ABSTRACT

This is a project on Brain Computer interfacing, which a system that is a direct communication pathway between the brain and an external computing device. We are looking at *SSVEP*, out of the many possible *BCI* paradigms. This Steady State Visually Evoked Potential is a phenomenon which is the response of the brain to a flickering source of light. The response has been observed to have a waveform embedded in it, which is frequency and phase locked to this flickering stimulus.

The EEG waveform would be taken non-invasively from the occipital lobe of the brain by electrodes placed on the scalp of the person, and then used for classification. This project implements an SSVEP classifier using a statistical analysis of the EEG waveform. We are using a recently emerged EEG processing technique that relies on *covariance matrices* and their inherent geometry in a Riemannian space to cluster and classify EEG signals.

We have implemented the needed signal processing techniques on MATLAB and have also built an astable multivibrator circuit to control an array of flickering LEDs that act as the flickering stimulus. The dataset comes from the internet as well as recordings from the OpenBCI Hardware.

Keywords: BCI, SSVEP, Riemann Clustering, Riemann Manifold, covariance matrices

Chapter 1

Introduction

This chapter provides a high level overview of the human nervous system to readers interested in designing and using BrainComputer Interfaces (BCI). Essential neuroanatomy and physiology as well as the terminology used in BCIs are introduced.

1.1 The Central and Peripheral Nervous System

The human nervous system can be broadly divided into the central nervous system (CNS) and the *peripheral nervous system* (PNS).
The CNS consists of the brain and the *spinal cord*. is the main pathway that conveys motor-control signals from the brain to muscles all over the body and sensory feedback information from the muscles and skin back to the brain. The neurons in the spinal cord are also involved in reflex actions and rapid responses to dangerous stimuli such as fire. The reflex arc illustrating the response to an external stimulus is shown in Fig 1.1.
The PNS consists of the somatic nervous system (neurons connected to skeletal muscles, skin, and sense organs) and the autonomic nervous system (neurons that control visceral functions such as the pumping of the heart, breathing, etc.). It is common to talk about efferent neurons, which transmit information from the CNS to the PNS, and afferent neurons, which transmit information from PNS to CNS.

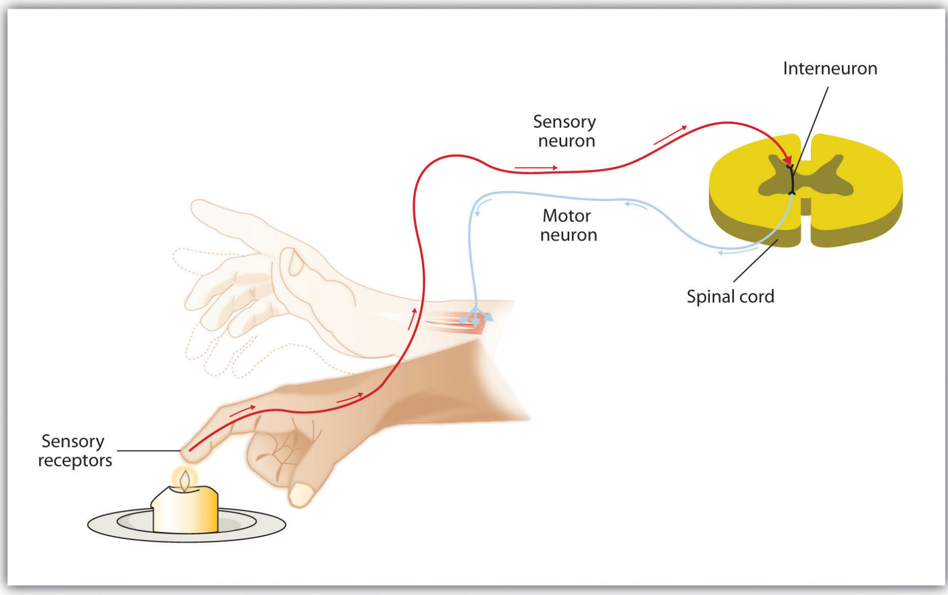

Figure 1.1: Response to an external Stimulus [2].

1.2 General description of the human brain

The brain is the central organ of the nervous system which controls, and is associated with all voluntary and involuntary actions of the body. The brain integrates and assimilates all the sensory inputs it receives and also regulates other bodily functions such as hormonal stimulations to other organs of the body and temperature regulation. The brain is contained in, and protected by the skull bones of the head.
The structure of the brain can be divided into three parts. The cerebrum, the cerebellum and the medulla oblongata. The focus of the present work is electrical activity in the cerebrum or cerebral cortex. The cerebrum is divided into two cerebral hemispheres namely, the left and the right hemisphere which are connected by a structure called the corpus callosum. Each hemisphere is conventionally divided into four lobes: the frontal lobe, the parietal lobe, the temporal lobe and the **occipital lobe** (which is of special significance in this work). These lobes are separated by sulci: the central sulcus (also known as the fissure of Rolando), the lateral sulcus or Sylvian fissure, the parieto-occipital sulcus and the temporal-occipital sulcus.

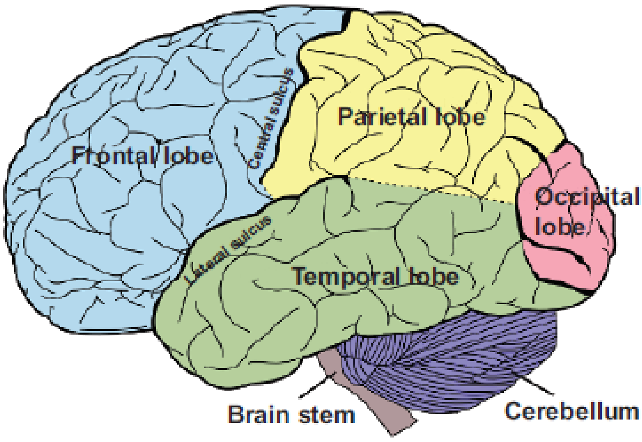

Figure 1.2: General view of the cortexs surface, main lobes and sulci.[1]

1.2.1 The occipital lobe

The occipital lobe is separated from the parietal lobe by the occipitoparietal sulcus and from the temporal lobe by the pre-occipital notch. The primary visual cortex (V1) and the associative visual cortex are located near the occipital lobe. Notably, there is a systematic correspondence, with every point in our visual field being represented in a specific area of V1. This property relating V1 to the retina is known as retinotopy.

1.2.2 The visual cortex

When visual stimuli appear within their receptive field, the neurons of the visual cortex fire causing action potentials. This is the specific region within the entire visual field that produces an action potential, corresponding to a neuron. There is a phenomenon called neuronal tuning where the neuron responds to particular stimuli within its field. In V1,the tuning is such that a neuron may fire to any vertical stimulus in its receptive field, however in another area the neurons might be tuned to fire for a horizontal stimulus. As a case of complex tuning, in the inferior temporal cortex, a neuron may fire only when a certain face appears in its receptive field since they are also conditioned for pattern matching and face recognition.

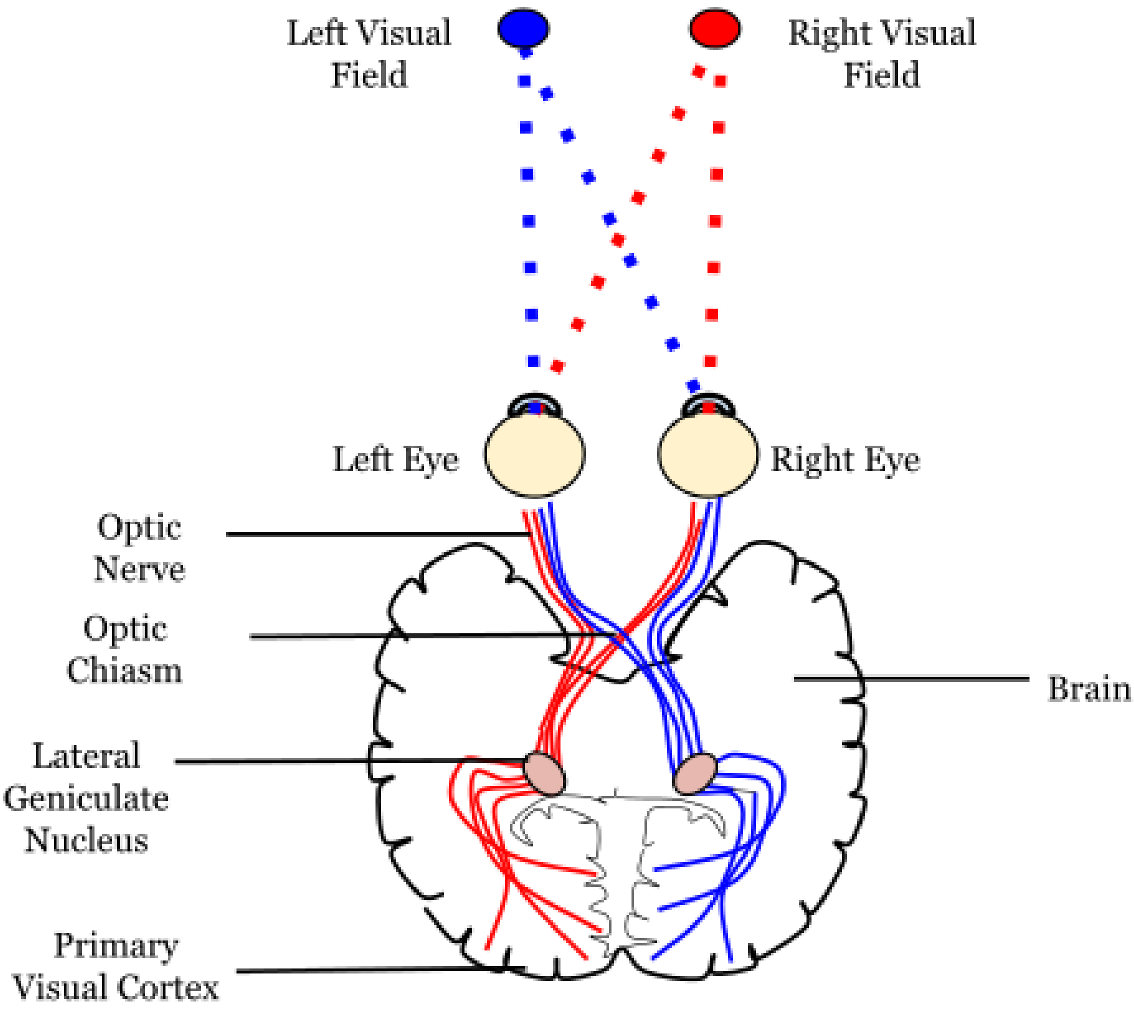

Figure 1.3: The visual pathway[3].

1.3 Introduction to Brain-Computer Interfaces

A Brain-Computer Interface or BCI is a direct communication pathway between an animal or human brain and an external device.
Designing a BCI requires knowledge of several disciplines. BCIs, whose architecture is summarized in Figure 1.4, are systems usually composed of six main stages[1]:

- **Brain activity recording** The raw signals from the users brain are recorded. Different kinds of measuring devices can be used the most common one is electroencephalography (EEG) .
- **Preprocessing** any noise present in the recorded signal is cleaned up and removed and a clean signal is passed down to the lower stages.

- **Feature extraction**The signals are described in terms of 'features' for example, the strength of a signal on an electrode or the signal frequency.
- **Classification** within a certain window a class set of features are drawn from the signals. This signifies type of identified brain activity pattern (for example the imagined movement of the left or right hand). This type of a classification algorithm is called as a "classifier".
- **Translation**links a command with a given pattern of brain activity which is identified in the users brain signals. In motor imagery, or example, when imagined movement of the left hand is identified, it can be translated into the command: "move cursor on toward the left". This command can then be used to control a given application, such as a wheelchair or text editor
- **Feedback** to inform a user about the results of his brain activity is sent. This is to help the user learn to modulate brain activity and hence improve his or her control of the BCI.

Two stages are generally necessary in order to use a BCI: (1) an offline calibration stage, where the systems appropriate settings are measured and determined, and (2) an online operational stage, where the users brain activity is analysed and on detecting a specific predetermined pattern, is translated into an application command. There is ongoing research to help avoid the costly offline calibration stage and the present SSVEP detection approach is a step in that direction.

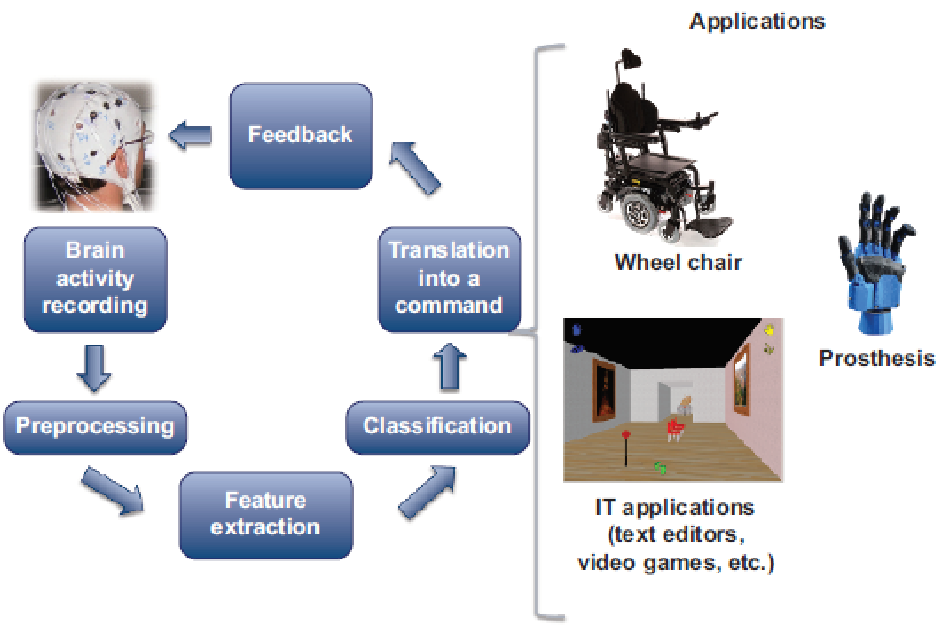

Figure 1.4: Architecture of a BCI working in real time, with some examples of applications[1].

1.4 Types of BCIs

The different properties of BCIs enable us to classify them into different categories. They can be classified as active or reactive or passive; as synchronous or asynchronous; as dependent or independent; and as invasive, non-invasive or hybrid, each described below.

Active/reactive/passive: If a user is actively involved in carrying out voluntary tasks, the BCI is classified as active. If a BCI uses imagined hand movement (motor imagery) as mental commands is an active BCI. If a users brain reacts to a certain stimuli, these types of BCIs are called reactive BCIs. Out proposed BCI system based on the SSVEP paradigm is a reactive BCI. A BCI that does not analyse brain signals to carry out commands but instead is used to analyse the state of the users brain is termed as a passive BCI. An application monitoring a users attention or concentration level is a passive BCI.

Synchronous/asynchronous:If the actions of the user are controlled and modulated by the system such that the user can only take those actions at a certain time, it is a synchronous BCI. If user interaction is allowed at any time, the interface is considered asynchronous. The proposed system is an asynchronous BCI system.

Dependent/independent: A BCI that is dependent on motor control is called a Dependent BCI system. Otherwise, it is independent. If the user has to move his/her eyes in order to observe stimuli, it a reactive BCI, (in our case, the stimuli is a flickering box) then BCI are dependent (it depends on the users ocular movements). If the user can control a BCI without any movement at all, the BCI is independent.

Invasive/non-invasive: Invasive BCIs use data gathered from sensors implanted within the body (usually inside the skull for Brain interfaces) whereas non-invasive BCIs employ surface data, that is, data gathered on or around the head, such as around the scalp.

