Problem Solving, Concentration |
| Beta (β) | 12-35 Hz | Anxiety dominant, active mind, busy |
| Alpha (β) | 8-12 Hz | Very relaxed, passive attention |
| Theta (θ) | 4-8 Hz | Deeply relaxed, inward focused |
| Delta (δ) | 0.5-4 Hz | Sleep |

### 1.3.2 Applications of EEG Signal

There are several studies which have documented about the EEG area of applications. Tzallas et al [7] mentioned how better temporal resolution of EEG signal is engineered to detect epileptic seizures. For example, Adeli et al [8] found differences in the beta and gamma frequency bands after examining EEG signals collected form three different groups consisting of healthy (normal) subjects, epileptic subjects during a seizure-free interval (interictal) and epileptic subjects during a seizure (ictal). Yang [9], evaluated the effect of fatigue on functional corticomuscular coupling (fCMC). Gang et al [10] wanted to overcome accidents by developing a drowsiness detection system to find the parameters related to driver drowsiness. Apart from these, a research field of data mining has evolved to process the large volume of EEG data collected from multiple channels [11]–[13]. EEG analysis opened up another popular research field as sleep analysis. A study by Kassebaum [14] reported that a frequency domain-based state-space analysis of EEG is effective for identifying sleep stages. EEG is also used as a communication channel or a control signal in BCIs [15].

## 1.4 Signal Acquisition

Advancement in digital technology has laid the foundations of modern EEG equipment with high performance and low cost. Signal acquisition tools incorporate powerful computers for faster recording and data analysis. EEG signal acquisition system comprises recording electrodes with conductive media, amplifiers with filters, analog-to-digital (A/D) converter, and a recording device such as electronic devices or digital memory. The 10/20 international electrode placement system is recommended by the American EEG Society. This standard considers the left-side electrodes as odd-numbered and right-side electrodes as even-numbered. In this convention, two adjacent electrodes are placed 10% or 20% apart of the skull. Figure 1.2 shows the 10/20 International Standard. It is noticeable that F stands for frontal regions, C described the central region, Z refers to skull midline on top or zenith, P is for parietal and T indicates temporal region. In addition, A symbolizes anterior and frontpolar is designated by FP. To identify a site, brain lobe is indicated by a letter and the hemisphere location is marked by a number. Sometimes10/20 system is modified with added electrodes such as electrocardiogram (EKG), eye tracking system, electromyogram (EMG), and extracerebral electrodes to get rid of signal artifact.

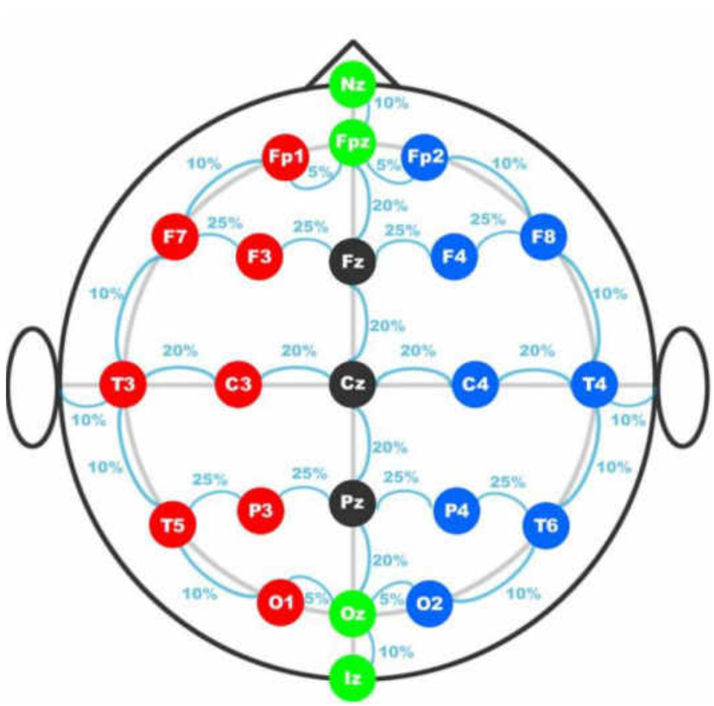



**Figure 1.2: Electrode distribution in 10/20 international system (adapted from [16]).**

The placement of the electrodes over the scalp maintains a pattern of connection between 16 or more electrodes which is termed as montage. The EEG can be monitored with either a bipolar montage or a referential one. Bipolar montage includes two electrodes per single channel, so each channel (waveform) has a reference electrode. For example, the channel "Fp1-F3" is a bipolar montage which represents the difference in voltage between the Fp1 and F3 electrodes. The referential or unipolar montage means that a common reference electrode for all the channels and each channel represents the difference between a certain electrode and the designated reference electrode. EEG reference is connected to either ear. In addition, there are average reference montage and Laplacian montage. Average reference montage uses the average of all the electrodes and this averaged signal is considered as the common reference. Laplacian montage almost similar as average reference montage except that a weighted average of the surrounding electrodes is used as a reference. Indeed, there is an inappropriate practice of using “ground” and “reference” interchangeably. Though both “ground” and “reference” are established at a different position than the "recording" electrodes, the location of the ground could be placed anywhere on the subject body. In general, the ground does not have any standard position and is used to prevent power line noise at 60 Hz from interfering with the small biopotential of EEG signals of interest. By design, ground is used for common mode rejection and no standard position is required in this mode. Scalp midline positions on the forehead are popular choice for a ground electrode for EEG recordings as they do not amplify the brain signal in any half of the brain with respect to the other one. Another popular reference convention is “summed ears,” or "linked ears," which leads to a physical or mathematical average of electrodes attached to either earlobes or mastoids. EEG montage stages incorporate the data collection processes mainly with wired or wireless EEG systems. In case of wired EEG data collection, the electrodes are placed on different spots of the scalp as designated by the type of application. For example, a wearable cap with the electrode tips is used to cover the head of a subject during EEG data acquisition for spelling words in a BCI speller (Figure 1.3). A short discussion on the merits and demerits of the wired or wireless EEG systems are presented below.

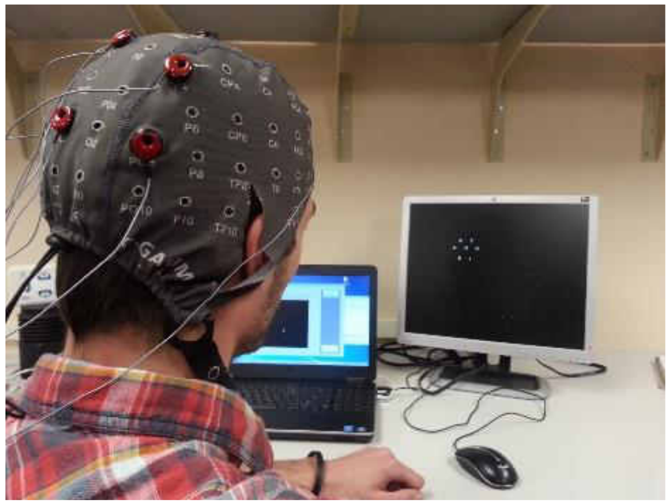


**Figure 1.3: EEG data acquisition using a hand-free BCI speller paradigm.**

### 1.4.1 Wired EEG Systems

#### *1.4.1.1 Merits*

- Electrodes are easily identifiable.
- Allows connection status and impedance checking.

#### *1.4.1.2 Demerits*

- Setup time is longer than other, may take 5-10 minutes.
- Long and loose wires may result in an antenna effect causing signal artifacts.
- Restrict the subjects' mobility from one place to another.
- Large number of electrodes and connected wires may be perplexing to find the end point.

### 1.4.2 Wireless EEG systems

#### *1.4.2.1 Merits*

- First of all, such a system eliminates requirement of any wire connection and uses wireless transmission.
- Allows the subject to move during data collection.
- Subject is free to change and adjust the posture to be in comfortable position.

#### *1.4.2.2 Demerits*

- As it does not have direct conduction medium, wireless system can easily be interrupted by external noise.
- Accuracy is comparatively less than that of a wired system

## 1.5 Brain-Computer Interfaces (BCI): Definition and Categories

A Brain-Computer Interface allows controlling computers or external devices using neuronal activity for people with and without disabilities. According to Wolpaw et al. [17], BCI is a communication system between brain and machine which can learn and interpret the signals from an active brain to execute commands or control the devices bypassing the normal neuromuscular pathways. As the name suggests, BCI has evolved from an interdisciplinary study which is a combination of engineering, cognitive neuroscience, psychology, machine learning, human-computer interaction and others. It's interesting to note that limited number of sensors results in overlapping of the measurable brain characteristics which are separated with the help of specific tasks performed by the BCI users. However, advances in digital technology, remarkable progress in cognitive neuroscience, pattern recognition and signal processing algorithms have channeled the knowledge in understanding the brain functions to change the world with the application of BCI as a new modality in human-computer interactions. BCI extends its benefits not only to the disables through neuroprosthetics and rehabilitation, but also to the able bodies to live in smart homes along with embodied health monitoring and entertainment devices.

### 1.5.1 BCI Systems and Modalities

In order to identify user intentions in brain activity, invasive or noninvasive electrophysiological control signals can be collected and recorded applying suitable hardware and software technologies. BCI hardware captures physiological signals from the brain. Among these signals Electroencephalography (EEG), magneto encephalography (MEG), functional Magnetic Resonance Imaging (fMRI), functional Near Infrared Spectroscopy (fNIRS), Electrocorticography (ECoG) and Subcortical Electrode Arrays (SEA) are all in use for BCI system and analysis[18]. Distinctive cognitive functions are formulated by several patterns of brain activity. With the help of EEG, brain activity in the neocortex is measured as voltage differences over the scalp. Since the first paradigm design and experiment with a P300 BCI system in 1988 by Farwell and Donchin, many BCI applications have been developed and refined as assistive technology, device control, user state monitoring, training and education, gaming and entertainment, safety and security, speech synthesizers, assistive appliances and neural prostheses among others[19]. Many BCI applications are based on event-related potentials (ERP) which are potentially suited for patients with neurodegenerative diseases or severe motor impairment[20].

However, these nonmedical BCI applications are continuously facing the challenge of being transferred from the research laboratory into real-life situations regarding the usability and the acceptability, hardware convenience, cost of the equipment, setup time, and interface with existing systems. Additionally, there is a step of significant difficulty experienced by BCI researchers in applying appropriate signal processing strategy. In this paper, efforts were made to address the existing solutions regarding the BCI signal processing. As many BCI communication and control systems have been realized with the EEG data acquisition, this study focuses on revealing the complexity and difficulty issues as well as the possibilities which lies under the fact that optimization of accuracy and speed heavily depends on a suitable signal processing scheme.

### 1.5.2 Dependent and Independent BCI

An independent BCI does not require any motor control by the user whereas a dependent BCI requires a volunteer action or certain level of motor control by the subject. Therefore, a dependent BCI mostly suit for the able-bodied persons. Dependent BCI systems are more comfortable and easier to use. To help the people with severe disability in any motor control, an independent BCI is more appropriate.

### 1.5.3 Invasive and Non-invasive BCI

Brain activities cause an influx of ions that depolarize the neurons and thousands of such spatially aligned neurons generates electrical potentials. The electrophysiological activity can be measured as the summation of these electrical potentials both invasively and noninvasively. Both of the invasive and noninvasive techniques are used in medical application to obtain high temporal and spatial resolution. BCI systems can vary depending on the different placements of sensors as portrayed in Figure 1.4.

In case of invasive technique, sensors are implanted under the skull. Electrocorticogram (ECoG) and intra-cortical neuron recording (INR) are two invasive

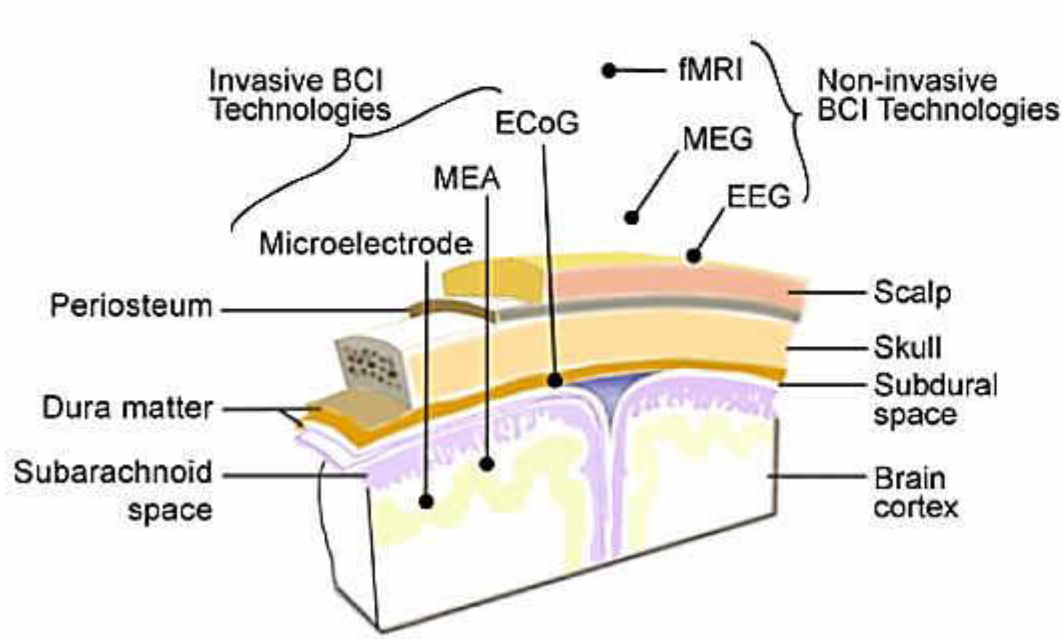



**Figure 1.4: BCI types depending on the sensor placement [21].**

techniques for recording electrophysiological signals. Both of these techniques result in a very good signal-to-noise ratio but at the cost of minor surgery. INR inserts micro-electrodes through the cortex layer while ECoG sets a group of electrodes on surface of the cortex. Evidently, invasive techniques are limited only to specific applications. Moreover, invasive methods are not able to cover the whole cortex area. On the other hand, noninvasive positron emission tomography (PET), functional near-infrared spectrography (fNIRS) and functional magnetic resonance imaging (fMRI) involve with indirect measurement of the brain activity by estimating the cerebral blood flow optically and magnetically, respectively. In other words, these techniques use hemodynamic activity which causes the active neurons to obtain higher rate of blood glucose and oxygen than the inactive neurons making a difference in oxygen-rich and oxygen-poor blood. Eventually, these methods quantify the changes in blood-oxygen levels at various locations of the brain.

All of these methods suffer from the poor temporal resolution with delays around one to several seconds [22]. fNIRS technology is portable, safe and easy to use, resistant to motion artifacts and can be employed in a subjects' natural environment. In this method, near infrared light is projected into the brain from the surface of the scalp and optical scattering at various wavelength are measured to localize and estimate blood volume and oxygenation changes. Such a quantification allows to generate a functional map of brain activities in terms of the degree of oxygen concentration. Likewise, fMRI and PET use the differences in blood-oxygen consumption levels. Though the fMRI system has very good spatial resolution, it is expensive and not portable as fNIRS. PET uses fludeoxyglucose (FDG) as a radioactive agent to map the neural metabolic activity in terms of regional glucose uptake. However, fNIRS, fMRI and PET share a common drawback of having a low temporal resolution. In general, these techniques require 2-5 seconds after the neural activity to detect the change of local blood flow.

Among other noninvasive techniques, such as MEG and EEG measures magnetic field and electric potential of the brain with a very good temporal but low spatial resolution. MEG device is almost as bulky and costly as fMRI, an exception to EEG. Among the current non-invasive methods, EEG is one of the popular and heavily used measurement techniques for BCI considering clinical as well as nonmedical applications. However, setting up the EEG sensors and probes might require several minutes. Due to the distance between the sensors and brain, the measured EEG signals are relatively noisy and weak in magnitude (5-100 μV) which needs to be filtered and amplified before further analysis. Afterward, these signals are translated into device output commands and feedback to user by BCI software. In fact, EEG became relatively simple to use and inexpensive as a result of the recent advances in wireless systems and electronics. Therefore, last few decades' plethora of BCI studies mainly focused on the EEG-based BCI system. A typical EEG signal window is presented in the Figure 1.5.

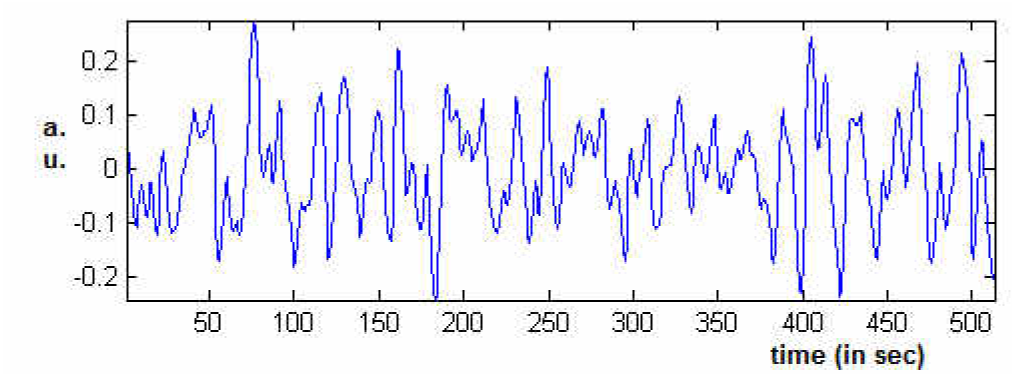



**Figure 1.5: Sample EEG data recorded using a single electrode.**

### 1.5.4 Synchronous and Asynchronous (self-paced) BCI

Functional connectivity within the cortex changes with the sensorimotor stimulation, motor behavior, and mental imagery. Such actions may cause amplitude suppression known as event-related desynchronization (ERD) or amplitude enhancements refereed to event-related synchronization (ERS) in certain frequency components (alpha and central beta). For instance, imagining a left-hand movement is known to trigger a decrease of power (ERD) in the μ and β rhythms, over the right motor cortex. In case of a synchronous BCI, the users' interaction with the targeted application is time controlled as the system informs the user of the moment when he has to interact with the application. So, the system does not respond to the user action if it falls outside the desired time period. Most attractive advantage of synchronous BCI is that the system knows the exact time span when the mental states should be classified. On the contrary, in an asynchronous or self-paced BCI, the user can perform a mental task to interact with the system any time while can do nothing to stop the interaction or make the BCI system inactive. In ideal case, all BCI should be self-paced, flexible and comfortable. However, such a technique is difficult to implement, and need to monitor and analyze the brain signal at a continuous pace to detect whether the user is trying to interact with the system. In addition, the asynchronous BCI need to determine the mental task that the user is performing. As a consequence, vast majority of BCI systems are synchronous and BCI interests are just gradually started increasing to address the challenges of self-paced BCI.

### 1.5.5 Active, Reactive and Passive BCI

Depending on the extracted information and techniques, BCI systems fall under three different categories such as active, reactive and passive systems.

Motor imagery is an active BCI where the user, voluntarily and without any external intervention, practices a mental task to generate commands to control an external device or application. A machine algorithm is used to detect the specific pattern of brain activity in real time so that the resulting information is capitalized to control a device by thought. In addition to motor imagery, visual imagery, spatial imagery involving navigation in familiar surroundings and auditory imagery of music are some other active BCI systems. However, due to the potential use as communication channel for disable individuals, motor imagery is the most investigated area of research to design an active BCI. In fact, actual movement performance and activity during motor imagery shows similar pattern in brain wave. For example, mu rhythms of EEG are altered during actual motor activities in terms of hands or finger movements. The EEG can be recorded at sensorimotor cortex at its three primary frequency components: a component between 9-11 Hz, a component near 20 Hz and one near 40 Hz. The left hand, right hand and foot movement has been utilized as attractive motor imagery tasks for controlling cursor movement as well as navigating web pages. On the other hand, visual imagery is associated with the imaginary 'observation' of an object with the mind. This allows to study certain or entire characteristics of the object from the EEG signal. For instance, sensory features such as the form and color of the object may be used as specific attributes. Similarly, auditory prompts can be presented to the participants to classify food, tool, human faces, buildings, animals, or other man-made objects.

BCI systems designed with the use of visual evoked potentials and P300 are few examples of reactive BCI. In this technique, brain reaction to an external stimulation are measured and mapped to generate a system output. Therefore, the user indirectly modulates the brain action to perform a specific task. In reactive BCI, temporal and spectral characteristics of the EEG signal changes depending on the presented stimulus and the task to do. The two most popular techniques that use evoked potentials are (1) visual evoked potential (VEP), and (2) P300, which is a component of an event-related potential (ERP). Both of these potentials are greatly pronounced in the EEG signals. An ERP is the measured brain response that is the direct result of a specific sensory, cognitive or motor event. ERPs can be classified according to the latency at which their components occur after stimulus presentation. ERPs with short latency typically occur at $<$ 100ms after stimulus. These components are generated during the sensory stimulus processing stages in the brain, and they are named exogenous components because they are a direct response to an outside stimulus source. ERPs with long latency occur at greater than 100ms after stimulus and represents the cortical processing stages. They are called endogenous components since they are less determined by the physical features of the stimulus. Neurophysiologic signal

P300 is the component of the ERP elicited by rare, task-relevant events in the process of decision making, and as such is an endogenous component. It is called P300 because it evokes a positive peak over the parietal lobe with a latency of around 300ms after a decision has been made and is recorded with EEG over the central-parietal scalp. P300 peak is evoked by an oddball paradigm where the users' pay attention to rare or infrequent stimuli in a random series of stimulus events of two categories: target event and non-target event. This signal is present in every human and therefore requires little to no initial user training, making it a popular technique for BCIs. In fact, users are asked to count the number of times the object is flashing which make them focus on the assigned task and verify the counted number with the actual set value for each experiment. However, the day to day mental load and physical stress varies with the human body. So, a short survey is taken from the subject before every experiment to measure their cognitive state and rest level. For example, if they were not confident enough about proper rest, the test was kept on hold for later. However, a person with proper rest and relaxed condition still can get poor results in BCI tests if they are BCI illiterate. In order to take care all such unexpected possibilities, every test was conducted twice.

