Selection of optimized feature and translation for discrimination of Brachium, Antebrachium and Carpus movement from EEG signals using EMOTIV head set

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Declaration

I hereby declare that this thesis contain literature survey, validation study and original research work by undersigned candidate as a part of his Master of Mechatronics Engineering studies.

All the information obtained and presented in this thesis document is accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Abstract

Brain Computer Interface (BCI) systems have ushered a new era of neural engineering research. At the core of BCI research is development of data acquisition, filtration and classification techniques that can accurately decode the brain activity that occurs while performing a motor task. In this study we investigate the classification accuracy of Linear Discriminant Analysis, Quadratic Discriminant Analysis, Naïve Bayes, Quadratic Support Vector Machine and Radial Based Function Support Vector Machine and Multilayer perceptron classifiers for classifying the flexion/extension of forearm and wrist. Moreover, Hjorth Parameters and Power Spectral Density are employed as feature extraction techniques to derive four different feature vectors that are later used to train our classifiers. At the culmination of this study, it is shown that QDA classifier trained with average band power (PSD) feature vector has the highest classification accuracy at 80.20% followed by Quadratic Support Vector Machine trained with Activity feature vector at 76.92%. Apart from enhancing accuracy of classifying the four fundamental upper limb movements, this study will eventually contribute towards developing better controllers for neuro-prosthetic devices. The study has been performed experimentally with Emotiv headsets equipped with fourteen electrodes to acquire EEG data from two human test subjects in synchronous mode. Classification and data analysis has been performed offline however in future the study will be extended to an online BCI system.

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CHAPTER 1: BRAIN COMPUTER INTERFACING

1.1. INTRODUCTION

Research has shown that evoked potential of the human brain not only represents brain function, but also the responses to actions or emotions. Thus it is inferred, that the response of central neural system is hormonal and neuromuscular in nature. This pattern of response, of the central nervous system, can be disturbed due to damaged nerve axons or amputations. Consequently the ability of such individuals to perform Activities of Daily Life (ADLs) is significantly degraded. It is hence imperative to restore the proper hormonal and neuromuscular response of the central nervous system of individuals with damaged nerve axons and amputations. In case of damaged nerve axons, the response can be corrected by repairing the damaged axons. However, for amputees, restoring the response of central nervous system to correct pattern is intractable. Thus, neuro-prosthetic devices are employed to harness the evoked potential of the brain and replicate actual limb movements. At the heart of such neuro-prosthetic devices lie Brain Computer Interfaces or BCIs for short. In fact, the BCI analyzes and processes the evoked potential arising from the central nervous system, and in response generates inputs for the controller of a neuro-prosthetic device.

Brain Computer Interface (BCI) systems are the hallmark of modern neural engineering research that promises to enhance the mobility and manipulability of patients who are unable to perform motor tasks such as upper and lower limb movements. BCI systems provide an alternate channel for flow of neural signals from brain to human muscles by bypassing the damaged conventional neural pathways[1]. Although BCI offers a wide array of possibilities in areas such as locomotion, environmental control, entertainment, motor restoration and communication control[2], one of the key application areas is the control of neuro-prosthetic devices for restoration of motor activities[3]. Neuro-prosthetic devices can be controlled by harnessing the evoked potential, which is a measure of neural activity across various lobes of the human brain, through a BCI. In fact BCI measures the evoked potential of central nervous system's response to an activity and generates control signals that can be used to control neuro-prosthetic devices[3].

Several brain activity monitoring techniques have been developed over the recent years that are used to measure the evoked potential of human brain. However in recent years, EEG has found rapid infusion in BCI research due to its non-invasive nature since the electrodes for detecting and recording neuro electrical signals, are placed on the outer surface of scalp. Contrary to ECoG which provides higher spatial resolution, EEG offers higher temporal resolution for monitoring of neuro electrical signals[4]. Among various motor activities, EEG has been applied to monitor neuro electrical signals generated during wrist and upper limb movements [5][3].

The underlying technology in BCI systems is machine learning, also known as pattern recognition. Various machine learning techniques are used to extract certain patterns from EEG signals. The patterns gathered from EEG signals are then employed for classifying different limb movements. The overall EEG data (or signal) acquisition and processing occurs in three stages namely; signal acquisition, filtration and preprocessing and feature extraction and classification. In the signal acquisition stage, EEG signals are gathered through electrodes placed on the skull, as directed by a well-defined protocol. During filtration and pre-processing, artifacts and undesirable components of EEG signals are removed through high and low frequency pass filters. The filtered EEG signals are composed of the desired frequency band that contains information on specific limb movements. This information is extracted from the filtered signals using feature extraction. Feature extraction is one of the key aspects of limb movement classification, and requires the formation of a distinctive feature vector. The feature vector should be built up of features that are free of non-stationary artifacts. Following the formation of an efficient feature vector, classification of the limb movements based on classification of the extracted features of EEG signals, is undertaken. To achieve maximum classification accuracy, selection of correct classification technique is as important as the extraction of useful features. Thus in this stage, multiple classification techniques and extracted features are tested to select the best performing classifier and feature combination. After selection of optimal classifier-feature pair, the EEG signals are classified into different limb movements and appropriate control signals for the neuro-prosthetic devices are generated.

In the last two decades, research into BCI systems was confined to three research groups only. However, today it is an active research area with over one hundred academic and dedicated research groups focused on developing low cost and effective BCI technologies. Such rapid growth and keen interest in BCI technologies has been driven by the promise of transforming the bio-medical landscape. Improvements in computer technology, in areas of both software and hardware, have paved way for more comprehensive analysis of brain signals and neurological data. With a rapidly ageing global population and increasing requirements for assisted living, research and development of BCI technologies needs to be further accelerated.

1.2. NEUROIMAGING TECHNIQUES:

Two types of brain activity can be monitored by using different types of neuro-imaging techniques.

- Electrophysiological
- Hemodynamic

Electrophysiological activity exchanges information between the neurons, which is generated by electro-chemical transmitters. Ionic current is generated by the neural activities, which flows inside or across different neuronal assemblies. Thus the ionic current flows from source to sink via dendritic trunk. This intracellular current is called primary current. The extracellular flow of current produced by mean of primary current is also called secondary current [2]. The main source of measuring Electrophysiological activity given below:

- Electrocorticography (ECoG)
- Magneto-encephalography (MEG)
- Electroencephalography (EEG)

Whereas in hemodynamic process, different physical activity cause to prominently activate neurons with the greater rate the neurons of inactive region, with the help of glucose emitted by blood. The glucose and oxygen delivered through the blood stream results in a surplus of oxy-hemoglobin in the veins of the active region, and in a distinguishable change of the local ratio of oxy-hemoglobin to de-oxy-hemoglobin[2]. These changes can be quantified by neuroimaging methods are:

- Functional Magnetic Resonance (fMRI)
- Near Infrared Spectroscopy (NIRS)

Hemodynamic process is indirect approach to measure electrophysiological activity but it is not able to directly image neuronal activity.

Table 1.1: Summary of NEUROIMAGING method

Neuroimaging method	Activity measured	Direct/ Indirect Measurement	Temporal resolution	Spatial resolution	Risk	Portability
EEG	Electrical	Direct	~0.05 s	~10 mm	Non-invasive	Portable
MEG	Magnetic	Direct	~0.05 s	~5 mm	Non-invasive	Non-portable
ECoG	Electrical	Direct	~0.003 s	~1 mm	Invasive	Portable
Intracortical neuron recording	Electrical	Direct	~0.003 s	~0.5 mm (LFP) ~0.1 mm (MUA) ~0.05 mm (SUA)	Invasive	Portable
fMRI	Metabolic	Indirect	~1 s	~1 mm	Non-invasive	Non-portable
NIRS	Metabolic	Indirect	~1 s	~5 mm	Non-invasive	Portable

Currently brain computer interface images brain activity through electroencephalography. Electroencephalography is a noninvasive technique, widely used for neuro- imaging due to its high temporal resolution, portability and a few risk to the end user. EEG based brain computer interfacing uses a set of sensors which acquire EEG signals from different lobes of brain. More over the quality of EEG data is most likely affected by the scalp, different types of brain layers and background noise. Noise is the most important factor which effects the electroencephalography and other neuro-imaging techniques. It reduces the probability to extract meaning full data from electroencephalographic signals by reducing signal to noise ratio (SNR). Partially and severely paralyzed patients have been successfully used noninvasive BCI techniques to control neuro-prosthetic devices.

1.3. TYPES OF BCI:

Various types of communication protocols are used in BCI systems. Two of the most important and popular BCI systems based on communication modes, will be discussed here. Two most frequently used protocols used in BCI are:

a. Synchronous Brain Computer Interface
b. Asynchronous Brain Computer Interface

Here we will define and discuss the difference between synchronous and asynchronous brain computer interfacing and explain that, why synchronous brain computer interfacing provides lower overhead and causes greater throughput in comparison with the asynchronous brain computer interfacing.

1.3.1. SYNCHRONOUS BRAIN COMPUTER INTERFACE:

When the data is transmitted by the sender it is necessary for the receiver to properly check the moment at which every character, cell or data set starts or vanishes. If the transmitter and receiver are interfaced according to niqust criteria, proper synchronization between the two occurs. This assures minimal loss of data and reduced lag with higher processing speeds. It does not offer more natural mode of iteration. It uses a pre-defined time window any data set out side this window is ignored.

Since the mental activity is already known, the user needs to give the commands in the pre-determined period of time. Niels et al used a thought translation device for the paralyzed patients. A comparison study on features and classifier is done using synchronous BCI. Two most common techniques studied in brain computer interface are linear classifier i.e Linear Discriminant Analysis (LDA) and Support Vector machine (SVM) and Dynamic classifier i.e Hidden markov model. These two types of classifier have not been compared with each other yet [2].

1.3.2. ASYNCHRONOUS BRAIN COMPUTER INTERFACE:

In asynchronous BCI, data is transferred without use of external clock. In this mode of communication the transmitter and receiver are not continuously engaged. Our ultimate requirement is to design such a BCI communication system which can operate in user driven mode. Some types of features like band power, frequency, AAR coefficient and fractal dimension are used and effective classifiers like Fisher linear discriminant analysis and support vector machine are used. Asynchronous BCI provides natural iteration, but its implementation and evaluation is relatively complex. The results of dynamic classifiers are not much precise in this field.

TABLE 1.2: Main differences between exogenous and endogenous BCI.

Approach	Brain signals	Advantages	Disadvantages
Exogenous BCI	– SSVEP – P300	– Minimal training – Control signal set-up easily and quickly – High bit rate (60 bits/min) – Only one EEG channel required	– Permanent attention to external stimuli – May cause tiredness in some users
Endogenous BCI	– SCPs – Sensorimotor rhythms	– Independent of any stimulation – Can be operated at free will – Useful for users with sensory organs affected – Suitable for cursor control applications	– Very time-consuming training (months or weeks) – Not all users are able to obtain control – Multichannel EEG recordings required for good performance – Lower bit rate (20–30 bits/min)

TABLE 1.3: Differences between synchronous and asynchronous BCI.

