Linnæus University
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Master Thesis

Analysis of Real Time EEG Signals

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Date: 12-05-2014
Subject: Electrical Engineering
Level: Masters
Course code: 5ED06E

Abstract

The recent evolution in multidisciplinary fields of Engineering, neuroscience, microelectronics, bioengineering and neurophysiology have reduced the gap between human and machine intelligence. Many methods and algorithms have been developed for analysis and classification of bio signals, 1 or 2-dimensional, in time or frequency distribution. The integration of signal processing with the electronic devices serves as a major root for the development of various biomedical applications. There are many ongoing research in this area to constantly improvise and build an efficient human- robotic system.

Electroencephalography (EEG) technology is an efficient way of recording electrical activity of the brain. The advancement of EEG technology in biomedical application helps in diagnosing various brain disorders as tumors, seizures, Alzheimer's disease, epilepsy and other malfunctions in human brain.

The main objective of our thesis deals with acquiring and pre-processing of real time EEG signals using a single dry electrode placed on the forehead. The raw EEG signals are transmitted in a wireless mode (Bluetooth) to the local acquisition server and stored in the computer. Various machine learning techniques are preferred to classify EEG signals precisely. Different algorithms are built for analysing various signal processing techniques to process the signals. These results can be further used for the development of better Brain-computer interface systems.

Keywords: Signal processing, biomedical, bio signal, EEG, pre-processing.

Acknowledgements

We would like to thank our supervisor prof. Sven Nordebo for his valuable inputs, suggestions and guidance to complete our thesis successfully. We thank the governing body of Linnaeus University, Vaxjo for the beautiful, clean environment and lab facilities provided to us. Thanks to our solid academic training, today we can write hundreds of words on virtually any topic without any problem.

Thanks to our beloved friends and family members in Vaxjo, Oskarshamn and in India for their moral support by giving us words of fine encouragement.

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Abbreviations

EEG	**E**lectro **E**ncephalo**G**ram
BCI	**B**rain **C**omputer**I**nterface
MATLAB	**MAT**rix **LAB**oratory
LABVIEW	**LAB**oratory **V**irtual **I**nstrument **E**ngineering **W**orkbench
ADHD	**A**ttention **D**eficit **H**yperactivity **D**isorder
EP	**E**voked **P**otential
ERP	**E**vent **R**elated **P**otential
ICA	**I**ndependent **C**omponent **A**nalysis
CSP	**C**ommon **S**patial **P**atterns
PCA	**P**rincipal **C**omponent **A**nalysis
CSSD	**C**ommon **S**ubspace **S**patial **D**ecomposition
CSD	**C**urrent **S**ource **D**ensity
DFT	**D**iscrete **F**ourier **T**ransform
FIR	**F**inite **I**mpulse **R**esponse
IIR	**I**nfinite **I**mpulse **R**esponse
SSVEP	**S**teady **S**tate **V**isual **E**voked **P**otential
CAR	**C**ommon **A**verage **R**eference
SL	**S**urface **L**aplacian
AR	**A**uto **R**egressive
PSD	**P**ower **S**pectral **D**ensity
STFT	**S**hort **T**ime **F**ourier **T**ransform
LDA	**L**inear **D**iscriminant **A**nalysis
RFLDA	Regularized **F**ishers **L**inear **D**iscriminant **A**nalysis
SVM	**S**upport **V**ector **M**achine
NN	**N**eural **N**etwork

MLP	**M**ulti **L**ayer **P**erceptron
LVQ	**L**earning **V**ector **Q**uantization
FIRNN	**F**inite **I**mpulse **R**esponse **N**eural **N**etwork
TDNN	**T**ime **D**elay **N**eural **N**etwork
HMM	**H**idden **M**arkov **M**odel
GMM	**G**aussian **M**ixture **M**odel
KNN	**K** **N**earest **N**eighbor

Symbols

V	volt
Na^+	Sodium ion
K^+	Potassium ion
Hz	Hertz
α	Alpha
β	Beta
γ	Gamma
θ	Theta

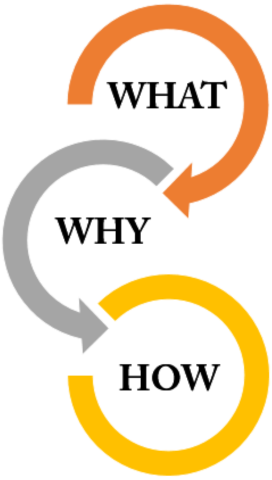
Chapter 1

Introduction: The overall Picture

This chapter projects the overall review by defining its what, why and how. It shows the project incitement and idea. Finally, an overall picture of the report structure is given.

1.1 WHAT is the purpose of the project?

The main drive of this thesis, is to examine and travel around the possibilities that stays within Brain-Computer Interface domain, using user friendly gear that have come into public market recently. The motivating force for using electroencephalography technology, method of recording electrical impulse of brain using electrodes from the scalp (explained in chapter 3) is Bain Machine Interface (BCI) system. The main focus have been about developing applications in a medical context, helping paralyzed or disabled patients to interact with the external world, by mapping brain signals to human cognitive and/or sensory motor functions [1].



More specifically, this project focuses on acquiring and pre-processing of real time brain signals utilizing a single dry electrode positioned on left side of forehead. The raw EEG signals are transmitted in a wireless mode (Bluetooth) to the local acquisition server and stored in the computer. Various machine learning techniques are preferred to classify EEG signals precisely. Different algorithms are built for analysing various signal processing techniques to process the signals. These results can be further used for the development of better Brain-computer interface systems.

1.2 WHY EEG signals are used?

Electroencephalography (EEG), records and measure electrical activity of the brain which is the main essence of this project. The Human brain is the most complex part of the whole body. It generates different kind of mind waves in different mental states. These waves helps in better understanding of the human activities, for example hand or leg movement, eye blink etc. Brain waves have fascinated many researchers. There have been continuous improvement in the development of human machine interaction system with the help of EEG signals.

1.3 HOW EEG signals are analyzed?

The Brain signals are captured using a single electrode sensor placed on the forehead. They are connected to a computer via wireless mode. There are many software used and evolved recently for analyzing real time EEG signals. Most used software's among them are MATLAB, Openvibe, Labview and Bioelectromagnetism.

The tool used in this thesis is Openvibe, which is an open source software. The Openvibe platform has many unique features which will help you to develop BCI applications. They have easy scripting, powerful signal processing techniques, multi-platform and support Brain Computer Interface applications. This software helps in analyzing EEG signals.

1.4 Brain-Computer Interfaces

Building an BCI system needs multidisciplinary specialisations such as signal processing, computer science, neurophysiology. Indeed, in order to use a BCI, two phases are generally required: 1) an offline training phase which calibrates the system and 2) an online phase which uses the BCI to recognize mental states and translates them into commands for a computer [2]. An online BCI requires to follow a closed-loop process, generally composed of six steps: brain activity measurement, pre-processing, feature extraction, classification, translation into a command and feedback [3].

The whole structure of BCI is summarized in the below diagram. They define the most important steps in an online BCI. Before operating such a BCI, offline calibration is done.

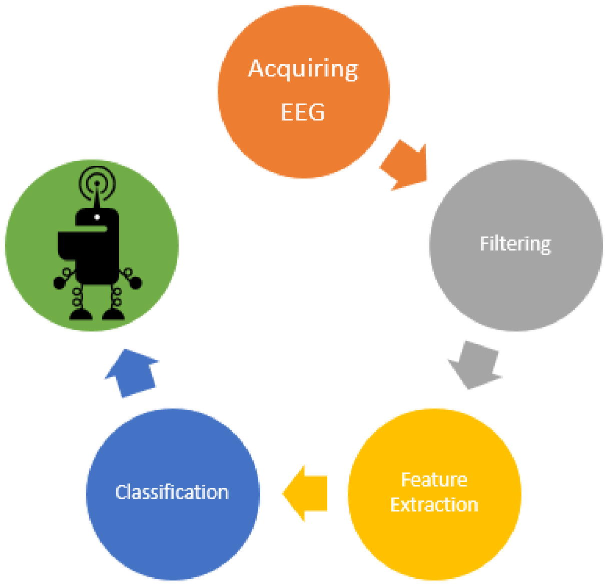


FIGURE 1.1: Overall BCI system

- **Measurement of brain activity:** this step consists in using various types of sensors in order to obtain signals reflecting the user's brain activity [4]. In this thesis, we focus on EEG technology.
- **Preprocessing:** this step consists in cleaning and de-noising input data in order to enhance the relevant information embedded in the signals [4].
- **Feature extraction:** feature extraction aims at describing the signals by a few relevant values called "features" [4].
- **Classification:** the classification step assigns a class to a set of features extracted from the signals [5]. This class corresponds to the kind of mental state identified. This step can also be denoted as "feature translation" [5].

- **External application:** once the mental state is identified, a command is associated to this mental state in order to control a given application such as a speller (text editor) or a robot [6].

In the below chapters, a clear description on each process is given.

Chapter 2

EEG Technology: Biological Background

For better understanding of the readers, the basic structure, function of the brain and the EEG Technology is explained under this section.

2.1 Human Brain

The Brain is the most wonderful creation in human body. It is made of large number of neuron network which are interconnected to each other and help to produce electrical impulse in and out of the brain. It is approximately made of 100 billion of neurons.