Hybrid: When signals of varied natures are combined in the same BCI, it is considered hybrid. A BCI that uses both imagined hand movement (motor imagery) and brain responses to stimuli (SSVEP) is considered hybrid. A system that combines BCI commands and non-cerebral commands (e.g. muscular signals like jaw movements) or more traditional interaction mechanisms (like a computer mouse) is also considered hybrid. In sum, a hybrid BCI is a BCI that combines brain signals with other signals of different natures.

1.5 Selected pathologies that use BCIs as assistive technology

1. Spinal cord injuries: : spinal cord injuries are most often the result of trauma. It is clinically described as the level of the spinal injury in terms of the lesional syndrome (last healthy metamerism).
   These injuries are divided into complete (all motor and sensory functions are affected) and incomplete injuries (partial injury). Tetraplegia as a condition refers to injuries affecting all four limbs, and paraplegia refers to injuries affecting only the lower limbs.
   Spinal chord injuries are classified according to the affected area. BrownSquard syndrome or hemiparaplegic syndrome: is where the spinal injury is unilateral, with paralysis on the side of the body where the lesion occurred.

2. Locked-in syndrome: locked-in syndrome (LIS) is also known as cerebromedullospinal disconnection or de-efferented state: it is the result of a nervous System injury to the motor pathways at the brain stem. Sensory and cognitive functions are preserved. The patient is hence conscious and fully aware of the environment. Ocular movement is largely unharmed hence the patient can communicate to the external world through eye movements. Establishing effective communication can be accelerated through the usage of BCIs.

3. Hemiplegia: Hemiplegia is characterized by a bodily motor deficit in the primary motor cortex or of the subcortical pyramidal tract. The deficit can either be total or partial. Hemiplegia is most often the result of a cerebral accident or stroke and causes other symptoms based on the affected area.

4. Amyotrophic lateral sclerosis (ALS): also known as Lou Gehrigs disease is a form of degenerative, and rapidly progressive damage to both central motor neurons and peripheral motor neurons.. Atrophy, fasciculations and quick reflexes, as well as spasticity are the resulting disorders. Although sensory damage is absent, the disorder affects the limbs and hence communication is difficult. A BCI in this context will be helpful.

Chapter 2

EEG Data acquisition and Processing

2.1 Principles of EEG acquisition

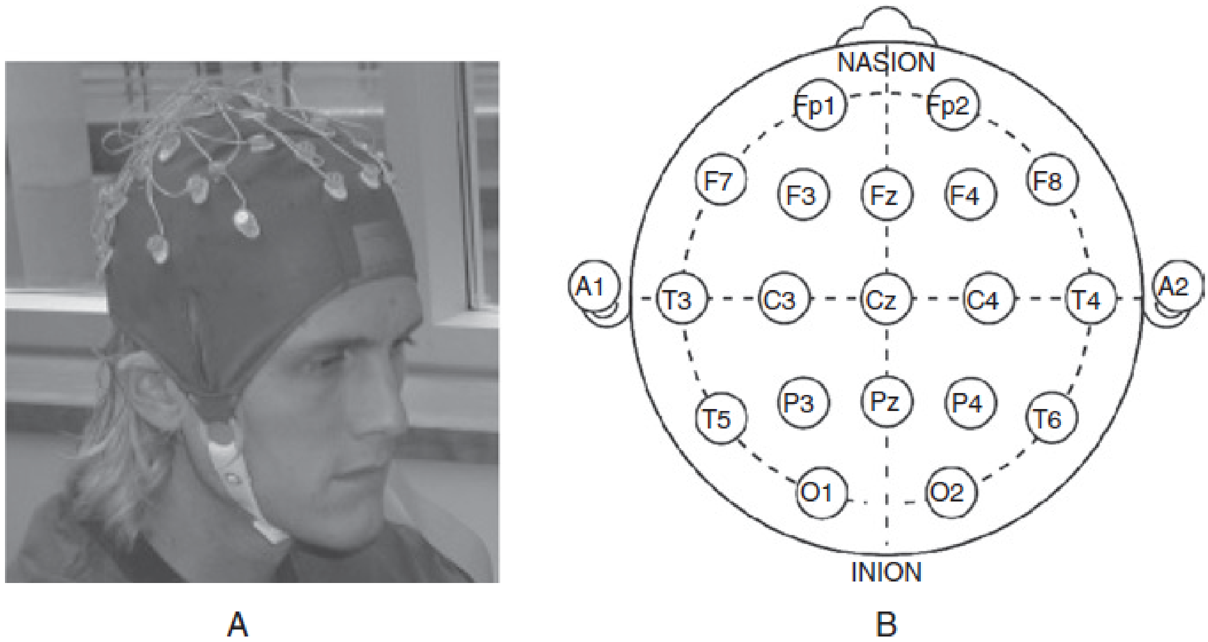

Figure 2.1: (A) Subject wearing a 32-electrode EEG cap. (B) International 1020 system for standardized EEG electrode locations on the head. C = Central, P = Parietal, T = temporal, F = frontal, Fp = frontal polar, O = occipital, A = mastoids (image A courtesy K.Miller; image B from Wikimedia Commons).

Electroencephalography or EEG provides electrical potential measurements in the form of a time signal for each electrode. Though they dont contain all the information of events transpiring in the brain, they contain significant data nonetheless about events that can be measured externally. This information is widely used in fields like neuroscience, psychology and cognitive science to study the electrophysiological nature of brain phenomenon. The information provided by EEG is not uniform, it is varied: it can show amplitude variations of the electric potential at certain frequencies or variations in spatial distribution. Thus, to observe these phenomena, a variety of methods are used to analyse signals in time, in frequency or in space.

Due to its very low amplitude (10-100 μV), EEG data can only be measured through an amplifier. Originally, EEG amplifiers were analog and resembled a seismograph, using a pen to trace signals on a roll of paper. Nowadays, most amplifiers are digital: they perform an analog to digital conversion and supply data in the form of sampled and quantized signals.

EEG signals indicate the average potential of many thousands of neurons firing radially from the area of measurement on the scalp. Tangential currents are not detected by EEG. Since signal attenuation is inversely propotional to the square of the distance, any potentials developed deep withing the brain will have attenuated by the time the EEG electrode picks it up. Hence EEG signals are mostly surface-level signals. EEG has good temporal resolution but poor spatial resolution

The poor spatial resolution of EEG is caused primarily by the different layers of tissue interposed between the source of the signal and the sensor placed on the scalp where each layer exacerbates the attenuation. These layers act as a low-pass filter to smear the original signal. The measured signals are in the range of a few microvolts justifying the use of powerful amplifiers and signal processing instruments for their processing.

Muscular artifacts and power-line noise (e.g., 50 Hz power-line interference) are common causes why the EEG signal gets corrupted due to its very low amplitude and vulnerability to noise. Muscle artifacts such as eye movements, talking, chewing, and head movements can all cause large artifacts in the EEG signal. Subjects are hence typically instructed to avoid all movement as much as possible, and powerful artifact removal algorithms are used toremove these artifacts. Various psychological states such as boredom and distraction can also lead to artifact generation.

2.2 EEG Montage

EEG data is acquired through a set of electrodes placed on the scalp. Data is in the form of time signals each keyed to a certain electrode channel placed on the scalp. As only the channel's potential measured, the channel's signal does not directly relate to an electrode's electrical potential and potential differences need to be measured. Montages are used for measuring these potential differences..

Monopolar - The potential difference between an active site and common reference electrode is measured. The common electrode should be in a location so that it would not be affected by cerebral activity. The main advantage of the unipolar montage is that the common reference allows valid comparisons of the signals in many different electrode pairings. Disadvantages of the unipolar montage include that there is no ideal reference site, although the earlobes are commonly used. In addition, EMG and ECG artifacts may occur in the unipolar montage.

Bipolar The potential difference between two active scalp sites is measured. Any activity in common with these sites is subtracted so that only difference in activity is recorded. The advantage in this configuration is the common noise between the two electrodes is eliminated and the signal-to-noise ratio is improved.

The choice of montage used to be crucial in the times when analog amplifiers traced measurements on strips of paper. But with digital amplifiers, it is now possible to process the data a posteriori in order to transform one montage to another.

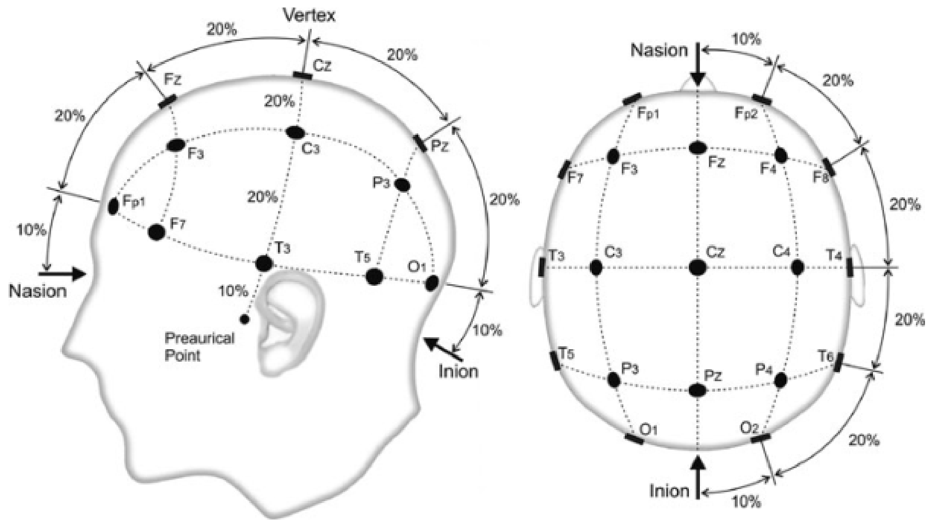

Figure 2.2: 2 International 10–20 Electrode System [5]

EEG recording and 10–20 System - It involves the subject wearing a cap or a net into which the recording electrodes are placed. In some cases, scalp locations may be prepared for recording by light abrasion to reduce impedance caused by dead skin cells. A conductive gel or paste is injected into the holes of the cap before placing the electrodes.

The international 10-20 system is a convention used to specify standardized electrode locations on the scalp. This is illustrated in Fig. 2.1. The mastoids located behind each ear (A1 and A2) can be used as reference electrodes. Other possible reference electrode locations are nasion, at the top of the nose, level with the eyes; and inion, at the base of the skull on the midline at the back of the head. From these points, the skull perimeters are measured in the transverse/coronal and median planes. Electrode locations are determined by dividing these perimeters into 10 percent and 20 percent intervals. The international 1020 system ensures that the naming of electrodes is consistent across laboratories. The number of electrodes actually used in applications can range from a few (for targeted BCI applications) to 256 in high-density arrays. Either bipolar or unipolar electrodes can be used for measuring EEG [RP Rao].

2.3 Brain Rhythms

Clinical experts in the field are familiar with manifestation of brain rhythms in the EEG signals. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another, such as wakefulness and sleep. The characteristics of the waves also change with age. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called alpha (α), theta (Θ), beta (β), delta (δ), and gamma (γ).

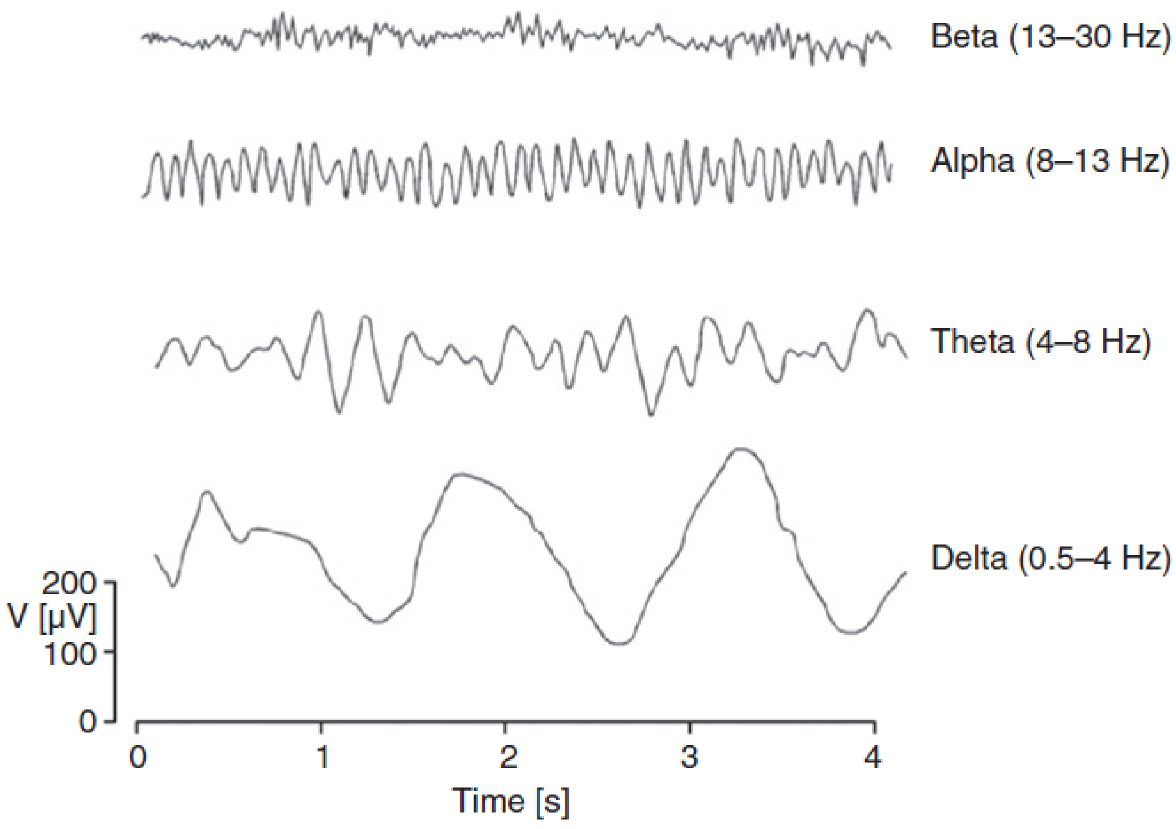

Figure 2.3: Examples of EEG rhythms and their frequency range. (Adapted from http://www.bem.fi/book/13/13.htm).

The broad classification of EEG Oscillations is described below [EEG Signal Processing Chambers]

Delta waves - Delta waves lie within the range of 0.5-4 Hz. These waves are primarily associated with deep sleep and may be present in the waking state. It is very easy to confuse artefact signals caused by the large muscles of the neck and jaw with the genuine delta response.

Theta Waves - Theta waves lie within the range of 4-7.5 Hz. The term theta might be chosen to allude to its presumed thalamic origin. Theta waves appear as consciousness slips towards drowsiness. Theta waves have been associated with access to unconscious material, creative inspiration and deep meditation.

Alpha Waves - Alpha waves appear in the posterior half of the head and are usually found over the occipital region of the brain. They can be detected in all parts of posterior lobes of the brain. For alpha waves the frequency lies within the range of 8-13 Hz, and commonly appears as a round or sinusoidal shaped signal. However, in rare cases it may manifest itself as sharp waves. In such cases, the negative component appears to be sharp and the positive component appears to be rounded, similar to the wave morphology of the rolandic mu (μ) rhythm. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration. The alpha wave is the most prominent rhythm in the whole realm of brain activity and possibly covers a greater range than has been previously accepted. It is reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, by anxiety, or mental concentration or attention.

Beta Waves - A beta wave is the electrical activity of the brain varying within the range of 14-26 Hz (though in some literature no upper bound is given). A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults. A high-level beta wave may be acquired when a human is in a panic state.

2.4 Sampling

To convert the recorded analog signal data into digital form, sampling is used. The data is sampled, i.e. measured at instants which are separated by the duration defined by the sampling interval and this is usually the same throughout the recording. The sampling rate (or sampling frequency) is the inverse of the sampling interval. For example, a signal sampled at 100 Hz has a sampling interval of 10 ms.