Approach	Advantages	Disadvantages
Synchronous BCI	– Simpler design and performance evaluation – The user can avoid generating artifacts since they can perform blinks and other eye movements when brain signals are not analyzed	– Does not offer a more natural mode of interaction
Asynchronous BCI	– No requirement to wait for external cues – Offers a more natural mode of interaction	– Much more complicate design – More difficult evaluation

1.4. AN OVER VIEW OF METHODOLOGIES USED IN THESIS

EEG signals are composed of six different bands or “rhythms” [5] which are

- Delta band (1-4Hz),
- Theta band (4-7Hz),
- Alpha band (8-13Hz),
- Beta band (13-30Hz)
- Gamma band (>30Hz)

Several studies have identified the usefulness of the gamma band in studying motor activities such as limb movements. This can be attributed the fact that gamma band exhibits enhanced power modulation prior to, during and after the execution of a limb movement[5][6]. Following the application of various filtration techniques to EEG signals, feature extraction and machine learning techniques can be used to classify upper limb movements[6].

Several studies on classification of limb movements have been performed with a large number of classifiers such as Quadratic Discriminant Analysis (QDA), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) by using features such as Power Spectral Density (PSD), Wavelet Transform, Auto Regression and Hjorth Parameters among others. Since the performance of a BCI system is tightly coupled with the performance of a classifier[2], varying levels of accuracy in classifying limb movements have been reported in these studies. Table 2.1-2.4 illustrates the various studies that have been performed through a combination of different classifiers and features for classification of several limb movements and motor imagery tasks.

In our study, a comparative analysis of the performance of Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naïve Bayes, Quadratic Support Vector Machine (Q-SVM) and RBF Support Vector Machine (RBF-SVM) has been performed in conjunction with Hjorth parameters and Average Band Power features for classification of four upper limb movements (wrist extension/flexion and forearm extension/flexion). At the culmination of our comparative performance analysis, a new combination of QDA classifier with PSD feature is proposed with a mean classification accuracy of 80.20%, for classification of forearm and wrist movements. To the best of our knowledge, no such work has been performed on accurate classification of the two forearm and two wrist movements with gamma band although this band contains prudent information regarding limb movements.

This thesis arranged as follows: Chapter II will discusses the existing BCI controlled systems and application. Chapter III will describe the data acquisition and test protocol need to acquire data. The advantages and specification of experimental setup will also be discussed in this section. More over this chapter also discusses the filtration and windowing technique. Chapter IV will briefly explains the feature extraction techniques used in this thesis. In Chapter V we will cover the explanation of complete architecture of six machine learning algorithms used to classify feature vector. The conclusion is drawn in Chapter VI. More over this chapter will discuss the validation study and Chapter VII will conclude the study.

1.5. SUMMARY:

This chapter discusses the basic theories behind Brain Computer Interfacing. More over this chapter describes various types of neuro-imaging techniques. Further we have discussed synchronous and asynchronous brain computer interfacing. A quick over view for the different EEG spectrums are given. Specifically we have considered ERS (event related synchronization) in low and high gamma frequency band to study aforementioned feature extraction techniques along with classifiers.

CHAPTER 2: LITRATURE REVIEW

2.1. INTRODUCTION:

Literature review is the important part of research. It provides us a path to trudge through. Analyses of previous work make us able to better understand the problem. After learning from previous research gaps, success of the researcher lies in exploring new aspect of problem and formulating a solution. Existing techniques, pertinent to BCI technology, are focused on determining how to generate control signals for a neuro-prosthetic device by harnessing the neural activity. Our thesis focuses on the optimization and analysis of the classification algorithm by selecting an efficient feature. Main aim of BCI in the field of biomedical engineering is to translate brain activity in to command for computer. This chapter provides us a quick over view of existing feature extraction and classification techniques used in BCI. It also describes various types of feature extraction techniques used to analyze spatial and frequency domain of electroencephalography. From this chapter we get an idea to analyzed and classify EEG based motor signal using Emotiv head set.

2.2. BCI APPLICATIONS USING EEG:

Different types of brain computer interface applications have been developed by the researchers. Thanks to the significant advancement in the area of BCI, especially EEG based BCI, quality of life for disabled people is set of improve. There are two potential groups, whom can benefit from effective BCI technology. First group is actually the patients who have either lost motor control or almost completely paralyzed. Second group of BCI potential users are the one with unsustainable neuromuscular control especially upper limb, lower limb, hand, locomotion control and speech control. Despite it, BCI is widely by the healthy persons for communication, environmental control and entertainment purposes. However currently in most application areas, BCI technologies are designed for demonstration and training purposes.

Recently three private organizations have shown their interest in this domain. They have designed hardware and software packages for BCI enabled control applications. These private startups and their product line up is presented below:

a. BVA Technologies - INC

- Control of digital video movies
- Control of music
- Home automation systems control

b. Emotiv EPOC
    - Used for gaming
    - Used for simulations

c. Smart Brain Games
    - Used in Biofeedback devices in the areas of Health, Learning and Entertainment.
    - Used in neuro feedback devices in the areas of Health, Learning and Entertainment.

Though BCI systems have become significantly advanced, yet there are still many challenges particularly for online tasks. One of the most important performance metrics in BCI systems is the evaluation is its accuracy of classifying various neural signal while executing a specific task. Consequently, the performance of BCI system and its application are different in each case. Five main areas of application related to BCI are described below.

2.2.1. COMMUNICATION CONTROL:

Developing a mode of communication between a human and computer is a very essential part of BCI. It deals with the communication disability due to neurological disorders. One of the most popular applications is the development of virtual on screen keyboard, where users can chose alphabets using BCI. Control of slow cortical potentials may be used to select alphabets. Depending upon this type of control signal, Birbaumer et al [7] developed an on screen display speller, which was used to control a cursor to select alphabet. This system was tested on two patients and they had achieved a rate of two characters per minute while writing text message. Another type of control application was developed to detect ocular artifacts or eye blink detection [8]. It was further used by different research groups for rejection of ocular artifacts in order to enhance the performance of classifier. This technique was also used to select the blocks or characters in a virtual keyboard [9]. Both above discussed techniques used the same approach, the virtual keyboard consist of a total twenty six English alphabets, twenty seven symbols and space to separate characters, organized in the matrix. Likewise, both applications used the same protocol for writing a single letter. Spellers have the spelling rate of one character in a minute [9]. Obermaier et al designed a speller based application including virtual keyboard using the standard Graz BCI [10]. Protocol for selection of letter was quiet identical to the previously discussed approaches. In the current case, motor imagery was used for the selection of letters and maximum spelling rate of speller achieved was 0.85 letters in one minute.

P300 event-related brain potentials are also playing an important role in BCI speller applications. BCI system using P300 mode of protocols have been proven suitable for paralyzed and partially paralyzed patients[10]. Due to consistent and spontaneous response of P300 protocol, it does not require much training and is portable. Furthermore, P300 based application products are commercially available due to its recent advancement [11].

Farwell and Donchin in 1988 have designed ever best P300 spellers. They have achieved the spelling rate of two characters per minute and it provides relatively high accuracy. By reducing perceptual errors the performance of Farwell and Donchin based P300 speller can be improved [12].

Ahi et al had improved the performance of Farwell-Donchin speller application. He minimized the number of false positives by using dictionary [13]. The dictionary proposed by Ahi et al is used to check the text misspelled or proposed word by the user. In case of misspelled text it provides certain suggestion accordingly.

Some other application of BCI related to communication is the control of Internet browsers. It is very important application for disables because nowadays internet has become the essential part of daily life. In the area of BCI an EEG based SCP controlled internet browser, called Descrates, was developed [14]. The main disadvantage of this application is that the limited number of internet pages can be browsed. Another prototype named Nessi was also developed to overcome previous issues and provide better usability [15]. Recently Jinghai et al developed an evoked potential based web browser. VEPs are also used to improve the functionality of browser [16]. ERPs based web browsers has an advantage of comparatively high surfing speed.

2.2.2. ENVIRONMENTAL CONTROL

From previous study we have realized that BCI plays an important role for the independence of patient. People suffering from the sever paralysis are home bound thus BCI based environmental control applications are very important for them. Brain computer interface based environmental applications are focused on the control of home appliances like lights, television, mouse control, joystick and etc. For the better assistance of these devices for patients, researchers are trying to make these assistive devices more efficient and less intensive. The work of Cincotti et al discussed the control of domestic environment via BCI technology [17]. In his work fourteen patients suffering from severe neurodegenerative disorder were considered. Fourteen test subjects tested a device which enabled the control of different types of peripheral devices. This application provides user to interact with the external environment via a BCI based application and it is supported by the different motor level with different capacities for every user.

Wei Tuck Lee et al had developed a brain computer interface for smart appliances using Emotiv head set[18]. He developed a virtual room environment which allows indoor and outdoor access like TV control, light control, temperature control and door opening/closing. These applications were embedded in to a GUI which is used to select the desired home icon via raising eyebrows (single or multiple smirks). Initially four test subject were used to train and test the system [18]. A similar application was developed by Dong Ming et al In his work, EEG controlled mouse control system were designed to control the movements of curser in four directions via motor imagery[19].

An adaptable learning technique is used to recognize the cursor control pattern in multi class EEG spectrum. Mahalanobis distance classifier was used to recognize the pattern and produce the trigger signal to control cursor. The maximum classification accuracy achieved by this system was 80% [19].

Invasive BCI have also been used in different environmental control applications. Hochberg et al implanted Brain-Gate sensors in the primary motor cortex of a tetraplegic patient for cursor control. In this work patient could access and control e-mail applications and operate various home appliances via motor imagery [20].

2.2.3. LOCOMOTION:

BCI plays an important role in the area of navigation and transportation. BCI is nowadays use in navigation and transportation. Portability is very important in these types of applications. We know that EEG signals are very sensitive to noise and highly random, that is why delay between commands causes high uncertainty. Due to this issue, Serruya et al uses invasive technique to acquire EEG data from a monkey [21]. He implanted electrodes in the motor cortex of the monkey since invasive technique of data acquisition provides high spatial resolution. Initial experimentation showed that monkey was able to control cursor. Locomotion based applications were also used to control wheel chair, steer a tractor and continuous control of various mobile robots in a controlled environment.

Literature survey suggests that, Tanaka et al in 2005 had developed the first application to control wheelchair using EEG [22]. In his work, the user could maneuver on the floor by motor imagery i.e. user decide to move toward left or right by imagining left limb or right limb movements respectively. Six test subjects were used to train and test the system. Thus the demonstration of wheel chair control via EEG signal showed liability and the results was pretty encouraging. But low data transfer rate and accuracy provided by this BCI system showed that there was still room for more advancement. Different improvements have been proposed during past few years. Synchronous BCI based on P300 protocol have been introduced which assure better performance. It has overcome the low data transfer rate and reduces number of iterations. Rebsamen et al [23] designed designed a simplified control of wheelchair that uses a guide path defined by patient. These guide paths were automatically accessed by the wheel chair and the system uninterruptedly receives the information about the direction. User was required to select the destination and only had to decide when to start and stop the wheel chair. Autonomous maneuvering of wheelchair depended on an odometer and a bar code scanner placed on the floor along the paths. The preceding research was not capable of dealing with the populated and unknown scenarios for path planning of wheel chair or mobile robot. Iturrate et al proposed a dynamic system which has capability to modify the surrounding scenarios[24].

Different studies showed that user needs help while driving wheelchair to tackle with the complex environment[25]. Three levels of assistance may be possible in the shared control like obstacle avoidance and orientation restoration, which can be only activated as per patient requirement[25]. Before getting direction by the user, the shared control inspect the situation from data delivered by laser scanner. Scanner inspect the whole scenario and formulate a decision to avoid obstacle.