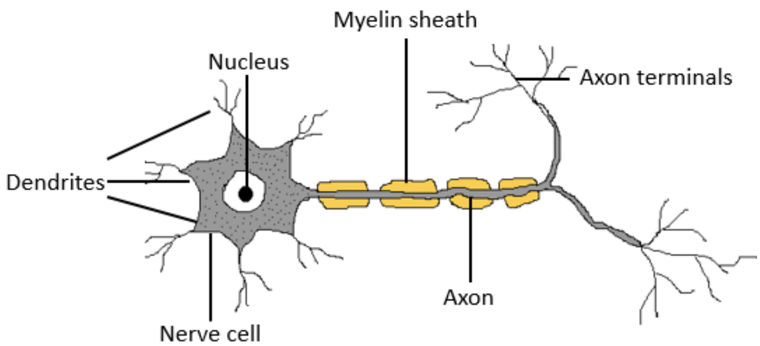


FIGURE 2.1: Structure of a single neuron

A neuron has a cell body (or Soma), many dendrites and a long axon which carries the electrical impulse away from the cell body. They are of many types. The function of each neuron is dependent on its structure. It helps in controlling the behaviour, body movements and various other aspects of human body coordinating with central nervous system.

The brain has three main parts: Cerebrum, Cerebellum and brain stem. Cerebrum is the largest section of the brain. Cerebral cortex is the outermost layer of gray matter making up the superficial aspect of cerebrum. Cerebrum is responsible for problem solving, thinking, movements and feeling. Cerebellum controls coordination and balance. Brain stem controls autonomous functions such as heart rate, breathing, digestion and blood pressure. There are four major lobes in the Brain. They are Frontal, Parietal, Occipital and Temporal lobe.

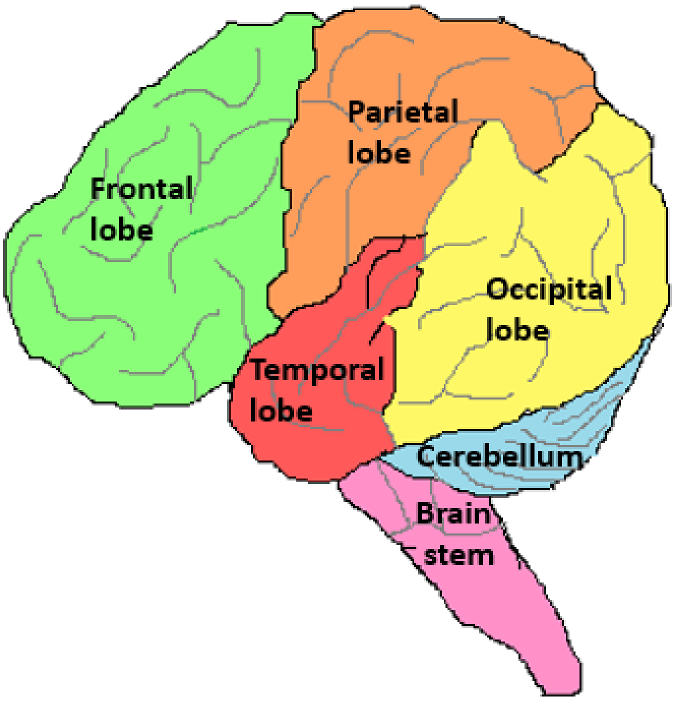


FIGURE 2.2: Basic structure of brain

2.2 Electroencephalography(EEG)

This section explains the brain activity which is the root of EEG analysis. It also gives an overview of total EEG technology.

2.2.1 How and Why Brain Activity Is Measured

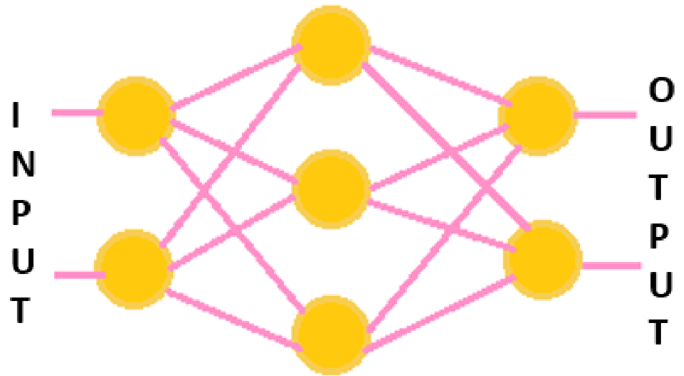


FIGURE 2.3: Artistic illustration of a single neuron and its synapses.

The brain waves have always been an interesting area for many researches. Electroencephalography is the measure of electrical activity of the neurons. Around 80 years ago, Hans Berger, a German scientist discovered electroencephalography (EEG). They help in identifying epileptic seizures, brain dead, tumors, sleep disorders, depth of anesthesia in patients, states of deep sleep and many other important functions.

There are two general approaches for measuring the electrical activity of the brain. They are invasive and non-invasive. In an invasive method, the electrodes are physically implanted inside the human brain. They require surgical procedures and are not generally recommended. In an non- invasive method, electrodes are placed on the surface of the skin to measure the electrical potential generated by the muscle neurons. They are safe and painless. Both the methods give different views and allow us to visualize the brain and to monitor what occurs.

In EEG, brain-related electrical potentials are recorded from the scalp. The electrodes are held in position on the scalp with special pastes and their diameter typically range from 0.4 to 1 cm. Electrodes, made of conducting material such as silver are used to read this electrical impulse. The brain signals vary from 30 V to 100 V. These signals are weak and has to be amplified. When the brain neurons communicate with each other, they give rise to current which in general termed as **action potential**. In medical terms, action potential occurs when there is a discharge due to fast opening and closing of Na^+ and $K+$ ion channels in the neuron membrane. If the membrane depolarize to some threshold, the neuron will ”fire”. Tracking these discharges over time reveals the **brain activity** [7].

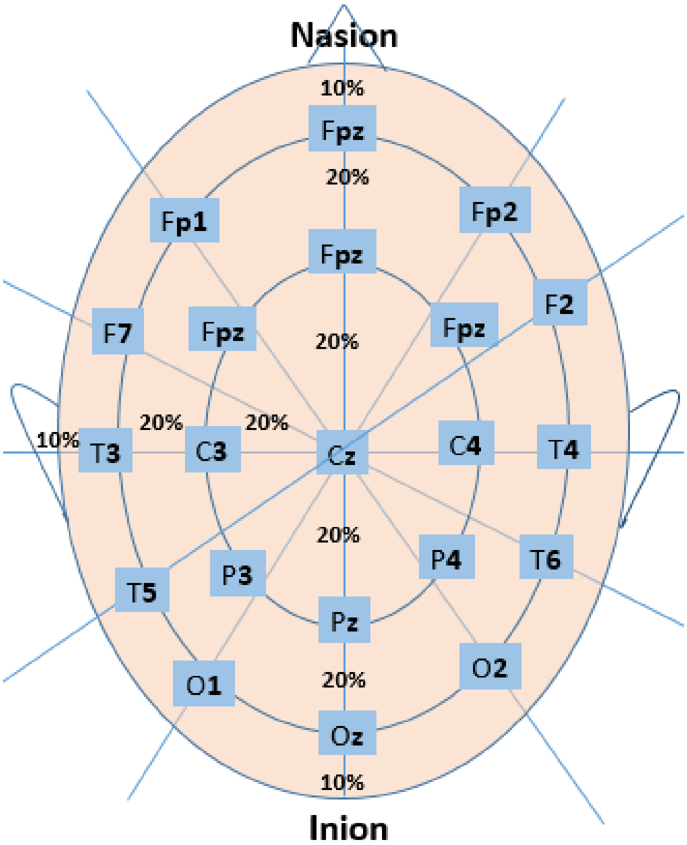


FIGURE 2.4: Conventional 1020 EEG system for positioning 21 electrodes

In this project, a single dry electrode is used for analysis of EEG signals. They collect signals from a single point on the forehead, namely **FP1** as shown in the below picture.

FIGURE 2.5: EEG headset utilized in this project

2.2.2 Brain Activity Patterns

The Brain waves can be classified using their frequency, amplitude, shape and the position of electrodes on the scalp. The EEG applications focus on a relatively narrow band, from 0.1 Hz to 100 Hz, as most of the EEG signal power lies in this frequency range.

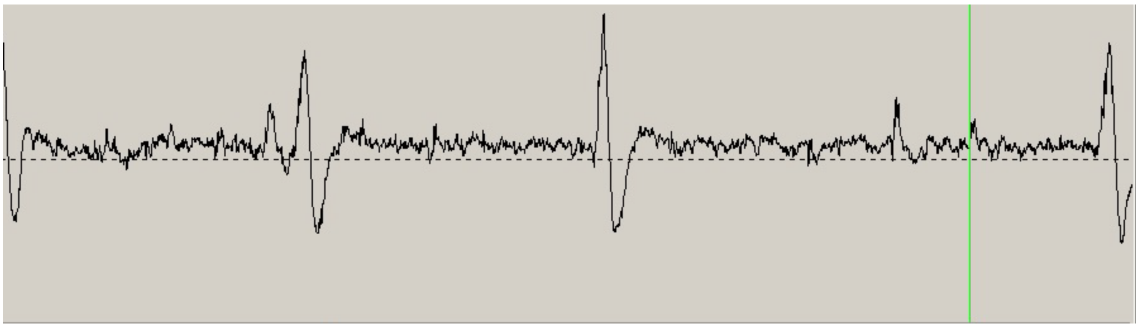
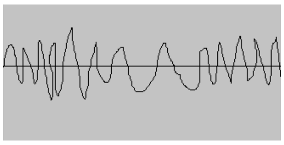
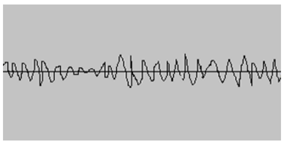


FIGURE 2.6: EEG signals over time

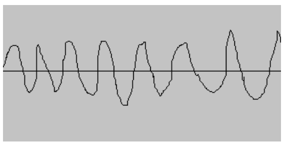
Time domain representation of different type of brain waves with time in x-axis is shown in the below diagrams for better understanding of further chapters. EEG signals are classified based on their frequency range.