The sampling frequency determines the temporal resolution as well as the analysable frequency spectrum. According to Shannons sampling theory, the sampling frequency must be greater than twice the target maximum frequency. The signal amplitude is coded with a finite number of bits. For instance, 16 bits provide 2^{16} values to encode the whole dynamic range of the EEG. With 16 bits, values between ± 600 μV have an amplitude precision of 0.0183 μV.

2.5 Segmentation

To aid processing and analysis, each event is marked with a time stamp in the signal. Each event is associated with a date (a time stamp) and a label specifying its nature. Events are sometimes marked by using specific software, during data review. It is more common to mark events during acquisition itself.

Epoching is the process where a particular segment of data is marked for data analysis through a time window. These data chunks are called epochs. In an EEG data set, we have epochs or trials of similar events. With these trials it is possible to classify new unkown data a priori using machine learning algorithms and other statistical methods. Trials are also important for EEG analysis, since they make it possible to obtain enough data to reduce the effect of noise. Ensemble averaging the repetitions yields ”evoked potentials”.

2.6 Frequency Domain Representation

2.6.1 Fourier Transform

We define a function’s (continuous) Fourier transform as:

$$\hat{f}(\omega) = \int_{-\infty}^{\infty} f(t)\exp(-i\omega t)dt$$

Consider a signal f measured on the interval [0, T] with N discrete samples separated by τ (the sampling interval): $f[n] = f(n\tau)$, $n = 0$...N 1. The discrete Fourier transform is defined for $k = 0$ to N-1 by

$$\hat{f}[k] = \sum_{n=0}^{N-1} f[n]\exp^{-2i\pi kn/N}$$

The Fourier transform of a signal is defined as the Fourier series of an N-periodic Dirac comb obtained by periodization of $f[n], n = 0, ..., N1$, which involves only N samples of the signal.

The Fast Fourier Transform or FFT is he most common digital method for calculating the discrete Fourier transform (DFT), a recursive algorithm that is valuable because of its low computational complexity: it only grows by a factor of $NlogN$ with the number of samples N is used..

2.6.2 Frequency Filtering

Noise reduction: Undesirable behaviour can cause drastic signal deviations which can be easily detected and removed (e.g. because of loose electrode contact with the scalp).

Component separation: The signal components of interest can be identified directly in temporal signals, especially in low-frequency components or in large amplitude changes and these components can be isolated. The components are generally better identified after spatial filtering as there may be many contributors to one component. important in order to filter signals in the appropriate band.

2.7 Feature Extraction

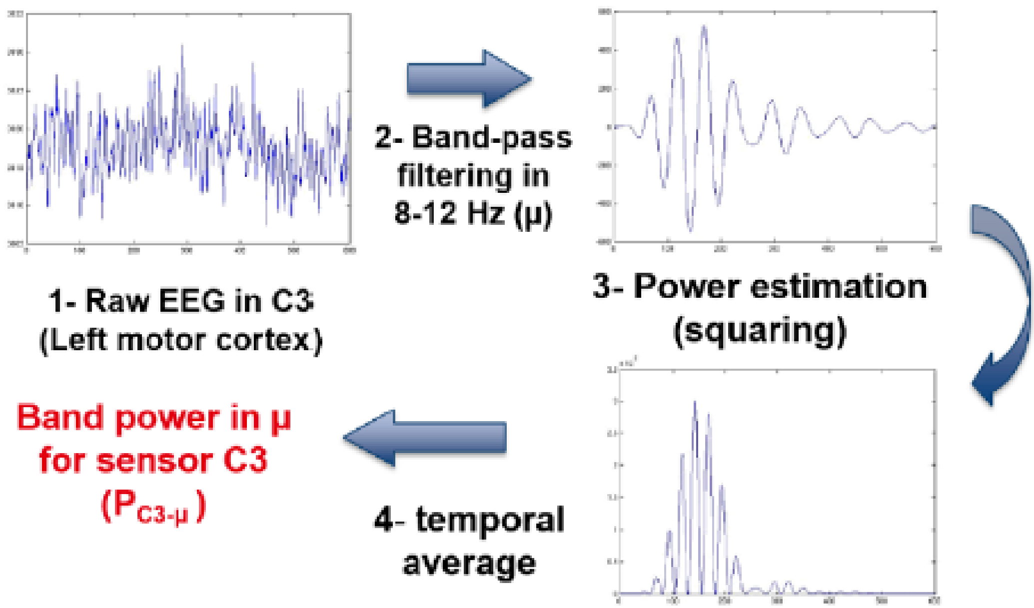

Figure 2.4: An example of band power calculation for an electrode placed at C3 in the motor cortex.

In BCI design, there are three main sources of information that can be used to extract EEG signal features:
–Spatial information: This depends on where the electrodes are placed and in which cortical region of the brain. This method is used to extract brain signals from one

focused brain region and ignoring the others. In the context of this project the Occipital lobe are has been widely used and the electrodes are placed in and around that region.
–Spectral (or frequency) information: Here, the signal power band is used as a feature. This gives information about which frequency signal has the highest power. This is widely used in this project.
–Temporal information: Describes the variation of the amplitude of the signal over time. Time windows are used to window the signal and each window is used for further processing. It is usually necessary to use different sources of information for different types of BCIs. Our BCI which works on Evoked Potentials (EP) mainly uses spatial and temporal information.

Chapter 3

Literature Survey

3.1 EEG Feature Extraction and Signal Enhancement Methods

- To extract any features of EEG there is need to consider internal and external noise factors. So, to consider that we utilize some basic pre-processing techniques.
- EEG signal is found below 30Hz which contains required information for further analysis. Hence, Temporal filtering is used to remove internal and external noise. Then, higher frequencies are removed using simple low pass filters.
- Since, we are using low EEG signals then we have to perform enhancement methods to analyze signals. Enhancement methods include several factors such as neuromechanism, recording methodology, number of electrodes used etc.
  So, therefore some of the Spatial filtering techniques used here are:
  1. Principal Component Analysis: It is a linear mapping that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components [8]. [**?**]
  2. Bipolar and Surface Laplacian: Bipolar signals can be extracted to highlight the electrical potential differences between two electrodes of interest. Laplacian filter extracts local activity around a particular electrode by subtracting the average activity present in the four orthogonal nearest-neighbouring electrodes [**?**].
  3. Common Spatial Pattern (CSP): It is also one of the spatial filtering technique that is used to find Projection matrix. By using, Projection matrix different classes of single trial EEG data are decomposed and spatial structures of event related synchronization/desynchronization in EEG context is found. H. Ramoser et al. designed optimal spatial filters by method of CSP for filtering single-trial EEG during imagined hand movements [7].

     So, by using this technique we can maximize difference between certain set of classes with the help of Projection matrix. [9]. Fabien Lotte et al.

has improved the BCI designs using regularized common spatial pattern technique [10] [12].

3.2 Types of BCI

3.2.1 Selective Attention Based BCIs

Selective attention based BCI requires external stimuli which is provided by BCI system. Stimuli can be somatosensory or auditory. Here, each stimuli based on particular command and users should focus on corresponding stimulus. In a typical BCI setting, each stimulus is associated with a command, and the users have to focus their attention to the corresponding stimulus [12]. BCIs applicable to this kind of brain patterns are as follows:

- Steady State Visually Evoked Potentials (SSVEP): Here, focusing on one particular stimuli produces SSVEP in the visual cortex that has same frequency as target.In this, target flicker flickers at certain set of different frequencies in the range of 6-30Hz. Paying attention to one of the flickering stimuli elicits an SSVEP in the visual cortex that has the same frequency as the target flicker [12] Cheng et al. studied results from SSVEP BCI on virtual telephone keyboard allowing 13 keyboards [17]. Notable study on SSVEP BCI has been reported in [**?**].

- P300 Based BCIs:P300 is a elicited brain pattern that is formed due to selective attention to flashing letter or symbol. Selective attention to a specific flashing symbol/letter elicits a brain pattern called P300, which develops in centro-parietal brain areas (close to location Pz) about 300ms after the presentation of the stimulus [12]. Thulasidas et al. have implemented a text input application (speller) based on the P300 event related potential and have obtained high accuracies by using an SVM classifier [**?**] It is developed in centro-parietal areas of brain (close to Pz) after nearly 300ms occurrence of stimulus. Well known work on this field presented in [15].

3.2.2 Motor Imagery Based BCIs

Motor imagery means a neural activity that is produced when a subject itself imagining particular action or movement. It is a spatiotemporally neural activity which is similar to the actual movement but smaller in magnitude. Various statistical and machine learning methods can be applied to differentiate between two or more imagined movements and allowing every imagined movement to be mapped to particular control signal. A variety of machine learning algorithms can be applied to discriminate between two or more types of imagined movements, allowing each imagined activity to be mapped to a particular control signal [12].

Notable reports on this field are : The Berlin BCI system is used with minimal subject training and also covers important ML concepts for BCI [13]. Saha et al. have performed two fold classification of MI using SVM as a classifier [11]. Some motor imagery was performed by subjects using LDA as a classifier [**?**]. Some similar studies using CSP have been done by Lotte et al. [10] The Berlin BCI system using minimal subject training covering important ML concepts for BCI [13] and Saha et al. have performed two class classification of motor imagery using SVM as a classifier [11].

3.2.3 Steady State Visually Evoked Potentials (SSVEP) based BCI

is a phenomenon in which periodic response evoked in the brain when a subject is visually focusing on a stimuli that flickers continuously at frequency of 6Hz and above. It is normally detectable at the occipital region of scalp. SSVEP signal arises when person is hisattention on flickering visual stimulus and less demanding as compared to some mental issues. Since, it is based on detection of increment on a power spectrum SSVEP is favourable type of input signal. Using simple frequency domain algorithms relative information between stimulus and triggered response can be found. For SSVEP kind of BCI flickering adjustments are required to provide visual stimulus to the subject. As long as, artefacts are not overlapping with stimulus SSVEP is less sensitive to artefacts. So, most application using this is for subjects which control eye movement.

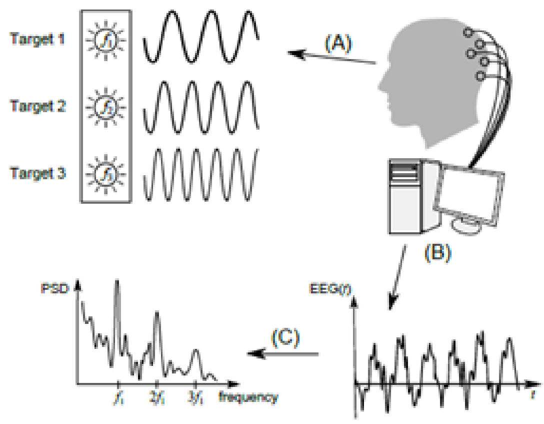

Figure 3.1: Basic idea of SSVEP decoding (A) Subject looking at target 1 having a flickering light with frequency $f1$. (B) EEG gets recorded and then pre-processed. (C) Some salient peaks at $f1, 2f1$ and $3f1$ in the obtained frequency spectrum gives a suggestion as Target 1 being the subjects choice.

SSVEP is a response to a repetitive stimulus that is flickering at particular frequency and it is recorded in the occipital lobe of skull. When flickering frequency is at high rate starting from lets say 6Hz, the EEG signal overlap and leads to steady state signal resonating at stimulus rate and its harmonics. By this, one can detect whether a person is looking at stimulus say f1 or not, by verifying the occurrence of the frequencies f1, f2, .fn which represents the spectrum of pre-recorded EEG signal. Similarly, linking each stimulus which is flickering at certain frequency to a particular command, a multi-command frequency -coded SSVEP can be implemented. Notable work on this is presented in [**?**]. Some multi-command frequency-coded SSVEP-based BCI can be implemented as well [21]

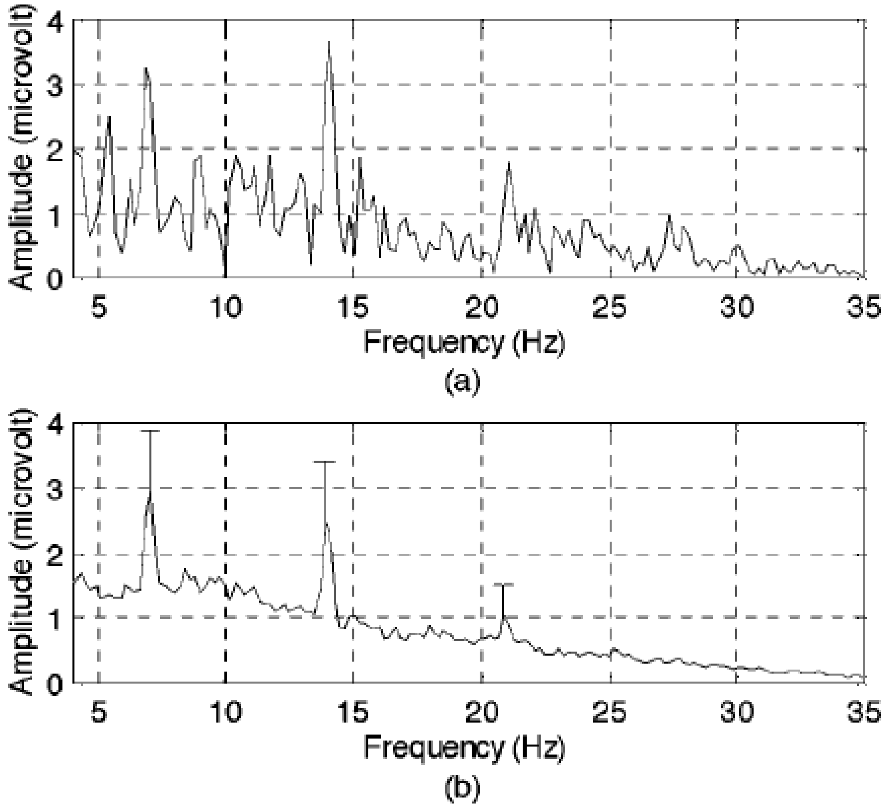

Figure 3.2: (a) Amplitude spectrum of a single SSVEP trial. (b) Mean spectrum averaged over 40 trials [18]

3.3 Types of SSVEP Algorithms

3.3.1 Support Vector Machines (SVMs)

A Support Vector Machine (SVM) is a discriminative classifier which is based on a separating hyperplane. In other words, an optimal hyperplane which classifies new test inputs if found using given labeled training data (supervised learning). In two dimentional space, the hyperplane is a line dividing a plane into two parts with each class on either side. Given a set of training examples, each marked as belonging to one of the two categories, an SVM training algorithm builds a model that assigns new examples to one of the categories. Therefore it is a non-probabilistic binary linear classifier. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on [17]

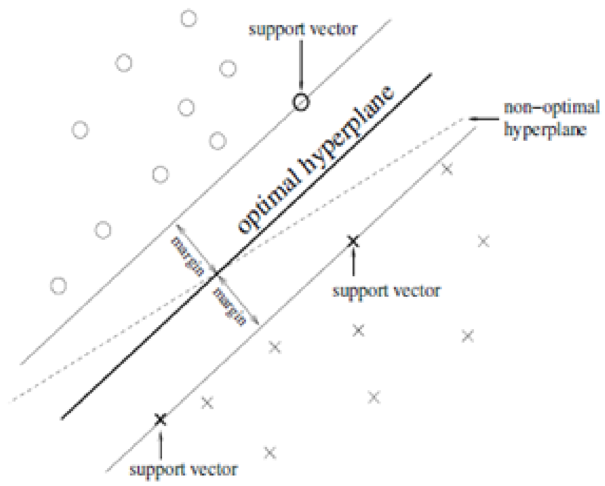

Figure 3.3: SVM finds the optimal hyperplane for generalization.

Since SVM uses a discriminating hyperplane that identifies classes, the selected hyperplane is the one that is maximizing the margins between classes or simply, the distance from the nearest training points to the support vectors (see Figure 3.2). Maximizing these margins has been found increasing generalization capabilities. SVMs use a regularization parameter C which enables any accommodation for outliers and also leaves room for errors on the training set. Tese type of SVMs classify wotj linear decision boundaries, thus earning the name linear SVM. This has been successfully applied, to large number of synchronous BCI problems.