Jaime Gomez-Gil et al had used Emotiv head set to steer a tractor [26]. Emotiv head set provide a low cost data acquisition and processing solution. It is equipped with fourteen saline electrodes as discussed in previous chapter. A single test subject is used to train and test the system. In this application system can be controlled via both eyes looking to the right and jaws opened, both eyes looking to the left and jaw opened, both eyes looking to the right and jaw closed and eyes looking to the left and jaw closed. In his work system performance was compared with the manual and GPS based guidance. Initial experimentation showed that the performance of BCI based system to steer tractor is lower than the manual guidance. All three systems were tested to follow the straight line, BCI controlled system shows deviation of 16 cm from the straight line, via GPS guidance, system shows deviation of 4cm and manual guidance shows deviation of 9cm form the desired path. Thus the work of Jaime Gomez-Gil et al proved that it is possible to steer the tractor for agriculture purpose using Emotiv headset. Since standard deviation of error to the desired trajectory in actual environment showed that, the difference is acceptable for most of the agricultural tasks [26].

2.2.4. ENTERTAINMENT:

Video game industry has too adopted the entertainment based brain computer interface technology. Some of the entertainment oriented BCI applications include packman game, pong, pinball, tennis computer game, world of war crafts and etc. This application plays an important role in evaluating brain tasks. S. Hjelm et al in 2000 developed a game named Brainball [27]. The concept of this game is to become more relaxed than your competitor. Alpha and beta rhythmus were considered as the measure of relaxation. Pineda et al, in 2003 developed a BCI controlled 3D shooter game. In this game, keyboard was used to control forward and backward movements, while left and right movements were controlled via BCI. 3D shooter game via BCI were tested and trained by four test subjects.

In 2011 Lopetegui et al has developed and presented his work in the 16th international conference of computer games [28]. His work was focused on the development of EEG controlled tennis game. Data was collected from the three sensors over motor cortex, only the mu rhythm were considered (8 – 12 Hz). Supervised learning algorithm were used to distinguished between three movements of tennis avatar (Upward and downward vertical movements and neutral state) using EEG signal from somatosensorial and motor cortex, were along Simple direct media layer library is used to interface learning algorithm with HMI. The work of Bram van de Laar et al was also of great importance in the area of EEG controlled computer gaming[29]. He had introduced the two avatars in his application: one was bear shaped and other was druid shaped. His experimental setup consisted of Emotiv headset[29].

Brain computer interfaces are not only used to aid disabled or paralyzed persons with motor substitution, motor recovery, and novel communication possibilities, but also as a modality for healthy users in entertainment and gaming.

2.2.5. MOTOR RESTORATION:

Spinal injury and different types of neurological diseases associated with the loss of motor functions badly affect the quality of patient's life and create dependency to access the basic services. There are two ways to help paralyzed or disable persons and to make them a valuable part of our society and independent.

- Repair the damaged Nerve Axon
- Develop a Neuroprosthetic device

Most of the time successful restoration of motor function is possible. It may relieve their social and psychological sufferings. But in some cases of severe spinal cord injury or the loss of limb repairing of nerve axon is useless. EEG-based brain computer interface have been developed to control neuroprosthetic devices because EEG signals are unaffected by electrical activation of upper extremity muscles. Today BCI is a fast-growing emergent technology in the area of prosthesis control through EEG signals. Miguel Nicolelis, a professor at Duke University, in Durham, North Carolina, has been a prominent proponent of using multiple electrodes spread over a greater area of the brain to obtain neuronal signals to drive a BCI. Such neural ensembles are said to reduce the variability in output produced by single electrodes, which could make it difficult to operate a BCI. A precise survey of existing control techniques associated with the real movement or motor imagery is presented below.

2.3. EXISTING CONTROL TECHNIQUES FOR MOTOR ACTIVITY:

The work of Petar Horki et al is quiet identical to our work. In his work O1, O2 and Cz sensors location were used to acquire data. SSVEP BCI was used to trigger hand and forearm movements (extension and flexion) and the average number of correctly classified instants was 76 + 4% [33]. Whereas our work involves a different electrode placement sssas shown in the Fig 1B. The mode of data acquisition protocol is quiet similar to the work of Petar Horik et al [30]. The classification accuracy achieved by Horik et al was 76+ 4% [30] while we achieved the mean classification rate of 80.20% using QDA with PSD feature.

The work of Neethu Robinson et al used Regularized Wavelet-Common Spatial Pattern as a feature to classify upper limb movement in four orthogonal direction using Fisher linear discriminant analysis to achive classification accuracy of 80.24%[5]. His experimental setup used F3, F4, FC5, FC6, C3, C4, CP5, CP6, P3 and P4 electrodes to record data. EEG data was recorded usinng a Neuroscan Syn Amps equipped with128 channel. The data acquisation protocol involves 2D movements in four directions using right hand while holding the MIT MANUS robot. MIT MANUS robot recorded the position, velocity and force applied by the hand in two dimensional space at every instant. A display screen placed in front of the subject provided the preparation, rest and movement cues. The subjects were instructed to minimize eye movements to reduce EOG artifacts.

Ricardo C Caracillo et al [31] also followed the same 10-20 electrode placement system. He uses the following channels for data acqusitatiion: O1, O2, P3, P4, C3, C4, F3 and F4. RC Caracillo et al estimated mean power of EEG signal using PSD and then used LDA for the classification of four upper limb movement with the accuracy of 83.69% (Hand v/s arm) 67.95% (Right v/s Left limb).

Gernot R. Müller-Putz et al developed a controller for neuro prosthetic device using asynchronous BCI based on steady state visual evoked potentials (SSVEPs)[32]. User could control the two dimensional prosthetic hand movements via EEG signal. Four healthy test subjects were participated to train and test the system. The movements were classified into right hand close, right hand open, wrist clock wise and wrist counterclock wise movements. The online classification accuracy of system was found to be 44% and 88%. While controlling neuro prosthetic hand through asynchronously mode, the test subject reached a performance of 75.5s to 217.5s to copy a series of movements, whereas the duration of fastest response was 64 s. The number of false negatives varied from 0 to 10. It could be stated that the SSVEP-based BCI, operating in an asynchronous mode, was feasible for the control of neuroprosthetic devices.

EEG

Anwesha Khasnobish et al classified the left/right arm movement [33]. Author's work classified the raw EEG for left hand and right hand movement, followed by further classification of each hand movement into elbow , finger and shoulder movements. EEG data was acquired from the two electrodes namely, C3 and C4. Features were calculated by using power spectral density (PSD) estimation and wavelet coefficients estimation form the alpha and beta frequency bands. Depending upon these features the quadratic discriminant analysis, linear support vector machine and radial basis function support vector machine were used to classify the movements. For left hand verses right hand movement, the maximum classification rate was achieved by radial based function support vector machine by using wavelet coefficient feature. The maximum classification accuracy was 87.50% . For the multi-class classification, i.e. discrimination between Finger movement, elbow movement, and shoulder movement classification the maximum classification accuracy of 80.11% for elbow, 93.26% for finger and 81.12% for shoulder was obtained using power spectral density as a feature for RBF SVM.

Saugat Bhattacharyya et al used BCI competition II 2003 dataset provided by the University of Technology, Graz to analysis the performance of linear discriminant analysis, K nearest neighbours and qudratic discriminant analysis[4]. After preprocessing the signals from C3 & C4 electrodes, the feature were acquired from the data set using wavelet coefficients, and PSD of the alpha band, further mean power of the associated bands had also considered as features for classification purpose. Three different learning algorithms were used to discriminate between left and right hand movements. Firstly, features were individually fed in to classifiers and all features were tested together and fed them to QDA, LDA and KNN classifiers. The total feature vector which consisted of all features i.e. wavelet coefficients, PSD and average band power estimate performed better with the machine learning algorithms and showed less variation as compared to the individual feature estimation techniques. The maximum classification achieved by LDA, QDA and KNN is 80%, 80% and 75.71% respectively. Wavelet coefficients performed best with QDA classifier with an accuracy of 80%. PSD vector resulted in superior performance of 81.43% with both QDA and KNN. Average band power estimate vector showed highest accuracy of 84.29% with KNN algorithm. Table 2.1, 2.2, 2.3 and 2.4 showed the literature survey for classification of different ERD/ERS.

For spinal cord injured persons Gernot et al had restored the grasp function by developing a BCI controlled [32]. Steady state visual evoked potentials (SSVEP) was used to control four movements of two axis prosthetic hand based on self pased asynchronous mode of communication. Four healthy and neurologically stable persons were participated to train and test the system. During on line classification maximum and the minimum accuracy was 44% and 88% respectively. By using steady state visual evoked potentials based system, multi class classification was found to require less training. However, since it required ocular contacts, it has low demand as compared to the other BCI systems and user may not necessarily concentrate on the motor imagery simulations. In fact, the user could shift his attention to another stimuli while trainning. Gert Pfurtscheller, Gerd Korisek, Herbert Gaggl, Brendan Z. Allison and Rupert

Ortner developed an appalication of orthosis control[34]. The BCI application or system could be controlled by asynchronous mode of communication i.e. the subjects could perform task without any external guidance, whenever they want. Seven subjects were chosen to perform four upper limb movemets based on Steady State Visual Evoked Potentials. An asynchronous SSVEP based BCI system or application can be used to control two degrees of freedom artificial limb [35]. In this work the SSVEP based BCI was used to toggle orthosis open, orthosis closed, elbow extension and elbow flexion. Eight healthy subjects and a paraylsed patient were able to control the neuroprosthetic device online. Total number of correctly classified instants were varying from 69% to 83% where average number of true positive were 76% and the false negative rate varying between 1% to 17%.

Pfurtscheller et al [36] had developed a brain computer interface system for tetraplegia patient. In his work he used motor imagery induced beta bursts to open and close an orthosis. The patient was taken in consideration for several months of training. After training, patient was able to better control the system with 100% accuracy. Imagery movements were considered for training i.e. imagined right hand movement and both feet imagined movements. The spatial features were used to discriminate foot motor imagery. This type of motor imagery-based orthosis generally requires long training times to achieve control over brain waves.

Xiao-Dong ZHANG et al analyzed the EEG signal to discriminate multi class hand movements [37]. Two different methods were analyzed to investigate EEG patterns for the control of a neuro prosthetic hand. Four activities were recorded to train the setup, which includes arm extension, arm flexion, hand crawl and open. Through number of on line and offline trials were recorded to discriminate EEG signals. By using band power feature extraction technique and neural networks classifier, multi class hand movements had shown prominent results.

Christoph et al presented an EEG-based rapid prototyping, which could perceive the imagined task. It could be either left hand or right hand movement using an linear discrimination analysis and AAR model[35]. Similarly the work of Ramoser et al introduced an optimal spatial filtering technique of a single trial EEG while imagined hand movement [38].

Bianchi et al proposed a time frequency analysis and spatial filtering technique to evaluate the event related synchronization in the beta band of EEG corresponding to fingers movements[39]. Erfanian et al discussed the enhanced resource allocation neural network to discriminate the hand movement via EEG signals[40]. Mahmoudi et al presented a new approach to control the orthosis via EEG signals for amputee test subject[41]. Kurillo et al. analyzed electroencephalographic correlation for tracking grip force, and proposed different correlsation analysis between orthosis grasping and orthosis relaxation[8].

Table 2.1: Accuracy of machine learning algorithms in movement intention based BCI.