A speller with a 6x6 matrix consisting of English alphabets was the first P300 based BCI where rows and columns flashed randomly. After a few trials of random flashing, the target latter can be identified with the evoked P300. Decreasing the number of flashes per trial, it is possible to enhance the speed of speller paradigm. However, there is always a tradeoff between the spelling speed and classification accuracy. Likewise, a steady-state visual evoked potential (SSVEP) is developed in the visual cortex during an individual's focus or constant attention to a visual object flickering with a frequency above 6 Hz.

SSVEP based BCI system can be used to control the cursor movement in multiple directions or to communicate with other persons. Depending on the user's intention or application, flickering objects of different shapes, colors or other attributes can be employed to design a SSVEP based paradigm. The changing frames of monitor makes the eyes get tired quicker than P300 BCI. As a consequence, the observer can lose his interest resulting in inadequate attention. Eventually, this necessitates the change in color or intensity of the flickering objects which can bring better effect of visual feeling in the user's mind. This action also points to the importance of electronic monitor over the LED arrays. Electronic monitor offers better resolution, soothing feeling of vision, adjustable intensity, and inter space between graphical objects. However, the high flickering graphics can be tearing to incomplete shapes causing frequency mismatch. A monitor with higher refresh rate can remove such limitations. Other reactive BCI examples are somatosensory and auditory potentials.

Passive BCI systems measures the user's mental state from the arbitrary brain activity without any external stimulus or voluntary control. Workload, fatigue, excitement, level of engagement are some states of mind which are used to design a passive BCI. Human satisfaction and emotion is embodied with the human cognition that allows to evaluate human interaction, and therefore passive BCI may also be referred to as cognitive monitoring.

## 1.6 Feature Extraction Methods in EEG Based BCI Systems

In general, any signal processing is comprised of two different stages as feature extraction and algorithm for translating the features to a corresponding class. However, acquired EEG signals suffer from noise with very low signal-to-noise ratio. In addition, sensor artifacts, sensor failure, or subject fatigue leads to non-stationarities due to various physiological and environmental factors. So, designing an effective interference tool is critical to extract information about the salient EEG features. Such step also aimed at preprocessing and artifacts removal.

The first stage is employed to reveal the brain signal features that can be modulated by a BCI user. However, various methods can be applied to the digitized EEG signal such as spatial and spectral analysis, measurements of voltage distribution, and detection of action potentials of individual neurons. This stage is immediately followed by translation procedure. All signal features are mapped to some classes representative of device commands by employing either linear or nonlinear method. These device independent signal features can be applied to build a functional or communicative relationship between the user and the device under operation. In order to satisfy the criteria of an application, BCI system needs an effective translational algorithm which requires adaptation to the specific signal features that can be either be controlled or learned by the user to improve individual performance. In sum, the effective interaction between the user and the BCI system necessitates incorporation of a better signal processing method.

Evoked potential or evoked response is different from spontaneous potentials. After the presentation of a stimulus to a human or an animal, electric potential shows significant voltage fluctuations resulting from evoked neural activity. In general, low amplitude evoked potentials are time-locked to the stimulus and amplified through signal averaging and other techniques. Signal averaging allows to average repeated responses thereby cancelling the random noises.

EEG recording for BCI research needs a large number of descriptors which are commonly used with cognitive research, too [23]. Key descriptors to categorize and describe the complex brain activity have been briefly highlighted in Table 1.2. Though behavioral and functional aspects are major concern in BCI, many other aspects of EEG activity such as spatial distribution, frequency, amplitude, morphology, and periodicity are identically worthwhile[24].

**Table 1.2: Important measurement parameters of EEG signal**

| EEG Signal Features | Description | Comments |
|---|---|---|
| Morphology | Waveshape | Brain activities form waveshapes that are the identifier of some events or characteristics. |
| Repetition | Defines the re-occurrence of waveform types. | Rhythmical repetitive waveforms. Also, may gradually increase and then decrease in amplitude. |
| Frequency | Number of repetitions of similar waveforms in a single unit of time. | --- |
| Amplitude | microvolts (μV);<br>peak-to-peak or from the calibrated zero reference | Typical range: 10 ~100 μV. |

| EEG Signal Features | Description | Comments |
| --- | --- | --- |
| Distribution | Electrodes records electrical activity which are spatially oriented over different parts of the head | Spatial orientation is described using electrode names, not by head regions or brain areas. |
| Phase Relation | Change in troughs and peaks of the wave components over time considering single or multiple channels | Phase refers to the temporal relationship between different components of a rhythm. |
| Timing | Relative occurrence of activity in time at different channels | --- |
| Reactivity | Changes that can be introduced by one or multiple features as mentioned above due to various maneuvers or functions; appears as some normal and abnormal patterns | Used to train or evaluate the subjects condition; study of drug addiction |

### 1.6.1 Signal Amplitude

The temporal resolution of EEG signal can be utilized by extracting the EEG amplitude in a simplest but still efficient way. The time course of the EEG signal amplitude provides temporal information that could be extracted as electric potentials. In this case, a feature vector is made up of the concatenated raw amplitudes of the signals from the different electrodes. Sometimes these feature values are preprocessed before feeding as input to a classifier. In general, the classification algorithm allows to reduce the amount of data to be used by preprocessing methods such as down sampling or spatial filtering. It is a very common feature extraction technique in P300 classification methods. Similar to as many other features, low signal to noise ratio of EEG signal need to be taken care of along with the variability of the responses to stimuli within a single subject [25].

### 1.6.2 Power Spectral Density (PSD)

The power of the different frequency contents of a signal is measured as Power Spectral Density (PSD) features from the user's EEG signal within a preset time window. Such a frequency-based power distribution sometimes simply termed as power spectrum which gives valuable insight about the BCI signal. The major aspect of this feature is to estimate the signal-to-noise ratio of the power spectrum in each stimulus frequency [26]. As the fast Fourier transform (FFT) has low computational cost, PSD features can be computed by squaring the Fourier transform of a signal as a nonparametric power spectrum estimation method or by finding the Fourier transform of the autocorrelation function of the EEG signal [27]. PSD features have proved to be proficient in differentiating and detecting a large number of neurophysiological signals which leveraged it probably to be the widely used features for BCI applications [28]. However, PSD features from a single channel (or a bipolar montage) can be sensitive to noise once the signal-to-noise ratio is very small.

### 1.6.3 Canonical Correlation Analysis (CCA)

It is quite apparent from the previous sections that low amplitude of EEG signal has pinpoints to the necessity of improving signal-to-noise ratio and many different algorithms stride to reach this goal. With no exception, CCA processes the signal as a form of array using channel covariance information so that the BCI system may have improved the signal-to-noise ratio. CCA is a multivariable statistical method used to recognize the frequency. If a specific frequency is buried into the low power EEG signal, CCA employs another set of noise free data as a reference to determine any underlying correlation between these two sets of data. CCA is actually an extension of ordinary correlation where two sets of variables are employed [29], [30]. A pair of linear combinations are formed for two sets which are called canonical variables. CCA maximizes the correlation between the two canonical variables. In the following step, it computes a second pair of canonical variables which has a next highest correlation but completely uncorrelated with the first pair of canonical variables. This action is repeated to construct more canonical variables until the number of pairs of canonical variables equals the number of variables in the smaller set. Among the CCA generated canonical correlation coefficients, the largest coefficient has the best description capacity to describe the relation of the two corresponding sets. Note that although CCA generates multiple correlation coefficients, in this paper we only consider, which has the best description capacity.

### 1.6.4 Independent Component Analysis (ICA)

ICA is one of the better feature extraction and classification methods which maximizes the non-Gaussianity of statistically independent components (ICs). Many other authors have employed ICA as a preprocessing tool for artifact removal in brain signal analysis [31]. However, some studies suggest that such action may also suppress the power spectrum of the underlying neural activity [32].

As ICs are generated after mixed signal decomposition, satisfaction of non-Gaussianity is critical to the estimation of original signal [33]. Typical ICA steps involve mixed signal separation, artifacts removal from EEG signal, and eliminating noises. Implementation of ICA results in removal of the irrelevant and redundant information, thereby a significant reduction in computational costs. Major advantage of ICA is that this statistical procedure blindly splits the mixed signals into its sources without any previous information on the nature of the signal. However, another lead assumption involved in ICA claims that the observed EEG signal comprises of mutually independent cognitive activities or artifacts.

ICA expresses an EEG signal $\boldsymbol{x(t)}$ in terms of their sources $\boldsymbol{s(t)}$ as:

$$\boldsymbol{x}(\boldsymbol{t}) = \boldsymbol{f}\big(\boldsymbol{s}(\boldsymbol{t})\big) + \boldsymbol{n} \tag{1.1}$$

In equation (1.1), $\boldsymbol{f}$ is any unknown mixer function, and $n$ is a random noise. The dimension of $s(t)$ depends on the number of sources. The dimension of output vector $\boldsymbol{x(t)}$ is same as the number of data channels. In general, the number of sources is usually assumed to be less than or equal to the number of channels [34].

Source vector $\boldsymbol{s(t)}$ is estimated by inversion of $\boldsymbol{f}$ and then, by mapping $\boldsymbol{x(t)}$ to the source space. Based on $\boldsymbol{f}$ function ICA can be defined for two different models, either a linear or nonlinear function. If the linear model appears too simple to explain the complexity of the observed data $\boldsymbol{x}(t)$, nonlinear assumption is applied in those cases. However, indeterminate nature of the nonlinear problem makes it too complex to compute.

In case of linear approximation, equation (1.2) can be re-written as a matrix multiplication where $\boldsymbol{A}$ is the mixing matrix:

$$\boldsymbol{x(t)} = \boldsymbol{As(t)} + \boldsymbol{n} \tag{1.2}$$

Above approximation in equation (1.1) works reasonably well in brain signal processing applications on the assumption that the observed data is noiseless or that the signal-to-noise ratio is too high [35], [36]. In addition, ***s(t)*** and $\boldsymbol{A}$ are obtained from ***x(t)*** by means of certain algorithms such as Infomax [37]. Moreover, FastICA and JADE are two other widely used algorithms. Here, FastICA will be discussed in more detail.

Before applying FastICA algorithm, a whitening process need to be implemented. For any signal *x*, the whitening process involves linear transformation of the observed signal which is applied to reduce the parameters to be estimated. The components of the transformed signal $\tilde{x}$ are uncorrelated with their unity variance as in equation (1.3).

$$\boldsymbol{\varepsilon}\{\boldsymbol{\tilde{x}\tilde{x}^T}\} = \mathrm{I} \tag{1.3}$$

The whitening transformation is always possible. A popular method is to use the eigenvalue decomposition of the covariance matrix, $\boldsymbol{\varepsilon}\{\tilde{\mathrm{x}}\tilde{\mathrm{x}}^{\mathrm{T}}\} = \mathbf{EDE^T}$, where E is the orthogonal matrix of eigenvectors of $\boldsymbol{\varepsilon}\{\mathbf{\tilde{x}\tilde{x}^T}\}$ and D is the diagonal matrix of its eigenvalues. In equation (1.4), the whitening transformation is operated by

$$\boldsymbol{\tilde{x}} = \boldsymbol{ED^{\frac{1}{2}}E^T x} \tag{1.4}$$

If the observed signal $\boldsymbol{x}$ is distributed by an ICA data model as:

$$\boldsymbol{x} = \boldsymbol{As} \tag{1.5}$$

In equation (1.5) s is the matrix of independent components and A is the activation matrix (s and A will be discussed later). Substituting equation (1.5) into equation (1.4) gives

$$\widetilde{\boldsymbol{x}} = \boldsymbol{E}\boldsymbol{D}^{\frac{1}{2}}\boldsymbol{E}^{\boldsymbol{T}}\boldsymbol{As} = \widetilde{\boldsymbol{A}}\boldsymbol{s} \tag{1.6}$$

Where $\widetilde{\boldsymbol{A}}$ is an orthogonal matrix in equation (1.6) since

$$\boldsymbol{\varepsilon}\{\widetilde{\boldsymbol{x}}\widetilde{\boldsymbol{x}}^{\boldsymbol{T}}\} = \widetilde{\boldsymbol{A}}\boldsymbol{\varepsilon}\{\boldsymbol{s}\boldsymbol{s}^{\boldsymbol{T}}\}\widetilde{\boldsymbol{A}}^{\boldsymbol{T}}=I \tag{1.7}$$

Therefore, the number of parameters to be estimated is reduced from $n^2$ (in $A$) to $\frac{\mathrm{n(n-1)}}{2}$ (in $A$) because $\widetilde{\boldsymbol{A}}$ has only $\frac{\mathrm{n(n-1)}}{2}$ degrees of freedom in equation (1.7).

### 1.6.5 Minimum Energy (ME) Method

The minimum energy combination method combines an arbitrary number of electrodes to cancel as much of the noise as possible. This purpose is satisfied by removing any potential SSVEP components from all the electrode signals. To accomplish this, SSVEP components are projected onto the orthogonal complement of the SSVEP model matrix **X**.

$$\dot{\mathbf{Y}} = \mathbf{Y}-\mathbf{X}(\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-\mathbf{1}}\mathbf{X}^{\mathbf{T}}\mathbf{Y} \tag{1.8}$$

After this operation, $\dot{\mathbf{Y}}$ will contain only noise under the assumption that just slightly small unavoidable effect the projection in (1.8) has on the noise. In the next step a weight vector $\widehat{\mathbf{w}}$ with unity norm is constructed to minimize the resulting energy of the set of electrode signals$\dot{\mathbf{Y}}\widehat{\mathbf{w}}$. So, following problem is optimized:

$$\min_{\widehat{\mathbf{w}}} \left\| \dot{\mathbf{Y}}\widehat{\mathbf{w}} \right\|^2 = \min_{\widehat{\mathbf{w}}} \widehat{\mathbf{w}}^{\mathbf{T}} \dot{\mathbf{Y}}^{\mathbf{T}} \dot{\mathbf{Y}} \widehat{\mathbf{w}} \tag{1.9}$$

The quadratic form on the right hand side in (1.9) is bounded by the minimal and maximal eigenvalues, $\lambda_1$ and $\lambda_{Ny}$ ($\lambda_1 \leq \lambda_{Ny}$ ), of the symmetric matrix $\dot{\mathbf{Y}}^{\mathbf{T}}\dot{\mathbf{Y}}$.

So, the smallest eigenvector $\mathbf{v_1}$ appears as the solution to the minimization problem, and the energy of the resulting channels combination equals the smallest eigenvalue $\lambda_1$. Moreover, the matrix $\dot{\mathbf{Y}}^{\mathbf{T}}\dot{\mathbf{Y}}$ is symmetric, and the eigenvectors are orthogonal. Eventually, use of the second largest eigenvector $\mathbf{v_2}$ to select the combination of the electrode signals produces a second channel signal which is uncorrelated with the first channel, and results in somewhat higher energy $\lambda_2$. Therefore, columns in the weight matrix **W** are chosen as eigenvectors. Although the weight matrix **W** have some negligible effect, it is easy to predict that the SSVEP response is more easily detectable in the first set of channels with the lowest possible content of noise components.

In particular, the weight matrix is chosen as in equation (1.10):

$$\mathbf{W} = \left( \frac{\mathbf{v_1}}{\sqrt{\boldsymbol{\lambda_1}}} \quad \cdots \quad \frac{\mathbf{v_{Ns}}}{\sqrt{\boldsymbol{\lambda_{Ns}}}} \right) \tag{1.10}$$

where, $N_s$ denotes the number of channels. The normalization of each eigenvector with the square-root of the corresponding eigenvalue resulting in channel signals $\mathbf{s}_1$, …., $\mathbf{s}_{N5}$, will have the same energy. The number of eigenvectors to include in the weight matrix depends on the number of channels need to be produced. In summary, no single optimal solution exists for this model selection problem. In general, $N_s$ is chosen to discard as close to 90% of the noise signal energy as possible.

### 1.6.6 Principal Component Analysis (PCA)

PCA is a second-order statistic used to maximally decorrelate the components of an input in temporal domain. These components are utilized to compute orthogonalized and normalized features. One of the advantages of PCA components is that the artifacts can be removed using PCA correlation to clean up EEG signal. For instance, PCA decomposes a multi-electrode EEG trial (such as 32 channels) into linearly uncorrelated components, and then reconstruction is performed by omitting unwanted artifact components such as EOG (originating from the eye). This technique also provides the insight of the data structure which reveals the simultaneous artifact by separating the data according to the variance [38].

## 1.7 Classifiers Used in EEG Based BCI Systems

The main purpose of a classifier is to translate the extracted features into commands using either regression or classification algorithms [39]. The algorithms used to classify the features are known as "classifiers". However, BCI community mostly uses classification algorithms to identify the neurophysiological signals. Previously extracted feature vector is automatically assigned to a class in a classification step. The kind of mental task performed by the BCI user is represented by this class. Training sets are feed into a classifier in a training phase so that the classifier can learn to identify the class of a feature vector. The feature vectors of the training sets are labeled with their class of belonging. Depending on the taxonomy of the different classification algorithms, classifier families can be categorized into five main groups: linear classifiers, nonlinear Bayesian classifiers, artificial neural networks, nearest neighbor classifiers and hybrid classifier or classifier combinations. Selection of classifiers depends on the classifier properties befitting a specific application. For example, discriminative classifiers learn to discriminate the classes or the class membership to classify the feature vectors. Such classifiers are associated with low complexity and stable performance so that any insignificant or small variations in training set does have very little to no effect on their classification performance. In general, linear classifier applies discriminative algorithms to discriminate or distinguish the classes with a linear function. Due to the nature of these algorithms, BCI societies favor Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA) more than other nonlinear classifiers [40].

### 1.7.1 Support Vector Machine (SVM)

In fact, SVM is one of the popular modern classifiers that have been designed to provide several desirable performance characteristics. The major goal of a SVM is to find the hyperplane which apparently maximizes the data separation by keeping the nearest training points at possible farthest distance optimizing the generalization capabilities. The regularization parameter of SVM enables it to avoid data over-fitting. Like many other classifier, SVM can create both linear (linear support vector machine or, LSVM) and non-linear (Gaussian support vector machine, or GSVM) boundaries to classify the data. In that case, kernels are used to non-linearly map the input data to a high-dimensional space which is then linearly separable [41]. A number of different kernels exist, but the most popular in BCI literature is the Gaussian radial basis function (RBF) kernel. For example, the use of the RBF kernel adds another parameter that needs to be tuned through cross-validation, i.e., $\gamma$ (kernel bandwidth, in equation (1.11)):

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0. \quad (1.11)$$

For the two linearly separable classes shown in Figure 1.6, binary classification is performed by constructing a hyperplane as described by the weight vector $\boldsymbol{w}$ and the bias term $\boldsymbol{b}$. Each sample of training datasets is denoted as $\boldsymbol{x_i}$ and the corresponding class labels as $\boldsymbol{y_i}$. However, all of these can be achieved only at the expense of execution speed. Usually, just one sequence of the observed signal is not enough for correct classification due to its noisy component. Therefore, it is recommended that several sequences need to be combined to generate final classification results.

The category label of an incoming data $\boldsymbol{x}$ can be predicted by using equation (1.12)

$$\boldsymbol{f(x) = w.x + b} \quad (1.12)$$

In equation (1.12), the input data vector $\boldsymbol{x}$ is projected on the weight vector $\boldsymbol{w}$ which is perpendicular to the separating hyperplane. The sign of the projection would unveil the predicted class label as either positive or negative. The hyperplane can be described by the vector $\boldsymbol{w}$ and bias term $\boldsymbol{b}$, and $\boldsymbol{w}$ (in Figure 1.6) only for optimized separation. These necessary vectors are called support vectors [42].