3.3.2 Linear Discriminant Analysis (LDA)

LDA is a method to find a linear combination of features that separates two or more classes of objects or events. LDA (also known as Fishers LDA) is to uses hyperplanes to separate the data representing the different classes. For a two-class problem, the class of a feature vector depends on which side of the hyperplane the vector is. In LDA it is assumed that the conditional probability density functions are normally distributed.
This technique has a very low computational requirement which makes it suitable for online BCI system. The disadvantage of LDA is that its linearity, that can provide poor results on complex non-linear EEG data .

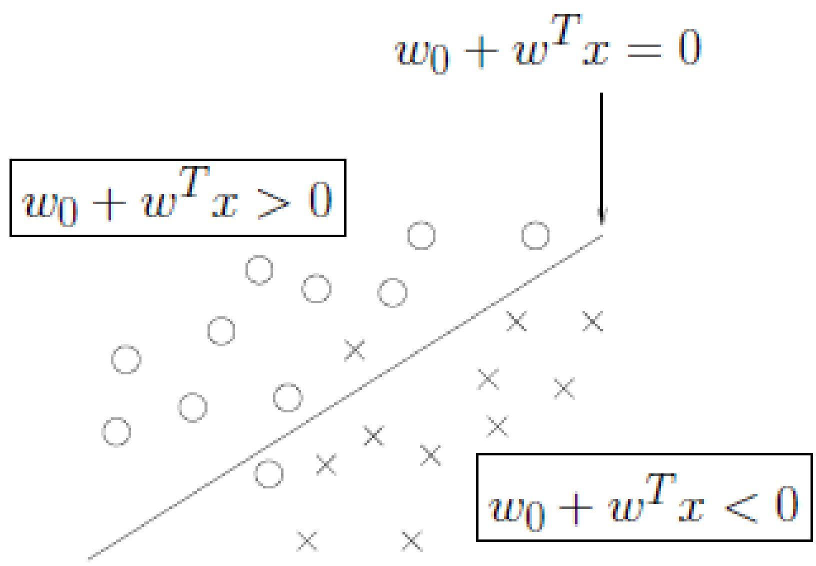

Figure 3.4: A hyperplane seperating two classes namely circles and crosses.

LDA assumes zero mean, unit variance guassian distribution of the data, having equal covariance matrices for both classes. The hyperplane is got when seeking the projection which maximizes the distance between classes. This also includes means and minimizing any interclass variance.
Solving any N-class problem $(N > 2)$ uses several hyperplanes. The strategy employed is the famus "One versus all" stratergy. Here, the target class is the first class and all other classes are grouped as the "other", collectively. Computationally, this method is much more frugal and can be easily suited in any BCI application. LDA has been used successfully in a large number of BCI systems like the motor imagery based BCI ones, P300 spellers, asynchronous or multi-class BCI. The drawback of LDA lies in its linearity that provides poor results on any complex non-linear EEG dataset [**?**].

3.3.3 Multivariate Linear Regression (MLR)

MLR is a statistical technique to predict the outcome of a response variable using several explanatory variables. MLR models the relationship between the explanatory and response variables. The model for MLR, given n observations, is:

$$y_i = B_0 + B_1 x_{i1} + B_2 x_{i2} + \ldots + + B_1 x_{i1} + E \tag{3.1}$$

$\forall i \in 1, 2 \ldots, n$ and y_i being the dependent variable , $x_i p$ being the independent variable

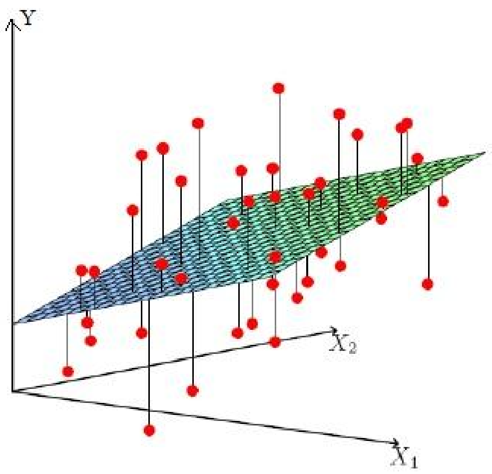

Figure 3.5: Regression performed with two independent variables from a single variate, $X : X1$ and $X2$ with one dependent variable Y [17].

It is used to determine a mathematical relationship among a number of random variables. In other terms, MLR aims to examine how multiple independent variables are related to one dependent variable. Once each of the independent factors have been determined to predict the dependent variable, the information on the multiple variables can be used to create an accurate prediction on the level of effect they have on the outcome variable. The model creates a linear relationship that best approximates all the individual data points.

The multiple regression model is based on the following assumptions:

1. Dependent variables and independent variables have a linear relationship.
2. The independent variables are not strongly correlated with each other.
3. Residuals should be normally distributed with a mean of 0 and variance σ.

The multiple regression model predicts outcome based on information provided on multiple explanatory variables. Still, the model does not achieve perfect accuracy as each data point can be slightly offset from the outcome predicted by the model. [**?**].

3.3.4 Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is a method of inferring information from cross-covariance matrices. Consider two vectors $X = [X_1, ..., X_n]$nd $Y = [Y_1, ..., Y_m]$

of random variables, and there is correlation among the variables, then canonical-correlation analysis finds the linear combinations of the X_i and Y_j which have maximum correlation with each other. The typical use for canonical correlation for experimental context is to find what is common amongst two sets of variables. Canonical correlation analysis is a type of correlation technique that focuses on two sets of variables.

Its strength is that it tries to find pairs of linear transformations for the two sets such that upon transformation, the new sets of variables have a maximal correlation. Some new upcoming SSVEP detection methods use CCA. Detection methods based on CCA also rely on the fact that a periodic pattern with the same frequency as the stimulus frequency or one of its harmonics can be traced back in the brain signals. [20] CCA works on two sets of variables. In one method, variables in a set are sig-

nals, recorded using multiple channels from local regions and the second set would be that of stimulus signals. All periodic signal are decomposable into a power series called the Fourier series. For example, a square-wave periodic signal, at a certain frequency is decomposable into the Fourier series of its harmonics.

$$y(t) = \begin{pmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ y_4(t) \\ y_5(t) \\ y_6(t) \end{pmatrix} = \begin{pmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \\ \sin(4pift) \\ \cos(4\pi ft) \\ \sin(6\pi ft) \\ \cos(6\pi ft) \end{pmatrix}, t = \frac{1}{S}, \frac{2}{S}, \ldots, \frac{T}{S}$$

Where f is the base frequency, T is the number of sampling points, and S is the sampling rate. Fig. 3.5 illustrates the use of CCA in EEG signal analysis.

3.3.5 Power Spectral Density Analysis (PSDA)

Power Spectral Density Analysis relies on the fact that a periodic pattern with the same frequency as the stimulus frequency or one of its harmonics can be traced back in the brain signals. When a SSVEP is present in the brain signals, the magnitude of its periodic pattern only covers a narrow bandwidth and can easily be measured in the frequency domain.
The PSDA method approximates the frequency of an SSVEP signal according to the peak of spectral amplitude. Power spectral density function shows the variations of energy as a function of frequency.
Power spectral density function (PSD) shows the strength of the variations(energy) as a function of frequency. In other words, it shows at which frequencies variations

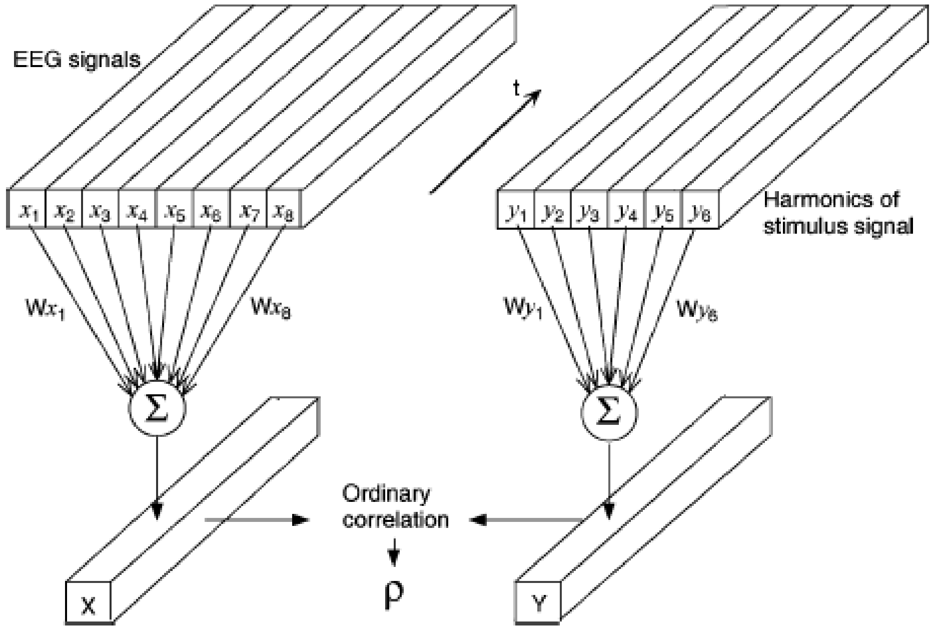

Figure 3.6: x_1 to x_8 are 8 EEG channel EEG data and y_1 to $y_6$are Fourier series representation of a period signal. The CCA finds the linear combination coefficients w_{x_1} to w_{x_8} and w_{y_1} to w_{y_6}, that give the maximum correlation between X and Y [20].

are strong and at which frequencies variations are weak. The unit of PSD is energy (variance) per frequency(width) and you can obtain energy within a specific frequency range by integrating PSD within that frequency range.

Power spectral density function (PSD) shows the strength of the variations(energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak. The unit of PSD is energy per frequency(width) and you can obtain energy within a specific frequency range by integrating PSD within that frequency range. Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it [**?**].

3.3.6 Riemannian Manifold Clustering

This method is what we will be looking at and it uses the fact that any covariance matrix can be considered a point on a manifold or a surface. This surface is a subset of all possible Riemannian manifolds. The definition of this manifold is that it one which is endowed with an inner product defined on the tangent space, which varies smoothly from point to point. [3]
Basically if we could visualise this surface in 2 dimensions, we will see that EEG epochs set in one particular SSVEP frequency would have its covariance matrices clustered up. This is depicted in the figure shown below.

The cluster A would belong to one particular class and the cluster B would belong to another class. The centroid of these clusters could be found out and then that centroid would be the final trained classifier.

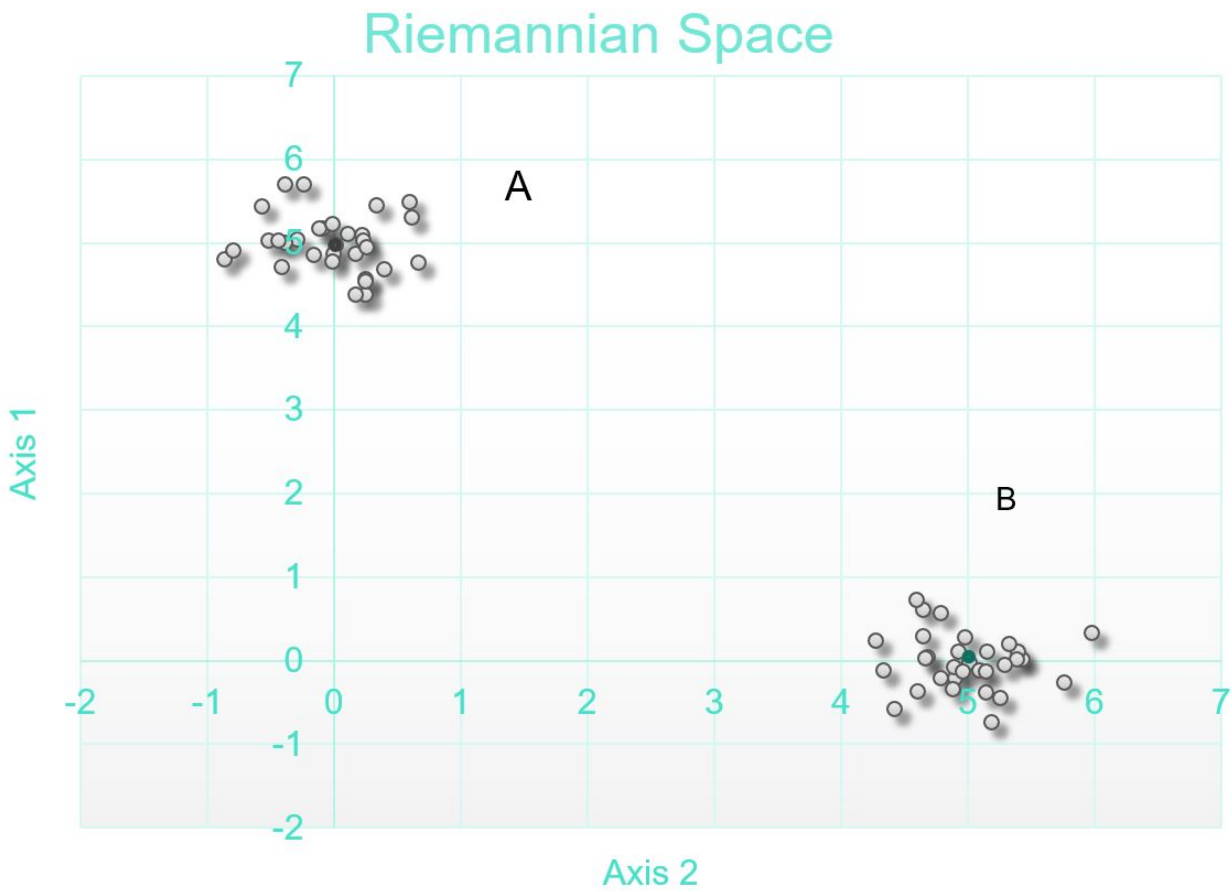

Figure 3.7: A 2D depiction of clustering in the Riemannian space. Note that it is just an illustration

This centroid, once computed will then help us classify new epochs. This would be done by utilising the notion of distance in this new space which is further dealt with in the system design and the implementation part of this report. The figure below depicts the trained classifier with the centroids for clusters A and B from figure 3.6.