AUTHORS	PROTOCOL	FEATURE	CLASSIFICATION	ACCURACY	REFRENCES
Y. Wang et al	BCI Competition 2003 Data set IV	ERD	Perceptron	84%	[42]
M. Congedo et al		CSP	Perceptron	83%	[43]
W. Xu et al		PCA + CSP	Support Vector Machine	90%	[44]
K. R. Muller et al	Finger on different Data set	Amplitude value of EEG	Gaussian Support Vector Machine	93.3%	[30]
			Linear Support Vector Machine	92.6%	
			RF Linear Discriminant Analysis	93.7%	
			Linear Discriminant Analysis	90.7%	
			K Nearest Neighbor	78%	
B. Blankertz et al		Amplitude value of smoothed EEG	KNN	78.4%	[45]
			Linear Support Vector Machine	96.8%	
			RF Linear Discriminant Analysis	96.7%	
			Linear Discriminant Analysis	96.3%	
G. Pfurtscheller et al		Band Power	Neural Networks	85%	[46]
S. G. Mason et al	Finger in asynchronous mode	Bi scaled Wavelet	Neural Networks	81%	[47]
J.F. Boriso et al		Normalized Wavelet		97%	[48]

Table 2.2: Accuracy of classifiers in pure motor imagery based BCI: two-class & and synchronous

AUTHORS	PROTOCOL	FEATURE	CLASSIFICATION	ACCURACY	REFERENCES
S. Lemm et al	On BCI competition 2003 Data set III	Morlet Wavelet	Bayes Quadratic	89.3%	[49]
K. Tavakolian et al		*regate Average Rule*	BGN	83.57%	[50]
			Multilayer Perceptron	84.29%	
			Bayes Quadratic	82.86%	
S. Solhjoo et al		Raw EEG	Hidden Markov Model	77.5%	
		Power Spectral Density	Gaussian Classifier	65.4%	[51]
			Linear Discriminant Analysis	65.6%	
			Bayes Quadratic	63.4%	
			Mahalanobis Distance	63.1%	
Saugat Bhattacharyya et al	On BCI competition 2003 Data set II	Wavelet coefficients	LDA	48.57%	[4]
			QDA	80%	
			KNN	65.71%	
		Power Spectral Density	LDA	80%	
			QDA	81.43%	
			KNN	81.43%	
		Average band power estimate	LDA	78.57%	
			QDA	77.86%	
			KNN	84.29%	

Table 2.3: C_1 be the imagined left hand movements, C_2 be the Imagined right hand movements, C_3 is Imagined lower limb movement. Accuracy of Classifiers for motor imagery.

AUTHORS	PROTOCOL	FEATURE	CLASSIFICATION	ACCURACY	REFERENCES
A. Rakotomamonjy et al	BCI Competition 2003 Data set II b (P300 Speller)	RAW EEG Signals	Voting With Linear SVMs	100% 4 Repetitions	[52]
			Linear Support Vector Machine	100% 10 Repetition	
U. Hoffmann et al			Boosting With OLS	100% 4 Repetitions	[53]
M. Kaper et al			Gaussian Support Vector Machine	100% 5 Repetitions	[54]
V. Bostanov et al		Wavelet Transform	Linear Discernment Analysis	100% 6 Repetitions	[55]
J. Kalcher et al	$C_1 + C_2 + C_3$ On different Data set	Band Power	LVQ Neural Network	90%	[56]
B. Obermaier et al		Band Power	Hidden Markove Model	77.5%	[57]
F. Cincotti et al	$C_1 + C_2$ In asynchronous mode	Wlench Power Spectral Density	Mahalanobis Distance	90%	[17]
			Gaussian Classifier	80%	
			Hidden Markove Model	65%	
R. Scherer at al	$C_1 + C_2 + C_3$ In asynchronous mode	Band Power	Linear Discernment Analysis	95%	[58]
Saugat Bhattacharyya et al	BCI Competition 2003 Data set II	Wavelet Coefficient + PSD + Average Band Power	LDA	80%	[4]
			QDA	80%	
			KNN	75.71%	

Table 2.4: Accuracy of Classifiers for motor imagery and different types of movement execution data Protocol.

AUTHORS	PROTOCOL	FEATURE	CLASSIFICATION	ACCURACY	REFERENCE
J. Zhou et al	shoulder/elbow torques using 10/20 electrode placement system	Principal Component Analysis + Hilbert transformation	K Nearest Neighbor	89.9%	[59]
			Regression Tree	84.9%	
			Support Vector Machine	92.9%	
Ricardo C. Caracillo et al	Right and Left Limb execution	Periodogram Mean Power	Linear Dsiciminent Analysis	67.95%	[31]
	Hands versus arms			82.69%	
Liao. K et al	Thumb V/s index Finger	PCA+Moveme nt Related Spectral Changes	Support Vector Machine	71.27%	[60]
	Thumb V/s Middle Finger			74.34%	
	Thumb V/s Ring			77.55%	
	Thumb V/s Little			78.16%	
	Index V/s Middle			69.15%	
	Index V/s Ring			73.48%	
	Index V/s Little			79.64%	
	Middle V/s Ring			71.15%	
	Middle V/s Little			77.49%	
	Ring V/s Little			80.21%	
G.V. Sridhar et al	On Different EEG data	PCA	Multi-layer Perceptron	85.71%	[61]

Table 2.5: Properties of classifiers in Brain Computer Interfacing

Classifier	Linear	Nonlinear	Generative	Discriminant	Regularized	Stable	Un-stable	High dim. Robust
LDA	X			X		X		
QDA		X		X		X		
Linear SVM	X			X	X	X		X
Quadratic SVM		X		X	X	X		X
RBF SVM		X		X	X	X		X
MLP		X		X			X	
Naïve Bayes		X	X	X			X	
KNN		X		X			X	
NN		X		X			X	

Matthew S. Fifer et al [35] used intracranial electroencephalographic (iEEG) signals from two human subjects to control reaching and grasping movements with the Johns Hopkins University Applied Physics Lab (JHU/APL) Modular Prosthetic Limb, a dexterous robotic prosthetic arm. In his work he performed functional mapping of high gamma activity while the subject made reaching and grasping movements to identify task-selective electrodes. Independent, online control of reaching and grasping was then achieved using high gamma activity from a small subset of electrodes with a model trained on short blocks of reaching and grasping with no further adaptation. Mean classification accuracy, during independently executed over reach and grasp movements, for Subject 1 and Subject 2 were %85%, 81% and 80%, 96% respectively. Whereas simultaneous execution meant that classification accuracy was 83%, 88% and 58%, 88% respectively. We demonstrate the potential feasibility of verifying functionally meaningful iEEG-based control of the MPL prior to chronic implantation, during which additional capabilities of the MPL might be exploited with further training.

The above work implies that non motor area over the cerebral cortex is also of great importance. Similarly Table 2.1 – 2.4 shows the complete comparison study of feature extraction and classification techniques of other research groups used to discriminate different types of upper limb movements or motor imagery.

2.4. SUMMARY:

A thorough review of prior research into the problem of accurate classification of neural signals is driven by the need to substantially improve over existing techniques. Considerable works has been done till date to explore EEG based BCI, changes of EEG due to motor imagery, different algorithm for feature extraction and classification of EEG due to motor imagery and different control techniques with the help of imagery signal. While some studies may not present a significant leap forward, others are path breaking since they have enabled future researchers to think differently. Therefore, a detailed study has been undertaken regarding previous work that ultimately helps us to formulate and propose a new set of BCI classifier-feature combination for enhanced accuracy. This chapter has discussed various areas of BCI controlled applications and systems, like communication control, environment control, entertainment control, locomotion control and motor restoration.

CHAPTER 3: DATA ACQUISITION AND FILTRATION

3.1. DATA ACQUISITION:

In our study EEG signals were gathered from two healthy h uman test subjects who were verified to be neurologically and physiologically stable. The signals were recorded using an Emotive headset equipped with fourteen electrodes. The electrodes were placed on the scalp of each test subject according to the 10-20 placement system, which is an internationally adopted system that defines the placement of electrodes on test subjects for recording EEG signals[25]. The 10-20 placement system has been standardized by American Electroencephalographic Society as illustrated in Figure 3.1 A. For data acquisition, a test protocol based on the P300 protocol was devised after consultation with the ethical rules and regulations committee at the National University of Sciences and Technology, Pakistan. Two human test subjects aged 24 years and 28 years participated in a series of tests that required them to perform a set of forearm and wrist movements. Details of the test protocol are presented below.

The test protocol was devised to accurately record the EEG signals generated as the test subjects performed a pre-determined set of forearm and wrist movements. To enhance the accuracy of our test protocol, the two test subjects were asked to take one week of training for EEG recording. During our test trials, the subjects were seated in a comfortable chair with arm rests and asked to perform decoupled upward and downward movements of the right forearm and wrist. To avoid the inclusion of any undesirable noise and artifacts in our EEG signals, the test subjects were instructed to avoid any facial expressions and eye flickering. Thirty trials were performed on each test subject for a total of sixty data sets.

At the beginning of each trial the test subject was instructed to look at a computer screen which initially displayed a blank ticker. When the ticker started rolling, the test subject was given a time of five seconds to relax, blink or generate facial expressions. At the end of five seconds a red marker rolled into test subject’s view and the test subject was asked to perform a complete upward movement of right forearm in eight seconds after which another red marker appeared on the ticker which instructed the test subject to relax for another five seconds. The process was repeated for one downward movement of right forearm, one upward movement of wrist and one downward movement of wrist.

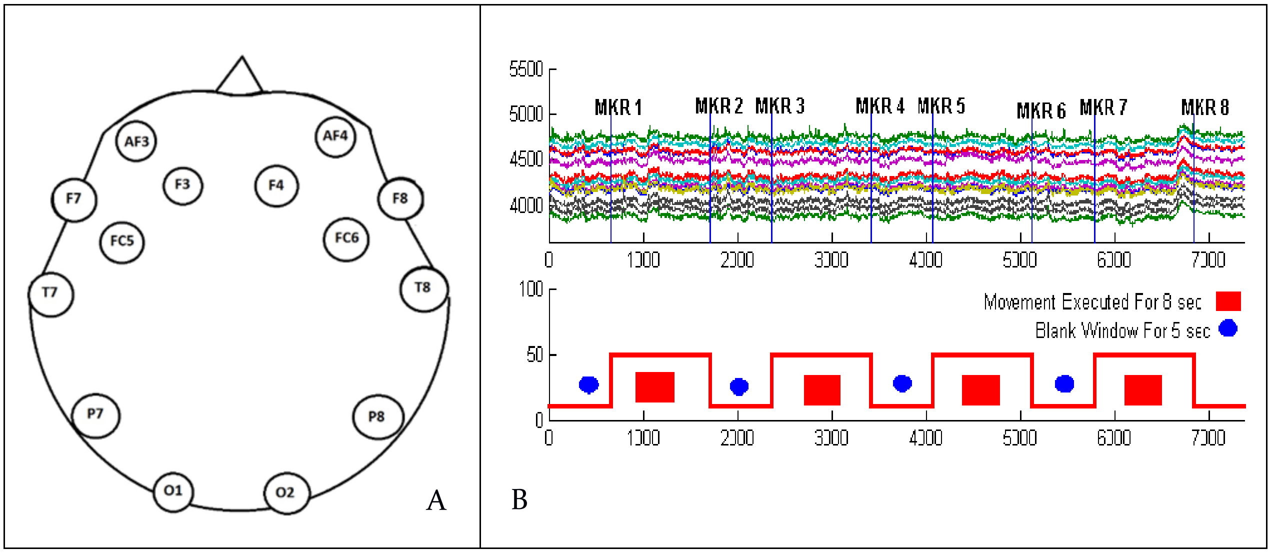

Figure 3.1 A: 14 Electrodes positioning over scalp. **B:** Single trial experimental paradigm as per test protocol.