Usually, $\boldsymbol{w}$ and $\boldsymbol{b}$ are tuned to maximize the distance between the parallel hyperplanes that separate the data. These hyperplanes can be constructed by the equations (1.13) and (1.14):

$$\boldsymbol{w.x - b = 1} \quad (1.13)$$

$$\boldsymbol{w.x - b = -1} \quad (1.14)$$

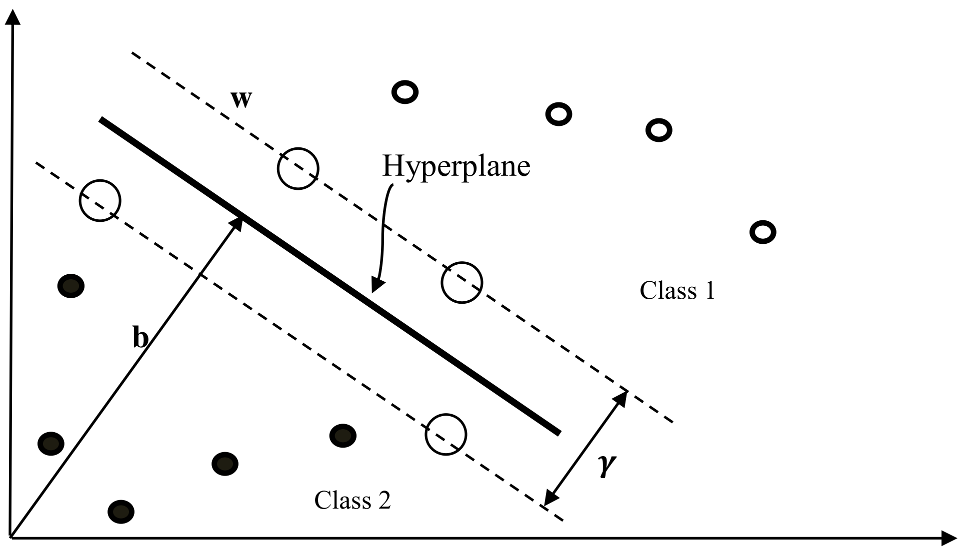



**Figure 1.6: Pictorial illustration of SVM. SVM finds the optimal hyperplane (solid line) to separate two classes by maximizing the margin γ. It is defined by the vector w and the bias term b. Only support vectors (bordered circle) are necessary to calculate w and b.**

The distance between these two hyperplanes is $\frac{2}{\|w\|}$. Therefore, to maximize this distance, $\|w\|$ need to be minimized. Hence the minimization has to subject to the following constraints expressed in equations (1.15) and (1.16).

$$\boldsymbol{w.x_i - b \geq 1} \text{ for } x_i \text{ from the first class} \quad (1.15)$$

$$\boldsymbol{w.x_i - b \leq -1} \text{ for } x_i \text{ from the second class} \quad (1.16)$$

Equations (1.15) and (1.16) can be rewritten as:

$$\boldsymbol{c_i(w.x_i - b) \geq 1} \text{ for all } 1 \leq i \leq \text{n}, \quad (1.17)$$

where *ci* is class label for *xi.*

Now the optimization problem limits to minimizing $\|w\|$. This constrained optimization problem can be solved using Lagrangian multipliers which finds a solution as

$$\boldsymbol{w = \sum_{i=1}^{n} \alpha_i x_i c_i}, \text{ here } \boldsymbol{\alpha_i} \text{ is a Lagrange multiplier} \quad (1.18)$$

### 1.7.2 Linear Discriminant Analysis (LDA)

In almost all cases EEG data acquisition results in high dimensional data which often might invite redundancy and make the data interpretation difficult. Linear Discriminant Analysis (LDA) is a well-known method for dimensionality reduction and classification. It separates the classes by projecting high-dimensional data onto a low dimensional feature space. The projection or transformation is optimized by combining the original features after faithful tuning of the coefficients generated from the transformation matrix. This requires maximizing the ratio of the between-class variance to the within-class variance as described in equation (1.19).

$$\boldsymbol{J}(\boldsymbol{w}) = \frac{\boldsymbol{w}^{t}\boldsymbol{s}_{b}\boldsymbol{w}}{\boldsymbol{w}^{t}\boldsymbol{s}_{w}\boldsymbol{w}} \tag{1.19}$$

In equation (1.19), $w$ is the transformation matrix, $S_b$ and $S_w$ are the between-class variance and within-class variance, respectively whereas $t$ represents the transpose operation. BLDA (Bayesian Linear Discriminant Analysis) and SWDA (Stepwise Linear Discriminant Analysis) are two improved versions of LDA. LDA classifies objects following a simple procedure that provides acceptable accuracy without high computation requirements. Due to rapid computation but limited resource requirement, LDA has obtained popularity in P300 speller, multiclass [43], or synchronous [44] BCIs. In order to obtain better classification result, signal should be free from outliers or any strong noise [45].

LDA is usually applied to separate two classes under the assumption that both are linearly separable. In order to distinguish the classes, a linear discrimination function is defined by LDA which represents a hyperplane in the feature space. The hyperplane bisects feature vectors into two classes based on their appearance on the side of the plane where the vector is found [45]. LDA can be extended to multiples classes with the use of several hyperplanes [43].

Mathematical representation of the hyperplane is as equation (1.20)

$$\boldsymbol{d}(\boldsymbol{x}) = \boldsymbol{w}^{\boldsymbol{t}}\boldsymbol{x} + \boldsymbol{w}_{\boldsymbol{0}} \tag{1.20}$$

Here, where, $w$ is known as the weight vector or transformation matrix, $x$ is the input feature vector containing n feature vectors $x_1, x_2, \ldots, x_n$ and $w_0$ is a threshold. Sign of $d(x)$ decides the class of the feature vector $x$.

Considering only two classes, the transformation matrix $w$ can be developed following the mathematical calculation presented in [46]:

$$\boldsymbol{w} = \sum\nolimits_{\boldsymbol{c}}^{-\boldsymbol{1}} (\boldsymbol{\mu}_{\boldsymbol{2}} - \boldsymbol{\mu}_{\boldsymbol{1}}) \tag{1.21}$$

The symbols in equation (1.21) are explained as:

$\mu_i$ is the estimated mean of class $i$;

$$\mu = \frac{1}{n}\sum_{j=1}^{n} x_j;$$

The average of the two class empirical covariance matrices,

$\sum_c = \frac{1}{2}(\sum_1 + \sum_2)$, estimated common covariance matrix;

Unbiased estimator of covariance matrix, $\sum = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)\,(x_i - \mu)^t$

BLDA is an extension of LDA which does not depend on the size of the samples. LDA does not perform well when the number of training examples are insufficient in comparison to the number of features. BLDA introduces a statistical method known as regularization. During regularization, Bayesian analysis is applied on the training data to prevent overfitting of high dimensional and possibly noisy datasets. Data overfitting is undesirable as it can cause the classifier to lose its generality. Over fitted classifier fails to perform well with other than training data or similar data. Eventually, BLDA algorithm provides higher classification accuracy and information transfer rates especially in those cases where the sample size is small [47]. However, BLDA requires more computation time than LDA which might be a crucial constraint in many BCI applications.

SWDA is also an extension of LDA. Automatic feature selection is the key advantage of SWLDA as it removes the insignificant features from the classifier. SWLDA selects the feature with both forward and backward regression for feature selection and combines it to the LDA to construct a classifier with significant features. Only the most statistically significant features with $p$-value $< 0.1$ are added in the classifier as predictor variables. Afterward, predictor variables with $p$-value $>0.15$ are removed by backward regression. The addition and removal processes repeat until any more feature fails to satisfy the criteria or bounded by a preset number of terms. This property makes the SWLDA more robust to the risk of having less training data which could corrupt the classification results. However, SWLDA can suffer from inefficient classifier model if there is not adequate discriminable information in the features [48].

### 1.7.3 Neural Networks

A Neural Network (NN) is composed of a number of artificial neurons which produce nonlinear decision boundaries to classify the features in a linear fashion. Among variety of NN used in BCI, Multilayer Perceptron (MLP) NN is widely used [49].

### 1.8 EEG Detectable Neurophysiological Potentials

Post-synaptic potentials are generated by thousands of neurons which is recorded by the EEG. Moreover, these neurons have the same radial orientation with respect to the scalp. Therefore, EEG signal processing stage involves detection of action-potentials of individual neurons using variety of pattern recognition methods. Brain activity patterns constitute these neurophysiological signals which are identified by BCI. In broad, there are two types of neurophysiological signals: 1) Evoked Signals, and 2) Spontaneous Signals. In the first case, the electric potential is developed as a response to an external stimulus where no mental task is needed from the user. On the other hand, spontaneous signal requires the user to execute voluntary efforts which is manifested by an internal cognitive process.

#### 1.8.1 Event-related Potentials (ERPs): P300 Potentials

The event-related potential (ERP) first reported by Sutton. An ERP is an electrophysiological response or electrocortical potentials triggered by a stimulation and firing of neurons. A specific psychological event or a sensor can be employed to generate the stimulation. In general, visual, auditory, and tactile are three major source of ERP stimulation. For instance, ERP can be elicited by surprise appearance of a character on a visual screen, or a 'novel' tone presented over earphones, or by sudden pressing a button by the subject, including myriad of other events. Presented stimulus generates a detectable but time delayed electrical wave in EEG. EEG is recorded starting from the time of presenting the stimulus to the time when EEG settles down. Depending on the necessity, simple detection method such as ensemble averaging, or advanced processes such as linear discriminant analysis or support vector machine algorithms are applied on EEG to measure the ERP.

The core purpose of a BCI is to detect brain activity in EEG and communicate that activity to a computer or electronic device. P300 BCI is such a safe and non-invasive system which requires the user wearing a small head cap carrying a set of electrical probes to detect brain P300 ERP. The P300 BCI has many potential advantages over many other input modes. Detection of P300 requires the subject properly recognizes the stimulus event to generate a strong and perceivable P300 ERP. Noticeable P300 amplitude also critical for information transfer which might not be possible if the stimulation is presented too fast or the targets appear too frequently. It is important to design a BCI paradigm with easily discriminable stimuli. BCI should be adjustable to the users' adaptability of signal detection by controlling the stimulus presentation at a slower rate, brighter intensity, or with otherwise increasing perceptibility. Studies also showing that target-to-target interval, or TTI plays an important role in evoking larger P300 ERP. If the overall BCI paradigm presents the stimulation at a constant rate, targets with low probability results in longer TTL which is also a useful mean to obtain perceivable P300 amplitude. In sum, for stronger P300 ERP the BCI system should maintain a minimum probability or, maximum TTI. Unfortunately, such an action reduces the frequency of the target stimulation and, thereby, reducing overall system speed. This tradeoff has been explored in several early BCI studies. It is evident that due to the nature of P300 ERP generation, P300 amplitude can be increased by incorporating high temporal uncertainty. In this case, subjects are completely unaware of the exact time of when the stimulation occurs. Few articles reported that P300 amplitude becomes larger for familiar or learned items. For example, if a list of characters is presented to a subject repeatedly, P300 amplitudes for repeated characters (which are recalled by the subject) are higher than the characters which are forgotten by the user.

In addition, there are several other factors which should be considered for P300 detection. Among these are attentional blink which occurs in case the intervals between two different targets become less than 500 ms, repetition blindness which leaves the second target unnoticed if two identical targets flash at intervals between 100 to 500 ms, and habituation which makes fainted P300 amplitude due to the repeated presentation of the same stimulus. Apart from this, human factors such as motivation, fatigue, and user comfortability affect the performance and accuracy of the P300 BCI, which should be considered in the design of paradigms.

### 1.8.2 Visual-Evoked Potentials (VEPs)

Visual evoked potential in EEG is measured over the visual cortex area. Evoked response in EEG signals to repetitive visual stimulations is called SSVEP. SSVEP-based BCI paradigm is designed to produce repetitive visual stimulations. It can be realized by making the stimulus flashing at a steady pace. SSVEP appears as an oscillation in the EEG signals with a steady flashing frequency that can be detected by the application of a suitable signal processing algorithm. The intention of the subject can be detected by identifying this frequency. Such an action can be translated to a control signal for a BCI system. Studies have found that SSVEP interfaces benefits from more brain states than P300 due to the use of multiple frequencies each representing a degree of freedom on a control paradigm. Similar as P300 paradigm, SSVEP needs to select the object within a time frame. Whereas P300 is detected in the time domain, SSVEP appears as a peak on the frequency spectrum close or equal to the frequency of the repetition of stimulus in which the subject focuses.

Detected SSVEP can be translated either to a character to spell a word or to a control signal to drive a device for a BCI system. SSVEP BCIs are not entirely dependent on muscle-based gaze control. However, the flickering stimulus is annoying to some users and produces fatigue to the eyes. At higher frequencies the annoying effect of the flickering stimuli reduces, making it more comfortable, but the SSVEP magnitude attenuates to such a level, which makes the SSVEP harder to be detected. Usually SSVEP-based BCI system benefit from higher accuracy and less or no training time, and fewer number of EEG channels.

A relationship study between SSVEP amplitude and the corresponding frequency found that SSVEP peak rises after 5 Hz and continues to increase until 15 Hz (Figure 1.7). After reaching the maximum response at 15 Hz, it starts decreasing following an irregular pattern as the frequency rises further up with almost insignificant SSVEP evoked potential at around 50 Hz [50]. Although it is evident that SSVEP is more pronounced at low-frequency stimulation, this lower band suffers from two major setbacks: human eyes become more tired at this frequency range and possible risk of prompting epileptic seizure for SSVEP in the 15 to 25 Hz range [50].

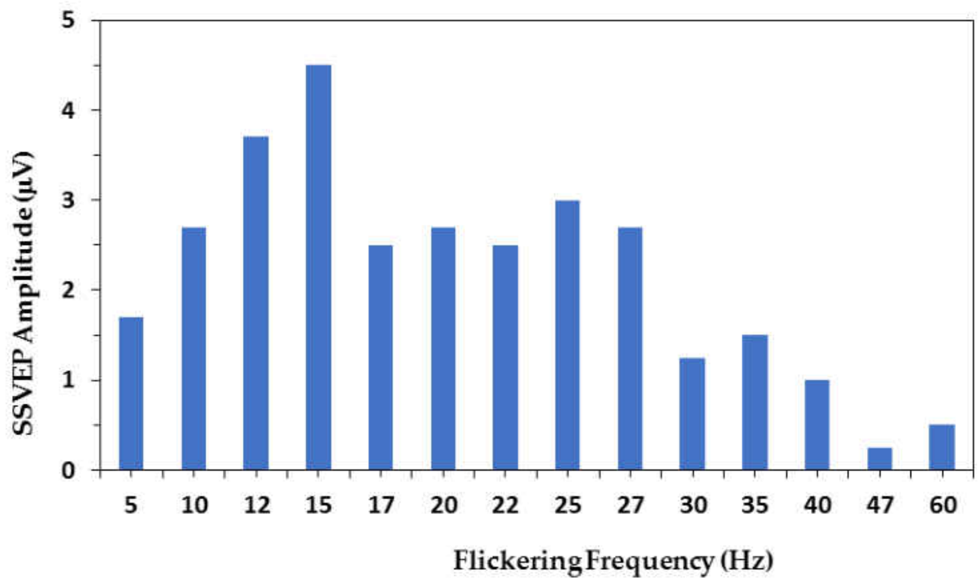



**Figure 1.7: SSVEP amplitude with different flickering frequency (adapted from [50]).**

### 1.8.3 Potentials in Spontaneous Signals

Sensory motor rhythms (SMRs) falls under the category of spontaneous signals generated during active BCI. Spontaneous signals are voluntarily generated by the user, so they are more general, natural and comfortable to the users. However, they don't rely on external stimuli which cause them to participate in long training time. Fortunately, recent advances in machine learning and signal processing methods can significantly reduce the training time. In fact, motor and sensorimotor rhythms are related to motor actions, such as arm movements. Voluntary control of these μ (≃ 8-13 Hz) and β (≃ 13-30 Hz) wave bands can be controlled for amplitude adjustment by a user which is measured over the motor cortex. Slow cortical potentials and non-motor cognitive signals are example of other spontaneous signals. For instance, slow cortical potentials (SCP) shows very slow variations of the cortical activity, which can last from hundreds of milliseconds to several seconds. Some the non-motor cognitive tasks are completed mentally which include generation of words, music imagination, mathematical computations, rotation of geometric figures, visual counting, among others.

## 1.9 BCI Applications

The major target of BCI application is to assist disabled people controlling a wheel chair or a virtual keyboard. In addition, consumer electronics market for various recreational applications is using the cognitive response to the exogenous stimulation such as controlling the devices as television, thermostat, and video appliance [51]. Moreover, SSVEP has been used to making a phone call by dialing the numbers [52]. BCI continuously evolving to encompass mainstream applications such as recreational activities, training, arts and music, among others [53]–[55]. Another suitable application of P300 BCI is P300 speller where user can select the letter using the stimulation. The P300 paradigm presents a visual matrix made up of letters of the alphabet. In such an arrangement, a P300 as well as SSVEP speller can be optimized to attenuate the selection time or increase the accuracy of the spelled letters. At a same time, other P300 BCI applications have been developed for attractive applications such as painting arts work, controlling smart home, designing games, stroke rehabilitation, lie detection, and furnishing internet tasks [56], [57].

## 1.10 Experimental Resources

Though the system design required tuning and adjusting the parameters at different stages using data acquisition from a good number of subjects and offline analysis thereafter, ten subjects were invited to take part in the experiments. All subjects were healthy with a mean age of 25.7 years (males, aged 21~30 years). None of them has any prior history of cognitive deficit. In a single sitting every subject was arranged to participate in three different tests for three systems. The EEG data for this study was acquired using Guger Technologies (g. tec) products [58] including; g. GAMMA cap, g. USBamp, and g.GAMMAbox. Subject's skull is coverd with g.GAMMA cap. Following the 10/20 international standard, Cz, Fz, Pz, P3, P4, Oz, O1 and O2 spatial locations were chosen as signal collection points with Fpz as ground and right earlobe as reference. Among these electrodes, Oz, O1 and O2 are used to collect evoked potentials due only to SSVEP. On the other hand, Cz, Fz, Pz, P3 and P4 locations are popular spots for P300 evoked potential extraction. The montage of this distribution is portrayed in Figure 1.8. Before an experiment, every subject needs to answer a set of questionnaires. Similarly, after the end of an experiment he/she needs to response to another set of post BCI questionnaire (APPENDIX B). The questions are mainly related with mental fatigue and physical tiredness. The responses and the feedbacks are stored for later analysis and justification of the results.

In this experiment, eight channels were used to extract EEG data from eight electrodes mounted on the cap. In addition, an LCD monitor was employed to present the stimulation to the BCI subjects. Subjects were seated 60 cm away from this 24-inch monitor with a refresh rate of 120 Hz. MATLAB and Simulink were utilized for real time control of the devices and processing of the experimental data. An NVIDIA GeForce graphics processing unit (GPU) was employed to draw shapes and pictures. The computational units with their specifications are listed in Table 1.3. For stimulus generation, a black background was employed with frequent appearance of white color characters to ensure a high contrast. A popular stimulus

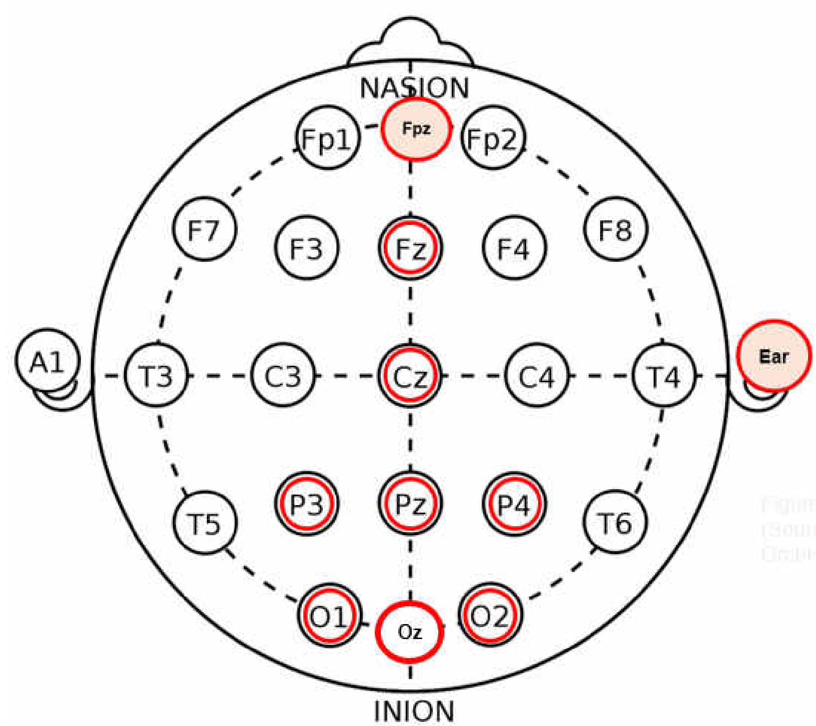



**Figure 1.8: EEG electrodes position for this research work.**

generation toolbox Physchtoolbox was used to design the paradigm. The equipment utilized for this research study is shown in Figure 1.9.

**Table 1.3: Specifications of paradigm components**

| Main Computer (CPU) & Graphics (GPU) | Paradigm Tools |
|---|---|
| Type: Intel Core i7-2600 CPU<br>CPU Speed: 3.4 GHz<br>Total RAM: 8 GB<br>GPU: NVIDIA GeForce GT 740<br>Total graphics memory: 8 GB | Monitor: 24″ LCD monitor,<br>Refresh rate: 144 Hz (max.)<br>Monitor to eye distance: 60 cm<br>Stimuli presentation tool: Physchtoolbox<br>Simulation Tool: MATLAB Simulink |

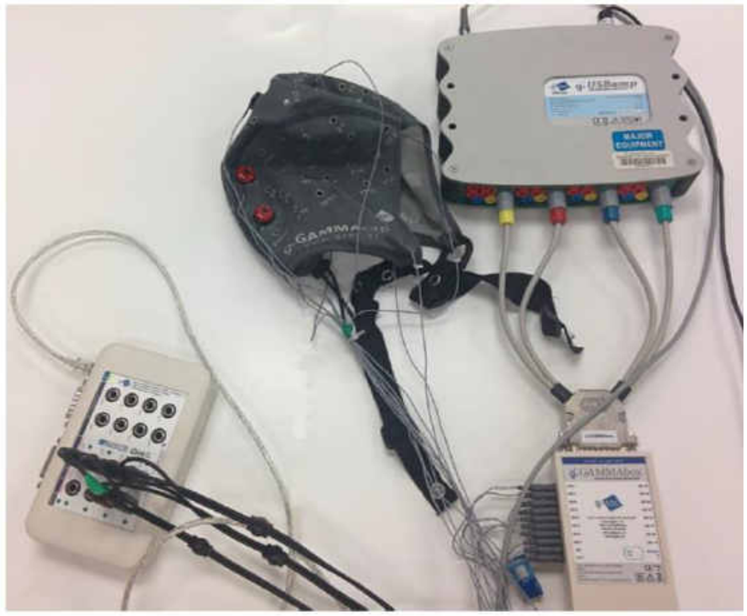


**Figure 1.9: g.tec equipment utilized for EEG data acquisition.**

## 1.11 Stimuli Presentation Devices

Stimuli presentation is a critical component in such kind of study. Many other studies used LED lights to create stimulation which sometimes resulted in eye fatigue and discomfort for the users. In addition, LED lights can’t be used to generate stimulus with graphical image. However, a screen on the monitor can be changed to contain variety of graphics for both future use and modification as required for set interface of a specific BCI paradigm. Keeping a similar note in mind, the paradigm was developed using the LCD monitor. More importantly, it allowed us to optimize the stimulus design and verify its suitability using various set of graphical elements and symbols. These are some of the vital characteristics of LCD monitor which keeps it apart from the limitations of LED. More specifically, the characters and symbols can easily be realized on an electronic monitor to eliminate possible interference from unwanted stimulation, and thereby to enhance the desired stimulation. Such properties are critical to integrate multiple paradigms in a single display. For instance, in this current research task SSVEP and P300 paradigm was fused together with the help of a LCD monitor which simply impossible with LED lights.