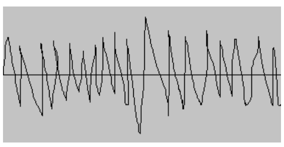
Alpha waves(α), are in the frequency range from 7.5 Hz to 12 Hz. These types of waves originate from occipital lobe and backside of the head. Alpha waves dominate in relaxed and calm mental states while being awake. They have higher amplitude compared with other waves.



Beta waves(β), ranging from 13 to 30 Hz, are associated to deep thinking, high concentration level and anxious state. They have large frequency band compared with others. Beta waves originate from central area of the brain and front side of head.



Theta waves(θ), are in the frequency range from 3.5 to 7.5 Hz. They originate from central, temporal and parietal parts of head. High level of theta waves generally occur in abnormal adults, usually one with AD/ HD. They arise during creative thinking, stressed and deep meditating state.



Gamma waves(γ), are the waves which lies in the frequency range of 30 Hz and above. Motor functions, simultaneous work ad other multi-tasking occur in this range of frequency.

Delta waves, are in the frequency range from 0.5 to 3.5 Hz. They are the slowest waves compared to others. Delta waves generally occur in deep sleep and sometimes when awake. They also occur in coma mental state. More of delta waves in awake state is considered to be a serious phenomenon.

MU is associated with motor activities, and is also found in the alpha wave frequency range, but where the maximum amplitude is recorded over motor cortex. So it basically triggers when there is an actual movement or there is an intent to move [1].

2.3 Real Time Application of EEG Technology

The most commonly practised application of EEG is to monitor and study EEG records manually, to look for, or to understand brain disorders and various damages, such as epileptic seizures, AD/ HD, tumors and so on. Moreover, EEG is a device used in healthcare sectors for monitoring patients brains and declare dead when no activity is monitored.

The study of brain waves and how they relate to different mental states, have led to number of alternative methods and beliefs on how to manipulate these waves. For instance, in order to become e.g more relaxed, focused and smarter, you can buy music that plays in specific Hertzes that promise to do just that [7]. An important information gained from this is that you should allow your kids listen to Mozart in their period of growth, enjoying the effects mentioned. Besides this somewhat regarded pseudoscience, there have been a lot of interesting studies of mental states and how they are effected [8].

2.3.1 Event Potential

EEG wave respond to the external as well as internal stimuli, like flash light, a tone or skipping. This is called Evoked Potential (EP), or Event Related Potentials (ERP). One of the well known ERP is P300.

2.3.2 Neurofeedback Training

Self-regulative abilities to do this comes by getting real-time visual and/or auditory feedback, and is like Operant conditioning. With frequent training, long termed effect is possible [8]. The electrical activity of the brain is picked by the electrodes located on the scalp. An amplifier is used to boost the signals before being fed to a computer. The EEG signals are identified and processed into feedback before being fed to the user. Using Fourier transform, the signals can be classified based on frequency bands. Their factors can then be used to calculate a ratio, for instance β/θ (Leins, Goth, Hinterberger, Klinger, & Strehl, 2007) [9]. The feedback is obtained from the height of ratio bar graph displayed on a monitor. The below diagram depicts a simple Neurofeedback principle.

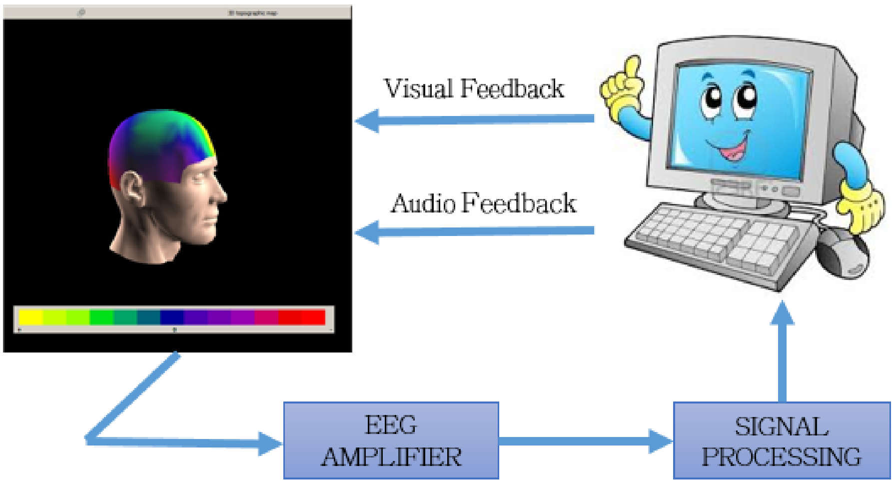


FIGURE 2.7: Neurofeedback principle

EEG helps in diagnosing AD/HD. AD/ HD people have slow waves and is very difficult for them to manage concentration and behaviour. More of beta and less of theta activity is required to reduce inattention.

Preprocessing, feature extraction and classification of EEG signals are briefly explained in the following chapters. These three BCI modules could be combined into a single and more general, higher level module, collectively called as “EEG processing”. In any BCI design, EEG processing plays a vital role as it is involved in developing a command for BCI application. A wide range of research is going on for the betterment of EEG processing in order to develop efficient BCI system.

One can keenly observe that the boundaries amongst the “pre-processing”, “feature extraction” and “classification” are not hard and sometimes the boundaries may even appear as indistinct. Thus, in certain applications pre-processing and feature extraction modules are united into a single algorithm, and the classification part can be missing or reduced to its simplest form where it is not so important. In general, it is very important to study these three in separate since they play different roles and have different objectives [10].

Chapter 3

Preprocessing of EEG signals

In order to perform feature extraction and classification from brain waves, it is essential to pre-process the raw brain waves for increasing the signal to noise ratio and enhance the relevant information entrenched in the EEG signal. Certainly, electrical activity of the eyes or of the muscles or high frequency noise from electrical net (50 Hz in Sweden) affects the EEG signal and makes them noisy [2]. The electrical activity of the muscle or eyes causes more disturbances as they have large amplitude when compared to EEG signal. One must be very careful while removing these noise from EEG signals; accidentally it may happen to remove the necessary information entrenched. Likewise, the remarkable part is removing the signals aroused due to background brain activity irrelevant to the signals of our interest [2].

To achieve the goal of pre-processing, EEG signals need to be measured using proper referencing and filtered using simple temporal & spatial filters or advanced filters like Independent Component Analysis (ICA), Common Spatial Patterns (CSP), Principal Component Analysis (PCA), Common Subspace Spatial Decomposition (CSSD), etc.,

3.1 Referencing

According to Hagemann et al., the differences between results of different studies are partly due to the differences in referencing [11]. In general, EEG signals are acquired from various electrodes placed in different positions on the cortex or scalp. The amplitude of the brain signal from a particular electrode is relatively measured, may be in reference with the amplitude of another electrode placed in some other position of the scalp or cortex [10]. Therefore, the result will be a mixture of brain activity at the given position, brain activity at the reference position and noise. Hence, the reference electrode must be placed in a way that the brain activity in that position is negligible or almost zero. In general, the nose, mastoids and earlobes are used as the reference site. The most commonly used referencing methods are as follows:

- **Common reference:** This is the widely used referencing technique in BCI design. In this method, only one common reference point is used for all the electrode and the reference point will be far from all the electrodes [10].
- **Average reference:** In this technique, average of the brain activity measured at all electrodes is subtracted. The basic principle of this method is, at any particular time the sum of the brain activity as a whole will be zero. Though, certain electrode's activities when it has comparatively low density and the activities of the electrodes at lower part of head is not taken into account, causes some practical issues. [12]
- **Current source density (CSD):** The current source density technique is nothing but "the rate of change of current flowing into and through the scalp" [10]. By Laplacian computing the sum of differences between a particular electrode and its neighbors give CSD estimation. The actual problem with this estimation of CSD is valid only if the electrodes are in a 2-D plane and placed at equal distance.

3.2 Simple Temporal and spatial Filters

Simple temporal or spatial filters are widely used in most of the BCI designs to improve the EEG signal quality by de-noising them.

3.2.1 Temporal Filters

Band-pass or low-pass filters are the commonly used temporal filters which filter out a very high or low frequency bands leaving behind the particular frequency band in which we are interested. For example, a BCI design uses motor and Sensorimotor rhythms, the signal in frequency band of 8-30 Hz is band-pass filtered since the signal relevant to motor and Sensorimotor actions present only in those range [2]. Noise due to external influence like electrical net interference (50 Hz in Sweden) and electrode polarization are removed using temporal filtering. Filtering is commonly done by using Discrete Fourier Transform (DFT) or Finite Impulse Response (FIR) or Infinite Impulse Response (IIR) filters.