The complete trial took fifty two seconds and was performed at a data sampling frequency of 128 Hz. Figure 3.1 B presents all the individual steps that were performed in a single trial.

Steps of Protocol:

1. Send marker no.1

   Move Right arm up…………………….... (8.-sec)

   Send marker no.2

2. Send marker no.3

   Move Right Arm down…….................... (8-sec)

   Send marker no.4

3. Send marker no.5

   Move Right wrist up ………………….... (8-sec)

   Send marker no6

4. Send marker no.7

   Move Right wrist Down………………...(8-sec)

   Send marker no 8

Figure 3.2 illustrate the four movements of the right forearm and wrist that were performed by each test subject. Figure 3.3 illustrates the underlying steps of our study ranging from data acquisition to classification (through different classifiers and features).

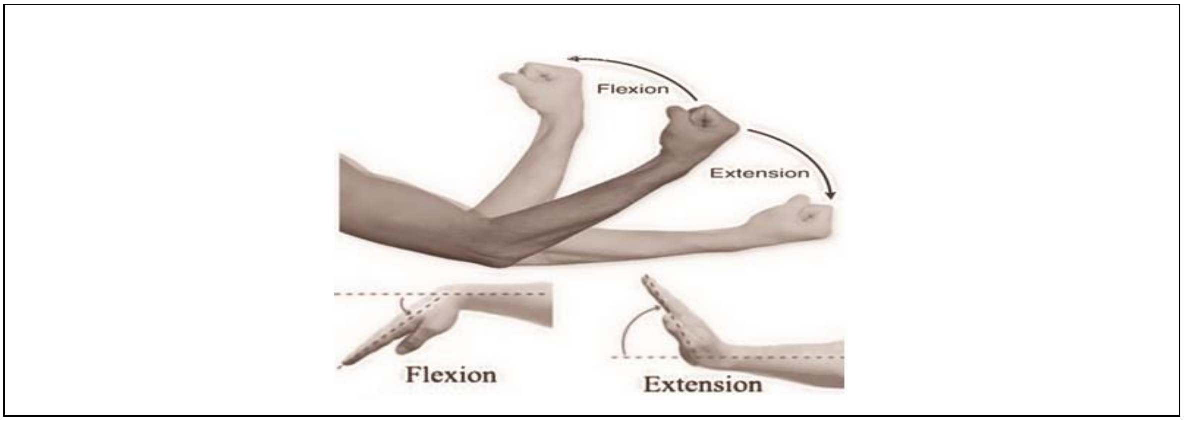

Figure 3.2: Test protocol for forearm and wrist (Extension/Flexion) for recording of Electroencephalographic data acquisition system.

1051 samples of data were recorded in each eight second upward or downward movement of the right forearm and wrist. Furthermore our study employed synchronous BCI for classification of the EEG signal data that was gathered during each trial. In synchronous BCI, EEG signals are analyzed during predefined time windows. Unlike asynchronous BCI, the onset of mental activity is known in advance and associated with a specific cue which ensures that artifacts generated by an unwanted movement or expression during the limb movement is avoided. Several letters in each location corresponding to specific brain regions in such a way that each letter represents different lobes.

- “A” represents Ear lobe
- “C” represents Central Region
- “Pg” represents nasopharyngeal
- “P” represents Parietal lobe
- “F” represents Frontal lobe
- “Fp” represents Frontal polar lobe
- “O” represents Occipital area

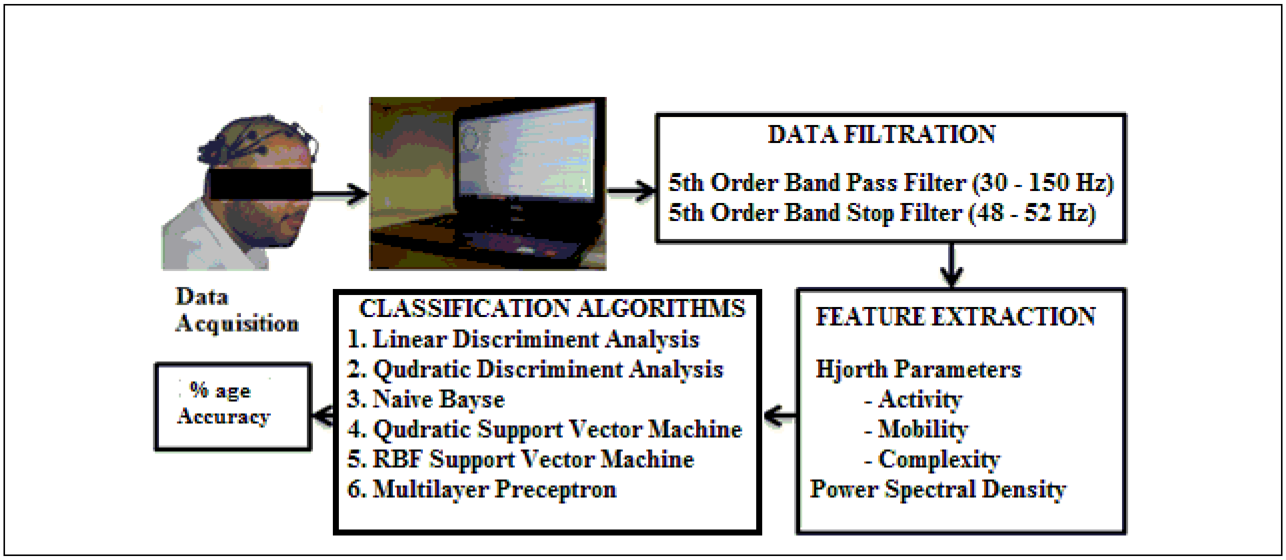

Figure 3.3: Schematic Diagram of Brain Computer Interface System for the Classification of Four Upper Limb Movements.

3.2. FUNDAMENTAL REQUIREMENT FOR DATA COLLECTION:

There are three fundamental requirements in data collection phase which assure that weather the given or used setup is feasible and reliable in real life. These fundamental requirements are

- Universality
- Consistency
- Collectability

First requirement for data acquisition step is universality, which means that all users are familiar with the system and they should be able to properly use the system. When we are talking about second fundamental requirement consistency, so we have noticed that EEG signals vary with time. It gets weaker and weaker by the age. One should assure the consistency of EEG signals that it should remain constant over time. Now considering the third requirement collectability, the most obvious thing in this is the use of Epoc Emotiv Head set. Users should assure the placement of sensors in the same place each time while recording. But it requires training of end users. Further the use of Emotiv head set is not comfortable when user where it for a long interval of time. Yes these are some of the problem currently faced by the users but we think that these are solvable issues.

3.3. FILTRATION:

After raw EEG signals have been acquired from sixty trials on two human test subjects, filtration techniques are applied to extract gamma band (30-150Hz) from raw EEG signals. Gamma band or “rhythm” signals in the raw EEG signal data contain information about certain motor functions and perceptions[62]. Several studies have revealed that during muscle contraction, a relationship exists between motor activity and gamma rhythms[63].However, other studies have pointed out that beta rhythm (13-30 Hz) originates during weak muscle contraction which suggests that a correlation exists between gamma or beta rhythm and muscle force[64].

Earlier gamma rhythms were not studied extensively in BCI research due to presence of undesirable ECoG and EMG artifacts [65]However, due to higher spatial resolution and data transfer rates, the gamma band has lately received a renewed and growing interest in BCI research. To extract gamma rhythm from the acquired EEG data set, a 5th order band pass filter was applied to extract gamma rhythm between 30-150 Hz. The gamma rhythm contains two distinct frequency ranges; the low frequency gamma band that falls between 30-50 Hz and a high frequency gamma band that extends from 50-150 Hz.

$$H(z) = \frac{b(1) + b(2)z^{-1} + \ldots + b(n+1)z^{-n}}{1 + a(2)z^{-1} + \ldots + a(n+1)z^{-n}} \tag{3.1}$$

Where H(z) is the Butterworth filter. Figure 3.4 Topoplots shows *ERS* and Time scaled power distribution from start to the end of four upper limb movements. Figure 3.4 (A & B): Are topographic distribution for single trial EEG data associated with wrist movement extension and flexion respectively. Figure 3.4 (C & D): Are Scalp Topography for single trial EEG data associated with elbow movement flexion and extension respectively.

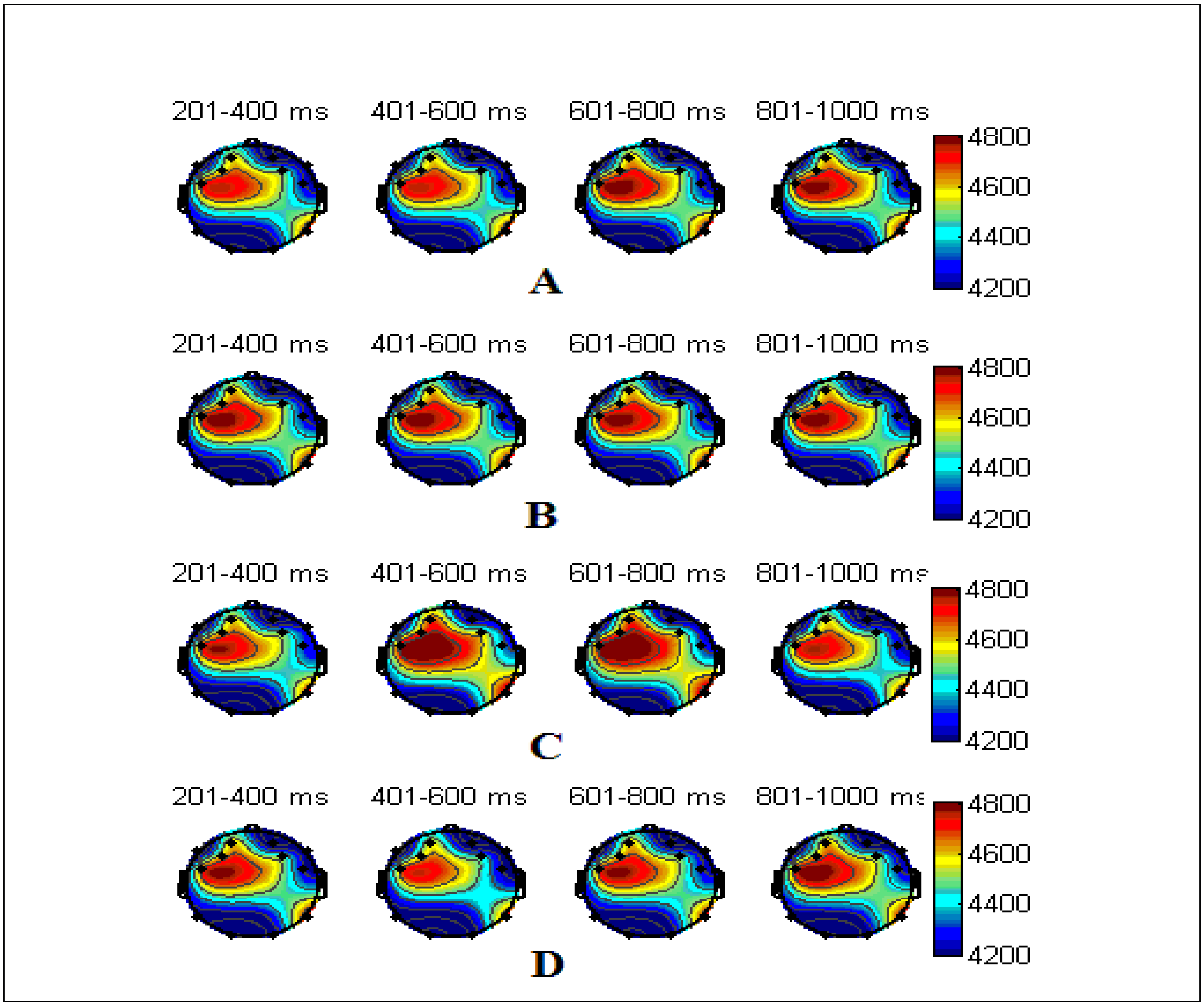

Figure 3.4: Topoplots shows *ERS* and Time scaled power distribution from start to the end of four upper limb movements. **A & B:** Are topographic distribution for single trial EEG data associated with wrist movement extension and flexion respectively. **C & D:** Are Scalp Topography for single trial EEG data associated with elbow movement flexion and extension respectively.