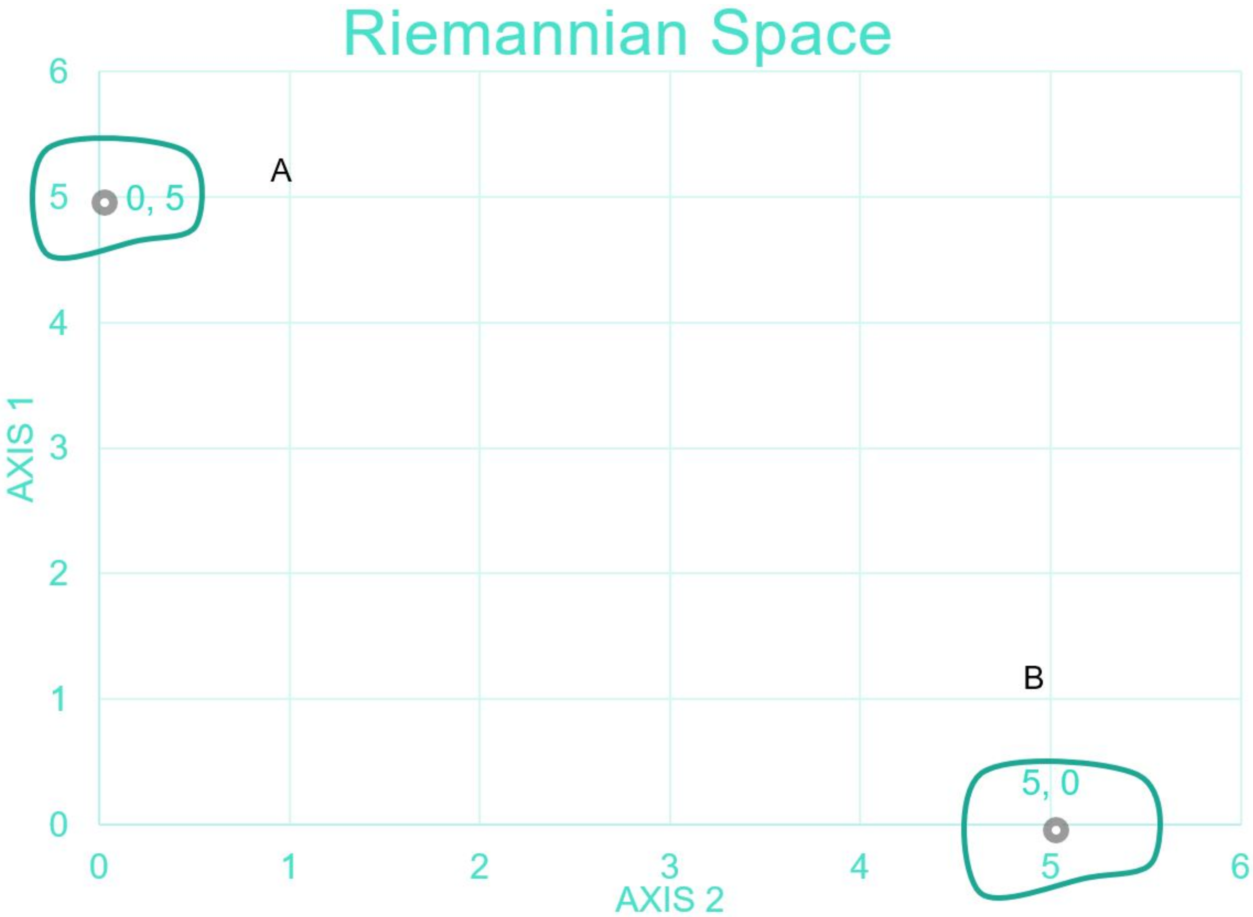

Figure 3.8: The Trained Classifier

Chapter 4

Hardware and Software Requirements Specification

4.1 Component Survey

BCI instruments can be either invasive or non-invasive in nature. The non-invasive methods resulting in EEG, MEG, fNIRS signals. The invasive methods outputting electrocorticography signals (ECog), local field potentials and even some single-init activity type of devices. The devices however, have a few components in common, such as the sensor, biosignal amplifiers, analog to digital converters, etc. All these devices work in tandem to relay information back to the user onto a computing device.

4.1.1 Hardware Survey

The hardwares surveyed for recording EEG signals are listed below. We have had access to only one of the components and have used datasets recorded on such a board. Since these instruments are expensive, we have not been able to purchase our own.

Device	**Price**	**No. of channels**	**ADC**	**Brand Name**
MindWave	$99.95	1	12-bit	NeuroSky
Emotiv	$399	14	16-bit	Emotiv Systems
OpenBCI	$499	8+8	24-bit	OpenBCI

Table 4.1: Some BCI hardware specifications

4.1.2 NeuroSky

In 2007 NeuroSky released the first affordable consumer based EEG along with the game NeuroBoy. This was also the first large scale EEG device to use dry sensor technology.

4.1.3 Emotiv

In 2009 Emotiv Systems released the EPOC, a 14 channel EEG device that can read 4 mental states, 13 conscious states, facial expressions, and head movements. The EPOC is the first commercial BCI to use dry sensor technology, which can be dampened with a saline solution for a better connection.

4.1.4 OpenBCI

This is the board that was used to record data with. The board comes from OpenBCI which is an open source brain-computer interface platform. The 32bit Board is an Arduino-compatible, 8-channel (can be extended to 16-channel) neural interface with a 32-bit processor. EEG, EMG, and EKG can all be looked at with this device. The core of this device is a PIC32MX250F128B microcontroller having the chipKIT bootloader that gives it lots of local memory and fast processing speeds. The board communicates wirelessly to a computer via the OpenBCI programmable USB dongle, which is based on the RFDuino radio module. The OpenBCI boards have a growing list of data output formats(csv, gdf, edf) , making them compatible with an expanding collection of existing biofeedback applications and tools. We have relied on the gdf format to record EEG data.

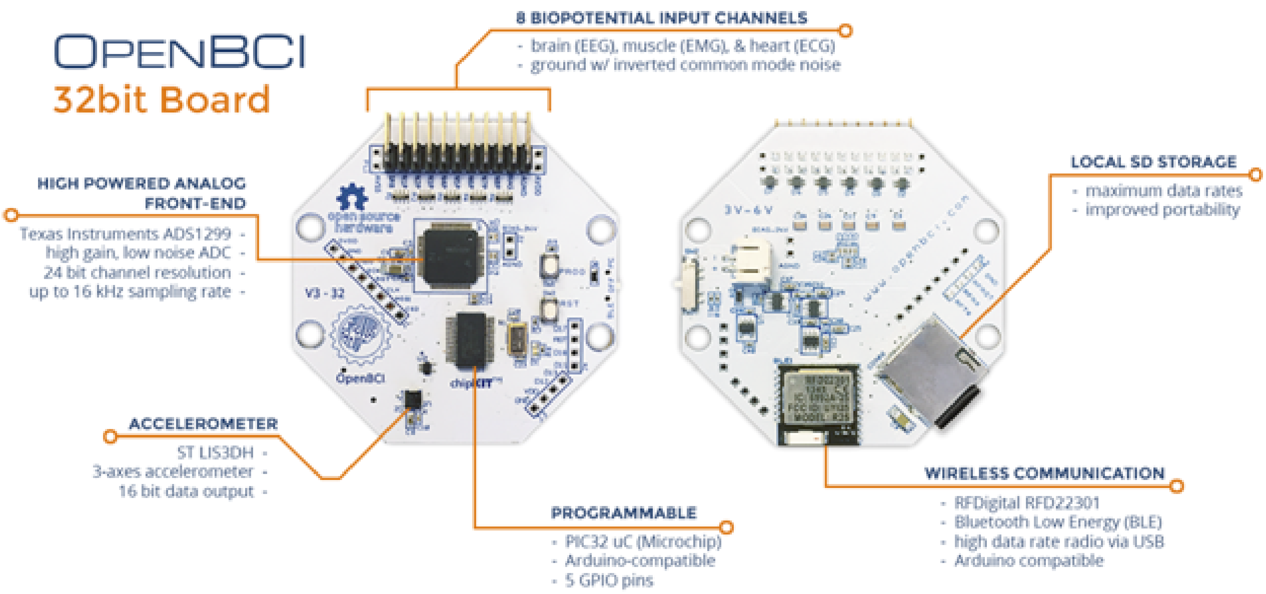

Figure 4.1: Overview of OpenBCI 32-bit Board Specifications

Technical Specifications

OpenBCI 32bit Board:

- 8 differential, high gain, low noise input channels
- Compatible with active and passive electrodes
- Texas Instruments ADS1299 ADC Analog Front End
- PIC32MX250F128B microcontroller w/chipKIT^{TM} bootloader (50MHz)
- RFduino^{TM} Low Power Bluetooth^{TM} radio
- 24-bit channel data resolution
- Programmable gain: 1, 2, 4, 6, 8, 12, 24
- 3.3V digital operating voltage
- $\pm$ 2.5V analog operating voltage
- 3.3-6V input voltage
- LIS3DH accelerometer
- Micro SD card slot
- 5 GPIO pins, 3 of which can be Analog

4.1.5 555 Timer

The well known integrated circuit chip used here is a device that can be used in a variety of oscillatory and timer applications. . The 555 can be used to provide time delays, as an oscillator, and as a flip-flop element. Derivatives provide two (556) or four (558) timing circuits in one package.[**?**]

The Astable circuit

The 555 timer can be used as an astable multivibrator, easily. The circuit we have implemented uses two variable resistors R_1 and R_2 that help manually adjust the dutycycle and frequency of the device to a very high accuracy and precision. The schematic was designed in Eagle software along with the circuit.

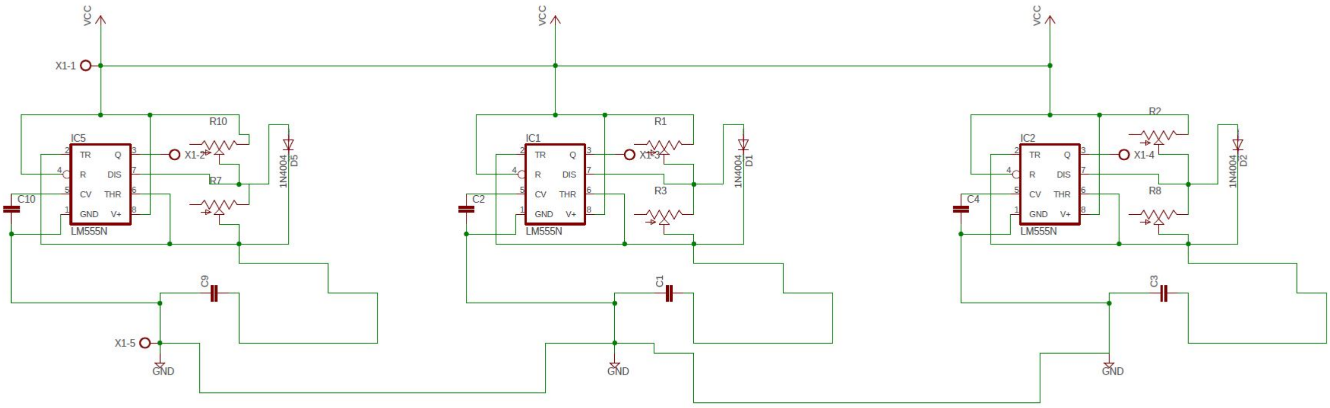

Figure 4.2: The circuit schematic of the astable multivibrator designed by us.

We have used three astable multivibrator circuits to achieve compactness and also to allow for control of 6 LEDs. Two PCBs were designed as 6 circuits could not be made onto a small enough board. The PCB schematic is shown below.

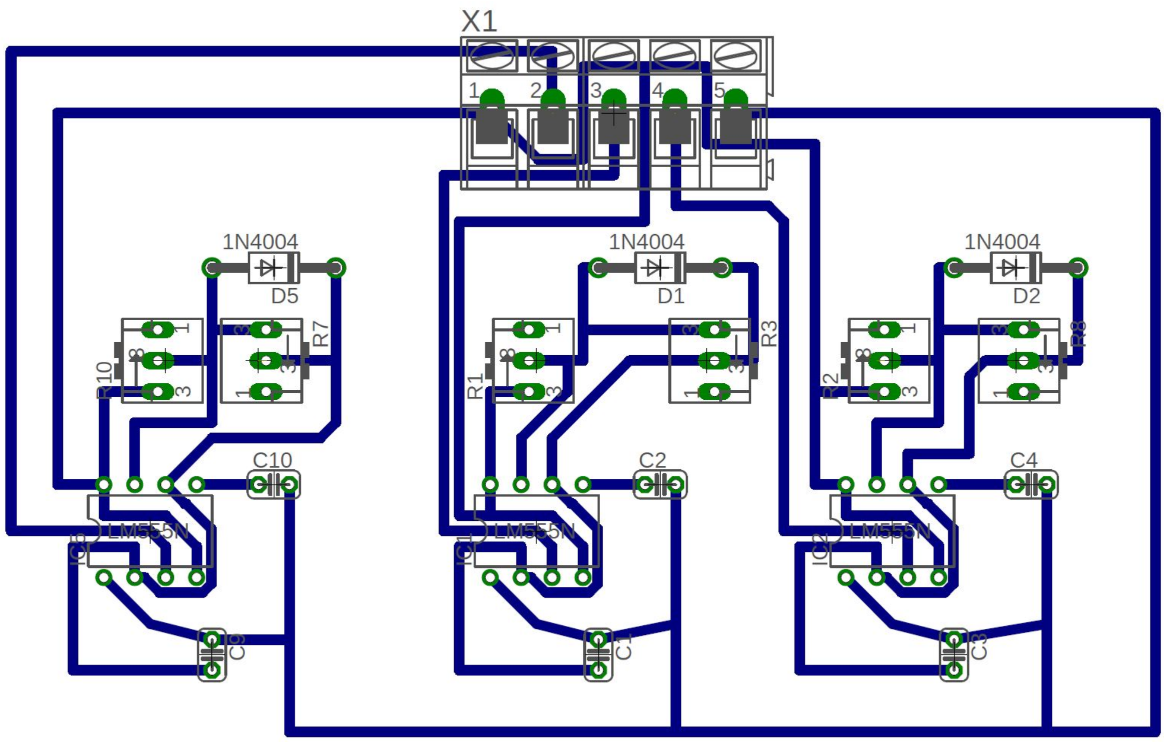

Figure 4.3: The PCB layout schematic of the astable multivibrator.

The routing was manually done on EAGLE and a 1mm drill was used to make the connecting rails. The board is a single layered design to accommodate for simplicity.

4.2 Software Survey

4.2.1 MATLAB

Proprietary scientific computing software from Mathworks. The capability of MATLAB can be extended by using external toolboxes such as:

- EEGLAB/BCILAB
  (a) Developed since 2010 at Swartz Center for Computational Neuroscience, UCSD (precursors dating back to 2006)
  (b) BCILAB is a MATLAB-based, cross-platform, offline and online analysis.
  (c) Largest collection of BCI algorithms.
  (d) Complex Internal Framework requires expertise to extend and is relatively little native support for acquisition systems but can tie into real-time experimentation frameworks (BCI2000, LSL)
- BioSig
  (a) BIOSIG toolbox contains many useful functions for biomedical signal processing.
  (b) Developed at TU Graz since at least 2002
  (c) One of the oldest open-source BCI toolboxes, for MATLAB/Octave (cross-platform)
  (d) Large amount of functionality : Various Biomedical Data Formats supported, Quality Control and Artifact Processing, Signal Processing and Feature extraction,Statistical analysis, False Discovery Rate (FDR), Statistical Toolbox for data with missing Samples(for handling NaN)
  (e) Offline analysis only. No real-time hardware or computation support
  (f) GNU license, General Public License.
- Barachant Covariance toolbox
  (a) This toolbox contain a set of matlab functions dedicated to covariance matrices estimation and manipulation.
  (b) The key functions mainly focus on Riemanian geometry of Symmetric Positive Definite matrices.
  (c) Functionality include: Various Geodesic distance metrics, Function for finding Mean of covariance matrices, tangent space of covariance matrices, multiclass classification.
  (d) GNU license, General Public License.

- Filter Designer
  (a) This toolbox contains appropriate matlab functions to implement different digital filters.
  (b) IIR and FIR filters can be designed just by inputting the passband and stop band frequencies and attenuation.
  (c) The tool also enables one to implement a code that accepts a digital stream of data as input and puts out a stream of filtered signals as its output.
  (d) The designer can be brought up by typing 'filterDesigner' on the matlab command line

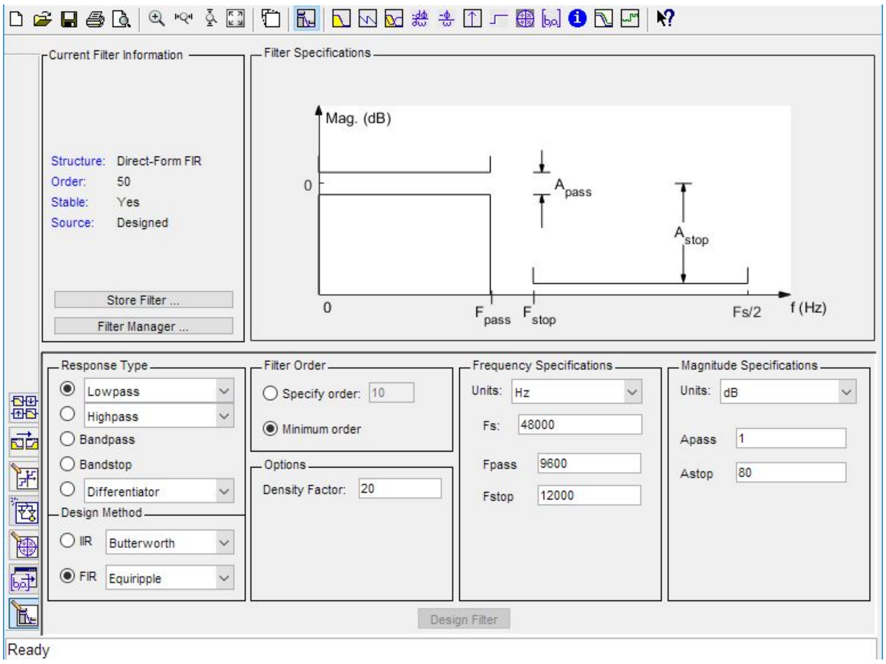

Figure 4.4: The filter designing tool in MATLAB.