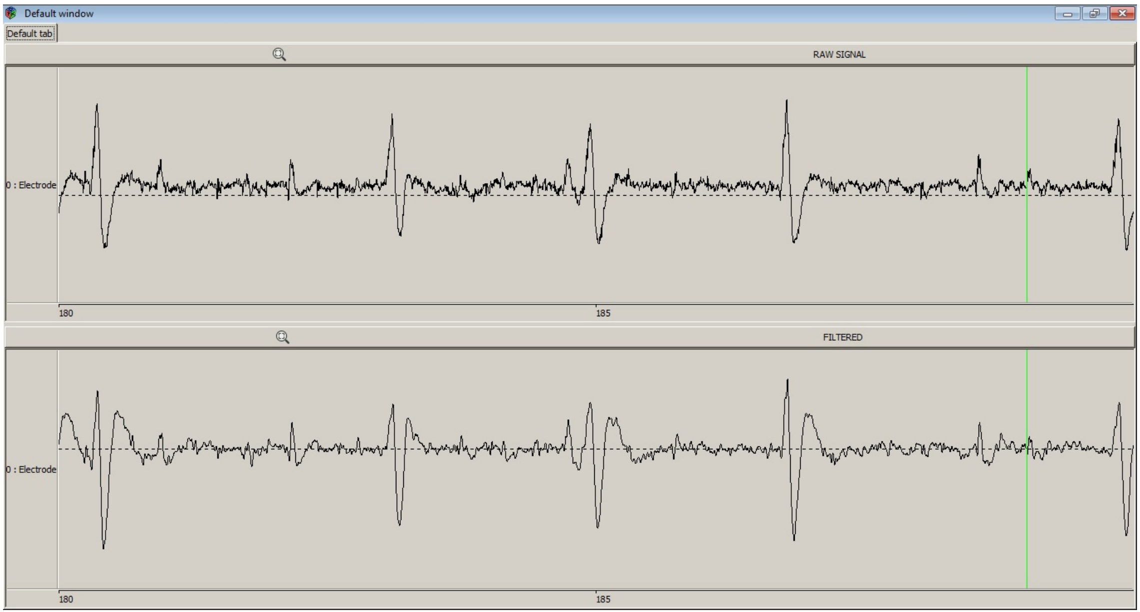


FIGURE 3.1: Temporal filtered signals distributed over time

3.2.2 Spatial Filters

Primary cortex of the brain is responsible for motor movements. Interest in high - frequency electroencephalographic (EEG) rhythms (above 20 Hz) has intensified since the recognition of the involvement of high-frequency beta (15-25 Hz) and gamma (>25 Hz) rhythms in cognitive processing [13, 14, 15]. They are generally used for pattern recognition, especially for imagined motor activities such as leg or hand movements. The recognition is easier if the patterns are obtained from a broad frequency band rather than from only the combined $\alpha - \beta$ bands [16]. These results are in agreement with Pfurtscheller and coworkers' recent observation in which the optimal band selection for the detection of motor- related mental tasks is the band from 8 to 30 Hz [17].

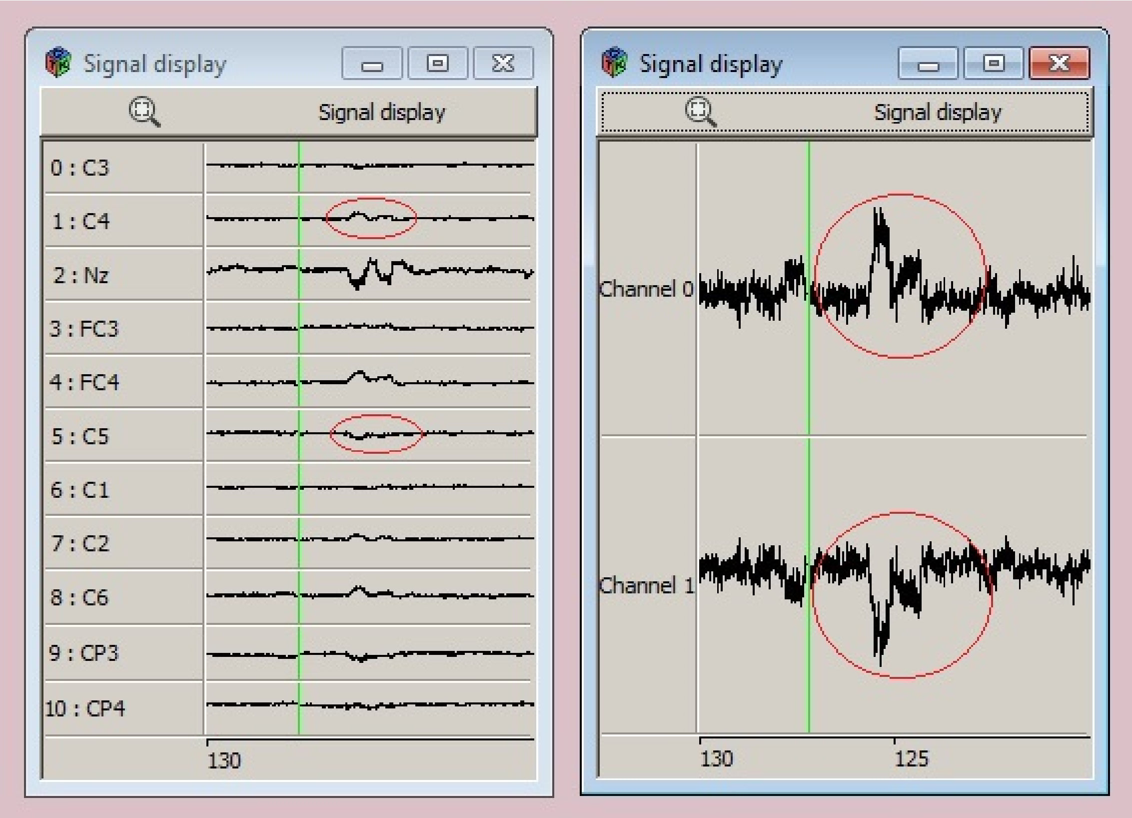


FIGURE 3.2: Spatial filtered EEG signals over time

In general, it is well-known that motor imagery causes decrease (ERD: Event-Related Desynchronization) or increase (ERS: Event-Related Synchronization) of Electroencephalogram (EEG) potentials in the (8-12 Hz) and (13-28 Hz) rhythms over the sensory motor cortex [18]. Each body limb is associated with the respective region of the brain [19], but finding a class-discriminative spatial filter has been of great interest in the BCI community [20, 21, 22] as the volume conduction effect of EEG [23].

For example, when building a BCI design based on Steady State Visual Evoked Potential (SSVEP), we need the brain signals only from the electrodes (O1 & O2) located in the visual region (Occipital Lobe) which contains the brain signals of our interest [24]. Similarly for a BCI design based on feet or hand motor imagery movement, the relevant brain signals are present only in the motor or Sensorimotor cortex region. Hence, the spatially filtered brain signals from the electrodes (C4 & C3) located on right and left motor cortex is sufficient for this particular BCI design [2].

Common Average Reference (CAR) and the Surface Laplacian (SL) filters are the most common spatial filters used to eliminate the noise from background brain activity.

3.2.2.1 Surface Laplacian Filtering

Electroencephalograph (EEG) based brain computer interfaces need spontaneous signals for on-line detection of various mental states. In the framework of the design of an electroencephalograph (EEG) based brain–computer interface (BCI), Wolpaw and Mc- Farland's results [25] indicate that EEG patterns are better detected with a surface Laplacian (SL) transformation of signals than with raw potentials. SL-transformed EEG data has been largely used in BCI research, although the accurate computation of SL- i.e., spline methods- requires the use of many EEG electrodes (typically, 40–64), which are available in the so-called high resolution EEG systems [26]. Surface Laplacian transforms determine density using data from all active scalp electrodes [27].

The main advantage of using surface Laplacian filtering in this algorithm is: 1) They increases the topographical specificity 2) It helps in filtering spatially broad features like volume-conduction effects. Nevertheless, it is not completely possible to individualise different type of brain waves at this stage of signal processing. But surface Laplacian to some extent have proved to be an efficient way for investigators in building and testing algorithms to discriminate signals from brain and from muscle. Generally, they could be distinguished by their topographical power spectral distribution with respect to frequency. There are ongoing researches to narrow down this path.

For example, let's consider the EEG signals from the electrodes C3, C4, FC3, FC4, C5, C1, C2, C6, CP3, and CP4. By doing surface Laplacian around C4 and C5 with spatial filter coefficient's 4; 0; -1; -1; 0; 0; -1; 0; 0; 4; 0; -1; 0; 0; -1; -1; 0; -1, we will get filtered output channel OC1 and OC2 as follows:

$OC1 = 4 * C3 + 0 * C4 + (-1) * FC3 + 0 * FC4 + (-1) * C5 + (-1) * C1 + 0 * C2 + 0 * C6 + (-1) * CP3 + 0 * CP4$

$$\boxed{OC1 = 4 * C3 - FC3 - C5 - C1 - CP3} \tag{3.1}$$

$OC2 = 0 * C3 + 4 * C4 + 0 * FC3 + (-1) * FC4 + 0 * C5 + 0 * C1 + (-1) * C2 + (-1) * C6 + 0 * CP3 + (-1) * CP4$

$$\boxed{OC2 = 4 * C4 - FC4 - C2 - C6 - CP4} \tag{3.2}$$

3.2.3 Advanced Filters

Unlike the above described simple temporal and spatial filter, there are some advanced filtering techniques used in the pre-processing of EEG signals which is described in the below section.