## 1.12 Stimulation Presentation Techniques

It is no surprise that a novice user's first experience of BCI begins with an interface paradigm. BCI paradigm gives the preliminary perception of the BCI tool in hand. So, it is an important part of a BCI system. Faster electronic tool and advanced computing algorithm allows the BCI community to evolve with new paradigms. However, the relative advantages and disadvantages of different BCI paradigms are not same and, thereby, need to be considered before letting it go into action. This section presents a comprehensive study about BCI paradigm with as much information as possible from the context of user experience.

### 1.12.1 Visuospatial Presentation

A BCI paradigm is a control interface that allows the users to perform mental tasks and obtain feedback through a display representing the users' intentions. In other words, visual paradigm is a key part of a usable BCI that the user can observe during BCI interaction. Therefore, the design and organization of a BCI paradigm are very important to satisfy the BCI goals. In order to design an interface, it is valuable to recognize the user experience of the interface. As the main purpose of the interface is to allow explicit control of computer or computer-controlled devices, understanding the cognitive state and activities of the user helps improve the quality of the BCI. Human brain activity can be controlled by the user's activities and desires, which, in turn, can be used to control the application, employing a BCI interface.

SSVEPs can be elicited by two major types of visual stimuli as shown in Figure 1.10. Each of these stimulators have their own merits and limitations. However, the underlying principle is always the same: a blinking or moving visual stimulus at a constant frequency elicits a response as a form of electric potential in the brain at the same frequency as the source. In addition, sometimes it generates several harmonics of the SSVEP frequency with weaker amplitude than the source potential. In general, LED brightness can be controlled according as the user's choice or comfortability. However, the high brightness of the LEDs may incite fatigue in the user when exposed for a long time [59]. During the design of high frequency paradigm, LED is much more preferable than LCD screens which usually have low refresh rates (60–250 Hz) which causes wear and tear in image for high frequency. Similarly, paradigm designed with LED stimulation allows oscillation over a larger frequency range compared to monitor frequency. Its implementation is also simplified by the use of a wave generator interconnected to the LED, allowing a precise oscillation in the desired frequency [60]. On the other hand, LCD screens allow more freedom in terms of stimulus shape, and they are also more convenient for generating more complex stimuli, such as checkerboard stimuli. Due to the advancement of electronic display, LCD refreshing rates can be high (>200 Hz), but SSVEP amplitude drops significantly for high refresh rates. LCD screen allows a variety of formats and colors of visual stimuli, besides being easily integrated to the interface of the application (Figure 1.11). However, it requires a greater effort of coding to achieve a precise oscillation, due to the fact that the operating systems execute different processes in parallel, that can influence in the rate of oscillation of the stimulus [61]. The processing of the EEG data is relatively simple for a low-complexity BCI comprising less than 10 frequency choices. BCI paradigm changes the color of the objects to simulate the required frequencies which is stimulates the cognitive cells mainly located over the occipital region.

Under such a situation, the computer can be used to stimulate the SSVEP and process the data in parallel. LCD screen becomes a better choice than LED where suitable frequency setting can be employed to remove or reduce the influence of the low-frequency components in the flickering paradigm.

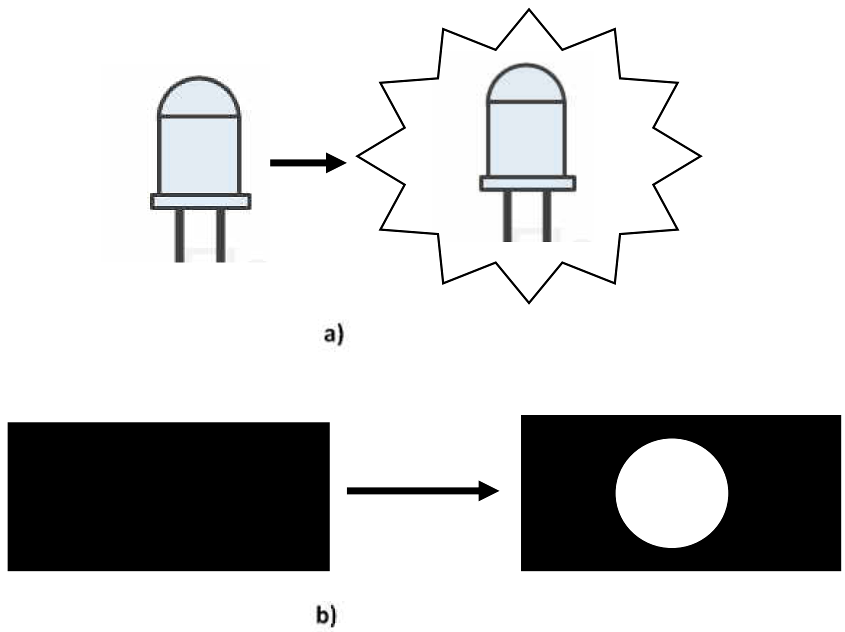



**Figure 1.10: Flash Stimulus; a) LED stimulator, b) Computer Monitor.**

**Figure 1.11: Two sequential and colorful LCD frames containing targets either in a new state or a quasi-state.**

The importance of a paradigm is underscored by the following functions, which are necessary to develop a BCI system: (a) representing visual control functions to the user, (b) providing the state of the BCI and feedback to the user, and (c) displaying the user's neural signals.

### *1.12.1.1 Matrix Presentation*

A matrix speller generally places the characters and symbols in row and column which begun its journey with the Farwell and Donchin matrix speller paradigm[62], the first BCI row-column speller (Figure 1.12). This alphanumerical square matrix interface paradigm was developed to produce P300 potential in EEG signal. Six rows and six columns of this matrix were constructed with characters and numbers. So far, this is the single mostly used matrix speller in BCI community. In this current study, the paradigm was designed to include more number of objects than the matrix speller.


**Figure 1.12: BCI paradigm as a matrix presentation.**

### *1.12.1.2 Region Based Presentation*

The region-based (RB) paradigm has moved the matrix presentation to another new level which allows to distribute the characters in larger area than row-column matrix paradigm [63], [64]. In this case, the visual space of the paradigm is partitioned into seven different regions in such a way that the inter region gap gets larger (Figure 1.13). In addition, an object selection is separated in two levels resulting in a decreasing near- target effect, human error and adjacency problem. Consequently, action in terms of users focus and attention to these two levels are needed to detect a single character. First level is used to select a specific region where the second level is used to extend the inter character gaps of the selected region. Such an expansion allows the user to have less interference from neighboring stimulations and better view of the target character. Such an arrangement of the stimulating objects allows to place spell 49 characters on the paradigm.

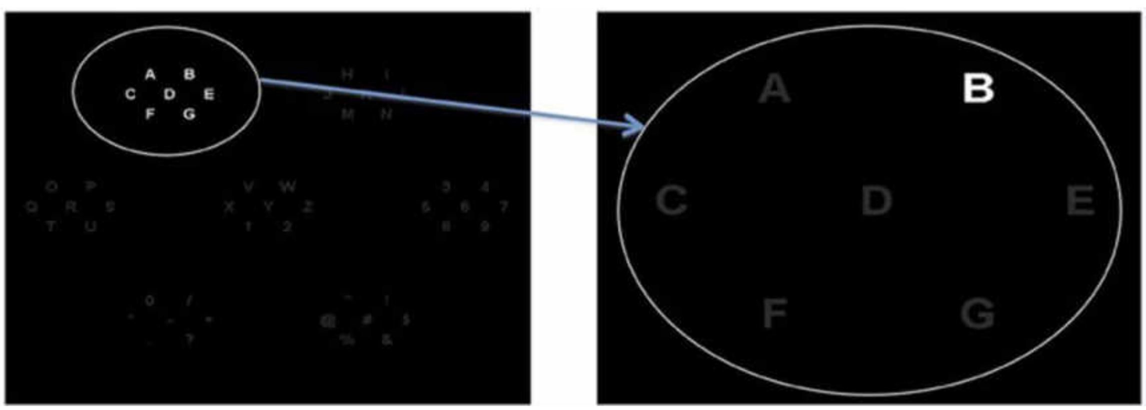



**Figure 1.13: Region based paradigm with two levels.**

## 1.12.2 Auditory Presentation

Visuospatial paradigm presentation technique requires the BCI users to have a good vision and the ability to engage the visual sensor during the stimulus presentation [65]. So, population with impaired vision need an alternative to visual presentation. Auditory paradigm makes it possible to stimulate the brain actions by utilizing different sounds (electric bell, phone ring, guitar chord, buzzing sound), pitch or pronunciation. Auditory stimulation has been employed to generate P300 potential [66]–[68]. Unfortunately, the BCI systems with auditory stimulation have poor performance than visual BCI. However, auditory BCI opened up a comparable alternative for people with visual disability. To increase the performance of the system, auditory system can be used to hybrid with visual or any other paradigm.

### 1.12.3 Tactile Presentation

Many users can't control their eye gaze or suffering from either visual or hearing impairments, but their tactile sensors are in good shape. Under such circumstances, tactile presentation paradigm can be utilized to spell the characters [69]. One such paradigm assigned a set of symbols to each of six fingers of a BCI user. It resembles to region based paradigm which works in visual domain. At first the user uses the tactile sensor to select a set of symbols by focusing on a specific finger. Afterward the correct selection, each of the six fingers is assigned a single character. This final stage requires the user pay attention for the second time to select a single character. A research group found that BCI with tactile paradigm shows almost same level of performance with close accuracy [70].

## 1.13 Data Acquisition and Artifact Removal

Raw EEG data is collected form the scalp when the user focuses on the stimulus paradigm. During the collection, EEG can be contaminated by undesirable potentials of non-neural origin which can have the amplitude as high as EEG [71], [72]. Data acquisition also involves amplification, filtering the undesired signal and noise, and Analog-to- Digital

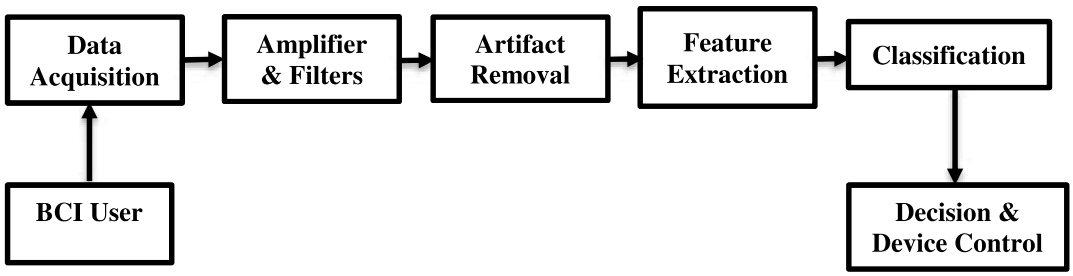



**Figure 1.14: Different stages of data acquisition and signal processing of a BCI system.**

conversion. Analog EEG signal is sampled at a rate which is typically 128 or 256 Hz. Amplified signal still can contain artifacts and redundancy in information. Instrumental artifacts come from external sources, such as electromagnetic interference, grid interference, impedance artifacts, among others. Instrumental artifacts can be reduced by electromagnetically isolating the equipment used and making the acquisition in a room with reduced level of waves coming from electronic equipment. In turn, the physiological artifacts originate from the user himself, through muscular movements, heartbeat, breathing, blink of an eye, among others. Compared to instrumental artifacts, these are more difficult to avoid because they are intrinsically related to biological functioning, however, they can be reduced by concentrating and reducing unnecessary movements during the acquisition process. The steps between BCI user and decision making are demonstrated in Figure 1.14.

So proper algorithms are necessary to eliminate the artifacts and noise to obtain clean EEG by offsetting the detrimental effects [73]. During offline analysis, simplest approach can be employed to discard the corrupted EEG. However, real-time operation demands the BCI system to employ faster computation method to remove the artifacts. For such operation, it is necessary to exercise enough precaution so that the underlying EEG activity is kept intact. That's why, researchers are more interested to invent and design BCI paradigms to extract features which are more robust to most artifacts [74]. Features are extracted from the processed and noise free EEG signal to feed into the classifier. Classifier output is used to drive the BCI dependent system. The classifier finds the feature pattern to identify the target features and isolate them from other feature classes. In other words, it maps the features to their corresponding category by learning the pattern of features from each individual class. Most classifiers consider the uncertainty in classification by following a probabilistic approach. Along with the desired classes, sometimes BCI control application employs one additional 'no' class to deactivate the selection of any control. Such command is useful when the user is paying no attention to the stimulus or the systems results in confusing and less reliable output to the device. Under these events, no appropriate control is detected which restricts the BCI from performing any further action.

## 1.14 Conclusion

This chapter started with an introductory description about BCI concept and its goal. Along with that, a short statement was presented on the research goal of this BCI research. The following chapter will continue with an expanded discussion about the research theme and motives set in this chapter. EEG signal is at the core of BCI which transports the critical information from the human brain to the outside world. Realizing the importance of EEG, a brief discussion on EEG acquisition and features were presented in the following sections. Once EEG is recorded, there are signal processing and feature extraction parts which have been described further with the context of capturing brain activity information. Such discussions were accompanied with a broad detail on BCI types, paradigms and its applications. Following chapters will present each individual BCI paradigm with the experiment results.

# CHAPTER II: P300-BASED BCI, MATERIALS AND METHODS

## 2.1 Standard P300 Speller

As suggested by its name, the P300 speller uses the P300 brain signal to spell words. This is a very popular BCI application which does not require users training and such system is useful for anyone who can control his gaze. Moreover, paralyzed persons such as persons suffering from Amyotrophic Lateral Sclerosis (ALS) get benefitted from such application [75], [76]. BCI speller has opened up the opportunities for people suffering from various neuromuscular disorders as brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis and other kind of neural impairment to use the alternative pathway [77]. Unfortunately, P300-based speller or other BCI applications require the user to constantly focus on and pay attention to fast changing and repetitive visual stimuli, which sometime can be tiring and inconvenient [47], [78]. However, persistent research in BCI to improve the accuracy and speed of P300 Speller has resulted in numerous P300 stimuli presentation paradigms.

It is mentioned earlier that activation of P300 response requires that the user is focusing on a particular stimulus (a target object or character) of a visual paradigm, presenting a set of stimuli (objects or characters). In fact, the positive electrical peak in P300 BCI appears in the EEG after 300 millisecond of the irregular visual stimulation. The initial P300 speller was a row–column matrix speller paradigm which had alphanumerical

Characters as shown in Figure 2.1. Rows and columns of this 6 × 6 matrix are flashed randomly, and the subject is seated in front of the screen. The subject is asked to pay his attention on the letter he wants to select and mentally count the number of times that the


**Figure 2.1: The P300 speller interface is displayed as 6 by 6 row–column paradigm (RCP) on the user's screen.**

attended character is flashed. As the letter to be selected flashes randomly which develops a rare event, a P300 is triggered in the user's EEG signals. During the brain signal measurement in the parietal area, the detectable P300 in EEG appears as evoked response 300 millisecond after the stimulation of the row and column, which contain the target character. The no flashing rows and columns do not generate P300. The absence or presence of the P300 is an indication of the line and column that contain the desired letter. Because of the nature of the stimulation mechanism and to the increase in the accuracy of detection, the P300 system requires multiple trials to reach acceptable accuracy [79]. The computational device can determine the target row and column after averaging several P300 responses.

### 2.1.1 Region Based P300 Paradigm

Progress in BCI research and applications significantly depends on a successful paradigm implementation. BCI paradigm requires simple interpretation and ease of use for end users so that electroencephalogram (EEG) data can be mapped to an application. To ensure these criteria, the paradigm design should be leveraged to deliver optimal performance.

The major idea behind the region-based paradigm (RBP) is to distribute the characters in larger area than row-column paradigm. Here, choice of an object is split in dual selection levels which decreased the near- target effect and human error and adjacency problem significantly [80], [81]. In this paradigm, space of the visual paradigm is divided into seven different regions (Figure 2.2). The desired characters are split into seven groups and each group is placed into a single region as shown in Figure 2.2. For any given spelling task, user has few seconds to focus on the characters before the action of each level. This action produces the P300 ERP for the first level target. It is important to note that regions are flashed in a random order by repeatedly changing its color between black and white. Choice of color was justified for better contrast in each color transition. Both levels are needed to detect a single character. In short, first level is used to select a group of characters in a region, which contains the target character while the second level is used to select the single target character from the chosen region. Following the similar procedure of two levels for each character, all characters are detected one after another in a given spelling task. Each time a target is flashed, a strong P300 potential is expected in the EEG wave.

Although the row-column paradigm contains 36 characters, the use of the seven-region paradigm allows one to allocate 49 characters. In addition, this arrangement allows one to distribute the characters spatially on the screen considering their probability of linguistics use in a word. As paralyzed people need to spell the desired word with minimum movement, the arrangement of the letters can be adjusted accordingly to optimize the performance [79].

The probability of characters' usage [82] was considered in distributing them into all seven regions and characters with close frequency of usage were placed in one region. After successful selection of a region in the first level, characters in the selected region are again subdivided into seven regions in the second level where each region consists of only one character [83]. Each region flickers for 8 times and such an arrangement makes the number of trials as 8. This means that each character is detected after eight trials. In addition, there is a transition period of 2 seconds from level 1 to level 2 and vice versa. There is also another 1 second of highlighting time for each target region which directs the observer where to focus on.

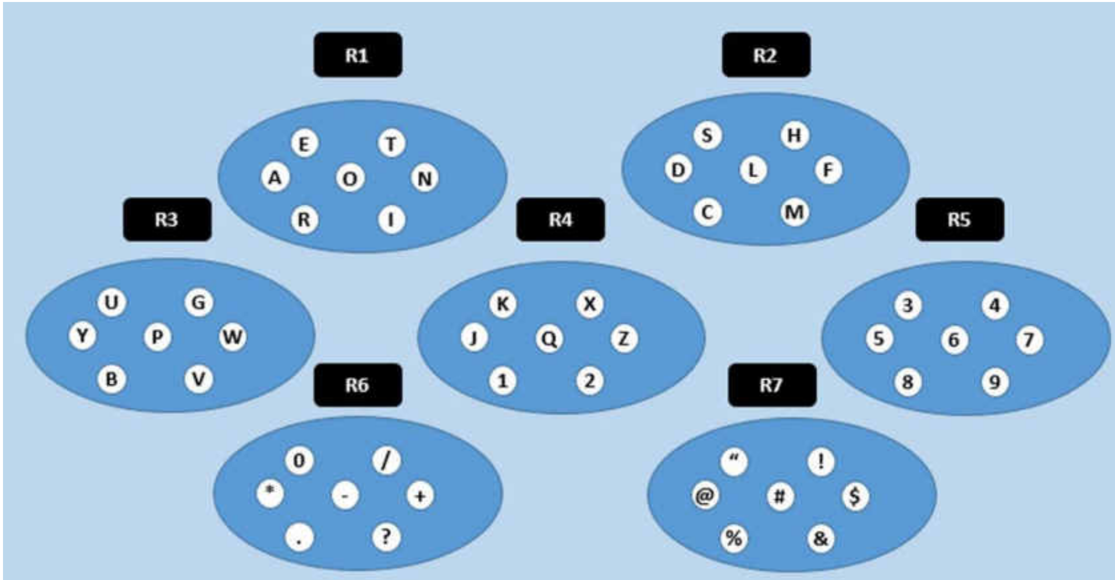



**Figure 2.2: Basic architecture of a region-based paradigm with the locations of seven regions. Here, "Rn" represents region 'n' and each region contains seven characters.**

### 2.1.2 Classification Architecture

Paradigm presentation and signal processing is two major parts for a BCI system. During the design of the BCI system it is a better practice to use these two functional units as sublayers of the system. Such an architecture lets the development of any sublayer independent of others. More importantly, it allows to integrate different algorithms and to test distinct classifiers keeping the other unit undisturbed. For instance, an application with a SVM classifier can be replaced by an LDA or any other suitable classifier of interest to enhance the system accuracy.

## 2.2 Experimental Setup

The paradigm design is usually a challenging task which requires a broad consideration about the application, the software, the users and the associated hardware. In order to make the system easy to access by the user and to allow flexibility changing the interface screen, an LCD monitor was used as a paradigm display. Use of the electronic display allows to adjust or extend the number of stimulating objects which is not easy in case of a LED stimulator. LCD monitor can show the objects with different shapes, colors, and frequency, all of which is useful for a designing a BCI speller (Figure 2.3). In this study a 24-inch monitor with a high throughput graphics card (NVidia GeForce) is used to shorten the required time for graphics generation. This monitor has a very high refresh rate as 144 Hz. As one of the goals of region-based paradigm is to offer large number of options to a BCI user, the designated targets need to be presented quickly and robustly to the user. Because of the high definition, the graphics can be generated without tear and wear. A BCI user sits at around 60 cm distance from the monitor. It leverages the benefits of a modern electronic display driver to make the BCI session pleasant for users during the EEG data collection.

MATLAB Simulink is used to coordinate the paradigm presentation and data acquisition using the monitor and the g.tec devices, respectively. In Figure 2.4, the model to collect the data in real time is presented. This model consists of the functional blocks representative of the devices and displays. One or multiple Simulink functions are employed to transfer the EEG data between blocks which assist the model to generate the paradigm in synchronous with the EEG data collection. At a same time, the EEG signal is processed and classified to display the result online. In addition to these actions, the data is stored in the computer memory for later use and analysis.