4.2.2 Eagle

Overview

EAGLE is a EDA (electronic design automation) software tool which is scriptable with PCB (printed circuit board) and CAM (computer aided manufacturing) features. It was developed by American Software Company AUTODESK. EAGLE is an acronym described by Easily Applicable Graphical Layout Editor. It is one of user friendly and powerful layout tool which consist of useful libraries for electronic circuit designers.

- EAGLE software application consist of following features that are important for any circuit design,

- a. Schematic Editor: EAGLE tool consist of Editor for making design of circuits which is the first task to be done in preparing PCB. The Schematics from this tool are stored under. SCH extension and electronic parts are stored under .LBR extension.
- b. Layout Editor: After schematic of circuit is made layout is prepared in Layout Editor. Here, the files stored are called board files and stored under .BRD extension. Based on the connections made in schematics this feature makes use of back-annotation(netlist data) and auto-routing for correct connections of circuit.
- Most of the design firms uses Standard file formats namely Sieb Meyer and Excellon formats which will be supported in EAGLE application tool and it supports Gerber and PostScript formats which are most common formats in EAGLE.
- EAGLE design software tool is an inexpensive and affordable tool for PCB designs and it runs on Linux, Mac and Windows.

Chapter 5

System Design

BCI Application

5.1 Overview

Here we deal with the algorithm used in the final BCI project in the offline methodology. For the training stage, the data is first pre-processed by first having the epochs extracted, then appropriate filtering done on it. Then the centres of the covariance matrices clusters are found and then the classifier is trained. To use it, new epochs are then run through the classifier with the same pre-processing. When SSVEP is detected, the overall accuracy is plotted on the screen along with the confusion matrix.

The basic idea of any brain computer interface is as shown in the figure. From the occipital lobe of the brain the SSVEP stimulus can be sensed on the scalp of a person, as this lobe is the one dealing with the visual processing. The electrodes used are gold cupped with some electro conductive gel applied onto it to facilitate an electrical connection.

An analog to digital converter is used to sample and quantise the EEG signals. This ADC is interfaced to a microcontroller that then relays these quantised bits to the PC via a bluetooth module. The signal is then processed as needed by the PC via a suitable program. An OpenBCI board was used for data acquisition. The board's specifications are given in the appendix and literature review.

For pre-processing the EEG data received onto the PC is passed through a digital IIR Chebyshev, type 1 band pass filter. Depending on the type of frequency we are trying to cluster up, the centre frequency changes for this filter. Once the frequency is chosen, an appropriate band pass filter is used with a bandwidth of 2Hz. This concludes the temporal filtering phase of the EEG epochs. Another temporal filter can be added to remove the effects of power-line noise or any other electrical activity, by using a notch filter around 50Hz. After this, the epochs are then subject to the algorithms discussed further.

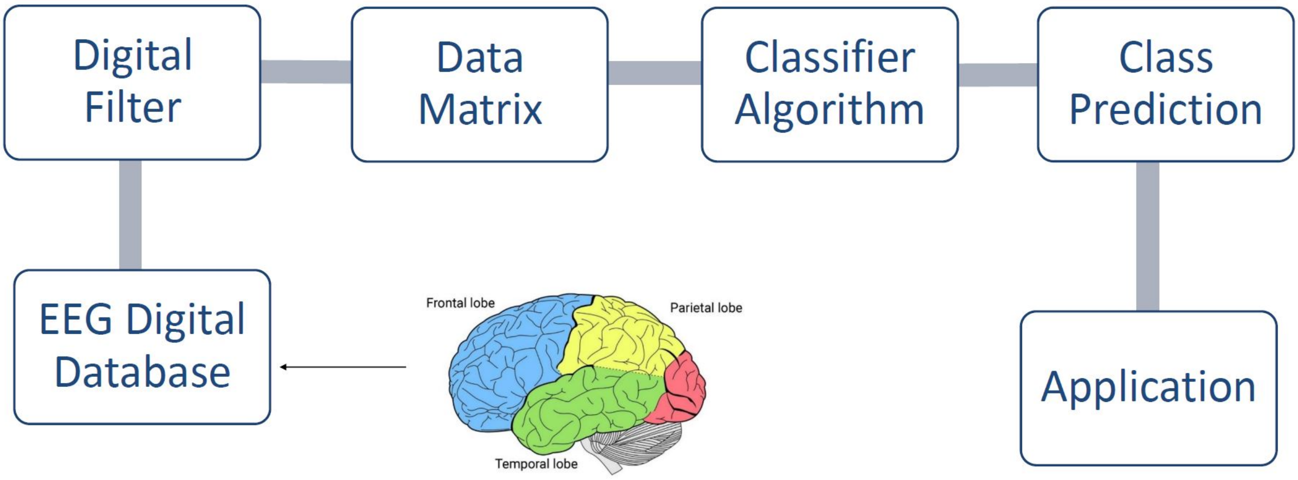

Figure 5.1: General setup of a BCI.

5.2 Offline Algorithm

5.2.1 Algorithm 1

Prerequisites:
The data stored in the form of a matrix, X where each of the trials out of I for a particular frequency, are stored in the rows. Each column contains the different frequencies out of F chosen.

$$X = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1I} \\ \vdots & & \ddots & \\ f_{F1} & f_{F2} & \dots & f_{FI} \end{bmatrix} \tag{5.1}$$

Each of the f sub matrices are the EEG epochs arranged as a $C \times N$ matrix of numbers, where C is the number of channels and N is the number of samples

$$f = \begin{bmatrix} sample_{11} & sample_{12} & \dots & sample_{1N} \\ \vdots & & \ddots & \\ sample_{C1} & sample_{C2} & \dots & sample_{CN} \end{bmatrix} \tag{5.2}$$

After this is done, the following algorithms are run.

Overview:

Inputs: The data matrix X. The labelling is inherently present in this structure.
Outputs: The predicted centres of the clusters.

1. Each of the sub-matrices f in a row is passed through a Chebyshev type 1 band-pass filter.

2. Next, each of these filtered sub-matrices then have their individual covariance matrices computed. The result will be a $C \times C$ matrix, which then replaces the original f matrix.

3. We are left with a structure named X_{cov} where

$$X_{\text{cov}} = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1I} \\ \vdots & & \ddots & \\ c_{F1} & c_{F2} & \dots & c_{FI} \end{bmatrix} \tag{5.3}$$

4. Each of the c covariance matrices are now points on a Riemann manifold where the distance between each point can be computed with

$$\delta(\Sigma_1, \Sigma_2) = \|Log(\Sigma_1^{-1}\Sigma_2)\|_F = \sum_{c=1}^{C} log^2(\lambda_c) \tag{5.4}$$

   Here $\|\cdot\|_F$ indicates the frobinius norm and here, is defined for the matrix the λ_c of the matrix $\Sigma_1^{-1}\Sigma_2$ as the sum of the squares of the logarithm of its eigen values

5. Knowing this distance, the centroid of the entire cluster of trials obtained can be found as Σ which is another covariance matrix that satisfies the following optimisation problem

$$\mu(\Sigma_1, \dots, \Sigma_I) = \underset{\Sigma \in M}{\arg\min} \sum_{i=1}^{I} \delta^2(\Sigma_i, \Sigma) \tag{5.5}$$

6. This is repeated for all the F classes, each having I trials

7. The result is the matrix χ that contains the covariance matrices' centres as arranged below.

$$\chi = \begin{bmatrix} \Sigma_1 \\ \vdots \\ \Sigma_F \end{bmatrix} \tag{5.6}$$

5.2.2 Algorithm 2

Overview:

Inputs: The covariance centres χ, the EEG epoch ε to be classified
Outputs: The predicted class of the epoch ε.

1. The epoch ε is taken as it is, without any filtering and converted to its covariance matrix, which should be of the same size as the ones used in training i.e $C \times C$
2. Calling this covariance matrix as κ, the distance between this and all the $\Sigma \in \chi$ is computed using equation 5.4.
3. The result is the $F \times 1$ matrix Δ containing distances between this κ and all other covariance centres χ

$$\Delta = \begin{bmatrix} \delta(\Sigma_1, \kappa) \\ \vdots \\ \delta(\Sigma_F, \kappa) \end{bmatrix} \tag{5.7}$$

4. The row j with the smallest number is found and from this, the covariance trial κ is classified as belonging with the cluster centred around Σ_j
5. The output prediction is the class labelled j

5.2.3 SSVEP Visual Stimulus

The visual stimulus to generate SSVEP signals is taken from a the led array that flickers a red led.

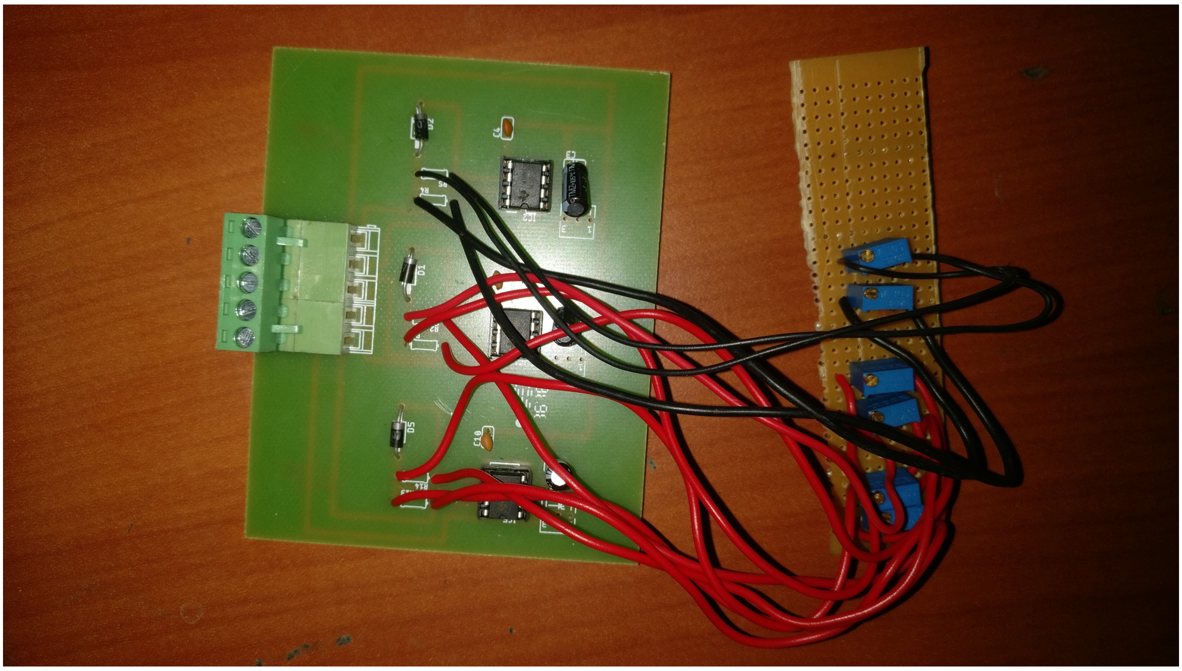

Figure 5.2: The LED controller circuit

5.2.4 SSVEP Experimental Protocol

1. To record data, the subject was made to look at the led array for a few seconds, when prompted.
2. After 5 seconds, the user is prompted to look away or rest for another 5 seconds or so
3. The user is again prompted to look at an led which is flickering at the same fixed frequency.
4. This is repeated for 8 times and then the user is made to repeat the same with another set of frequencies.

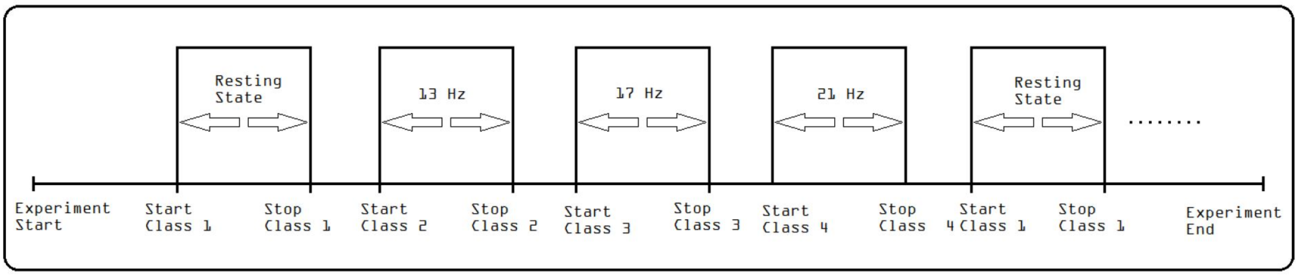

Figure 5.3: The SSVEP Protocol

Chapter 6

Implementation

6.1 Classification in MATLAB

6.1.1 Covariance

The implementation followed here closely replicates the algorithm and procedures depicted in the paper written by Emmanuel Kalunga. As mentioned earlier, the pre-processing is done using a Chebyshev type 1 filter. Then the covariance matrices are formed using an ignorance model of pdf and then, the clustering algorithm is performed this, as detailed in chapter 5.
The general formula for covariance that we use is the sample covariance matrix where:

$$\Sigma_{scm} = \frac{1}{N-1}\sum_{n=1}^{N}(f_n - \mu_f)(f_n - \mu_f)^T$$

Where μ_x is a vector having the means of each feature/channel in the EEG epoch f

In general, if there are tree random processes A, B, and C then the covariance matrix for them would be

$$C = \begin{pmatrix} cov(A,A) & cov(A,B) & cov(A,C) \\ cov(B,A) & cov(B,B) & cov(B,C) \\ cov(C,A) & cov(C,B) & cov(C,C) \end{pmatrix}$$

Which is a symmetric matrix that has positive eigen values.

6.1.2 Distance

For any function $d(x,y)$ to be called a distance, it must satisfy the following properties

1. $d(x,y) \geq 0$
2. $d(x,y) = 0 \implies x = y$
3. $d(x,y) = d(y,x) \geq 0$

4. $d(x,z) \leq d(x,y) + d(y,z)$

All this is satisfied by the distance metric

$$\delta(\Sigma_1, \Sigma_2) = \|Log(\Sigma_1^{-1}\Sigma_2)\|_F = \sum_{c=1}^{C} log^2(\lambda_c) \quad (6.1)$$

Here $\|\cdot\|_F$ indicates the frobinius norm and here, is defined for the matrix the λ_c of the matrix $\Sigma_1^{-1}\Sigma_2$ as the sum of the squares of the logarithm of its eigen values
The MATLAB code used is included in Appendix C.

6.1.3 Filter

A Chebyshev type 1 filter is an IIR filter with ripples in the passband and a smooth stopband. The one used by us, for a 17 Hz centre frequency has been computed to have an order of 13. The magnitude and phase plot obtained is as shown for a 17 Hz band pass filter.