3.2.3.1 Independent Component Analysis (ICA)

ICA is used when the EEG signals of our interest and noise like background brain activities signals has comparable amplitudes. In other words, the ICA is used when the brain signals 'm' (measured using many electrodes) are resulting from unknown linear mixing of several sources -'s'.

$$\boxed{m = As} \tag{3.3}$$

where 'm' is the matrix of measurements, with electrodes in row and time sample in column; 's' is the source matrix, with source in row and time sample in column; and 'A' is unknown mixing matrix which represents the linear mixing. The ICA to determine an estimate $\hat{s}$ of s without knowing A is given by the following equation:

$$\boxed{\hat{s} = Wm} \tag{3.4}$$

where 'W' is the de-mixing matrix. By comparing equation 3.3 and 3.4, one can say $W = A^{-1}$, with the problem being 'A' is unknown. "To solve this problem, ICA assumes that the sources -'s' is statistically independent, which has been revealed as being a reasonable hypothesis for numerous problems" [2]. In recent years, many ICA algorithms have been proposed and proved in the field of EEG signal processing for BCI design.

Chapter 4

Feature Extraction

Acquisition of large amount of data is obtained by measuring electrical activity of the brain through EEG leads. Moreover, the number of electrodes used for recording EEG signals generally vary from 1 to 256 and with a sampling frequency varying from 100 Hz to 1000 Hz. "Features " are the values which defines some relevant properties of the acquired signals. They are generally summed up into a vector named as "feature vector". Hence, feature extraction is an operation which converts one or several signals into a feature vector.

Determining and obtaining required features from EEG signals is an important step. The classification algorithm, which uses feature extracted from EEG signals will have problem if the information extracted is not relevant and do not describe the bio-signals involved, i.e., the mental state of the user.

There are many extraction techniques which were proposed and studied. These techniques can be divided in three main groups, which are: 1) the methods that exploit the temporal information embedded in the signals [28, 29, 30, 31, 32]. 2) the methods that exploit the Frequential information [33, 34, 35, 36, 37]. 3) the hybrid methods, based on time-frequency representations, which exploit both the temporal and Frequential information [38,39].

4.1 Temporal methods

Temporal variations of the acquired signals are used in temporal methods. They are specifically adapted to define Neurophysiological signals in a better manner. In this method, we can find the amplitude, auto-regressive parameters or Hjorth parameters for EEG signals.

4.1.1 EEG signal amplitude

The amplitude of raw EEG signals is obtained from different electrodes placed in various locations of the brain. They are preprocessed and aggregated into a single vector before being fed to a classification algorithm. In those case, pre-processing methods such as sub-sampling and spatial filtering is used to reduce the EEG signals.

4.1.2 Autoregressive parameters

AutoRegressive (AR) methods assume that a signal $X(t)$, measured at time t, can be modeled as a weighted sum of the values of this signal at previous time steps, to which we can add a noise term E_t (generally a Gaussian white noise):

$$\boxed{X(t) = a_1 X(t-1) + a_2 X(t-2) + \ldots.. + a_p X(t-p) + E_t} \tag{4.1}$$

where the weights a_i are the auto-regressive parameters which are generally used as features for Brain-Computer Interface [38, 39].

4.1.3 Hjorth parameters

Hjorth parameters defines the temporal dynamics of a signal $X(t)$, by using three measures that are the mobility, the activity and the complexity [40].

4.2 Frequential methods

EEG signals are made by a set of specific brain waves. The amplitude of these waves changes with the brain waves while doing any mental task such as motor imagery or other cognitive tasks. The brain waves generated are generally synchronized with the stimulus frequency. Hence, it becomes essential to extract Frequential information from brain signals. There are two main techniques, namely power spectral density and band power features.

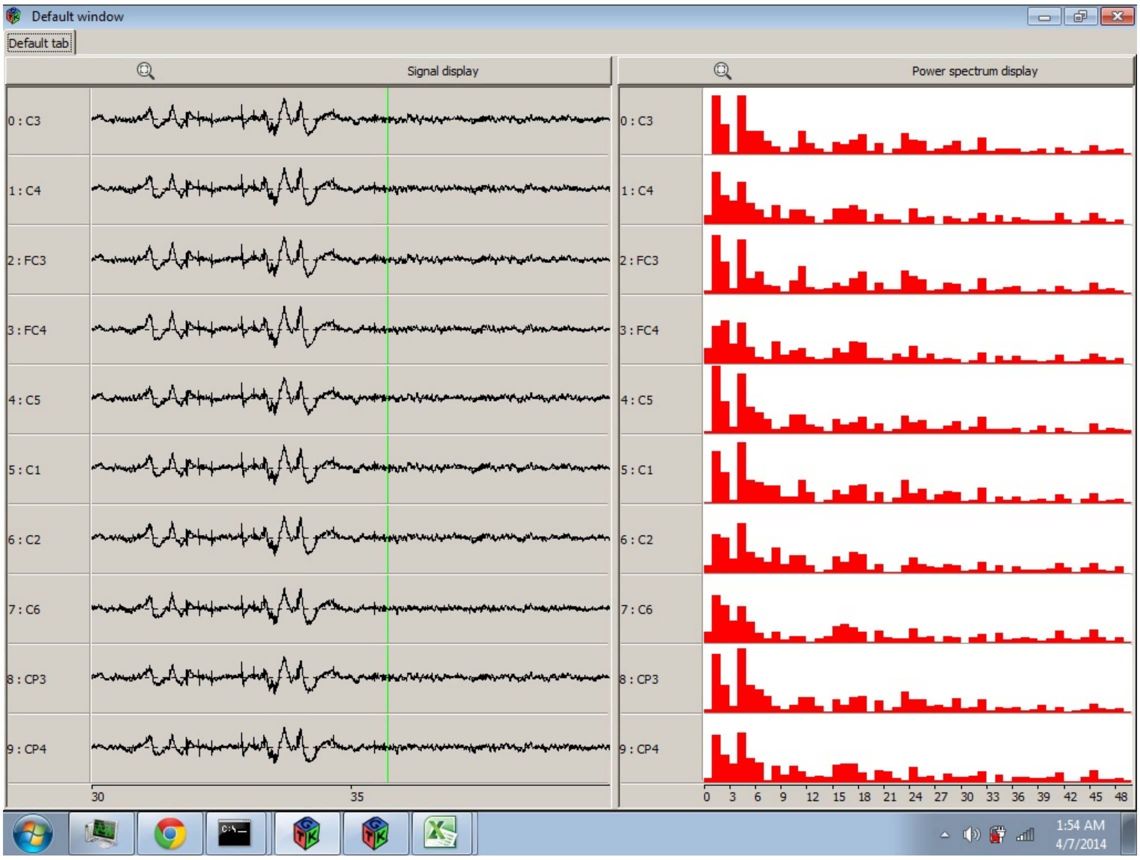


FIGURE 4.1: Raw EEG signal and their power spectral display

4.2.1 Power spectral density features

Power Spectral Density (PSD) features, defines the distribution of the power of a signal in frequency domain. PSD features is generally evaluated by taking square of the Fourier transform of a signal or by evaluating the Fourier transform of the Autocorrelation function of a signal. They are the most used features in the development of BCI and served as one of the efficient way to identify large number of Neurophysiological signals.

4.2.2 Band power features

Band power features, describes band-pass filtering a signal in a given frequency range, squaring them and finally averaging the signal values over a given time window. The normal distribution of the signal can be obtained by taking log transform of the values. These features have been successfully used for the classification of motor imagery movements.

4.3 Time-frequency representations

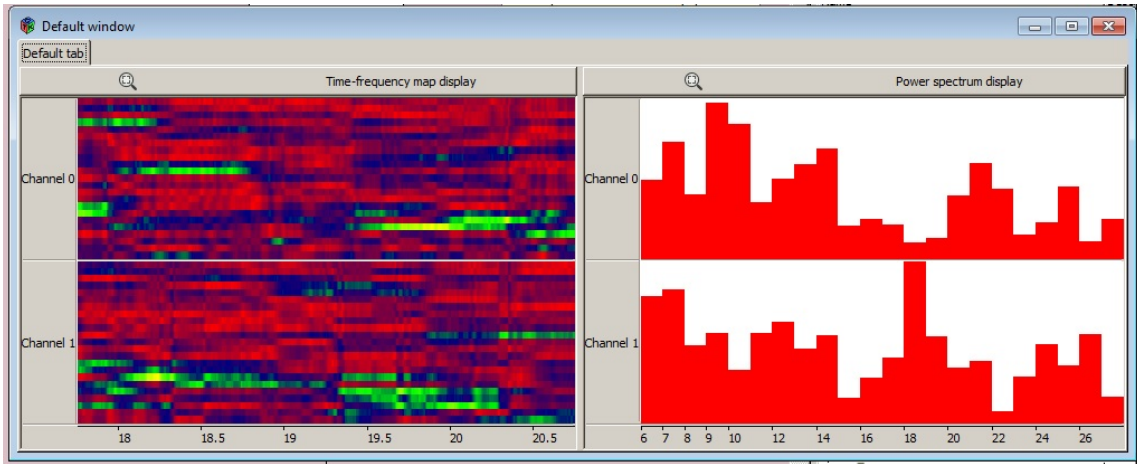


FIGURE 4.2: time-frequency representation of signal and their power spectral display

These methods are based on time-frequency representations such as the short-time Fourier transform or wavelets, and extracted information from the signals that are both Frequential or temporal. The main advantage of these is that they can identify sudden temporal fluctuations of the signals, while still holding Frequential information.

4.3.1 Short-time Fourier transform

The input signal is first multiplied by a given windowing function w over a short time period, provided w is non-zero. Taking Fourier transform of this windowed signal gives the Short-Time Fourier Transform (STFT). The STFT of $X(n, w)$ of a signal $x(n)$ is given by,

$$\boxed{X(n,w) = \sum_{n=\infty}^{+\infty} x(n)w(n)e^{-j\omega n}} \quad (4.2)$$

The main drawback of this method is that analysis window with a fixed size, leads to a similar temporal as well as Frequential resolution in all frequency ranges. Wavelet analysis tries to overcome this drawback.