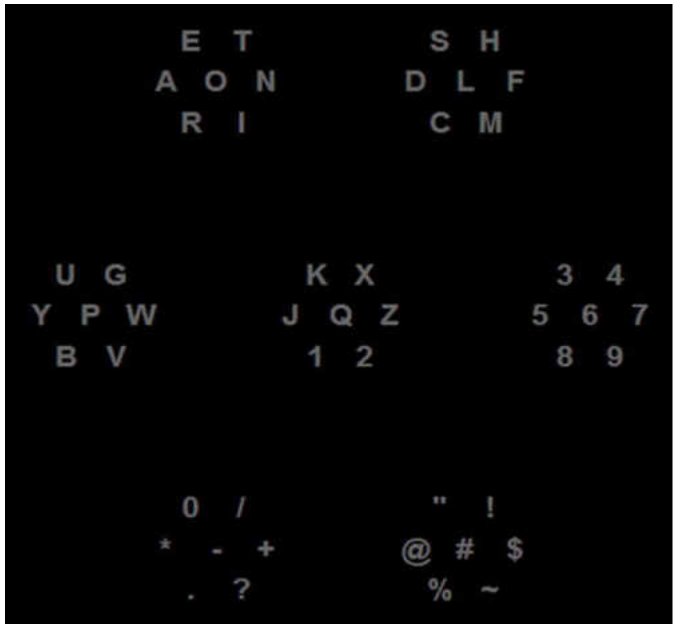



**Figure 2.3: LCD monitor display of P300 region-based paradigm at Level 1.**

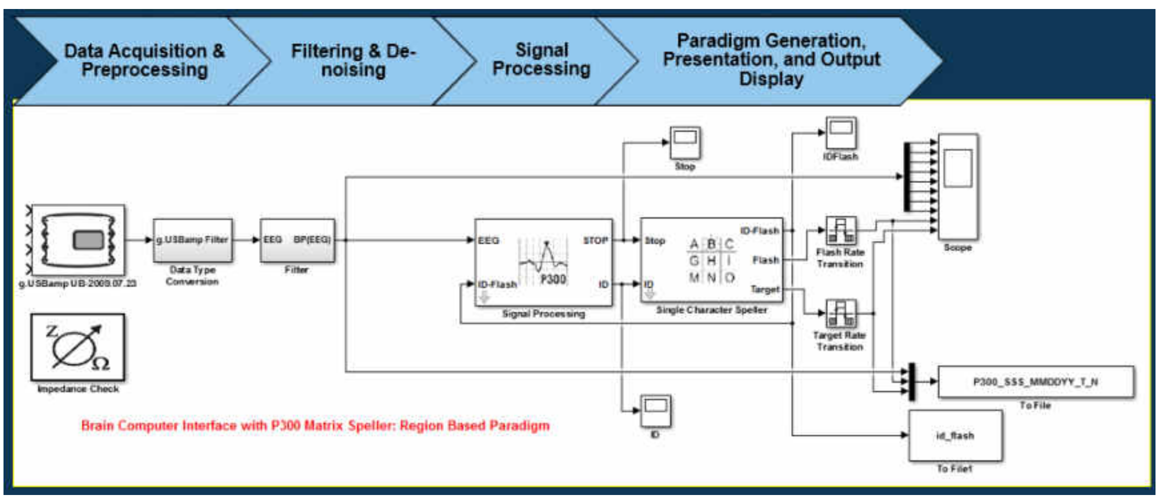



**Figure 2.4: Real-time SIMULINK model for P300 experiment with the 'g.USBamp' amplifier, filter, signal processing and paradigm blocks.**

During the online experiment, the subjects were required to spell a set of words and characters. The spelling tasks were kept similar in all three different paradigms. The target characters were carefully chosen in a fashion so that every region was spelled in each level.

Table 2.1 shows the chosen characters set and their corresponding locations for spelling task.

**Table 2.1: Target characters with corresponding region indices**

| Spelling Target | A | S | B | 2 | 6 | / | $ |
|---|---|---|---|---|---|---|---|
| Characters of Level 1 Region | ETAO NRI | SHDL FCM | UGYP WBV | KXJQ Z12 | 345678 9 | 0/*-+.? | "!@#$ %~ |
| Indices of Level 1 Region | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Characters of Level 2 Region | A | S | B | 2 | 6 | / | $ |
| Indices of Level 2 Region | 3 | 1 | 6 | 7 | 4 | 2 | 5 |

### 2.2.1 Software Framework

As mentioned earlier, paradigm was developed using a graphics toolbox, Psychtoolbox [84], which was integrated inside the MATLAB Simulink function. The major reason behind this is the capability of this toolbox to drive hardware devices using C++ library which makes the paradigm easy to implement and interact in real time.

## 2.3 Pre-processing and Feature Extraction

The EEG signal is pre-amplified by the active electrodes set on the scalp. Afterward, it passes through the USBamp which amplifies the signal for a second round. In addition, EEG passes through a bandpass filter with the cutoff frequencies at 2 and 30 Hz. In order to remove the artifacts due to power line, another notch filter at 60 Hz is employed before the bandpass filter. Filtering the signal and removing the artifact is a necessary part for getting a clean EEG signal. Appropriate algorithm to extract the features is needed to feed the following classifier. In this research work, EEG signal average was computed using a running averaging filter and the ensemble average values were used as features for a LDA classifier. In every single trial of the P300 experiments, individual P300 ERPs were collected and stored in a memory buffer from 100 milliseconds before to 700 milliseconds after each region flash. The signal processing software used the extracted 100 milliseconds EEG segment before each flash as a tool for baseline correction. The EEG signals were extracted using eight active electrodes. To obtain some computational benefits, the output of these channels was averaged over a moving time window. First of all, such an action reduces the trend or sudden drifts in EEG signal. Secondly, it ensures residual noise elimination by averaging action. In addition, this step results in a distinctive appearance of P300 potential if the EEG represents a stimulated output from a target object (Figure 2.5). On the other hand, if the EEG signal is obtained during a non-target stimulation, the processed EEG signal shows no discernible evoked potential. Such a EEG signal is presented in Figure 2.6 which has no apparent P300 peak. It is mention worthy that during the preparation of EEG signal for feature extraction, the EEG signal during the blank time or no-flickering event is used as a base of the following flickering event. So, a flickering event data is accompanied with a preliminary dark time as a representative of EEG base for every individual stimulation, either be a target or a nontarget. As the designed paradigm uses region based paradigm, the frequent/non-target probability is 6/7 or, 0.86 which is six times higher than the infrequent or, target probability 1/7 (=0.14). Eventually, for 'N' number of regions the infrequent occurrence probability becomes 1/N. Lower the probability of appearance of an oddball, higher the magnitude of P300 potential.

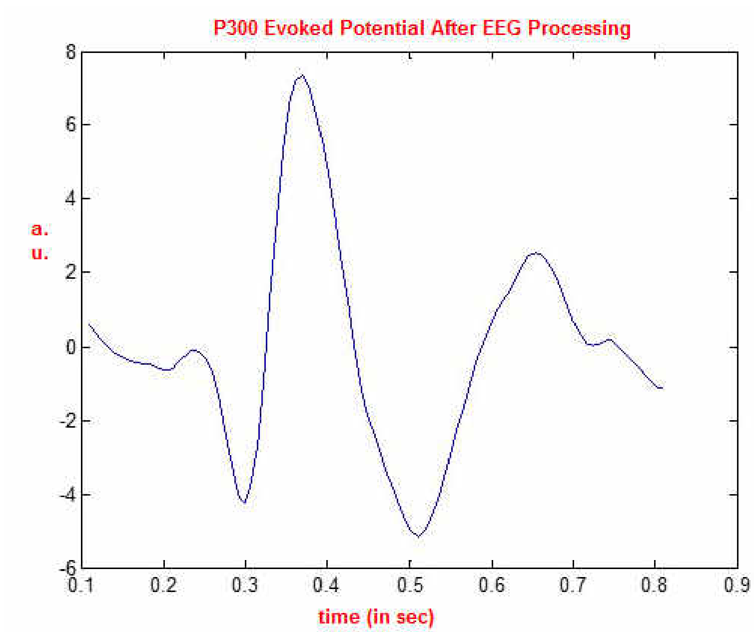



**Figure 2.5: EEG signal with P300 evoked potential generated by a flickering target.**

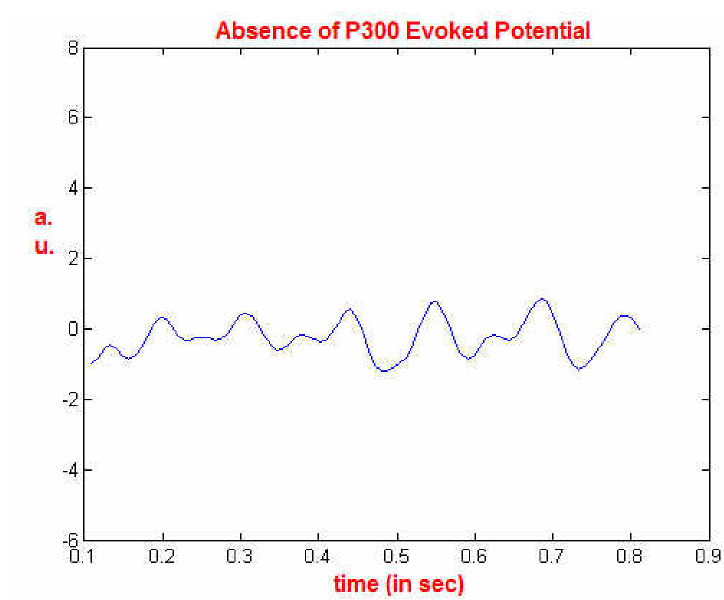



**Figure 2.6: EEG signal with no P300 evoked potential when non-target flickers.**

## 2.4 Performance Metrics

The speller performance is quantitatively measured with different parameters such as the system accuracy, spelling time, bit rate. However, the accuracy obtained in an experiment is very critical for clinical as well as non-clinical study. Apart from these, comfortability, acceptability of the system, apparatus cost, fatigue factor and mobility are some of the qualitative parameters considered as keys while developing a BCI system. In this study, accuracy has been paid all attention as correct spelling as critical to express the subjects thinking.

## 2.5 Result and Analysis

The system was designed in several steps and each step was associated with a verification either of the hardware platform or the software level function. A short but important pilot study was implemented to ensure that the system is satisfying the expectations and goals of this work. After the development of the structural frame of the P300 BCI speller, couple of subjects were agreed to participate in spelling two different but popular BCI words such as ‘WATER’ and ‘LUCAS’ [85]. Both subjects were male at their 20’s and the subjects did not receive any feedback while spelling these words. Two trials were utilized as a proof of concept for this research work. The results are presented in Table 2.2 and Table 2.3. It is apparent form the results in these two tables that the system was able to produce necessary stimulation to spell the words even as precisely as with 100% accuracy. However, the result also manifests a dependency on the subjects. For instance, subject P2 was not able to produce as good spelling result as subject P1. Following this similar fashion, every subject has tried to spell either ‘WATER’ or ‘LUCAS’ as the resultant EEG signal was used to develop a classifier for P300 BCI. An

LDA classifier was used to separate the P300 target from the non-target. At the feature extraction phase, ensemble average of all EEG signals for a single stimulating character was extracted to feed into the LDA classifier so that it can be get trained for every individual subject. With the average values of EEG signals for both target and non-target stimulations, the LDA creates a weight vector for the online trials.

**Table 2.2: Test results from P300 stimulation, pilot study with the word 'WATER'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| P1 | 100 | 100 | 100 | 100 | 100 | 100 |
| P2 | 60 | 15 | 70 | 65 | 65 | 40 |

**Table 2.3: Test results from P300 stimulation, pilot study with the word 'LUCAS'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| P1 | 100 | 100 | 100 | 100 | 100 | 100 |
| P2 | 30 | 60 | 45 | 65 | 38 | 63 |

Once the LDA based classifier is trained, it is ready to be employed in classification task. Table 2.4 shows the response of the subjects to the P300 BCI system using the 'ASB26/$' character set. It is mentioned earlier that the 'ASB26/$' characters were commonly used to compare the performance of the developed BCI systems. It is interesting to note that subject P1, who showed exact accuracy during the pilot study, performed same during the test character set. In addition, many of the other subjects were able to spell all characters correctly. Overall accuracy of the system lies within the range of 65% to 100% with the exception that subject P2 had obtained a poor accuracy (14% only) during the level 2 spelling. Once the experiment was done, he was asked if the extra gap between level 2 characters was helpful to concentrate on the target. In such a case, it was expected to increase the accuracy. The subject P2 agreed that inter character gap was beneficial. However, the attention of the subject was lapsed mainly due to the transition from level 1 to level 2 which caused incorrect spelling much more than that in level 1. In addition, the subject was tired and stressed as he sat for test at the end of a working day (see APPENDIX C). However, such a poor result effected the overall accuracy to a great extent. In fact, such a detrimental variability could be avoided just by inviting more subjects to test the systems.

**Table 2.4: Test results from P300 stimulation with the character set 'ASB26/$'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| P1 | 100 | 100 | 100 | 100 | 100 | 100 |
| P2 | 100 | 14 | 86 | 58 | 93 | 36 |
| P3 | 72 | 86 | 86 | 100 | 79 | 93 |
| P4 | 72 | 58 | 43 | 72 | 58 | 65 |
| P5 | 100 | 100 | 100 | 86 | 100 | 93 |
| P6 | 86 | 86 | 72 | 86 | 79 | 86 |
| P7 | 100 | 86 | 86 | 86 | 93 | 86 |
| P8 | 86 | 72 | 72 | 72 | 79 | 72 |
| P9 | 100 | 100 | 100 | 100 | 100 | 100 |
| P10 | 72 | 100 | 72 | 86 | 72 | 93 |
| Overall Accuracy= | | | | | 85.3 | 82.4 |

## 2.6 Conclusion

BCI speller with P300 evoked potential is usually mostly used BCI speller as demonstrated by myriad of researches and literatures. Subjects find it easier to pay attention for a while on the object which randomly flickers and allows the subject to rest one's eyes briefly when there is no stimulation from the target. However, the biggest notion of con for this system is to train the subject to generate a classifier. The training session is very important to ensure that the system can build a classifier. Such a classifier is subject specific and may or may not work well with a different subject. So, every time a subject is volunteered for a BCI task, a classifier is developed with a trial data set which is later used for BCI test. However, sometimes classifier for same subject can behave differently depending on the fatigue or mental status of the subject at a particular time of the test day. This underscores few important findings of the experiments with P300 BCI speller, 1) it needs an extra session for training the subjects and making a classifier, 2) not every subject can perform well with a specific speller, and 3) with the change in the subjects' mental condition, every time the outcome of the P300 speller might not be equal even with a same subject. To address these issues, having an alternative BCI speller is very useful to increase the system accessibility to new users.

# CHAPTER III: SSVEP-BASED BCI, MATERIALS AND METHODS

## 3.1 Standard SSVEP Speller

An SSVEP evoked potential is elicited over occipital areas of brain in reaction to visual stimuli flickering at a frequency higher than 6 Hz [86]. In SSVEP-based BCI system EEG signals are measured over the visual cortex area. It can be realized by making the stimulus flash at a steady pace. The stimulation occurs periodically with a certain frequency. As a result, SSVEP appears as an oscillation in the EEG signals with a steady flashing frequency that can be detected by the application of a suitable signal processing algorithm. SSVEP appears as a peak on the frequency spectrum close or equal to the frequency of the repetition of stimulus in which the subject focuses. Signal processing algorithm capitalizes the SSVEP to select the target object within a time frame. In a SSVEP speller, the detected SSVEP is translated to a character to spell a word.

### 3.1.1 Region Based SSVEP Paradigm

As mentioned earlier, region-based paradigm splits the choice of an object in two different levels [80]. Earlier chapter explains the interface in more details. However, in order to generate the SSVEP stimulation, standard region-based paradigm was modified so that each of the region is indexed by a single frequency. In fact, one circular shape was added to each of the region and this shape periodically alternates its color between black and white to generate SSVEP at a particular frequency. In case of the SSVEP interface, the characters are distributed around the flickering circle. For example, in order to spell a character at region five, the subject has to focus on the corresponding circle located at region five (Figure 3.1). SSVEP paradigm does not require the user to have any training. The location of seven different regions along with their corresponding frequencies are presented in Figure 3.2. For instance, circle at region five flickers at a rate of 14 Hz. The frequencies were chosen randomly in this pilot study to verify that the present SSVEP paradigm can be developed using LCD Monitor. In the second level, the selected region

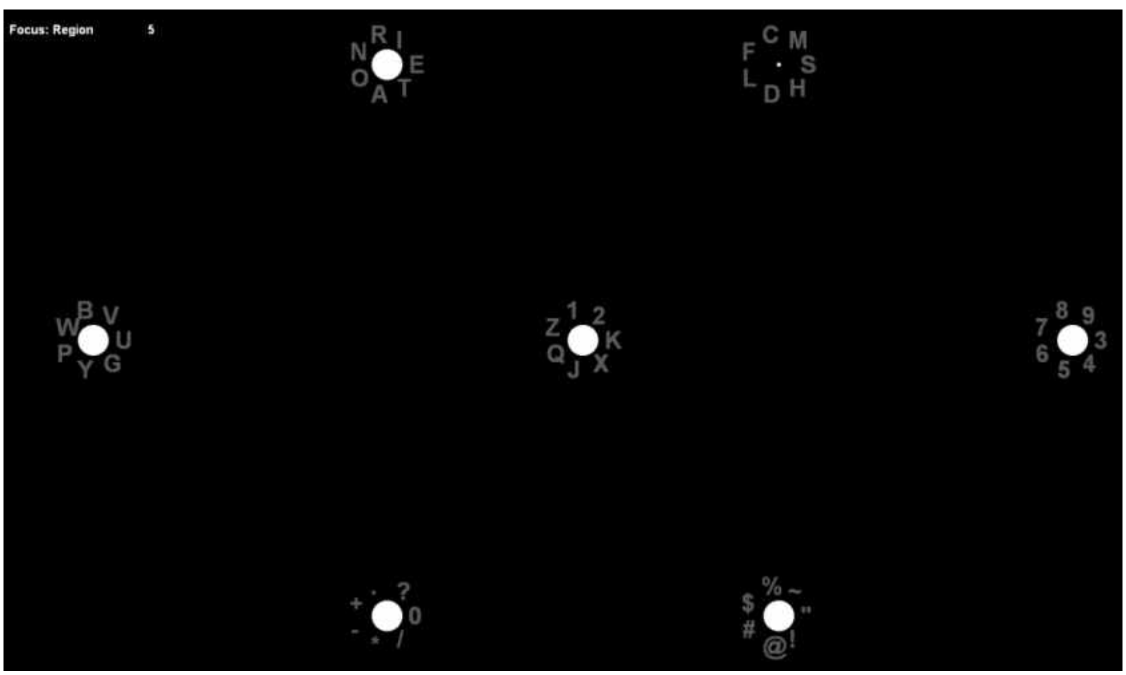



**Figure 3.1: First level of SSVEP region-based paradigm when the target is $5^{th}$ region.**

gets enlarged and user can select a single character out of these five objects. Interestingly, these two level operates with the same flickering frequencies. Due to the nature of two level operations, frequency reuse allows addressing 49 objects with the use of just seven frequencies.

As an LCD monitor us used as a display screen and the images are presented in a controlled manner, the paradigm can be customized. This paradigm can be customized to adjust the size and shape of the images and the characters. Preliminary experiments were designed to adjust the parameters of the SSVEP spelling paradigm to enhance the performance. Such trials were mainly executed to determine the frequency of the flickering circle as well as ensuring that the oscillating circular images originate peaks at desired frequencies, to find a better placement of the screen characters, to optimize the design of the SSVEP stimulus board, and to find a window time for the EEG signal processing for SSVEP peak detection. Following experiments were accomplished to evaluate the SSVEP spelling paradigm. Six subjects participated in the task. The accuracy of each frequency and average accuracy for each subject were considered.

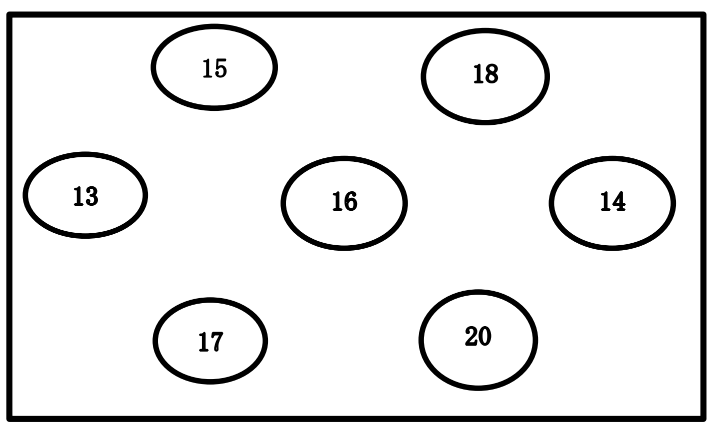



**Figure 3.2: Frequencies are given in Hz for each of the seven regions.**

In order to test the oscillating circles, MP35 device of BIOPAC was used [87]. A photodiode was deployed to collect the oscillating light form each of the flickering objects.