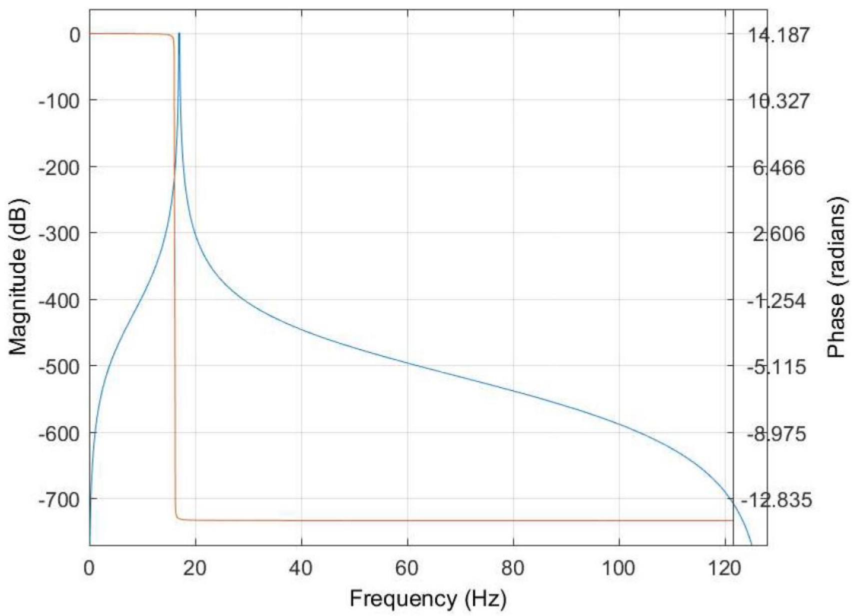

Figure 6.1: Magnitude and phase response of the bandpass filter used.

6.1.4 GUI

A graphical user interface was also created to help predict classes. The code was designed in a way so as to give the user the choice of choosing which classes they would like to run the algorithm against. The result is that an overall accuracy bar graph is plotted, along with a confusion matrix.
The GUI created is as shown in the picture below.

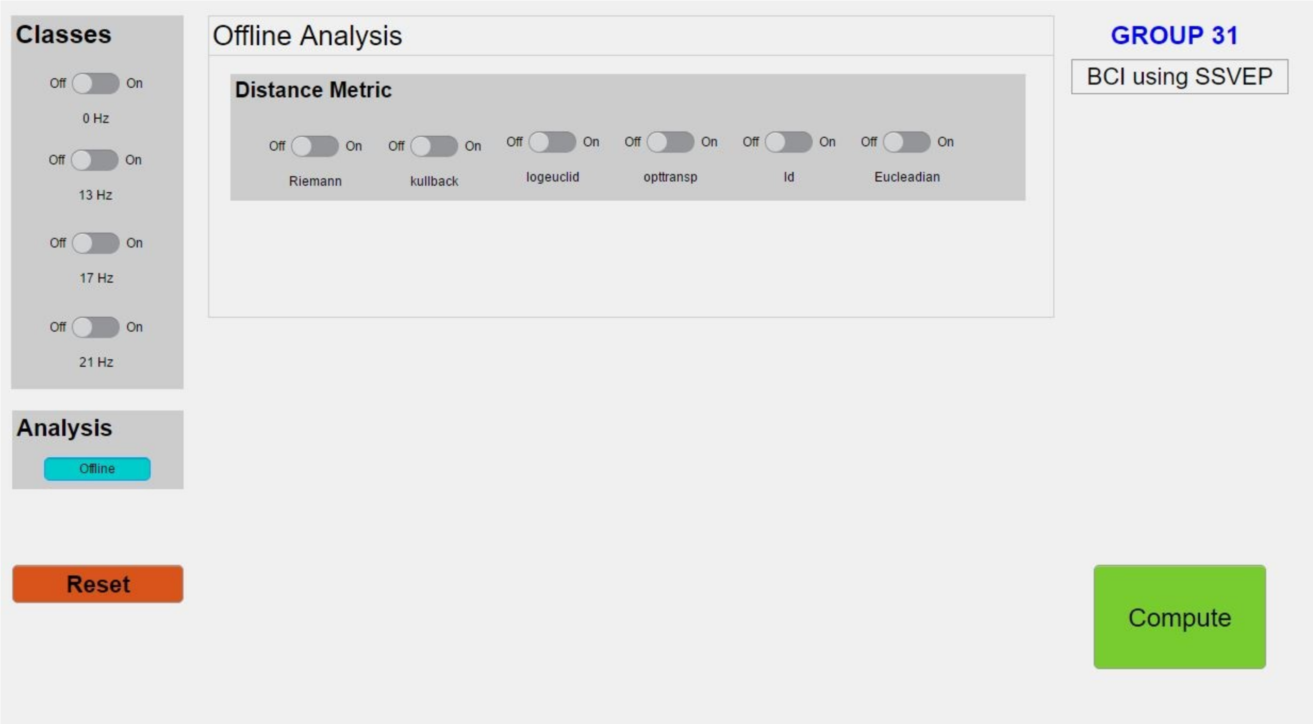

Figure 6.2: GUI Snapshot

Chapter 7

Result Analysis

The final outcome of our project is highlighted here. The offline analysis has achieved a GUI implementation on MATLAB that can allow for one to choose the number of classes to evaluate and different distance metrics being applied to them. The results are shown in the following sections

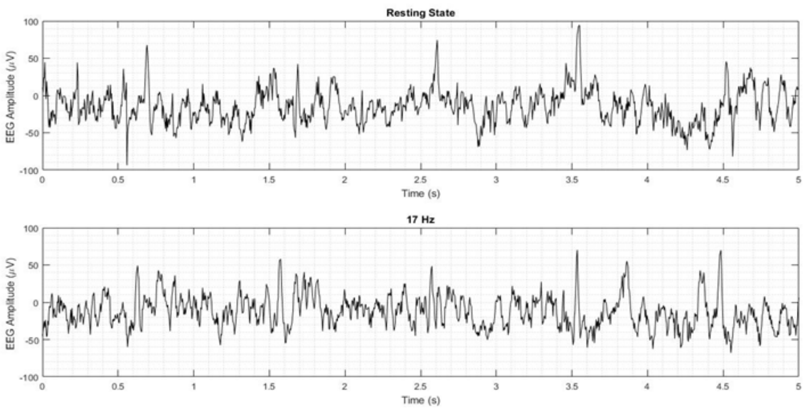

Figure 7.1: Time domain depiction of SSVEP. Normal brain activity is also depicted to contrast with.

For the offline analysis, the outcome was an overall accuracy score that looked at the amout of times a particular class was predicted correctly and more general confusion matrix, which gives a clearer picture of the behaviour of the classifier.

7.1 General Accuracy

As explained earlier, this was obtained by attempting to count the nnumber of times a particular class was correctly predicted, by feeding a labelled test set. The accuracy percentage was defined as:

$$Acc\% = \frac{\text{number of correct predictions for a class}}{\text{number of times that class was tested}} \tag{7.1}$$

Results are shown only for the Riemannian distance metric as that was observed to give the most consistently good performance overall, (empirically tested). The results for two class, three class and four class are summarised below. This was trained with 48 different EEG epochs and tested on 16.

- For two class, we have

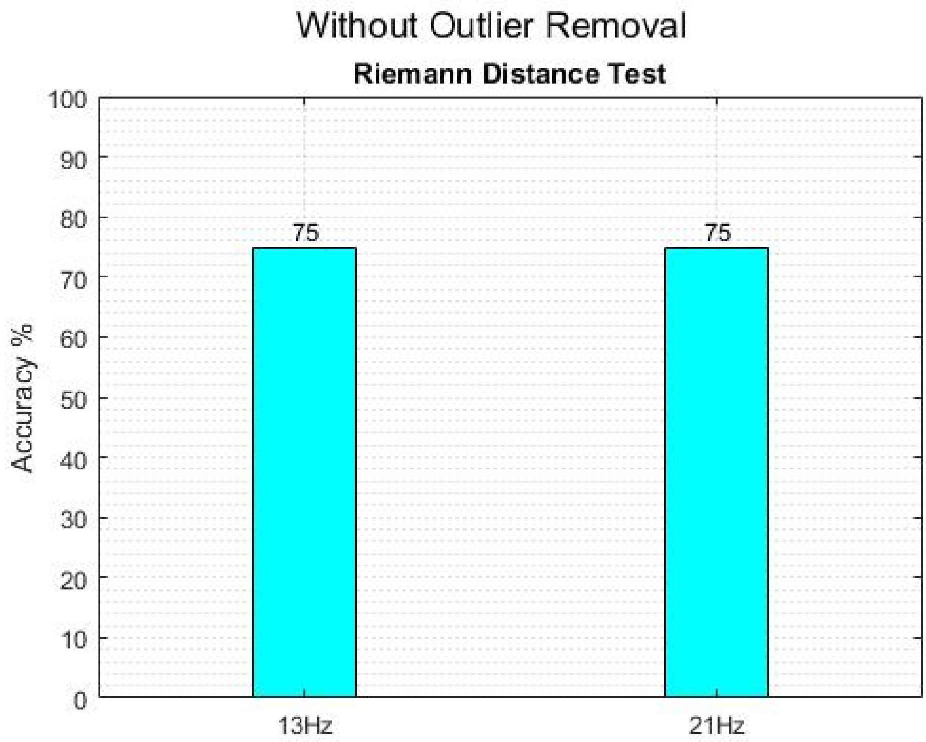

Figure 7.2: Considering only 13Hz and 21Hz frequencies

- For three class, we have

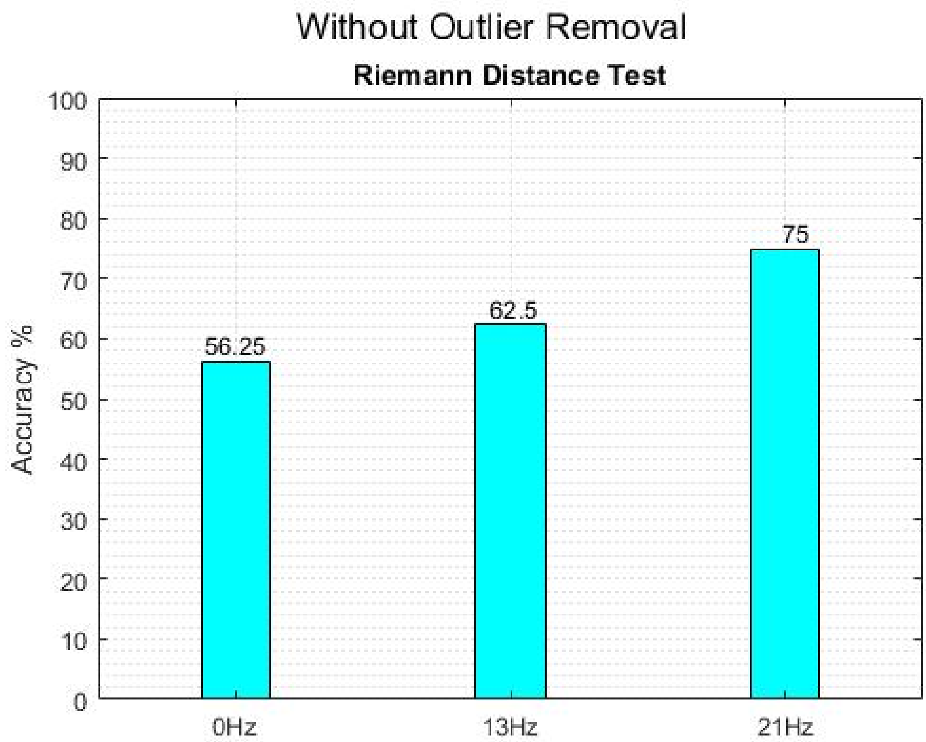

Figure 7.3: Considering no SSVEP as one class along with 13Hz and 21Hz frequencies

- For four class, we have

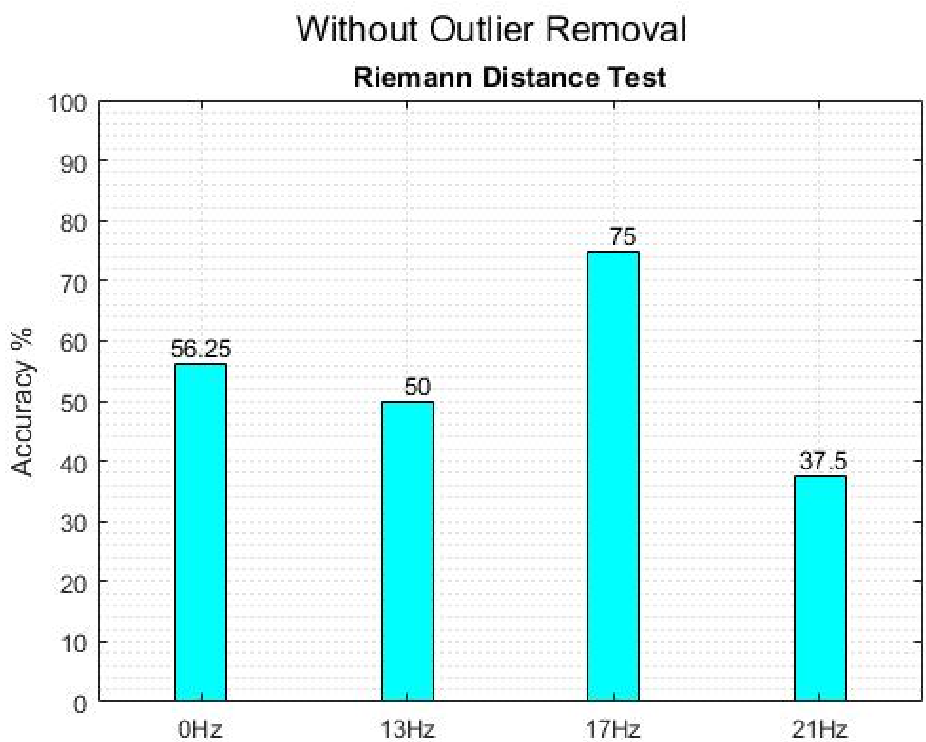

Figure 7.4: Considering four classes, namely 0Hz, 13Hz, 21Hz and 17Hz

1. As can be seen above, the main benefit of using the Riemannian clustering approach is the fact that no SSVEP conditions can also be classified. Unlike the generally used CCA method, that provides no way for the user to classify 0Hz. This means that in a CCA classifier, the machine would output one class even if the user is not looking at a flickering stimulus, thus can be prone to random fluctuating outputs.

2. Another thing to be noted here is that the accuracies fall off as the number of classes increase. This is due to the fact that on the riemannian manifold, the covariance matrices' clusters are close to one another.

7.2 Confusion Matrix

A brief look at what a confusion matrix is would help in understanding the following results if one is uncertain about it. This part can be skipped if one is already familiar with it.

7.2.1 Overview

1. A confusion matrix is just a table often used to describe the overall performance of a classifier and in turn, a classification model. This table considers all possible input and output combinations and tabulates them all.

2. A few parameters are also defined for this table to take into account the performance of the classifier by considering different aspects of the results obtained.

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Figure 7.5: An illustration of a confusion matrix

Confusion Matrix Parameters:

1. **True Positive (TP)**: A true positive is when the prediction is correct for ”positive class”.

2. **False Positive (FP)**: A false positive occurs when the prediction falsely classifies the output as belonging to the ”positive class”.

3. **False Negative (FN)**: A false Negative occurs when the prediction falsely classifies the output as belonging to the ”negative class”.

4. **True Negative (TN)**: A true negative occurs when the prediction correctly classifies the output as belonging to the ”Negative class”.

”Positive class” and ”negative class” simple are the two broad terminologies used to help understand the classification results. A class is ”positive” if it is the desired output under consideration. A class is ”negative if it is any other class other than the positive.

Performance Evaluation Parameters

1. Accuracy:

$$Accuracy = \frac{\sum TP + \sum TN}{\sum Total\ Population}$$

   Accuracy measures the degree of closeness of measurements of a quantity to that quantity’s true value

2. True Positive Rate (TPR) or Probability of Detection:

$$TPR = \frac{\sum TP}{\sum Condition\ Positive}$$

   True Positive Rate, also called sensitivity or hit-rate measures the proportion of positives that are correctly identified as such .