4.3.2 Wavelet transform

Wavelet transform, similar to Fourier transform decomposes a signal onto a basis of functions. This basis of functions consists of wavelets Φ_{ab}. Each one being a scaled and translated version of the same wavelet Φ, where Φ is the mother wavelet:

$$\boxed{\Phi_{ab}(t) = \frac{1}{\sqrt{a}}\Phi(\frac{t-b}{a})} \quad (4.3)$$

The wavelet transform $W_x(s,u)$ of a signal x is given by:

$$\boxed{W_x(s,u) = \int_{-\infty}^{+\infty} x(t)\Phi_{u,s}(t)\,dt} \quad (4.4)$$

where s and u are the scaling and translating factor of the signal $x(t)$. The wavelet transform makes it possible to analyze a signal in different scales simultaneously. This serves as the main advantage of wavelet transform. Adding to that, the level of resolution depends on the scale. Various kinds of wavelets have been used for BCI, such as Daubechies wavelets [41, 42], Coiflet wavelets [43], Morlet wavelets [44], bi-scale wavelets [45] or Mexican hat wavelets [46]. They all made it possible to reach very promising results.

Even though we have various feature extraction methods for BCI, it is difficult to identify the most efficient ones due to a lack of comparisons. To reach a good performance, it is important to extract a small number of features which represents subject- related information. It is necessary to extract the required features precisely to build a more efficient BCI.

Chapter 5

Classification of EEG signals

This chapter describes next key step for identifying Neurophysiological signals adapted by many researchers in the way of development of BCI technology. One can achieve this by either regression algorithms or classification algorithms.

The aim of the classification step is to automatically assign a class to the feature vector extracted from the former step. This class defines the mental task. This class is generally used by the BCI user and represents the type of mental task performed by the user. Classification is attained using algorithms known as ”classifiers”. Classifiers are smart enough to identify the class of a feature vector using training sets. The classifiers are divided into five major categories. They are namely, linear classifiers, neural networks, non linear Bayesian classifiers, nearest neighbor classifiers and classifier combinations [2].

5.1 Linear classifiers

Linear classifiers are characteristic algorithms that use linear functions to differentiate classes. They are the most widely used classifiers in BCI applications. They are two important Linear classifiers, namely, Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM).

5.1.1 Linear discriminant Analysis

LDA also known as Fisher's linear discriminant, main purpose of LDA is to employ hyperplanes to distinguish the data representing various classes. For a problem consisting of two-class, the class of a feature vector relays on which side of the hyperplane the vector is.

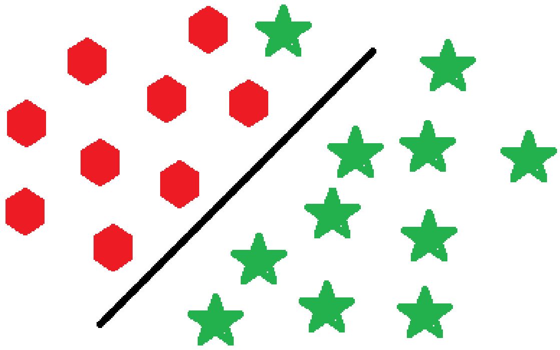


FIGURE 5.1: Picture depicting separation of the "red diamonds" and "green stars" by a hyperplane

This technique has very less mathematical calculations which makes it suitable for online BCI systems. They are simple to use and generally provides good results. The main drawback of LDA is their poor results on complex nonlinear EEG signals. In a regularized Fisher's LDA (RFLDA), a regularization parameter C is introduced. This parameter can penalize classification errors that tend to occur on training set. The resulting can accommodate outliers. They are less used than LDA for BCI applications.

5.1.2 Support Vector Machine

This classifier also uses a discriminant hyperplane to identify different classes.

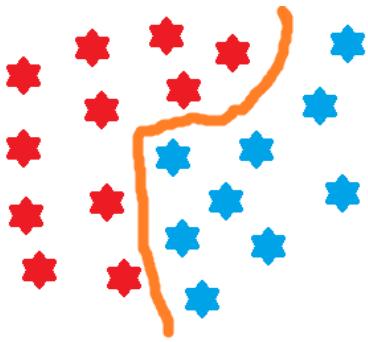


FIGURE 5.2: SVM finds the optimal hyperplane

An SVM, similar to RFLDA has a regularization parameter C that enables space to outliers and allows errors on the training set. The SVM using linear decision boundaries is known as linear SVM. Nonlinear decision boundaries are created with a little bit of complexity, using ”kernel trick”. Kernel function, denoted by $K(x, y)$, maps the data to another region of much higher dimensionality.

The kernel generally used is the Gaussian or Radial Basis Function (RBF) kernel, which is given by:

$$\boxed{K(x, y) = exp(\frac{-\|x-y\|^2}{2\sigma^2})} \tag{5.1}$$

Its corresponding SVM is known as Gaussian SVM or RBF SVM. The major advantage in SVM classifier is that they have good generalization properties.

5.2 Neural Networks

Neural Networks (NN) is an assembly of several artificial neurons which enables to produce nonlinear decision boundaries [47]. This section at first defines the most widely used NN for BCI, which is the MultiLayer Perceptron (MLP).

5.2.1 MultiLayer Perceptron

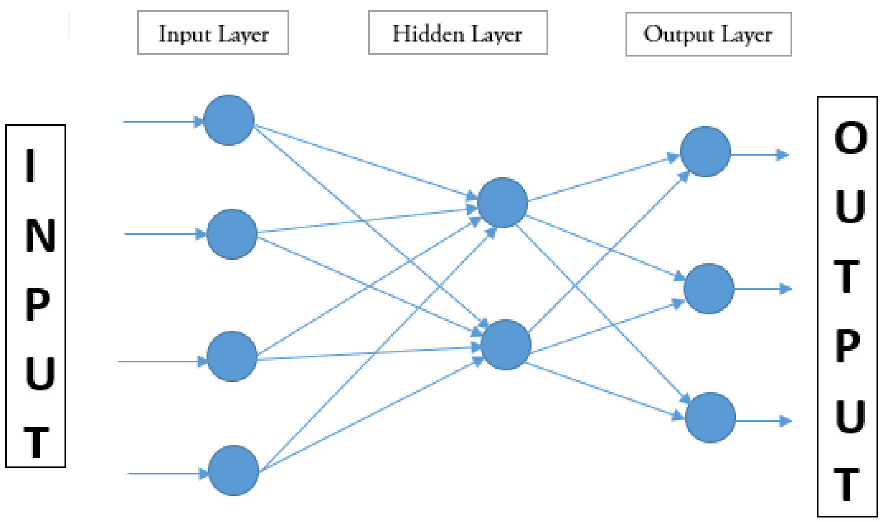


FIGURE 5.3: MLP architecture

An MLP is composed of several layers of neurons: an input layer, possibly one or several hidden layers, and an output layer [48]. The input of each neuron is connected to the output of the previous neuron's layer. The class of the input feature vector is determined by the neurons of the output layer.

Any continuous functions can be approximated by the NN and the MLP, when composed of enough neurons and layers. NN are flexible classifiers which can classify any number of classes. MLP is the most famous NN utilized in classification. A Perceptron is a MLP without hidden layers.

There are many other NN classifier used in the field of BCI such as Gaussian classifier, Learning Vector Quantization (LVQ) Neural Network, Fuzzy ARTMAP Neural Network, Dynamic Neural Networks like Finite Impulse Response Neural Network (FIRNN), the Time-Delay Neural Network (TDNN) or the Gamma Dynamic Neural Network.

5.3 Nonlinear Bayesian classifiers

There are two Bayesian classifiers, namely Bayes quadratic and Hidden Markov Model (HMM). They generate nonlinear decision boundaries. They are not as popular as linear or Neural Network classifiers among BCI applications.

5.3.1 Bayes quadratic

Bayesian classification aims at assigning to a feature vector the class it belongs to with the highest probability [49, 50]. The Bayes rule is used to compute the so-called a Posteriori probability that a feature vector has of belonging to a given class [50].

5.3.2 Hidden Markov Model

Hidden Markov Models (HMM) are popular dynamic classifiers in the field of speech recognition [51]. An HMM is a kind of probabilistic automaton that can provide the probability of observing a given sequence of feature vectors [51]. Each state of the automaton can Modelize the probability of observing a given feature vector. For BCI, these probabilities usually are Gaussian Mixture Models (GMM) [40].

5.4 Nearest Neighbor classifiers

These classifiers are very simple. A feature vector is assigned to a class with respective to its nearest neighbour(s). The neighbour can be a feature vector or a class prototype.

5.4.1 K-Nearest Neighbor(KNN)

This is the most basic and simple classification ever known. This type of classifier is generally used when there is no or very little knowledge about the EEG data. They bypass the probability density problem.

Chapter 6

Algorithm for a simple BCI system

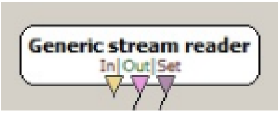
After a clear study on the behavior and the techniques involved in processing a EEG signal, the knowledge is now going to be used in creating an algorithm for extracting the features and making them as inputs to different applications.

Before moving further, let us first have an overview of the main component boxes utilized in this algorithm.

6.1 Main components

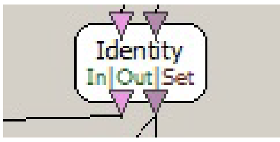
1. Wireless EEG Headset: This is the main component for this whole project being into action. They are wearable like regular headphones. This helps in collecting EEG data from a person using a single dry electrode placed on the forehead. It also contains another dry electrode which is connected to the left ear for reference.