Collected electric signal was stored in computer memory for frequency domain analysis (Figure 3.3). Depending on the frequency of flickering, the collected photo current frequency is changed. An FFT operation on such electric signal unveils a peak at the flickering frequency of the circle. In Figure 3.4, a peak at 14 Hz appeared when the

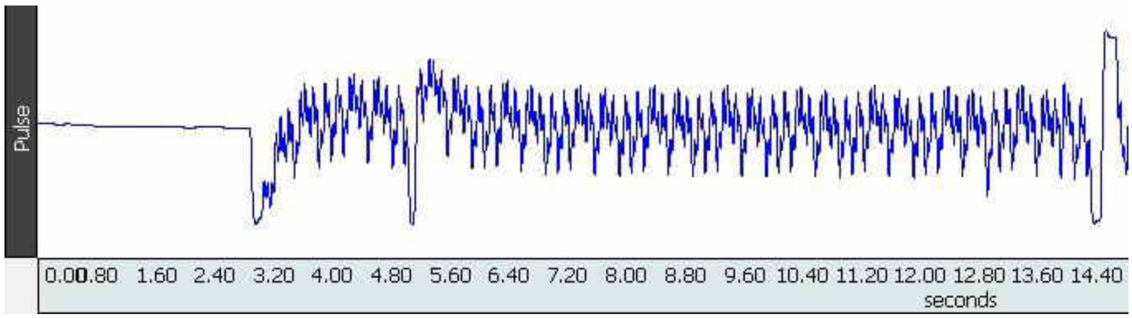



**Figure 3.3: Signal acquired using photodiode from a flickering object.**

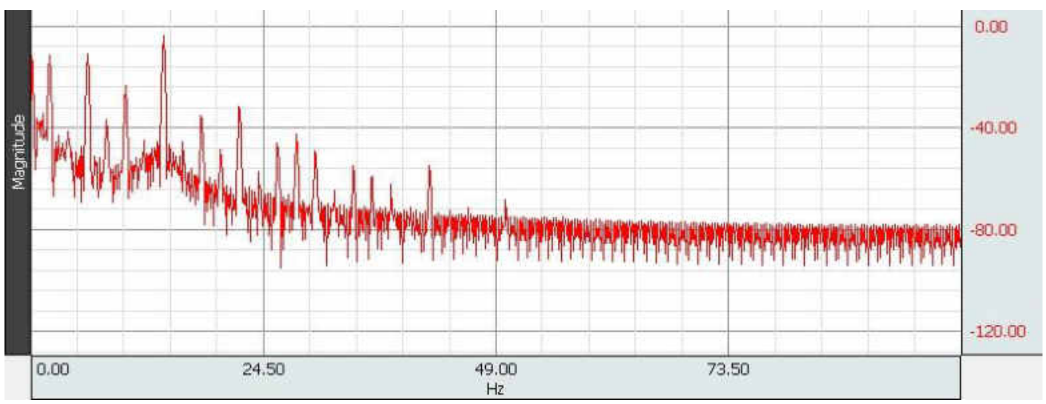



**Figure 3.4: Highest peak appeared at 14 Hz after FFT analysis of the signal shown in Figure 3.3.**

photodiode was placed on top of the monitor during the flickering of circle at region five. It is apparent that there appear some other peaks at different frequencies with smaller amplitudes. These additional peaks arise from missing video frames of the monitor which were unable to synchronize with the vertical blanking interval (VBI). However, effect of such peaks on EEG can be excluded by applying efficient signal processing algorithm.

### 3.1.2 SSVEP Detection Method

Distinctive cognitive functions are formulated by several patterns of brain activity. With the help of EEG, brain activity in the neocortex is measured as voltage differences over the scalp. In general, the process of any specific pattern detection from EEG is divided to three steps [88]: signal pre-processing, feature extraction, and classification. Signal pre-processing step begins with removal of noise such as artifacts or power line noise. Multiple filters are utilized to remove these contaminating signals. For example, band pass and notch filters can be engaged in EEG signal filtering. The first step also involves execution of an algorithm to process noiseless signal. An appropriate signal processing strategy is critical in revealing the complexity and difficulty issues as well as the possibilities, which lies in the fact that optimization of accuracy and speed heavily depends on a suitable signal processing scheme [89]. The features are extracted in the following step to reveal the brain signal features that can be modulated by a BCI user. Various methods can be applied to the digitized EEG signal such as spatial and spectral analysis and measurements of voltage distribution. In this stage, different feature extraction algorithms are applied to optimize the number of suitable features. Sometimes, feature selection is added with the second step. In the final step, the type of classifier and classification algorithm is chosen based on the type of BCI. The classification algorithms are employed for translating the extracted features to a corresponding target class. All selected features are mapped to some classes representative of desired commands by employing either a linear or a nonlinear method. These device-independent signal features can be applied to build a functional or communicative relationship between the user and the device under operation. In order to satisfy the criteria of an application, the BCI system needs an effective translational algorithm, which requires adaptation to the specific signal features that can either be controlled or learned by the user to improve individual performance. In summary, the effective interaction between the user and the BCI system necessitates incorporation of a better signal processing method [57].

## 3.2 Experimental Setup

This experimental study consisted 10 subjects. All the subjects have background in engineering and little or no familiarity with BCI system. Each experiment ran for 10-15 minutes which included two trials. In each trial the subject needed to spell ‘ASB26/$’ in two levels. Beginning and end of the session, subject was given a survey type questionnaire which has been included in the appendix of this thesis. Subjects were clearly notified at the beginning of experiment that they could quit the experiment anytime during the test if they experienced fatigue or needed a short break. The experimental studies were ethically approved by the Institutional Review Board (IRB) from the University of North Dakota (UND). It is well known that the IRB is responsible for ensuring the rights and welfare of human subjects in social behavioral and biomedical research. The IRB approval number for experiments performed for this research is IRB- 201006-372[90].

### 3.2.1 Software Framework

MATLAB and Simulink were the software utilized for performing and processing the experiments. The BCI paradigm is designed with MATLAB and Psychtoolbox [91]. Psychtoolbox is very useful to draw texts and images on the electronic monitor. The EEG data is collected during real time experiments and stored in the computer memory for future

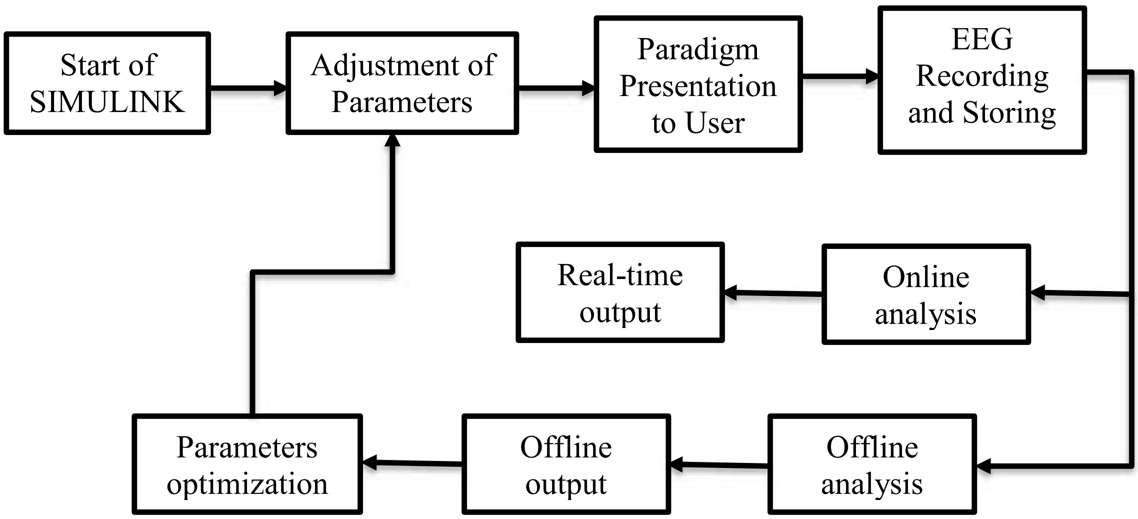



**Figure 3.5: System architecture of the real-time and offline operation.**

use or offline analysis for further study Figure 3.5. It is worth noting that any text or image could be used within the paradigm. Indeed, generating the characters can be done using the size of the monitor and geometry to accommodate the characters or images simply by providing their coordinates. During the experiment, subject focuses on the paradigm and EEG data is acquired using g.tec devices. The recoded EEG is representative of the user's brain activity which is stored for offline analysis. An offline analysis allows to tune the system parameters to optimize the desired output or to calibrate the system.

### 3.3 Pre-processing and Feature Extraction

This step consists in cleaning the signal by using band pass filter and denoising the input SSVEP data in order to enhance the relevant information embedded in the signals. Along with the band pass filter, a notch filter is used to make the signal free from the power line interference at 60 Hz. This stage also aims at features which are selected as few relevant values, in this case the correlated values are computed as features to detect the target frequency.

## 3.4 Performance Metrics

As mentioned earlier, system accuracy highlights the usefulness of a BCI system. the region based P300 paradigm evaluates the system performance using the correctness of the spelling task. Likewise, accuracy of the system is considered as most important parameter for SSVEP BCI.

## 3.5 Classification Methods

The frequency spectrum of the signal provides a window to explore the dominant components of a complex signal. This allows to obtain knowledge about the frequency domain features and power spectral density (PSD). Such knowledge can be utilized for SSVEP detection and classification as the signal shows higher peak at the stimulation frequency and its harmonics. The most frequently SSVEP signal processing methods have been listed in Table 3.1 with the reference to their relevant studies.

**Table 3.1: SSVEP signal processing methods**

| Classification Methods | System Performance |
|---|---|
| MCC (maximum contrast combination); maximizes SNR; object function is used for computing filter. | Average accuracy 95.5% and average bit rate is 34 bits/min [92]. |

| Classification Methods | System Performance |
| --- | --- |
| PCA (principal component analysis); decomposes signals; reduces the dimension of original data. | Average accuracy range 76.4%~91.8% for 8 experiments per subject [93]. |
| ACSP (analytic common spatial pattern); common spatial pattern method; reflects both amplitude and phase information. | Classification accuracy of 84%, 93%, and 94% for number of harmonics = 1, 2, and 3, respectively [94]. |
| EMD (empirical mode decomposition); compute the instantaneous frequency; reduces noise. | Average information transfer rate (ITR) 36.99 bits/min; accuracy 84.63% [95]. |
| Hilbert transform computes phases after spatial filtering; needs a shorter data length than that for the Fourier method. | Phase detection accuracy ranges from 70 to 94% [92]; Phase detection accuracy 99% [96]. |
| Wiener filtering together with a step-wise discriminant procedure to reduce feature vector dimensionality; Bayesian Classifier; use covariance information. | Accuracy 80% [97]. |
| MEC (minimum energy combination), 5 LEDs flickering at 13, 14, 15, 16 and 17 Hz respectively. Low-pass filter cut-off at | Average information transfer rate of 29 bpm, 97.5% accuracy [98]. |

| Classification Methods | System Performance |
|---|---|
| 32 Hz. cancel nuisance signals as much as possible. | |
| CCA (canonical correlation analysis); uses harmonics, considers user variation, interrelates two multi-variable data sets as a linear combination of original data. | Average accuracy 95.3%, information transfer rate 58 bits/min [99]. |
| Relative amplitude, phase and a combination of both to create the feature matrix; threshold and amplitude ratio criteria were used to select stimuli. | Average 92% correct selections and average selection time 2.1s [100]. |
| FBCCA (filter bank canonical correlation analysis); frequency range: 8–15.8 Hz, frequency interval: 0.2 Hz | 40-targets, multiple harmonic frequency bands get best performance, average and maximum accuracy is 92% and 99%, respectively. Average and maximum ITR of 151.18 bits/min and 172 bits/min, respectively. [101]. |

### 3.5.1 Minimum Energy Method

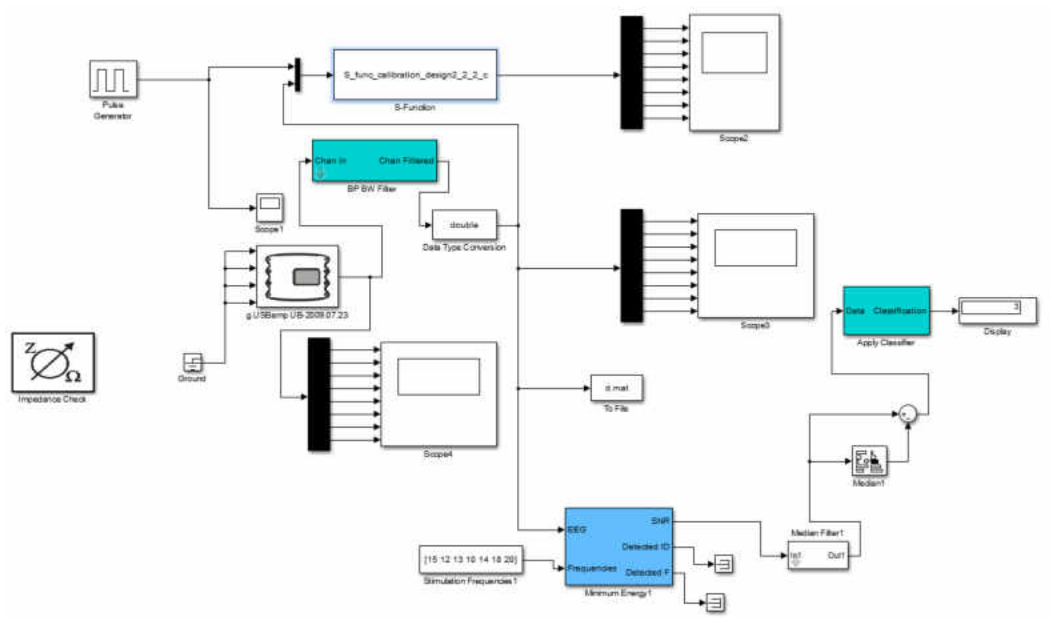


**Figure 3.6: Simulink model with minimum energy combination algorithm.**

The initial study of SSVEP system was developed with a classifier using MEC (Table 3.1). Earlier work applied minimum energy method to detect SSVEP from the EEG signal during the LED flickering in a four LED SSVEP paradigm [102]. This system was able to detect four different frequencies. However, the same method deemed inefficient when the paradigm was designed with LCD monitor in this study (Figure 3.6). Instead of the LED, different images of objects flicker on the monitor at different frequencies. The parameters which are adjusted during the classification process are length of the buffer, length of update window to apply MEC, number of harmonics, and order of auto regression model (Figure 3.7). In order to set the system prototype and find the causes behind such inefficiency, a study was performed with noisy and noiseless EEG waveforms with this classification model. However, the number of frequencies were kept under four. For instance, a pre-recorded SSVEP signal of 9.75 Hz were given as input to the Simulink model and an offline analysis was performed. After doing an FFT operation, a peak at 9.8 Hz was apparent (Figure 3.8). However, with the increase in the number of signal components, MEC fails to identify the correct frequency. In this study both noiseless and noisy SSVEP prototypes were used. The Table 3.2 lists the effect of increasing number of SSVEP signals.

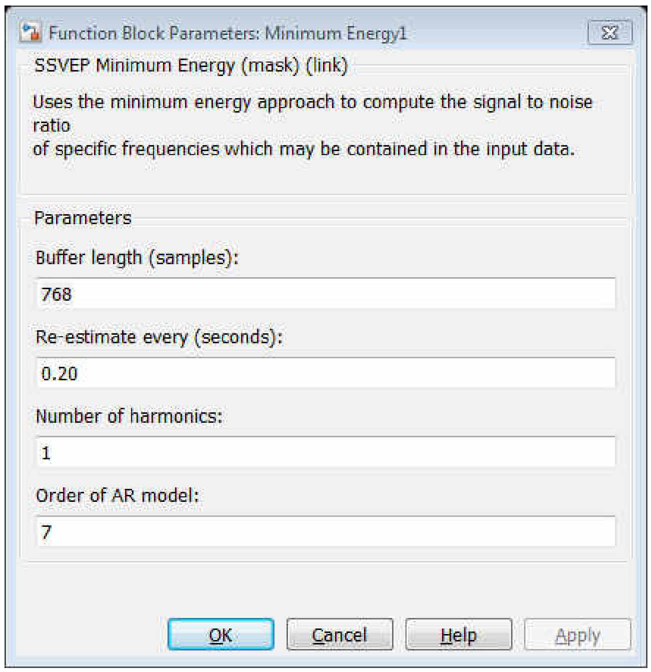



**Figure 3.7: Window to adjust minimum energy block parameters.**

One of the reason for it may be the lack of sufficient intensity of LCD monitor which suits MEC application. Another reason lies in the fact that the adjacent regions adds interference from neighboring regions to the EEG which is difficult to eliminate using

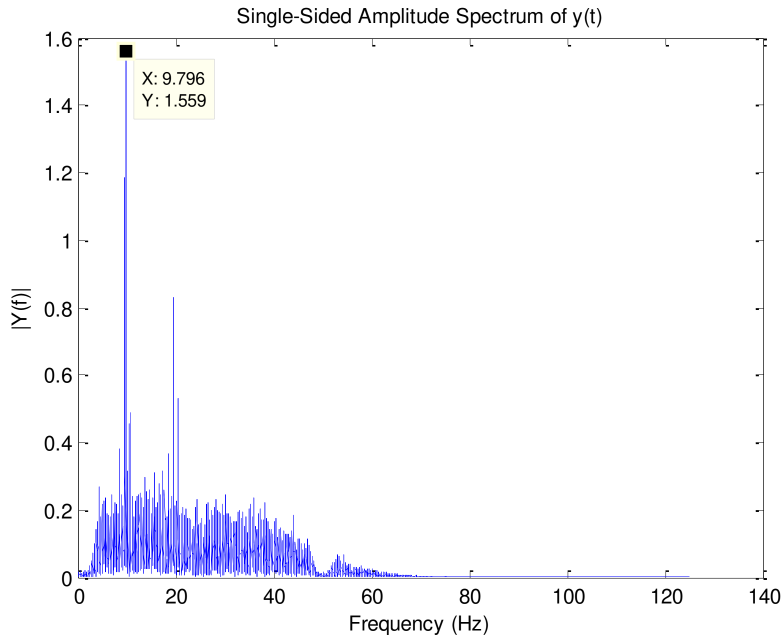



**Figure 3.8: Frequency spectrum of EEG signal when the target is 10 Hz.**

**Table 3.2: Degrading performance of MEC**

| Signal properties | MEC classifier accuracy |
|---|---|
| Noiseless, 2 signals (9.75 and 8.75 Hz) | 100% |
| Noisy, 2 signals (9.75 and 8.75 Hz), random noise amplitude low | 60% |
| Noisy, 2 signals (9.75 and 8.75 Hz), random noise amplitude high | 30% |

MEC (Figure 3.6). As a result, the Simulink model was modified to allow room for a new classification algorithm, namely CCA. Pictorial view of this model has been illustrated by Figure 3.9.

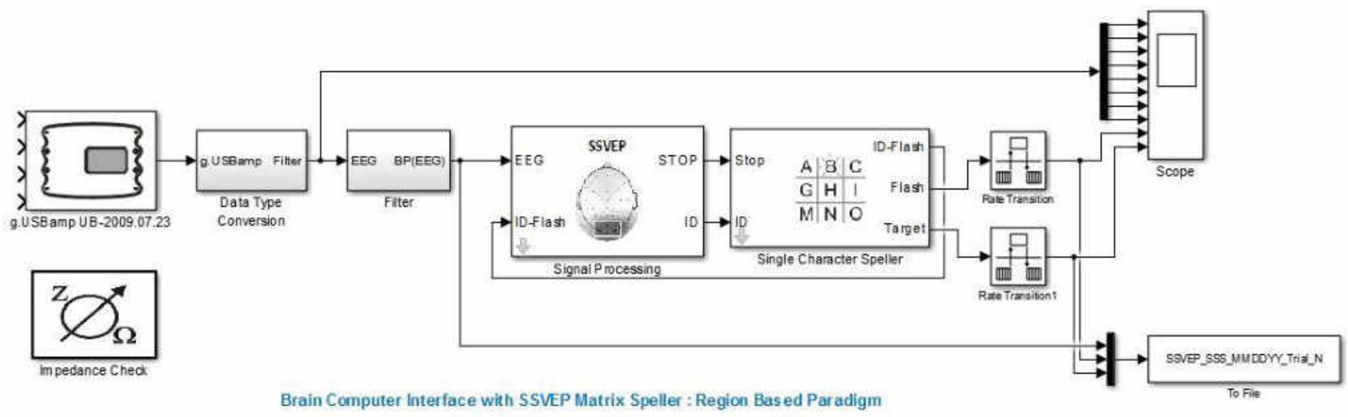



**Figure 3.9: Real-time SIMULINK model for SSVEP BCI.**

**Table 3.3: Specifications of SSVEP SIMULINK model**

| BCI System Parameters | Specifications |
|---|---|
| **Solver:** | Variable-step, ode45 |
| **g.USBamp:** | g.USBamp UB-2009.07.23 |
| **Simulink Block:** | Designed with Level 1 s-function |
| **Sampling Time, Ts sec:** | .0078 sec (frequency 128 Hz) |
| **Filter Type:** | Band-pass Filter, Notch Filter |
| **Filter Cut-off Frequencies:** | Band-pass: 2~30 Hz, Notch:60 Hz |
| **EEG File Name Convention:** | SSVEP_SSS_MMDDYY_Trial_N |
| **EEG Data Type:** | Double |
| **Additional Comments:** | Model is used for copy spelling only |

### 3.5.2 Result and Analysis

Before arriving to the final design, SSVEP paradigm was tested similarly as P300 BCI. During the pilot study, the SSVEP system was updated many times changing model parameters and signal processing algorithms. During the SSVEP BCI tests in this pilot study, the recruited subjects were asked to spell 'FLASH' and 'WATER'. The SSVEP frequencies were selected as 15 Hz (Region 1), 11 Hz (Region 2), 13 Hz (Region 3), 16 Hz (Region 4), 14 Hz (Region 5), 17 Hz (Region 6), and 20 Hz (Region 7). These frequencies are selected randomly within the range which elucidate sufficient stimulation on the visual sensor of the users. The result is presented in the Table 3.4. It is mention worthy that the frequencies in pilot study were different than the BCI tests conducted afterwards. In fact, results from pilot study helped to pick the target frequencies which were later used in the final BCI tests.

Due to the use of electronic monitor for generating SSVEP stimulation, EEG data acquisition should be synchronized with the monitor frame changes. Once the target is assigned, a burst of synchronization pulses is generated and applied to regulate the EEG data collection (Figure 3.10). This also ensures that time stamp is recorded at the beginning and end of a stimulation. In other words, every pulse indicates the stimulation duration. The number of pulses depend on the number of the target regions. For example, the 14 pulses in the Figure 3.10 indicates that there are 14 regions which require to spell 7 characters in each level. The pulse train is used to crop the EEG signals which is obtained as a result of the SSVEP stimulation. In general, the timely stamped EEG signal is analyzed to obtain the information about the stimulating frequency. So, it is critical have enough

EEG samples to apply frequency detecting algorithm and identify the target frequency. As the system spells the characters online, the duration of the pulse need to be adjusted at the beginning of each spelling test. After each pulse time, the detected frequency and the corresponding region is displayed on a LCD monitor. Similar as the P300 speller, a pilot study was performed with the words 'FLASH' and 'WATER' as a proof of concept for SSVEP stimulation. This time four male subjects volunteered to participate in that study. The accuracy was measured for every level and presented in Table 3.4 and Table 3.5.