An interesting aspect of our study is illustrated in Figure 3.4, where it is evident that the evoked potential generated in response to movement of forearm and wrist is being recorded in other areas beside the sensorimotor area. This can be explained by the fact that as a result of volume conduction. Figure 3.5 shows contour-plots and head-plots for forearm and wrist (Extension/Flexion). Contour plots shows interpolation b/w the sensor *F3* and *F4* for the four particular tasks from two test subjects. Whereas Head plots shows event related synchronization

(*ERS)* and Time scaled power distribution over left hemisphere of frontal lobe for particular movement

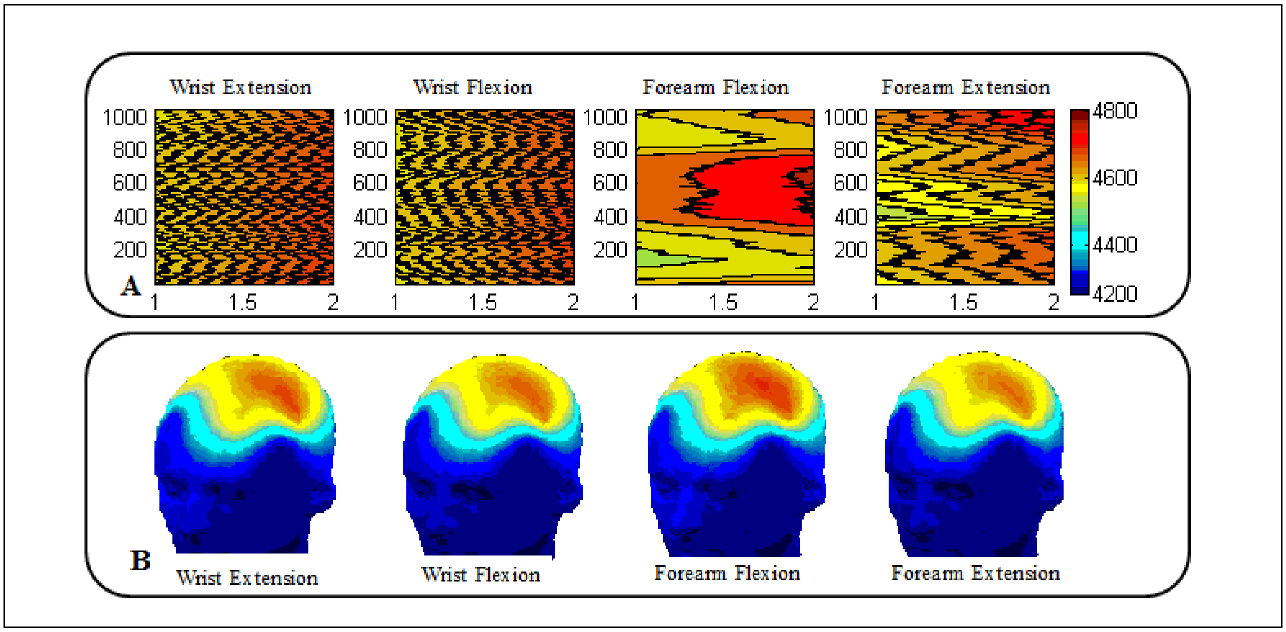

Figure 3.5 A: Interpolation b/w the sensor *F3* and *F4* for the four particular tasks from two test subjects. **B:** The Head plots for four particular tasks. Head plots shows *ERS* and Time scaled power distribution over left hemisphere of frontal lobe for particular movement.

3.3. WINDOWING:

Afterwards another 5th order band stop filter was applied to remove baseline noise that falls between the 48-52 Hz frequency ranges. After gamma rhythm has been extracted through filtration, a Gaussian windowing function is used to segregate the complete data set into time segments of 100 ms. The Gaussian window function creates a Gaussian distribution of the data within the 100 ms intervals. Mathematically the Gaussian window function is given as follows:

$$win_{Gaussian} = e^{\frac{-1}{2}\left[\frac{n}{\sigma}\right]^2} \tag{3.2}$$

Where σ: is the standard deviation and is also called probability density function (PDF) of the Gaussian window.

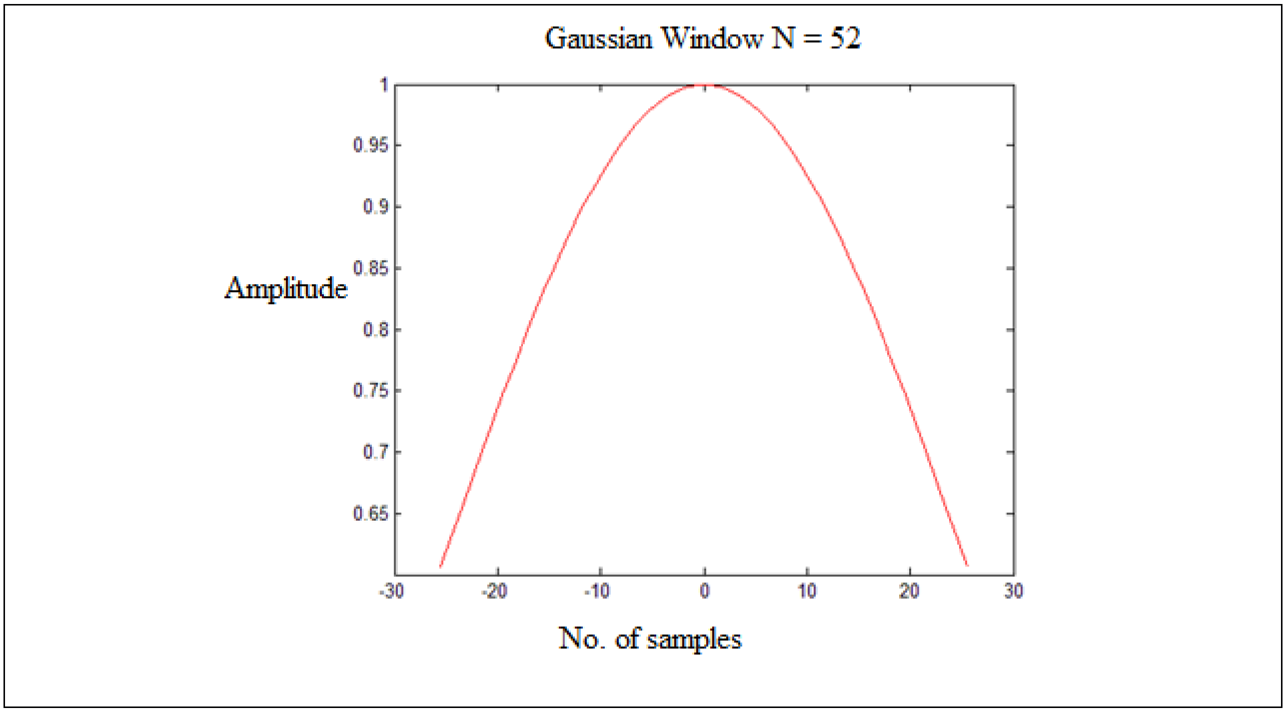

Figure 3.6: Gaussian Window

3.4. SUMMARY:

This chapter discusses data acquisition of electroencephalography signals as per protocol. Test protocol consists of the recording of four different types of upper limb movements e.g. right forearm (Extension/Flexion) and wrist (Extension/Flexion). Then this data is filtered using 5^{th} order Butterworth filter to extract gamma band from the EEG signals and then base line noise is removed. Once the filtration is done, it is better practice to make the window of data set before extracting features.

CHAPTER 4: FEATURE EXTRACTION

Feature extraction for a particular limb movement is crucial for accurately classifying the direction, velocity or force of the movement. Optimal selection of features of the gamma or beta rhythm dictates the computational complexity and accuracy of any classification algorithm for motor tasks or imagery. Aggregate Average Rule[50], common spatial pattern[66],Power Spectral Density[51], Wavelet Transform[4], Principal Component Analysis[61] and Hjorth Parameters[67] have been widely studied as feature extraction techniques in modern BCI research. In our study Hjorth Parameters and Power Spectral Density were employed for feature extraction of the gamma rhythm. Hjorth Parameters not only contain information about the frequency spectrum of a signal, they also help analyze the signals in time domain which renders them computationally less complex than other feature extraction techniques[67]. Details of Hjorth Parameters and Power Spectral Density are presented in the following sub sections.

4.1. Hjorth Parameters:

In this study the three Hjorth Parameters namely Activity, Mobility and Complexity were used for time domain based feature extraction of gamma rhythm. In the time domain, activity provides information regarding variance of the filtered EEG signal data in each Gaussian window. In the frequency domain, activity is indicative of the power spectrum of an EEG signal and returns a higher value if existence of high frequency signals is found. Activity can be mathematically expressed as:

$$Activity(x) = \frac{\sum_{n=1}^{n}(x_n - \acute{x})^2}{N} \tag{4.1.1}$$

where $x_n$is nth sample in the data set, $\overline{x}$ is the mean and $N$is the total number of samples.

Mobility is a measure of the standard deviation of the power spectrum of an EEG signal and is expressed as the ratio of variance of the first derivative of the signal to the variance of the signal. Mathematically it is expressed as:

$$Mobility = y(x_i) = \sqrt{\frac{var(x_i{}')}{var(x_i)}} \tag{4.1.2}$$

Where x_i represents the signal, x_i' is the rate of change of signals w.r.t time and $y(x_i)$ is the measure of signal's mean frequency. The third Hjorth Parameter, known as complexity is a measure of the similarity between the shape of an EEG signal and a pure sine wave [67].

Complexity is evaluated as the ratio of mobility of the first derivative of a signal to the mobility of a signal. Mathematically, complexity is expressed as:

$$Complexity = \frac{y(x_i')}{y(x_i)} \tag{4.1.3}$$

Where $y(x_i')$ is also known as the mobility of x_i' and $y(x_i)$ is the mobility of the signal x_i according to hjorth parameter.