2. Acquisition Client: they help in acquiring EEG data and distributing it into the algorithm. The output from the acquisition client can be stimulations, signals, experiment information and localized channel data.

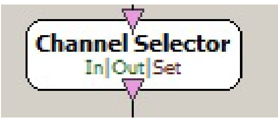


3. Generic Reader: they are used to store data in a format which is feasible for the box to read. They can read any data or file saved with the Generic stream writer box. The files saved likewise will have a variable number of streams.

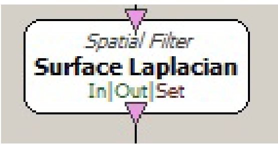
4. Generic Writer: This box dumps any stream of data into a binary file. They can have many number of input depending on the number of streams.



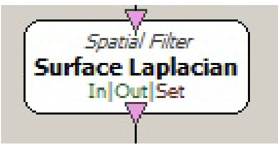
5. Identity: they help in duplicating output based on its input. They may have many inputs of various types. Each input has a corresponding output which is of the same type as input.



6. Channel Selector: The channels of interest are selected using channel selector. They can be selected either by channel name or index starting from 0. Besides, the channels can also be rejected instead of being selected.



7. Surface Laplacian: they help in discrimination of two sort of brain signals. They are constructed, such that, the variance of signals is minimum for one situation and maximum for the other. This can be used for discriminating signals of two commonly performed tasks, for instance movement of left versus right hand.



8. Temporal Filter: they are used to filter the input signal into a particular range. The plugin used in temporal filter allows the selection of the class of filter (Butterworth, Chebychev, Yule- Walker), the frequency band and also the kind of filter (low pass , band pass, band loop).

9. Time Based Epoching: Time based Epoching use the interval to control overlap of epochs. They generate 'epochs', i.e. signal 'segments' where length is configurable, as is the time offset between two consecutive epochs. Both input and output are of the same type 'signal'. They are generally needed for other signal processing boxes when the size of data blocks is not significant enough.

10. Stimulation Based Epoching: The stimulation based Epoching is same as Time based Epoching. The only difference is that it generates epochs when a stimulation is received. For instance, it is possible to start offset of a signal a few hundreds of milliseconds after the event or few milliseconds before the event.

11. Feature Aggregator: They aggregate the features received as inputs into a feature vector. This can be used for classification.

12. Classifier Trainer: they collect the feature vectors and label them depending on the input they arrive on. A training process is triggered when a particular stimulation occurs. The best example for classifier trainer is the one which is used in BCI pipelines to classify cerebral activity states.

Being understood the main components used in this algorithm, let us now take a closer look into it. The main concept of this algorithm is to acquire the signals and process them in a machine training method. EEG signals of a subject thinking about lifting his right and left arm are going to be evaluated in this algorithm. There are two set of operations before getting the final output.

6.2 Data Acquisition

EEG data sets for the Motor Imagery must be acquired from healthy person. This can be done with people who have very less or no idea about the EEG techniques.

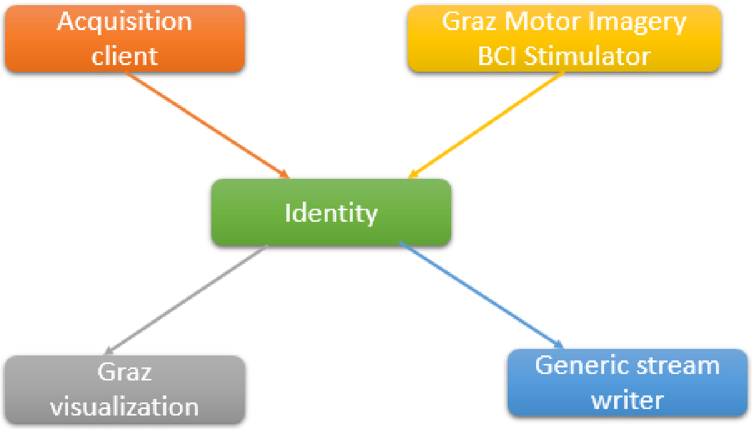


FIGURE 6.1: First part of the algorithm to collect EEG data

A exercise will be given to a subject in which random Left and Right arrows will be shown in a random design. Every time while the arrow is shown in the screen, subject have to think about lifting the corresponding arm.

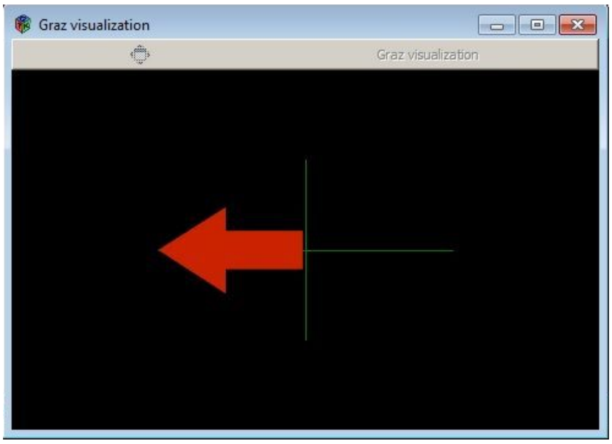


FIGURE 6.2: Left arrow shown to the user

A LUA stimulator will be used in this part of the algorithm to organize the right and left arrows shown in the screen. The timing for each arrow to be shown and the time between showing each arrow is specified. After each arrow is shown on the screen, 4 seconds from that point EEG data will be recorded. This is to know that at which point of time subject was thinking about the movements. The data is recorded in a file using a generic stream writer.

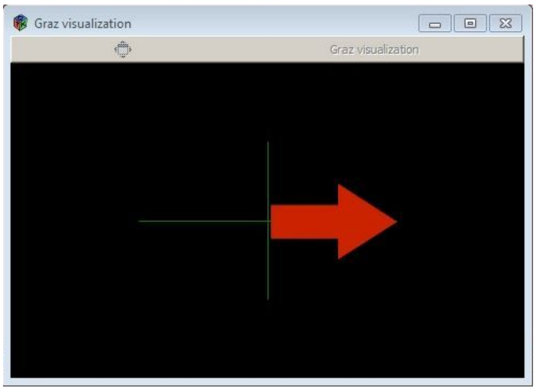


FIGURE 6.3: Right arrow shown to the user

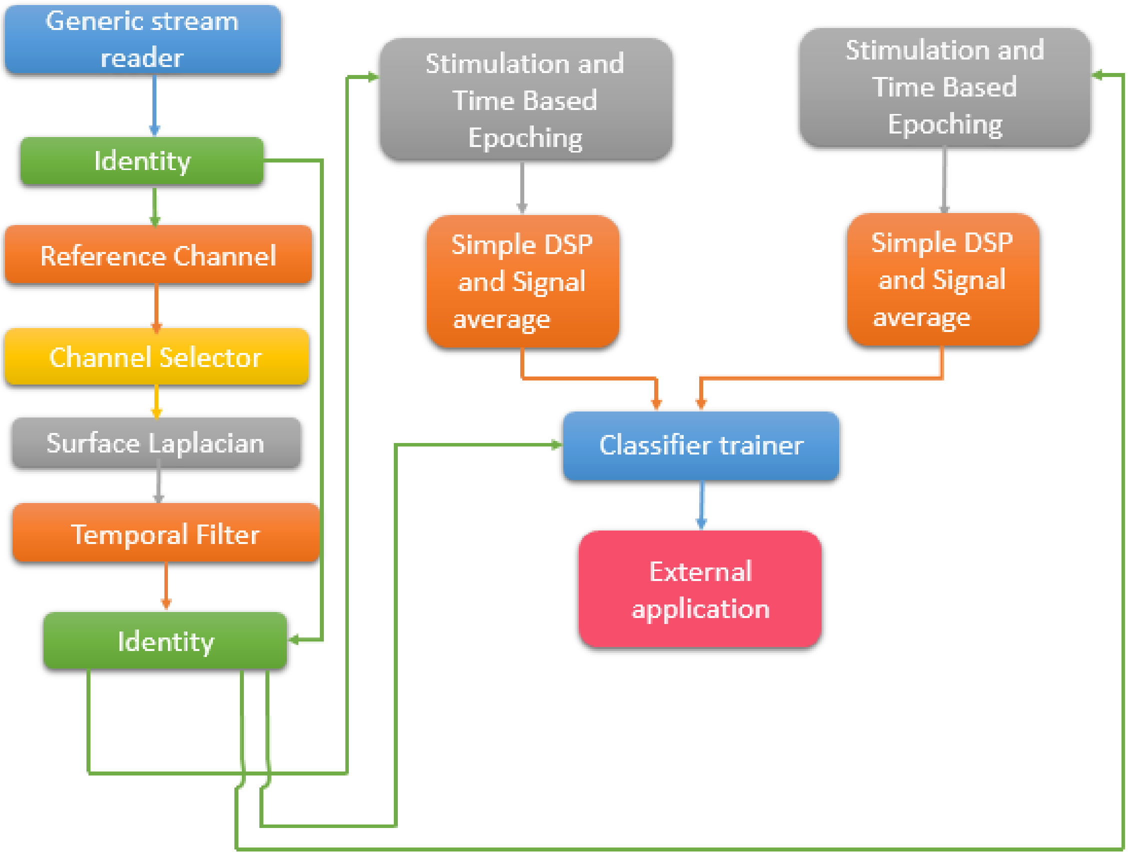


FIGURE 6.4: Second part of the algorithm for controlling an external application

6.3 Data labelling

The recorded data from the above section is used for further processing. As it is a difficult task to perform mathematical calculations on real time EEG signals, the first step in this process is to remove the signal to noise ratio. This can be done using a temporal filter or by using a reference channel. The filtered data is later sent to a surface Laplacian filter which is configured to produce two output channels from all the electrodes, in order to represent one on the right and one on the left. The processing of the signals from this part is carried out in two processing chains.