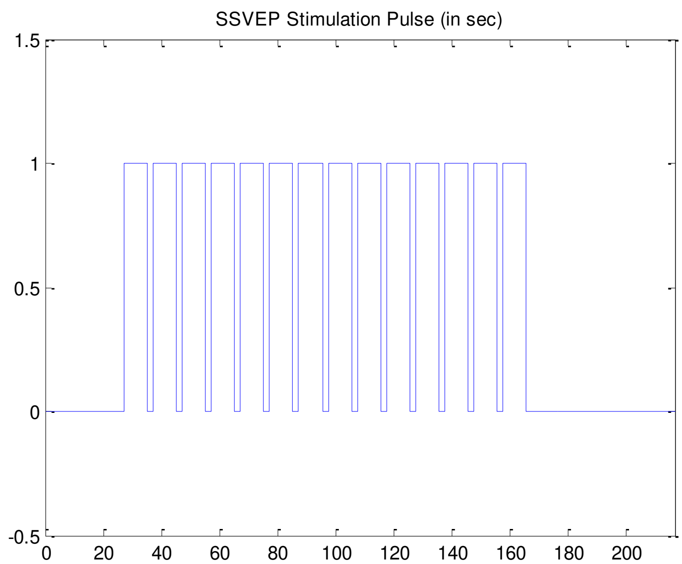



**Figure 3.10: Pulse train to synchronize the stimulation with the EEG data acquisition.**

**Table 3.4: Test results from SSVEP stimulation, pilot study with 'FLASH'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| S1 | 80 | 60 | 100 | 40 | 90 | 50 |
| S2 | 80 | 80 | 71 | 71 | 75.5 | 75.5 |
| S3 | 57 | 29 | 100 | 100 | 78.5 | 64.5 |
| S4 | 100 | 71.43 | 85.71 | 57.14 | 92.85 | 64.28 |

**Table 3.5: Test results from SSVEP stimulation, pilot study with 'WATER'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| S1 | 40 | 60 | 60 | 60 | 50 | 60 |
| S2 | 70 | 50 | 56 | 56 | 63 | 53 |
| S3 | 72 | 100 | 29 | 100 | 50.5 | 100 |
| S4 | 43 | 43 | 100 | 71.43 | 71.5 | 57.21 |

From the above tables (Table 3.4 and Table 3.5), it is obvious that the BCI performance among different subjects are not equal. On top of that, same subject can have different performance in different trials. For instance, subject S3 spells all correct letters for 'FLASH' in trial 2, but it was less than 60% accuracy in trial 1. Here, the lowest accuracy was 29% and highest accuracy was 100%. However, considering the two levels at a time, average accuracy of the subjects was 50% or more.

It is obvious from the pilot study that the system generates the desired frequency and the resultant stimulation. In order to make a comparison among designed BCI spellers, same set of characters 'ASB26/$' were presented to seven users to spell them using SSVEP stimulation (Table 3.6). Every subject attended two test trials. Considering both level 1 and level 2, the maximum accuracy at both level was 86%. It is noticeable that Subject S1, S7, S8, S9 and S10 have shown consistent performance in each level where the highest accuracy was 86%. Though these subjects have no to minimal familiarity with BCI speller, they were not needed any training as P300. So, it produces the result little faster than P300 BCI. From APPENDIX C, everyone was feeling drowsy, fatigued and/or stressed after the BCI tests. Though the test were pseudorandom, the subjects might get tired even at the middle of the experiments. Another possibility is that the subject is SSVEP illiterate. Under such instance, S2, S3, S4, S5 and S6 were having poor response from SSVEP stimulus due to the fact that such artificial paradigm is unable to elicit specific brain activity and thereby SSVEP potential don't get evoked in EEG signal.

**Table 3.6: Test results from SSVEP stimulation with the character set 'ASB26/$'**

| Subject Number | Trial 1 Accuracy % | | Trial 2 Accuracy % | | Average Accuracy (%) | |
|---|---|---|---|---|---|---|
| | Level 1 | Level 2 | Level 1 | Level 2 | Level 1 | Level 2 |
| S1 | 72 | 86 | 86 | 86 | 79 | 86 |
| S2 | 43 | 30 | 86 | 43 | 65 | 37 |
| S3 | 72 | 30 | 43 | 43 | 58 | 37 |
| S4 | 43 | 72 | 72 | 43 | 58 | 58 |
| S5 | 58 | 15 | 58 | 58 | 58 | 37 |
| S6 | 58 | 58 | 43 | 58 | 51 | 58 |
| S7 | 86 | 86 | 72 | 72 | 79 | 79 |
| S8 | 72 | 100 | 86 | 100 | 79 | 100 |
| S9 | 86 | 86 | 86 | 72 | 86 | 79 |
| S10 | 86 | 100 | 100 | 86 | 93 | 93 |
| Overall Accuracy= | | | | | 70.6 | 66.4 |

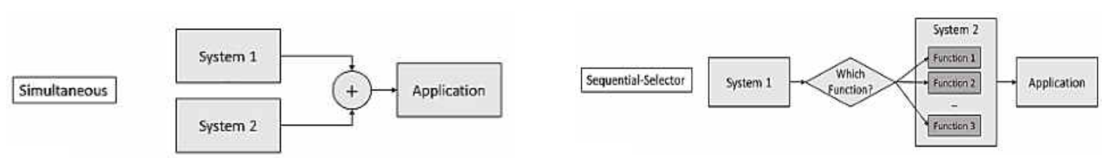
## 3.6 Conclusion

In fact, the major advantage of SSVEP system is that it doesn't require any training session which seemingly makes it a faster speller. When region-based paradigm is used to generate the SSVEP stimulation, the user has a large number of options or targets. Though each target selection requires two levels, second level allows the user to look on targets with broader gaps minimizing adjacency effects and, thereby, less interference. The variation in accuracy among two levels need to be minimized in the updated design. One of the possible reasons of such discrepancy is that when the subject switches from first level to second level, due the orientation of the characters on the screen, sometime the subject has to suddenly move from one corner of the paradigm to the other corner which might cost a loss of attention of the subject.

# CHAPTER IV: HYBRID BCI, MATERIALS AND METHODS

## 4.1 Architectural review of Hybrid BCI

In earlier studies, a systematic review of hybrid BCI was accomplished in terms of their taxonomy, usability, advantages, and disadvantage [103][104]. Two different modes of operation were discussed in these reviews: simultaneous and sequential architecture. For instance, simultaneous architecture requires any two BCI systems to work in simultaneous mode of operation to control two separate functions at same time and such a combination is expected to achieve higher accuracy and ITR, as well. In an earlier design, a simultaneous hybrid structure was comprised of ERD (imagined movement) to control the cursor in vertical position and SSVEP to control the cursor in horizontal position [105]. On the other hand, output of one BCI system is used as the input for another to control various functions of the second BCI system in sequential architecture. Such an operation with a BCI system working as a switch is also termed as asynchronous mode of operation [104]. These two architectures are pictorially explained in Figure 4.1.




a) b)

**Figure 4.1: Hybrid BCI architectures, a) simultaneous and b) sequential mode of operation.**

## 4.2 Paradigm Design

In hybrid BCI system, the paradigm was designed combining two different techniques together, namely P300 and SSVEP (Figure 4.2). In general, such a fusion gets better output and brings comfort to the users. A previous comparative study suggests that SSVEP possess a better suitability to combine with P300 for constructing efficient hybrid BCI due to various advantages [106]:

- SSVEP and P300 both are elicited by visual stimuli, so visual attention of subjects is sufficient to perform the BCI task
- SSVEP and P300 both are non-invasive causing less experimental set up time, low complexity, appreciable reduction in user effort and computational cost.
- both are measured in different domains (time domain for P300 and frequency domain for SSVEP), making the system less error prone.
- both are detected from different cerebrum cortex, making the subsystem independent of each other with an increase in accuracy.

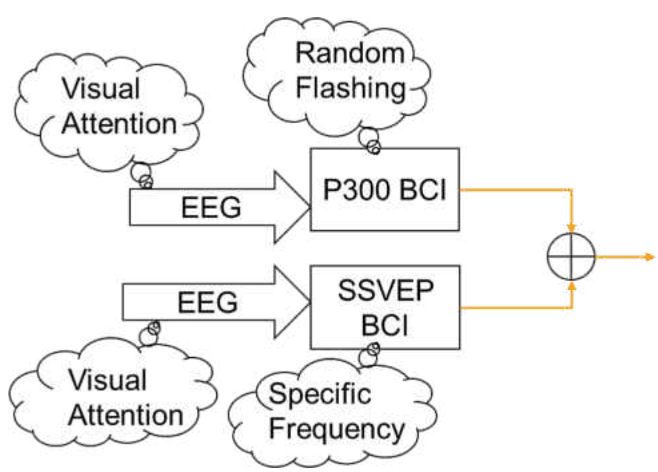



**Figure 4.2: Hybrid BCI system combining P300 and SSVEP.**

In earlier chapters, experiments were designed using region based paradigm where two levels were required to identify a character. However, combining these two techniques using region based paradigm allows the system to eliminate one level and make the hybrid system quicker than any of the individual BCI system. In other words, the user can pick the right character just using a single level. The paradigm was designed with seven regions where each region includes a circular area surrounded by seven characters or symbols. In the designed hybrid paradigm, the characters of a single region were randomly flickering around a white circle to generate P300 evoked potential and the white circle was changing to black shade with a constant frequency leading to SSVEP potential (Figure 4.3). So, the paradigm elicited both stimulation at the same time (Figure 4.4). In this model EEG is processed through the P300 and SSVEP signal processing blocks. As this is a pilot study, P300 and SSVEP signal processing blocks process the data offline and identifies the character by recording the identification number of the detected region as well as the flickering character after a single level stimulation. The P300 potential is used to recognize the character while the SSVEP is utilized to detect the region. It is notable that the symbols and characters alternates the color between black and white to increase the contrast so that stimulation is enhanced.

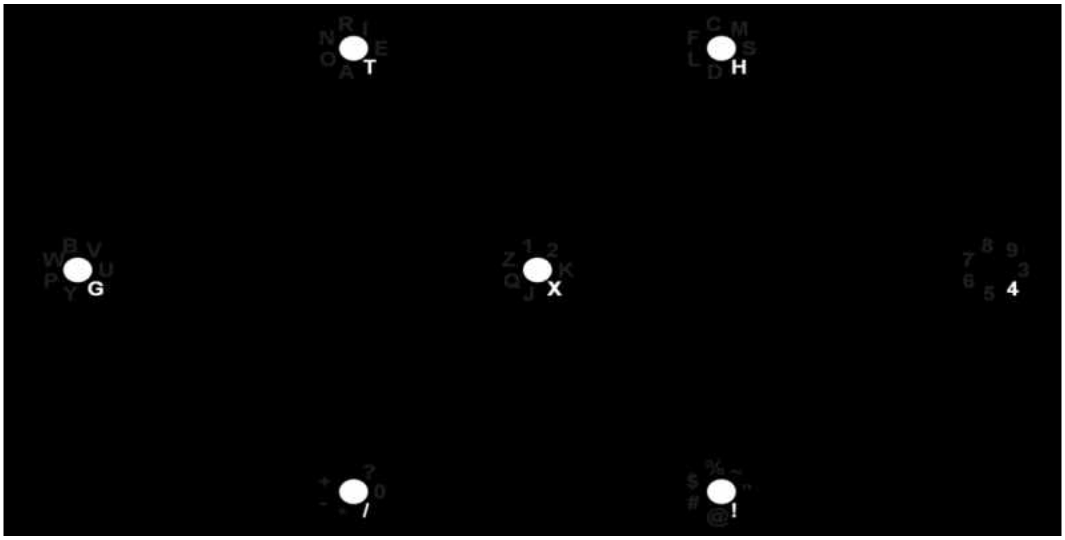


**Figure 4.3: Monitor frame at a single moment when both P300 and SSVEP stimulations are produced.**

In order to verify the frequency generated during SSVEP, a data acquisition kit from BIOPAC is utilized to measure the flickering frequency of every circle [87]. An attached photo diode is used to acquire the frequency of change of the flashing circle for a few seconds. The acquired diode current represents the alternating light of the circular area which is analyzed applying FFT. Such an action reveals the highest peak at the frequency of flashing circle. The same monitor was utilized to design P300 and SSVEP paradigm. Earlier paradigms utilized two levels to allocate 49 characters whereas hybrid paradigm allows room for same number of characters in a single screen but with the reduced font size. As a consequence, the resulting paradigm demands less effort from the user. Such a measure may lead to lesser fatigue for the human eyes.

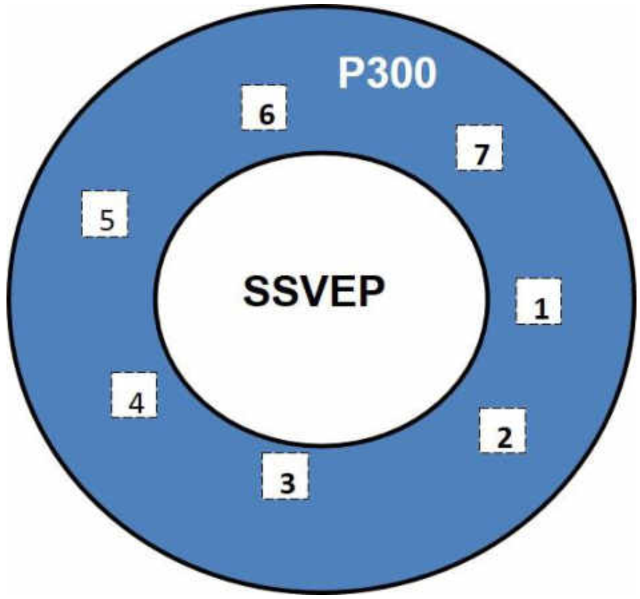



**Figure 4.4: A single region with the characters (annotated from 1 to 7) stimulating P300. These characters are located outside a white circle flickering at a single frequency.**

## 4.3 Classification Methods

In order to make a comparative study, the algorithms used for P300 BCI and SSVEP BCI are kept same as before. As mentioned in earlier chapters, the hybrid data was collected form same subjects who participated in tests with P300 and SSVEP speller in same set of experiments. In order to contain all seven regions, the spelling task was set with the characters ‘ASB26/$’. The P300 paradigm character flashes for 10 times during the SSVEP stimulation. In total, 10 subjects participated in the hybrid BCI tests. Every subject was engaged in three trials for each individual test. P300 BCI uses LDA classifier for character detection and SSVEP uses CCA algorithm to detect the stimulating frequency which presents a region. Table 4.1 lists the frequency and corresponding region.

**Table 4.1: Flickering frequency of 7 regions**

| Frequency (in Hz) | Region |
|---|---|
| 15 | 1 |
| 18 | 2 |
| 13 | 3 |
| 16 | 4 |
| 14 | 5 |
| 17 | 6 |
| 20 | 7 |

### 4.4 Performance Evaluation

As this has fused both the P300 and SSVEP, it technically removes the necessity of two different levels of region-based paradigm. In this case, one level is enough to find the region and identify it out of that region. Ten male users participated in all three BCI paradigm tests and their experimental results are presented in Table 4.2. A set of questions were asked to the users about the three different BCI speller. Indeed, the comfortability and preference of users were two key questions presented to the users. Most of them mentioned that hybrid BCI speller is much more soothing to look at and it doesn't require the subject to look directly on a steady flickering. This gave them less fatigue than the other two paradigms. The hybrid BCI speller is designed with the MATLAB Simulink as portrayed in Figure 4.5. The model is used to present paradigm to the user, extract and classify the EEG data, and finally save the EEG data for future analysis. However, SSVEP data is collected with the sampling rate whereas P300 data is stored after down sampling by two. The EEG down sampling reduces the computation time.

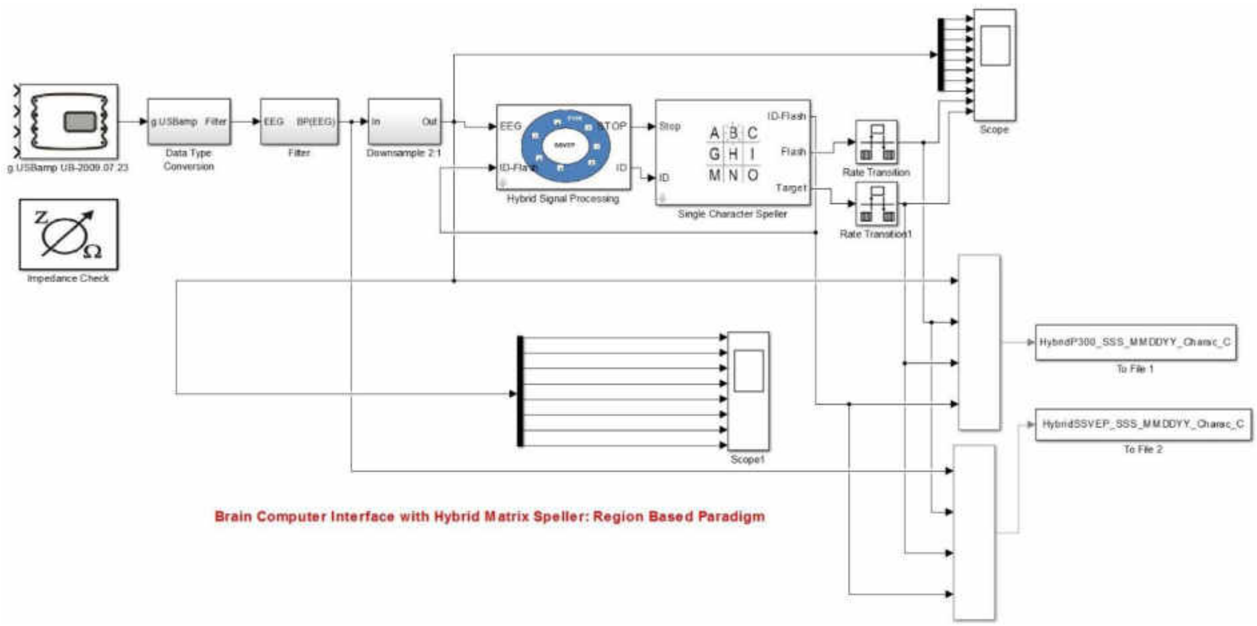



**Figure 4.5: SIMULINK model for the hybrid feature extraction, classification and paradigm presentation.**

### 4.5 Results and Comparative Analysis

Results from SSVEP stimulation and P300 stimulation of the hybrid BCI system can be analyzed separately. In addition, results obtained from hybrid system as a combination of SSVEP stimulation and P300 stimulation is represented in two different levels in Table 4.2. Due to the close existence of SSVEP and P300 stimulation, it’s a big challenge for separating them. Earlier study also shows that a subject can respond well to a specific paradigm while show little to no response at all to another type of paradigm. The hybrid system has been designed to take care of these issue by providing an alternative to a user. For example, subject 5 or P5 has shown strong response to P300 with an 100% accuracy. Same subject (S5) suffered from a low response to SSVEP with an accuracy of just 36%. However, this subject (H5) obtained an overall greater accuracy as high as 86% at one of the trials. Considering the exclusion of level 2, such a result is advantageous in many ways. For instance, removing a level makes the system much speedier, the subject gives attention only on the objects flashing to generate P300 ERP, and such an action ensures that their eyes are exposed to less fatigue than a lone SSVEP BCI system. In addition, hybrid system allows the user to watch all 49 characters at a time and select one of them without following a tedious two-level stage which exposes their eyes twice to the flickering object. In this study, almost all subjects were found with good responsivity to both P300 and SSVEP stimulation.

**Table 4.2: Test results from the Hybrid speller (acronym: subj.=subject, L1=Level 1, L2=Level 2, T1=Trial 1, T2=Trial 2, Acc.=accuracy in percentage)**

| Subj. | Trial | L1 | **ETAO NRI** | **SHDL FCM** | **UGYP WBV** | **KXJQ Z12** | **34567 89** | **0/*- +.?** | **"!@#$ %~** | Acc. (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | L2 | **A** | **S** | **B** | **2** | **6** | **/** | **$** | |
| H1 | T1 | L1 | √ | √ | X | √ | √ | √ | √ | 72 |
| | | L2 | X | √ | X | √ | √ | √ | √ | |
| | T2 | L1 | √ | √ | √ | √ | X | √ | √ | 86 |
| | | L2 | √ | √ | √ | √ | √ | √ | √ | |
| H2 | T1 | L1 | X | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | X | √ | √ | √ | √ | √ | √ | |
| | T2 | L1 | √ | √ | X | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | √ | √ | √ | √ | √ | |
| H3 | T1 | L1 | √ | √ | √ | √ | √ | √ | X | 86 |
| | | L2 | √ | √ | √ | √ | √ | √ | X | |
| | T2 | L1 | √ | X | √ | √ | X | √ | √ | 72 |
| | | L2 | √ | X | √ | √ | √ | √ | √ | |

| Subj. | Trial | L1 / L2 | ETAO NRI / A | SHDL FCM / S | UGYP WBV / B | KXJQ Z12 / 2 | 34567 89 / 6 | 0/*- +.? / / | "!@#$ %~ / $ | Acc. (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| H4 | T1 | L1 | √ | √ | X | √ | √ | X | √ | 58 |
| | | L2 | X | √ | √ | √ | √ | √ | √ | |
| | T2 | L1 | √ | √ | √ | X | √ | X | √ | 72 |
| | | L2 | √ | √ | √ | X | √ | √ | √ | |
| H5 | T1 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | X | √ | √ | √ | √ | |
| | T2 | L1 | √ | X | √ | √ | √ | √ | √ | 72 |
| | | L2 | √ | √ | √ | √ | √ | √ | X | |
| H6 | T1 | L1 | √ | √ | √ | √ | √ | X | √ | 72 |
| | | L2 | √ | X | √ | √ | √ | √ | √ | |
| | T2 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | X | √ | √ | √ | √ | √ | √ | |
| H7 | T1 | L1 | √ | X | √ | √ | √ | √ | √ | 72 |
| | | L2 | √ | X | √ | X | √ | √ | √ | |
| | T2 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | X | √ | √ | √ | √ | |
| H8 | T1 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | √ | √ | √ | X | √ | |
| | T2 | L1 | √ | √ | √ | √ | √ | X | √ | 72 |
| | | L2 | √ | √ | X | √ | √ | X | √ | |
| H9 | T1 | L1 | √ | √ | √ | √ | √ | √ | X | 72 |
| | | L2 | √ | X | √ | √ | √ | √ | √ | |

| Subj. | Trial | L1 | ETAO NRI | SHDL FCM | UGYP WBV | KXJQ Z12 | 34567 89 | 0/*- +.? | "!@#$ %~ | Acc. (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | L2 | A | S | B | 2 | 6 | / | $ | |
| | T2 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | √ | √ | √ | √ | X | |
| H10 | T1 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | √ | X | √ | √ | √ | |
| | T2 | L1 | √ | √ | √ | √ | √ | √ | √ | 86 |
| | | L2 | √ | √ | √ | √ | √ | √ | X | |

A concise form of the results in Table 4.2 is represented in Table 4.3. Few things can be learned from the given table. The average accuracy of the hybrid system is 79% which is not so high. In addition, eight out of ten subjects expressed their opinion in favor of hybrid. They found the system easier to focus on because hybrid system induces less fatigue to eyes than other two systems (APPENDIX C).