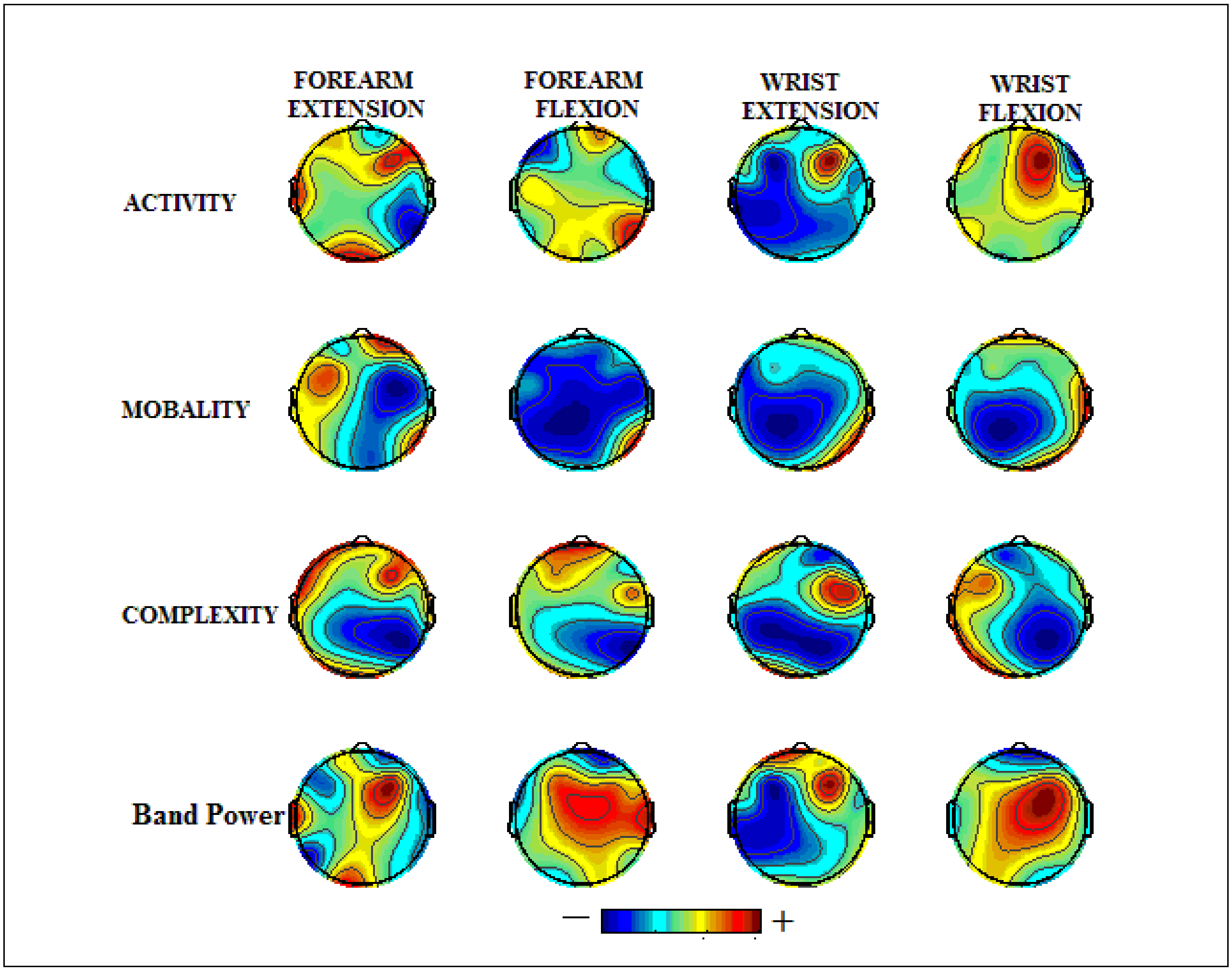

Figure 4.1: Pattern obtained from the aforementioned feature extraction technique. High weight locations are represented by the red for each task.

4.2. Power Spectral Density

Power Spectral Density of an EEG signal provides information about the power distribution of time series data over different frequencies and is evaluated using a Windowed Fourier

Transform. In our study Power Spectral Density was evaluated through the Average Band Power method. Mathematically it can be expressed as:

$$PSD_{Averagebandpower} = \frac{1}{2\pi}\int_{w1}^{w2} S_{X_w} . dw \qquad (4.2.1)$$

where S_{X_w} denotes the power spectral density of signal calculated using equation 4.2.2. While X_w is fourier transform of signal $x_i(t)$ calculated using 4.2.3.S_{X_w} is the power spectral density of the signal $x_i(t)$ and is given by equation 4.2.2.

$$S_{X_w} = lim_{T\to\infty}\left[\frac{E(|X_w|^2)}{2T}\right] \qquad (4.2.2)$$

$$X_w = \int_{-\infty}^{\infty} x_i(t). e^{2\pi ftj} . dt \qquad (4.2.3)$$

Figure 4.1 illustrates the topographical distribution of the four feature vectors generated in response to extension/flexion of forearm and wrist. The topographical distribution has been generated by plotting values of each feature vector over the complete scalp. These topographical plots clearly indicate that each feature vector has a distinct distribution over various lobes of the brain and can therefore be used to classify the four upper limb movements.

CHAPTER 5: CLASSIFICATION TECHNIQUES

Classification algorithm is used to recognize the intention of user on the basis of feature vector, which is the characteristic of neural activity. In our thesis we have chosen seven machine learning algorithms for the classification of two forearm and wrist movements (extension and flexion) and they are.

1. Discriminant Analysis:
    - Linear Discriminant Analysis
    - Quadratic Discriminant Analysis
2. Support Vector Machine:
    - Linear Support Vector Machine
    - Quadratic Support Vector Machine
    - Radial Based Function Support Vector Machine
3. Naïve Bayes
4. Neural Network
    - Multilayer Perceptron

5.1. DISCRIMINANT ANALYSIS:

We consider that X be the 14 component feature vector valued random variable. The aim of Discriminant Analysis is to assign objects to one of several classes. w_1, w_2, w_3 and w_4. Based on the feature vector X $=(X_1, X_2, X_3, X_4, X_5, X_6 \ldots \ldots \ldots X_{14})$.In this analysis each object is assumed to be the element of one if 1< i < 4. By using Bayes Rule we have the following mathematical expression.

$$P_{(w_i/x)} = \frac{P_{(x/w_i)} P_{w_i}}{P_x} \quad (5.1.1)$$

Where$P_{(w_i/x)}$is the probability of class being w_i given measured feature vector, it is also known Posterior. $P_{(x/w_i)}$ is the probability of likely hood with respect to feature vector X,. It is also called class conditional probability density function. P_{w_i} represents the prior knowledge of how likely we are to get the class before classification occurs, and it is also called Prior probability. While Px is evidence factor which guaranties that $P_{(w_i/x)}$ sum to one. While determining the maximum posterior distribution for a class, evidence (normalizing factor) can be ignored because it doesn't depends upon the class.

$$g_i(x) = P_{(w_i/x)} = P_{(x/w_i)}P_{w_i} \quad (5.1.2)$$

We can always multiply all discriminant functions with some positive constant or shift it by some additive constant without effecting the decision. Now replace every $g_i(x)$ with f (.), which will be a monotonically increasing function. The classification remains unchanged.

The observation leads to computational simplification and have analytical significance. By taking log on both sides we will get.

$$\log(g_i(x)) = log\,P_{(w_i/x)} = logP_{(x/w_i)} + logP_{w_i} \quad (5.1.3)$$

Where for multivariate normal density in "fourteen" dimensional conditional probability is given by.

$$P_{(x/w_i)} = \frac{1}{(2\pi)^{d/2}|\in|^{1/2}} exp^{[-\frac{1}{2}(x-\mu)^t \in^{-1}.\ (x-\mu)]} \quad (5.1.4)$$

X is d component feature vector: where d=14. μ is d component mean vector and $\in$ is 14X14 covariance matrix. Now above equation can also written as.

$$\log(g_i(x)) = logP_{(w_i/x)} = \log\left[\frac{1}{(2\pi)^{\frac{d}{2}}|\in|^{\frac{1}{2}}} exp^{\left[-\frac{1}{2}(x-\mu)^t \in^{-1}.\ (x-\mu)\right]}\right] + \log P_{(w_i)} \quad (5.1.5)$$

Prior probability $P_{(w_i)}$ is denoted by π_i with $\pi_1 + \pi_2 + \pi_3 + \pi_4 = 1$

$$\log(g_i(x)) = \log P_{(w_i/x)} = \log\left[\frac{1}{(2\pi)^{\frac{d}{2}}|\in|^{\frac{1}{2}}} exp^{\left[-\frac{1}{2}(x-\mu)^t \in^{-1}.\ (x-\mu)\right]}\right] + \log \pi_i \quad (5.1.6)$$

$$\log(g_i(x)) = log\,P_{(w_i/x)} = \log\left[(2\pi)^{-\frac{d}{2}}|\in|^{-\frac{1}{2}} exp^{\left[-\frac{1}{2}(x-\mu)^t \in^{-1}.\ (x-\mu)\right]}\right] + \log \pi_i \quad (5.1.7)$$

$$g_i(x) = -\frac{1}{2}(x-\mu)^t \ \in^{-1} (x-\mu) - \frac{1}{2}\log|\epsilon| + log\pi_i + constant \quad (5.1.8)$$

As $log\frac{1}{(2\pi)^{\frac{d}{2}}}$ is constant and have same value for each class. So $g_i(x)$ can be simplified as

$$g_i(x) = {W_i}^t . x + W_{io} \quad (5.1.9)$$

$$g_i(x) = \sum_{i=1}^{4} w_i\ .x_i + w_{io} \quad (5.1.10)$$

Where w_i the weight is vector $w.x \propto \in^{-1}(x-\mu)^t(x-\mu)$ and $w_{io}$is the bias threshold/ weight threshold. Discriminant classifiers is said to assign feature vector x to a class w_i if.

$$g_i(x) > g_j(x) \quad \text{for all } j \neq i \quad (5.1.11)$$

In case of two class classification of feature vector, very often single discriminant activation function is used instead of multiple discriminant functions. For example for the case given below data set X is assigned to the class W_1if $g(x)$ >0 else it will be assigned to other class W_2.