The output from the surface Laplacian will be stimulation based Epoched. This Epoching is configured in a way to remove the signal sets when subject was shown the left and right arrows. On the left processing chain, the stimulation Epoching time is set to the time when left arrows were shown. On the right, the time is set to the same time when right arrows were shown. Further, time based Epoching is done. In this Epoching, the signals are being split in 1s segments with overlap between consecutive segments. This leaves behind a bunch of Epoched signals.

The Epoched signals are filtered using a band pass filter to restrict them between 8 to 24 Hz band. Digital signal processing is done by squaring the Epoched signals to increase its amplitude and the average of all epochs is collected. The signal after averaging is sent to the feature aggregator which converts these data into a feature vector. The right and left hand movement vectors will be processed along with the raw stored signal by the classifier trainer which specifically recognizes the right and left hand movements from the stored signal and saves it in a separate file. This file is used in the next stage of signal processing.i.e., connecting it to control an external application such as robotic arm etc.

Chapter 7

Conclusion

This report presents an complete overview on EEG Technology, different processes involved in classification of EEG signals and an algorithm to represent a simple Brain-Computer Interface system that allow users to control an external application such as robotic arm with their brain waves. The brain signals were acquired using a single electrode placed on the forehead. EEG signals from the user are sent to the computer via Bluetooth. Various operations were performed on the collected EEG signals. For example filtering, Epoching, simple DSP and signal averaging. This information is used as input to a LDA classifier that is trained to classify two different mental tasks. Later, this classification is used to control the movements (left and right movement).

The major challenge and time-consumption in the project was testing the wireless headset with the use of real-time EEG input. The first step was to implement all the components of the system and make them interact with each other, then enable the system to recognize eye blinks in the incoming EEG signal samples.

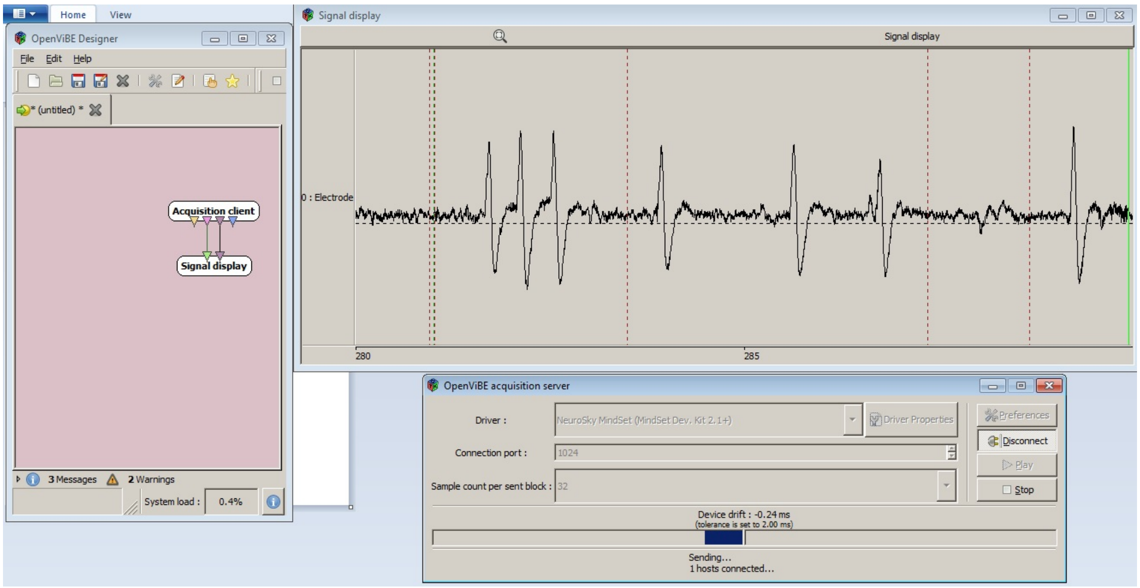


FIGURE 7.1: Real Time signals with eye blink

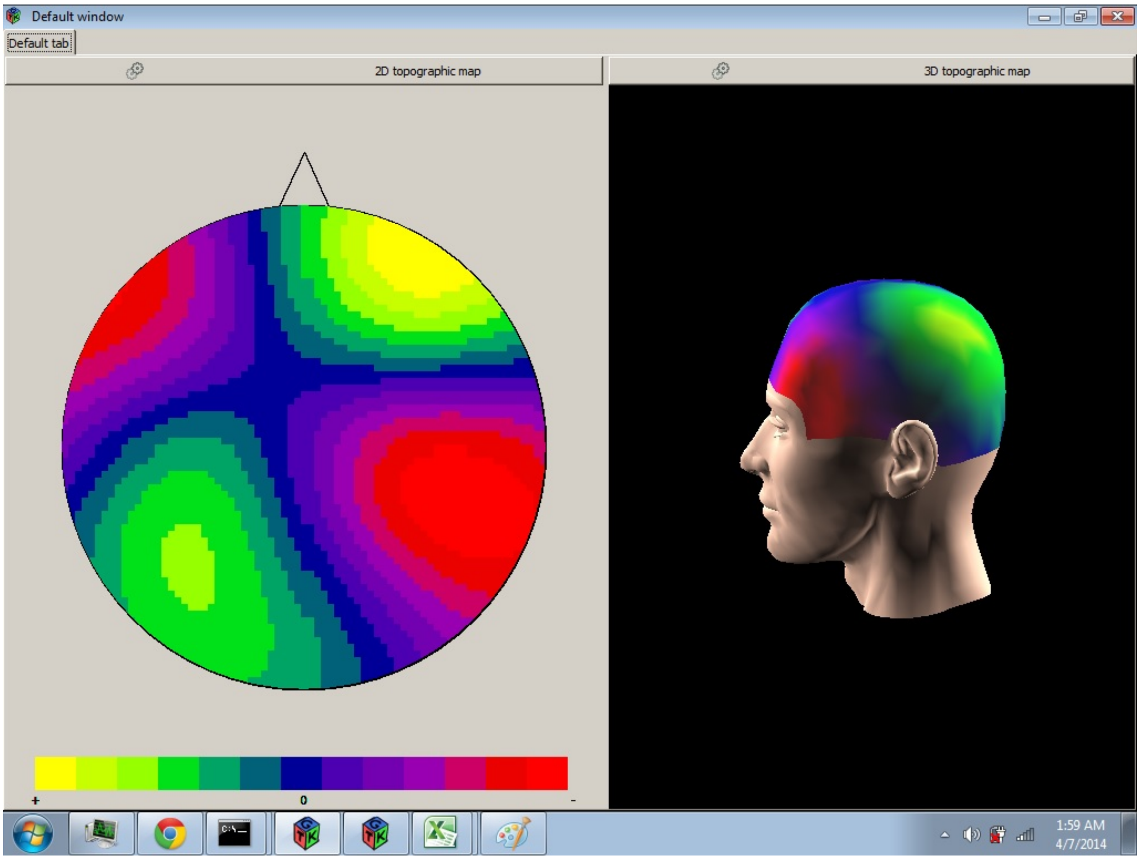


FIGURE 7.2: Topographical view of signals

Regarding the research questions, the following conclusions are made from the project findings:

RQ1: How could a single electrode placed on the forehead compensate a grid of electrodes places across the scalp?

The single dry electrode placed on the forehead can replace a grid of, or several electrodes is highly impossible. There are no papers of previous research or studies where single electrode have been used. The knowledge and experience from this study, is that mental tasks which are comparatively safe to classify did not happen. However, there can be other reasons besides single electrode, but at least it suggest that single electrode is not sufficient

RQ2: What are the advantages and limitations of single electrode headset?

The major limitation that was insightful with the single electrode headset was the static electrode location. It can be moved to a certain level, but not ample to get it away from the forehead. Also, one or two extra electrodes would have been great. Headset, featuring 14 electrodes would be the suggested option for this upgrade. It is a bit more expensive than single electrode headset. The limitation with the electrode position is that it is heavily influenced by eye blink and facial changes. However, the main requirement of dry electrode is placement of them in an area where there is no hair and subsequently forehead is a place where many people do not have hair.

7.1 Further Enhancement and Ideas

There are two main proposal for constant work with the system presented in this report.

1) Further development of the algorithm, improving signal processing, classification procedures and feature extensions.

This algorithm could be further build to control a remote application. A system build with signals from more number of electrodes would have high precision in classification of the signals. They are of great help for the physically impaired people, who would want to play a video game or drive a car. They could do this with the advancement in BCI technology just by imagining about it.

2) Use the current algorithm as a root for larger scale investigations with people, to do EEG surveys and monitoring studies.

- **More validations :** More number of verifications can be run over a period of time, to see if it is feasible to improve the control of system using brain waves. The aim and drive should be to surpass the need for the eye states, and rely on mental tasks only.
- **Research classification possibilities:** Describe new experiments to discover if there are other mental efforts that can be used for classification in the system. This could be turning, mental speech or specific recall.
- **Research placement possibilities:** Dismantle, if possible, the arm on the brainwave headset which clamps the electrode and find another placement for it. Check the possibility if those placements are suited for solving the classification tasks at hand. The troublesome part is that there can be no hair between the scalp and dry electrode

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