**Table 4.3: Test results from Hybrid stimulation with the character set 'ASB26/$'**

| Subject Number | Trial 1 Accuracy (%) | Trial 2 Accuracy (%) | Average Accuracy (%) | Easy to Look at |
|---|---|---|---|---|
| H1 | 72 | 86 | 79 | Hybrid |
| H2 | 86 | 86 | 86 | Hybrid |
| H3 | 86 | 72 | 79 | Hybrid |
| H4 | 58 | 72 | 65 | Hybrid |
| H5 | 86 | 72 | 79 | P300 |
| H6 | 72 | 86 | 79 | Hybrid |
| H7 | 72 | 86 | 79 | Hybrid |
| H8 | 86 | 72 | 79 | Hybrid |
| H9 | 72 | 86 | 79 | SSVEP |
| H10 | 86 | 86 | 86 | Hybrid |
| Overall Accuracy= | | | 79 | |

EEG extraction from three systems have opened up the opportunity to compare the hybrid systems with others, namely P300 and SSVEP systems. The key parameters of these three systems are listed in Table 4.4 . It is evident from this table that the hybrid system performance lies somewhere middle in these two systems if accuracy is the only considered parameter. However, level 1 and level 2 is merged together resulting in less spelling time. The hybrid system lowers the spelling time to almost half of any of the individual BCI. Such a gain in spelling time boosts the performance of the system. Most of the subjects also experienced that hybrid BCI does not make the eyes get tired so quickly as other two systems. Overall, these results show that P300 and SSVEP can be combined together to achieve better acceptability from the observers. In addition, the faster output of the system will save the time to communicate to the other people. It will also allow the investigator to design systems which can act in real time, thereby increases the possibility to be applied in clinical application.

**Table 4.4: Performance comparison of three BCI systems**

| BCI System | Level1 Accuracy (%) | Level2 Accuracy (%) | Total Spelling Time (sec) | Comment |
|---|---|---|---|---|
| P300 | 85.3 | 82.4 | 288 | -- |
| SSVEP | 70.6 | 66.4 | 232 | -- |
| Hybrid | Single Level, 79 | | 126 | Easy to look at |

Similarly, performance comparison of three systems were statistically analyzed to verify if there is any real improvement occurred in spelling time in the hybrid system. Total time of the experiments in all three systems have been reported in Table 4.5. Variance was tested using ANOVA and F-Statistic (8617.79) suggests that there is a difference between these groups. In addition, smaller p value (the p-value is $< .00001$) suggests that the compared groups differ significantly. So, it is quite evident that hybrid system takes lesser time than either of the other two systems.

**Table 4.5: Spelling time spent by each subject**

| Subject # | Spelling Time (sec) | | |
|---|---|---|---|
| | P300 | SSVEP | Hybrid |
| **1** | 290 | 233 | 132 |
| **2** | 286 | 237 | 122 |
| **3** | 289 | 232 | 125 |
| **4** | 287 | 234 | 125 |
| **5** | 288 | 232 | 126 |
| **6** | 282 | 232 | 129 |
| **7** | 285 | 228 | 121 |
| **8** | 288 | 228 | 124 |
| **9** | 291 | 233 | 130 |
| **10** | 292 | 230 | 127 |
| **Average** | **288** | **232** | **126** |

## 4.6 Conclusion

According to the feedback from the users it is quite obvious that the hybrid BCI can solve the long-standing challenge as providing dual option to the BCI user. In this study the combination of paradigm was accomplished in a same manner as done with another hybrid BCI. This design is a significant move from the contemporary hybrid BCI as here the P300 and SSVEP stimulation is activated same time in parallel to each other. So, two different stimulations are embedded in same EEG signal. Another advantage of the hybrid BCI is that it cuts the required time for stimulation detection almost by half of the usual time. However, to achieve the whole benefits of such a novel design, it is necessary to search for other suitable algorithms to eliminate the dependency on subjects' variable response to P300 and SSVEP stimulation.

# CHAPTER V: DISCUSSION

## 5.1 Contribution of This Work

In order to obtain the benefit from BCI, many groups are doing extensive research to control devices and communicate to external world. The research presented in this thesis explores the advantages of hybrid BCI comparing to the traditional BCI where only a single BCI technique is employed. In this dissertation, three types of BCI systems have been developed and applied to find the subjects response to various systems resulting in the variable accuracy. More specifically, this work is the result of a step by step strategies where system performance was evaluated in each model to enhance the target separation and to increase the subject comfortability during visual focus on a specific object. Apparently, this research has returned following BCI systems as outcomes:

- Conducted pilot experiments to capture information about suitable features which will increase the classification accuracy in P300 speller.
- Developed a BCI speller using P300 and conducted experiments with this model.
- Determined the suitable parameters for SSVEP speller paradigm, such as flashing frequencies, location of characters on the screen, and processing window size.

- Developed a BCI speller using SSVEP and conducted experiments with this model.
- Designed tests and protocols to estimate the features to strengthen the hybrid system performance.
- Designed a hybrid speller by combining the P300 and SSVEP systems.
- Conducted experiments with the new hybrid speller BCI.
- Accomplished a comparative study of P300, SSVEP and a hybrid speller paradigm to estimate the better system.
- Overall, there is a big jump from traditional LED system to LCD monitor which offers user friendly graphical interface and allows enough room to include large number of targets.

Results of this study was analyzed and published in some peer reviewed research papers.

## 5.2 Future Work

According to the results obtained in this research on the aspect of various BCI systems performance either for hybrid or for an individual technique, it is apparent that the task becomes easier for BCI user if there exist techniques which can fill the gap between the user's familiarity and complexity of a BCI system. In fact, application of hybrid BCI can open room to include more users for designing a system with less complexity but better accuracy. Ongoing advancement in sensor technology can make a strong bridge between data retrieval process and analysis algorithm of BCI for obtaining accuracy and faster operation. Our motive is to grab this opportunity and make the hybrid system more accurate and pleasant for use. In addition, the hybrid system would be made with the capability to work online or in real time. During the design phase, the signal processing and paradigm part were kept isolated from each other. It would allow one to use any paradigm independent of signal processing scheme. Apart from that, EEG signal would be collected from the target community who are suffering from disability and can't communicate well with other people. In this connection, patients with difficulties from ALS, ADHD, spinal cord injury, brain traumatic injury and others would get the benefit from BCI spellers.

To uncover the future BCI applications of other modalities, the underlying physiological mechanisms and brain responses in each application need to be carefully investigated. It is evident that P300 and SSVEP can be fused together to form a hybrid BCI with much more interesting features. The interfacing paradigm can be designed to capture these evoked potentials in a manner such that many human factors are properly taken care of to diminish their overall impact. Many new applications can develop with efficient design of the control interface. Visual image classification [107], attention monitoring [108], and neural rehabilitation are some other BCI applications that drew interests of researchers from various disciplines. So, hybrid BCI can be incorporated with these BCI systems to reduce the mental workload or fatigue. BCI rehabilitation can rewire the brain by manipulating the neural plasticity of paralyzed stroke patients [109]. An audiovisual BCI system combined visual (P100, N200, and P300 ERP) and audio stimuli (saying numbers) to detect the awareness of disorders of consciousness (DOC) patients [110]. It would be an interesting step to design such system with hybrid BCI. For example, another study used a combination of P300 and SSVEP to detect potential awareness in patients suffering from DOC [111]. Depending on the patients' health, classification accuracy varied from 46% to 100%. However, this visual hybrid BCI was able to detect the command following ability of some patients. As the traditional awareness measurement tool heavily depends on behavioral observations and DOC patients suffer from limited behavioral response, the hybrid BCI has potential application as a supportive awareness detection tool.

In order to promote BCI research just from the exploratory field to a clinical study with better acceptance, further insightful study and research need to be directed toward exploring other usability areas that are not yet exposed. This research has covered only one particular objective of BCI research, modulating brain activity applying external visual stimulation. Although there exist many obstacles for BCI researchers such as low accuracy and slow response time, BCI beyond laboratory experiments have increased over the last decade with the help of modern high-speed computational and sensor technologies to develop an alternative to traditional assistive and mainstream technologies. In fact, fundamental research on hardware, signal processing, machine learning, and neurophysiology is the main criteria for designing an interaction paradigm. Although every design is accomplished for keeping a specific application in mind, opportunities are revived with the potential space to accommodate other supplementary applications.

In addition to above viabilities, a need still exists to include different age groups in the BCI study. In this work, participants were from 21–30 years' age group who were both able bodied and easy follower of instructions. Future study can be designed with other age groups like 11-20 years whom sometimes difficult to instruct about the steps of the test. In addition, EEG from subjects with the age of 50 years or more can help to learn what are the modifications and features need to be added with the hybrid BCI so that use of this system can be extended to larger user groups. For example, challenges confronted by elderly people can range from struggle in paying attention to following what tasks to do so that P300 and SSVEP potential can be evoked simultaneously in the EEG signal. However, it should be kept in mind that most of the time subjects' recruitment is a cumbersome job. People might have personal and social commitments which can conflict and come on the way of scheduled test. In order to obtain appreciable number of samples, data collection should be spanned over few calendar years. Such attempts will allow the investigators to design a robust system independent of user's age and associated inabilities. In fact, added user comfort can be granted by replacing the wired data collection process with wireless cap. Advanced signal processing for EEG analysis would be helpful to reduce the noise during wireless data acquisition, which in turn, would be useful to increase the system accuracy, overall system performance and the user acceptance.

# APPENDIX A

## Biomedical Research Informed Consent Form

## Informed Consent

**Research Project Title**: Brain-Computer Interface (BCI)

**Researchers**: Dr. Reza Fazel-Rezai, Dr. Kouhyar Tavakolian, Md. Ali Haider, Nasim Taghizadeh Alamdari, Ajay Verma

This consent form, a copy of which will be left with you for your records and reference, is only part of the process of informed consent. It should give you the basic idea of what the research is about and what your participation will involve. If you would like more detail about something mentioned here, or information not included here, you should feel free to ask. Please take the time to read this carefully and to understand any accompanying information.

**a. Purpose of the research:**

The purpose of this study is to spell the characters / numbers using BCI speller. This will be accomplished by recording electroencephalogram (EEG) signals (brain signals) from a control group in a normal, everyday setting on a predetermined computer and running the program called P300 based BCI speller and will be monitored by qualified professionals (University of North Dakota faculty). This research will help determine the speed and accuracy of a speller program based on P300 potentials as well as provides a new visual paradigm towards brain-computer interface research. The overall accuracy and speed of typing would be increased based on this research and beneficial to the people with disabilities to spell faster and less hectic way.

**b. Research procedures:**

Before starting the test, you should sit on a chair in front of a computer screen and we will explain the experimental process to you as well as the tasks you should perform before the test. The task is to simply look at the seven regions consisting of seven different sets of letters, characters and numbers, while each character set / region is being flashed or intensified for a particular amount of time. Later, we place the electrode cap on your head and the experiment begins whenever you confirm that you are completely comfortable and ready to begin testing. During the experiment, the characters/ letters which you want to speller will be flashed on a computer screen distributed over seven regions, in a random sequence, and you will count how many time your particular character set flashes. Meanwhile, your brain signals are captured and transferred to the computer for further analysis. There are only four variations of these tests, each one resulting in a minimum duration of 20-30 minutes. The tests are carried out until the last character set flashes on the screen. The preparation time for the instruments take about 10 – 15 minutes and the whole procedure takes about 90 – 120 minutes. Before and after the experiments you would be asked to complete a questionnaire, form which includes multiple choice questions and questions regarding the comfort level during the experiment and any other suggestions you may have to improve the process. The questionnaire form should take approximately 5 – 10 minutes to be answered. The questionnaire explores the strength and weakness of the experiment from the user's point of view and it gives us the scope of improvement in a very short span of time. However, you are not obligated to complete the questionnaire form or the experiment. You may inform us to stop the test and let you exit the laboratory under any circumstances. Furthermore, in the case where the data is corrupt, your decision to retest is voluntarily.

**c. Risks and Benefits:**

In this experiment the brain signals are recorded and transferred to the computer. This process will be done using "g.tec P300 Spelling Device with g.USBamp and Simulink V2.09a." (www.gtec.at/) hardware and software which have been guaranteed to protect subjects from all types of power related hazards. Very minor risks are involved in this study. After completing a segment of testing, you may feel fatigued, drowsy, claustrophobic and or frustrated. On the other hand, this research has the benefit of improving the accuracy and speed of the spelling device for paraplegic persons.

**d. Recording devices:**

In this study, we will use the g.tec's newest high-end and high performance active electrode system for non-invasive electrophysiological derivations called g.GAMMAbox® which collects your brain signal activity during testing. These signals will be stored on a computer's hard disk anonymously and will be analyzed later.

**e. Assurance of Confidentiality:**

In this experiment, the data including the recorded signals and questionnaires will be collected and stored separately in confidential and safe place at our laboratory and advisor's office for a minimum of three years. Your information will never be shared anywhere unless with your written permission.

We have one computer in our laboratory located in Harrington Hall 120 D specifically for our research purpose where the digital data will be stored. This computer is password-protected, and nobody has access to it except the main researchers. The paper forms including the letters of consent and questionnaires will be kept safely in a cabinet (which is locked by the faculty advisor, Dr. Reza Fazel) located in the primary investigator's office. Our lab is also safely equipped by a key entry with limited access.

The title of data will be the date and the time of running the experiment. However, in case of giving the feedback we need to know whose subject the data associates with. For this purpose, we will specify the subject's name corresponding to the data in a different file and store it somewhere in our password-protected and absolutely safe computer.

All of the data will be completely destroyed at the end of the research. However, they will be kept at least for a minimum of 3 years. Data means paper forms and digital raw data which will be shredded by a paper shredder and will respectively be erased from the computer and only the results will be kept. Results, on the other hand, only include the final outcome of the research, the number of subjects, their average age and their gender.

**f. Feedback**

We can provide you the results of the experiment upon your request after analyzing the data. It is not possible to give you any feedback immediately after the test. In case of need of feedback, you may complete the "feedback request" form to request a summary of the results of your experiment. The feedback will be printed on paper with the "University of North Dakota" letterhead.

**g. Assurance of Voluntary Participation**

Your participation in this research is voluntary. Therefore, you can withdraw from the project at any time without any consequence. You can contact us via one of the emails mentioned below to withdraw from the test any time prior to the experiment. Furthermore, you can stop the administration of the test in the middle of it through verbal communication to the supervising researcher.

Your signature on this form indicates that you have understood, to your satisfaction, the information regarding participation in the research project and agree to participate as a subject. You are free to withdraw from the study at any time, and /or refrain from answering any questions you prefer to omit, without prejudice or consequence. Your continued participation should be as informed as your initial consent, so you should feel free to ask for clarification or new information throughout your participation. If you have any questions or concerns, please contact the principal researcher, Dr. Reza Fazel-Rezai:

**Reza Fazel-Rezai**, Ph.D., PE, IEEE Senior Member

Associate Professor

Address: Department of Electrical Engineering

Upson Hall II Room 160 N

243 Centennial Drive Stop 7165

Grand Forks, ND 58202

Email: rezafazel@mail.und.edu

URL: http://www.ee.und.edu/html/research/biomed.html

Phone: 1-701-777-3368

This research has been approved by the University of North Dakota Institutional Review Board (IRB). If you have any concerns or complaints about this project, you may contact the above-named person or the IRB Secretariat at (701) 777-4279. A copy of this consent form has been given to you to keep for your records and reference.

Participant's Signature __________________ Date ____________

Researcher and/or Delegate's Signature________________Date ____________

# APPENDIX B

## BCI Questionnaires

## Questions before a BCI Test

1. Overall, how are you feeling today? One being the worst and 10 being the best.

**1 2 3 4 5 6 7 8 9 10**

2. Do you feel well rested?

**Yes No**

3. Do you feel stressed?

**Yes No**

4. Can you sit at a computer performing tasks for up to 2 hours?

**Yes No**

5. Do you have any pre-existing medical conditions that require specific medical attention? **Yes No**

If yes, please explain

______________________________________________________

6. Do you have any allergies?

**Yes No**

If yes, please list

__________________________________________________________

7. Are you familiar with BCI?

**Yes No**

Please write any other comments or suggestions here:

__________________________ __________________

Participant's Signature Today's Date

## To be completed after BCI Test

8. Overall, how are you feeling after testing? One being the worst and 10 being the best.

**1 2 3 4 5 6 7 8 9 10**

9. Are you feeling drowsy?

**Yes No**

10. Are you feeling fatigued?

**Yes No**

11. Are you feeling stressed?

**Yes No**

12. What changes would you make to the procedures?

13. Were you easily distracted or unable to focus on the speller program?

14. Which paradigm is easier to look at: P300, SSVEP or Hybrid?

**P300 SSVEP Hybrid**

15. Do you wear glasses?

**Yes No**

Please write any other comments or suggestions here:

____________________________ ____________________

Participant's Signature Today's Date

# APPENDIX C

## Users Feedback

| Subject # (Sequence) | BCI Test | Questionnaires # | Response |
|---|---|---|---|
| 1 (P300, SSVEP, Hybrid) | **Before** | 1 | 9 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | **After** | 8 | 9 |
| | | 9 | No |
| | | 10 | Yes |
| | | 11 | No |
| | | 12 | ---- |
| | | 13 | No |
| | | 14 | Hybrid |
| | | 15 | No |
| 2 (Hybrid, P300, SSVEP) | **Before** | 1 | 10 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | **After** | 8 | 1 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | Yes |
| | | 12 | Lighting |
| | | 13 | No |
| | | 14 | Hybrid |
| | | 15 | Yes |

| Subject # (Sequence) | BCI Test | Questionnaires # | Response |
|---|---|---|---|
| 3 (Hybrid, SSVEP, P300) | **Before** | 1 | 6 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | **After** | 8 | 5 |
| | | 9 | Yes |
| | | 10 | No |
| | | 11 | Yes |
| | | 12 | --------- |
| | | 13 | ----- |
| | | 14 | Hybrid |
| | | 15 | Yes |
| 4 (P300, SSVEP, Hybrid) | **Before** | 1 | 7 |
| | | 2 | Yes |
| | | 3 | Yes |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | No |
| | **After** | 8 | 1 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | Yes |
| | | 12 | --------- |
| | | 13 | ------ |
| | | 14 | Hybrid |
| | | 15 | Yes |

| Subject # (Sequence) | BCI Test | Questionnaires # | Response |
|---|---|---|---|
| 5 (P300, SSVEP, Hybrid) | **Before** | 1 | 8 |
| | | 2 | No |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | **After** | 8 | 5 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | No |
| | | 12 | --------- |
| | | 13 | Yes |
| | | 14 | P300 |
| | | 15 | Yes |
| 6 (Hybrid, P300, SSVEP) | **Before** | 1 | 8 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | No |
| | **After** | 8 | 7 |
| | | 9 | No |
| | | 10 | No |
| | | 11 | No |
| | | 12 | Need Reward |
| | | 13 | No |
| | | 14 | Hybrid |
| | | 15 | Yes |

| **Subject # (Sequence)** | **BCI Test** | **Questionnaires #** | **Response** |
|---|---|---|---|
| 7 (Hybrid, SSVEP, P300) | **Before** | 1 | 7 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | No |
| | **After** | 8 | 8 |
| | | 9 | Yes |
| | | 10 | No |
| | | 11 | No |
| | | 12 | --------- |
| | | 13 | No |
| | | 14 | Hybrid |
| | | 15 | Yes |
| 8 (SSVEP, Hybrid, P300) | **Before** | 1 | 8 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | No |
| | | 5 | No |
| | | 6 | No |
| | | 7 | No |
| | **After** | 8 | 4 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | Yes |
| | | 12 | --------- |
| | | 13 | ----- |
| | | 14 | Hybrid |
| | | 15 | No |

| Subject # (Sequence) | BCI Test | Questionnaires # | Response |
|---|---|---|---|
| 9 (SSVEP, P300, Hybrid) | Before | 1 | 9 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | After | 8 | 5 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | No |
| | | 12 | big screen, large characters |
| | | 13 | No |
| | | 14 | SSVEP |
| | | 15 | No |
| 10 (P300, Hybrid, SSVEP) | Before | 1 | 9 |
| | | 2 | Yes |
| | | 3 | No |
| | | 4 | Yes |
| | | 5 | No |
| | | 6 | No |
| | | 7 | Yes |
| | After | 8 | 5 |
| | | 9 | Yes |
| | | 10 | Yes |
| | | 11 | No |
| | | 12 | --------- |
| | | 13 | Yes |
| | | 14 | Hybrid |
| | | 15 | Yes |

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