3. False Positive Rate (FPR) or Probability of False Alarm:

$$FPR = \frac{\sum FP}{\sum Condition\ Negative}$$

   False Positive Rate defines the probability of a false alarm.

4. False Negative Rate (FNR) or Miss Rate:

$$FNR = \frac{\sum FN}{\sum Condition\ Positive}$$

False Negative Rate describes the number of missed detections in the experiment .

7.2.2 Confusion Results

The following section displays the results obtained from the confusion matrix.

1. Using all the two classes, the confusion matrix is shown along with the tabulation of the error and hit rates.

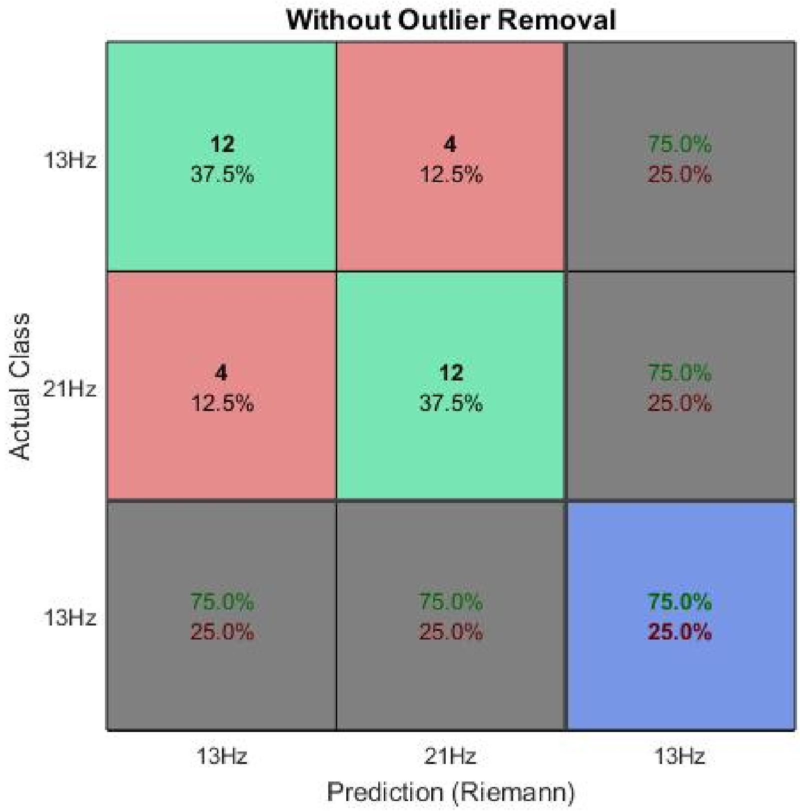

Figure 7.6: The confusion matrix for two classes

C/P	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate
13Hz	0.2500	0.2500	0.7500	0.7500
21Hz	0.2500	0.2500	0.7500	0.7500

Table 7.1: Two Class Results

2. Using all the three classes, the confusion matrix is shown along with the tabulation of the error and hit rates.

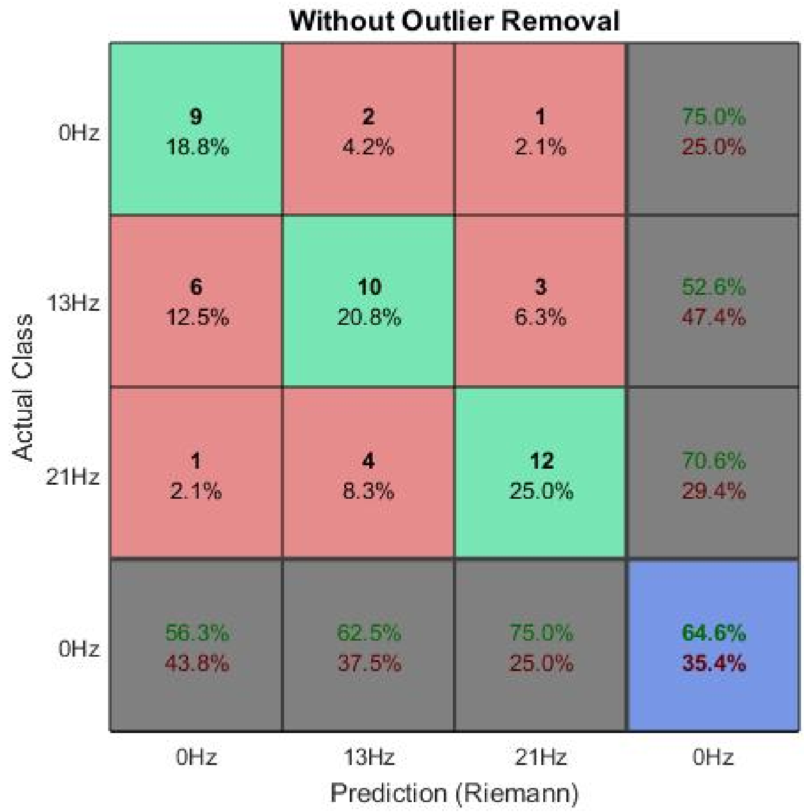

Figure 7.7: The confusion matrix for three classes

C/P	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate
0Hz	0.1944	0.2500	0.7500	0.8056
13Hz	0.2069	0.4737	0.5263	0.7931
21Hz	0.1290	0.2941	0.7059	0.8710

Table 7.2: Three Class Results

3. Using all the four classes, the confusion matrix is shown along with the tabulation of the error and hit rates.

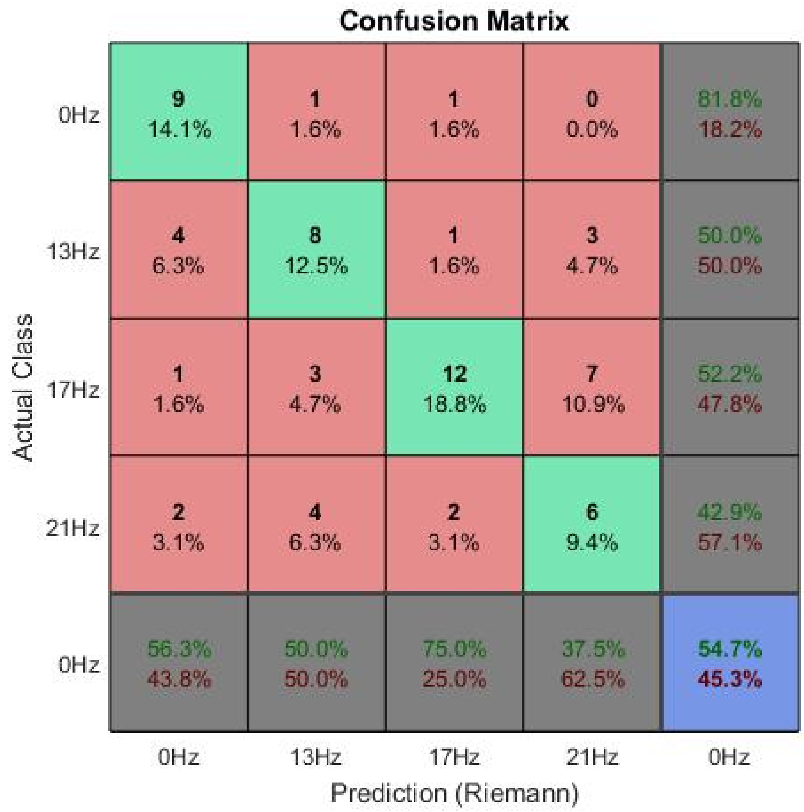

Figure 7.8: The confusion matrix for all four classes

C/P	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate
0Hz	0.1321	0.1818	0.8182	0.8679
13Hz	0.1667	0.5000	0.5000	0.8333
17Hz	0.0976	0.4783	0.5217	0.9024
21Hz	0.2000	0.5714	0.4286	0.8000

Table 7.3: Four Class Results

As we can see here again, the accuracy goes down with the number of classes. A side-note to be considered is that the ”Without Outlier Removal” heading refers to the fact that the classification was done by also including data points that are far off in the training set and can cause errors. The outlier removal designed was not used since it tend to over-fit the data and couldn't be generalised.

Chapter 8

Conclusion and Future Scope

8.1 Conclusion

This report is the culmination of work done in the field of brain computer interfacing for our final year project. Having explored the SSVEP paradigm, we have accomplished the task of building a statistical classifier that is more friendly and easier to implement on other larger modules. Focusing on offline analysis, we have understood the core idea of covariance of data giving us a vector metric to help cluster objects. The offline analysis was used to test the algorithm used and the results were looked at using the confusion matrix. MATLAB and its various toolboxes were used to help us process, extract and test the contrived codes, from the algorithms

The Achievements of our project were as follows

- Reviewing and understanding of different BCI algorithms used in classifying SSVEP signals.
- Understanding the Riemannian clustering and classification approach both in online and offline scenarios [3].
- Implementing an offline algorithm that has the capability to train and test as many classes as desired, using the riemannian clustering approach.
- Writing a custom MATLAB code for offline processing.
- Building a GUI for the code.

8.2 Future Scope

Since the availability of open source BCI equipment is slowly gaining mass popularity, it would only be a matter of time before it becomes mainstream. Although limited processing capabilities do exist for these boards, upgrades over time would certainly help create more engaging BCI applications. SSVEP can be seen in the following applications:

- Wheelchair Control: Some people that are paralysed from neck down would be unable to operate a joystick to move around a wheelchair. An array of LEDs flickering in front of them could be utilised as stimulus that can be assigned to different directions of movement. A person looks at one to move forward, another to go left, etc. The SSVEP classifier can then be used to control the movement of the chair.

- Writing: A robotic arm can be made to move a pen across a writing surface, controlled by the patient's SSVEP signals.

- BCI game development: Virtual reality can see the use of SSVEP to perform various tasks in games later in the future as both BCI and VR are slowly gaining traction.

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Appendix A

Project Planning

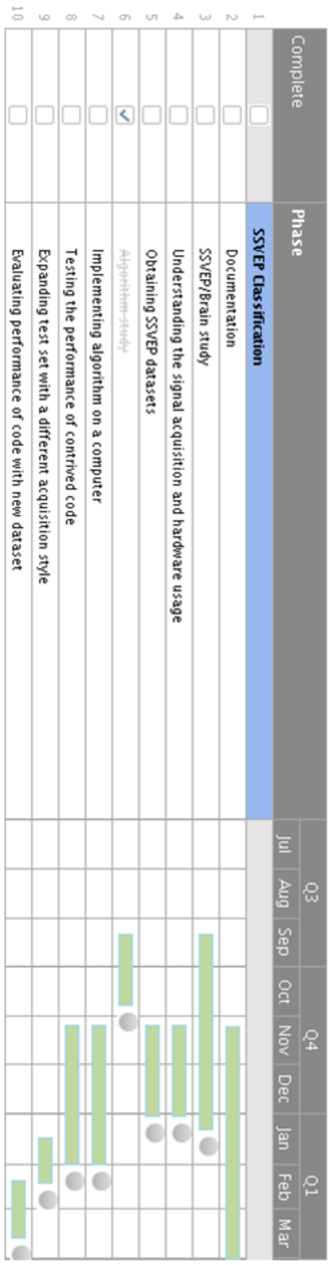

Figure A.1: The Gantt Chart

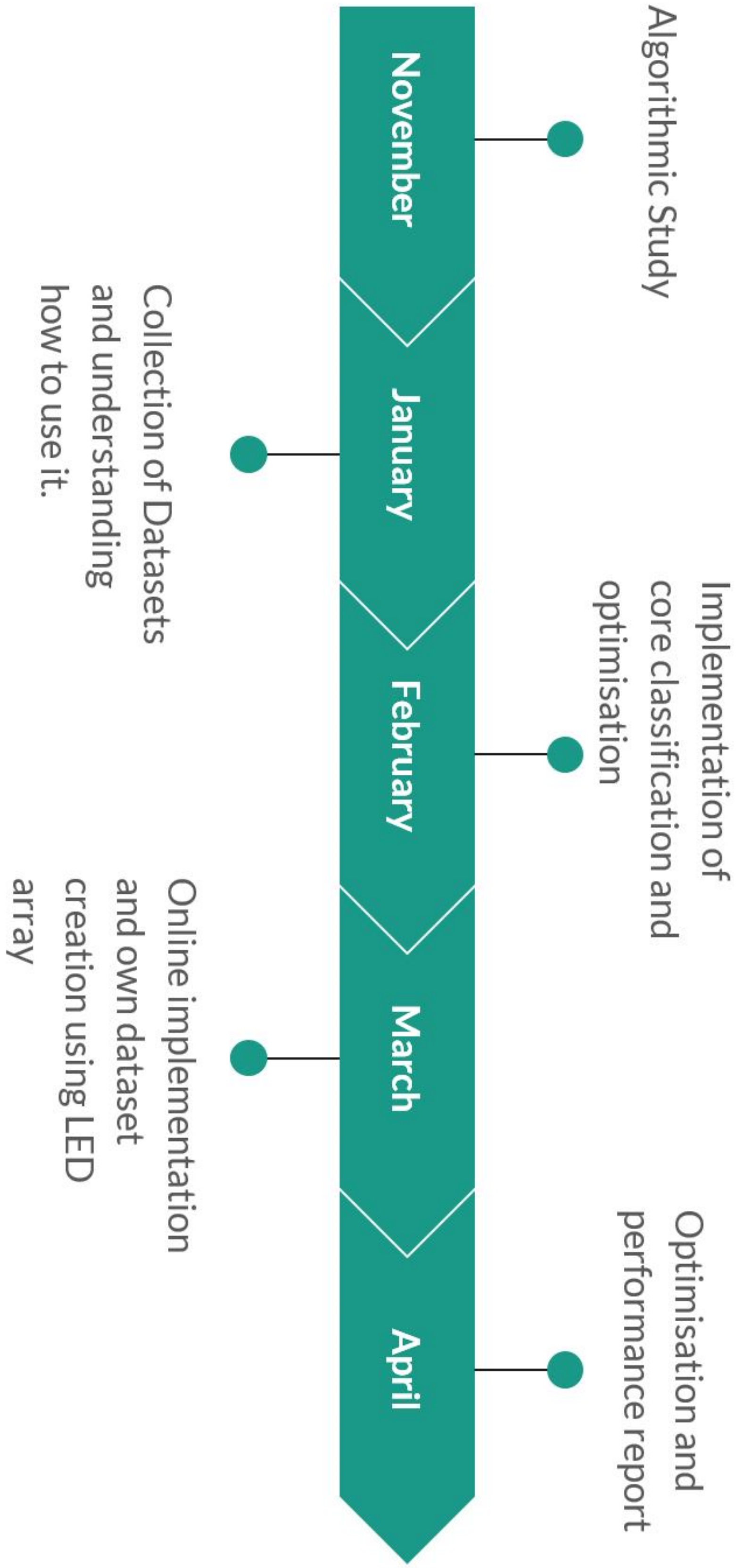

Figure A.2: Overall Plan

Appendix B

Technical Specifications

OpenBCI 32-bit Board[22]	
• 8 differential, high gain, low noise input channels	• Programmable gain: 1, 2, 4, 6, 8, 12, 24
• Compatible with active and passive electrodes	• 24-bit channel data resolution
• Texas Instruments ADS1299 ADC Analog Front End	• ±2.5V analog operating voltage
• PIC32MX250F128B microcontroller w/chipKIT^{TM}bootloader (50M Hz)	• 3.3–6V input voltage
• RFduino^{TM} Low Power Bluetooth^{TM} sradio	• LIS3DH accelerometer
• Micro SD card slot	• 5 GPIO pins, 3 of which can be Analog

OpenBCI Dongle [22]
• RFD22301 radio module from RFdigital^{TM}
• FT231X USB-to- serial converter from FTDI
• Can upload code to the OpenBCI board or the dongle
• Fully broken out and pin-compatible w/ RFduino form factor