$$g(x) = g_1(x) - g_2(x) \quad (5.1.12)$$

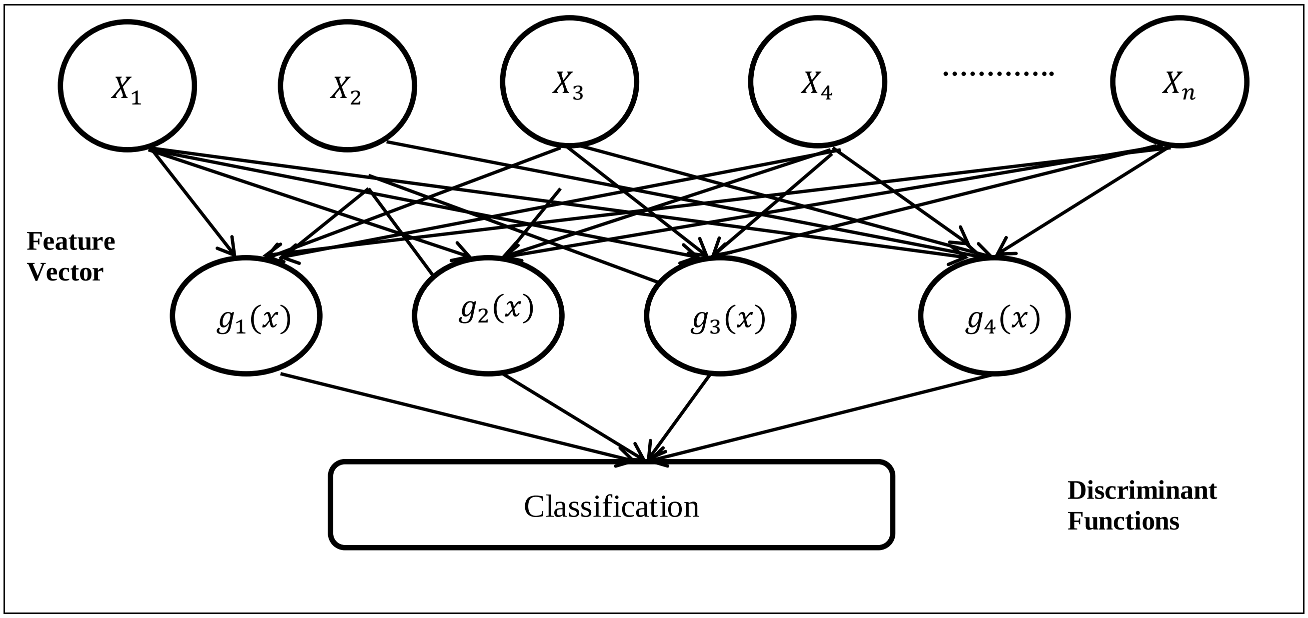

Figure 5.1: Discriminant Function Architecture

5.1.1. LINEAR DISCRIMINANT ANALYSIS:

Linear discriminant analysis is a preprocess machine learning technique .Its main objective is to separate the data by finding linear relation between them and draw a decision boundary which will separate the given class. It provides maximum separate ability of data by maximizing the ratio between there variances. Basically it calculates the variance of all classes to the within-class variance of data. Linear discriminant analysis will separate the data using linear hyper plane in feature space. So the linear separating plane can be mathematically represented by.

$$g(x) = W^T X + W_0 \quad (5.1.13)$$

X is the feature vector W^T is the weight and W_o is the threshold. Linear discriminant analysis is quite simple algorithm and requires less computational power that is why it is quiet good for on line brain computer interfacing. But it does not efficiently classify nonlinear or complex data. Weight can be calculated as.

$$W = \in_c^{-1} \ (\mu_2 - \mu_1) \quad (5.1.14)$$

Where $\mu_i$is the estimated mean of the particular class and $\in_c^{-1}$is common covariance matrix. Thus covariance matrix and mean is calculated as.

$$\in = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu)(x_i - \mu)^T \quad (5.1.15)$$

$$\mu = \frac{1}{n} \sum_{1}^{n} x_i \quad (5.1.16)$$

Where $x_i$is the feature vector containing n samples which belongs to R^d. The covariance estimation shown in equation (5.1.16) is unbiased and in usual circumstances shows good properties. Sometimes it gets imprecise in case of higher dimensionality of feature as compared to the number of trials available. The estimated covariance matrix is quite different from the real covariance matrix due to false positive. Some eigenvalues of real covariance matrix are under estimated while some of them are over estimated. It leads to systematic error and degrade the performance of classifier.

5.1.2. QUADRATIC DISCRIMINANT ANALYSIS:

Quadratic discriminant analysis for every class covariance matrix is separately calculated because in QDA covariance matrix is different for different class. It is a generalized version of LDA but can handle large data set. It tries to separate the data using higher order complex polynomial kernel (like conic section parabola and ellipse). In our case $\delta_k(x)$ is the hyperquadratic surface. In case of non-singular weight vector, linear data set in $\delta_k(x)$ is eliminated by translation of axes.

$$\delta_k(x) = -\frac{1}{2}\log|\sum k| - \frac{1}{2}\ (x-\mu_k)^T \sum k^{-1}\, (x-\mu_k) + \log \pi_k \qquad (5.1.17)$$

$\sum k$ is the covariance matrix, it should not be the identical matrix, $\boldsymbol{X}$ is the data set and μ_k is the estimation of mean for data. Now QDA with the posterior distribution is given by

$$\delta_{\hat{K}}(X) = \min_{1\leq k\leq K} d_k(X) \leftrightarrow \max_{1\leq k\leq K} p(k/x) \qquad (5.1.18)$$

The main advantage of quadratic discriminant analysis is that it can better handle nonlinear EEG signals and quiet simple to use.

5.2. NAIVE BAYESIAN RULE:

A type of statistical classifiers uses to predict probabilities of class membership . A Bayesian rule splits the posterior in term of prior distribution $\boldsymbol{p(c)}$ and likelihood $\boldsymbol{p(F_1 \ldots, F_n|C)}$. Bayes classifier assumes that the value of a particular feature of EEG signal is unrelated to the presence or absence of any other feature translation, given the class. It is mathematically expressed as follows.

$$p(C|F_1 \ldots, F_n) = \frac{p(c)\ p(F_1 \ldots, F_n|C)}{p(F_1 \ldots, F_n)} \qquad (5.2.1)$$

Where $p(C|F_1 \dots, F_n)$: represents the posterior probability, $p(c)$: is prior probability, $p(F_1 \dots, F_n|C)$: is likelihood and $p(F_1 \dots, F_n)$ is the evidence. While determining the maximum posterior distribution for a class, evidence (normalizing factor) $p(F_1 \dots, F_n)$ can be ignored because it doesn't depends upon the class.

$$Posterior\ probablity = \frac{Likely\ hood\ \text{X}\ prior\ probablity}{evidence} \tag{5.2.2}$$

If $p(C|F_1 \dots, F_n)$ is a discriminant function where *i = 1,2,3…n*. Thus for minimum classification error, $p(C|F_1 \dots, F_n)$ is mathematically expressed as.

$$p(C|F_1 \dots, F_n) = \frac{p(c)\ p(F_1 \dots, F_n|C)}{\sum_{i=1}^{n} p(F_1 \dots, F_m|C).p(F_1 \dots, F_m)} \tag{5.2.3}$$

Bayesian statistical classifiers are not very popular in the BCI community. Nevertheless, they have been used for classifying EEG signals. Bayesian classifiers is senstive to the curse of diminsionality.

5.3. SUPPORT VECTOR MACHINE:

It is a nonlinear classifier which separates the data using discriminant hyper plane. Thus the hyper plan maximizes the margin which causes to increases the learning rate and generalization power. By enhancing the generalization we attain the capacity to accommodate the outliers. It can be applied to binary or multi classes. It is a speedy classifier that is why it can perform much better in on line BCI.

Mathematically support vector machine is represented by following equations.

$$\propto_1 \emptyset_{(s1)}.\emptyset_{(s1)} + \propto_2 \emptyset_{(s2)}.\emptyset_{(s1)} + \propto_3 \emptyset_{(s3)}.\emptyset_{(s1)} + \propto_4 \emptyset_{(s4)}.\emptyset_{(s1)} + \dots\dots + \propto_n \emptyset_{(sn)}.\emptyset_{(s1)} = \boldsymbol{A} \tag{5.3.1}$$

$$\propto_1 \emptyset_{(s1)}.\emptyset_{(s2)} + \propto_2 \emptyset_{(s2)}.\emptyset_{(s2)} + \propto_3 \emptyset_{(s3)}.\emptyset_{(s2)} + \propto_4 \emptyset_{(s4)}.\emptyset_{(s2)} + \dots\dots + \propto_n \emptyset_{(sn)}.\emptyset_{(s2)} = \boldsymbol{B} \tag{5.3.2}$$

$$\propto_1 \emptyset_{(s1)}.\emptyset_{(s3)} + \propto_2 \emptyset_{(s2)}.\emptyset_{(s3)} + \propto_3 \emptyset_{(s3)}.\emptyset_{(s3)} + \propto_4 \emptyset_{(s4)}.\emptyset_{(s3)} + \dots\dots + \propto_n \emptyset_{(sn)}.\emptyset_{(s3)} = \boldsymbol{C} \tag{5.3.3}$$

$$\propto_1 \emptyset_{(s1)}.\emptyset_{(s4)} + \propto_2 \emptyset_{(s2)}.\emptyset_{(s4)} + \propto_3 \emptyset_{(s3)}.\emptyset_{(s4)} + \propto_4 \emptyset_{(s4)}.\emptyset_{(s4)} + \dots\dots + \propto_n \emptyset_{(sn)}.\emptyset_{(s4)} = \boldsymbol{D} \tag{5.3.4}$$

Where $\emptyset_{(s_1)}$: is the function represents hyperplane and is also called activation function. Now consider the following expression.

$$\boldsymbol{S'1} = \emptyset_{(s1)} \qquad \boldsymbol{S'2} = \emptyset_{(s2)} \qquad \boldsymbol{S'3} = \emptyset_{(s3)} \qquad \boldsymbol{S'1} = \emptyset_{(s3)}$$

Above equations is simplified to:

$$\propto_1 S'_1.S'_1 + \propto_2 S'_2.S'_1 + \propto_3 S'_3.S'_1 + \propto_4 S'_4.S'_1 + \ldots\ldots + \propto_n S'_n.S'_1 = A \tag{5.3.5}$$

$$\propto_1 S'_1.S'_2 + \propto_2 S'_2.S'_2 + \propto_3 S'_3.S'_2 + \propto_4 S'_4.S'_2 + \ldots\ldots + \propto_n S'_n.S'_2 = B \tag{5.3.6}$$

$$\propto_1 S'_1.S'_3 + \propto_2 S'_2.S'_3 + \propto_3 S'_3.S'_3 + \propto_4 S'_4.S'_3 + \ldots\ldots + \propto_n S'_n.S'_3 = C \tag{5.3.7}$$

$$\propto_1 S'_1.S'_4 + \propto_2 S'_2.S'_4 + \propto_3 S'_3.S'_4 + \propto_4 S'_4.S'_4 + \ldots\ldots + \propto_n S'_n.S'_4 = D \tag{5.3.8}$$

Initially we suppose that the bias is 1. By taking the dot product we get.

$$\boldsymbol{a_1 \propto_1 + a_2 \propto_2 + a_3 \propto_3 + a_4 \propto_4 + \ldots\ldots + a_n \propto_n = A} \tag{5.3.9}$$

$$\boldsymbol{b_1 \propto_1 + b_2 \propto_2 + b_3 \propto_3 + b_4 \propto_4 + \ldots\ldots + b_n \propto_n = B} \tag{5.3.10}$$

$$\boldsymbol{c_1 \propto_1 + c_2 \propto_2 + \propto_3 c_3 + c_4 \propto_4 + \ldots\ldots + c_n \propto_n = C} \tag{5.3.11}$$

$$\boldsymbol{d_1 \propto_1 + d_2 \propto_2 + d_3 \propto_3 + d_4 \propto_4 + \ldots\ldots + d_n \propto_n = D} \tag{5.3.12}$$

After calculating the learning rate from above equations: we will look at the discriminating surface.

$$\boldsymbol{w = \textstyle\sum_1^i \propto_1 S'_i} \tag{5.3.13}$$

$$\boldsymbol{y = w\,x + b} \tag{5.3.14}$$

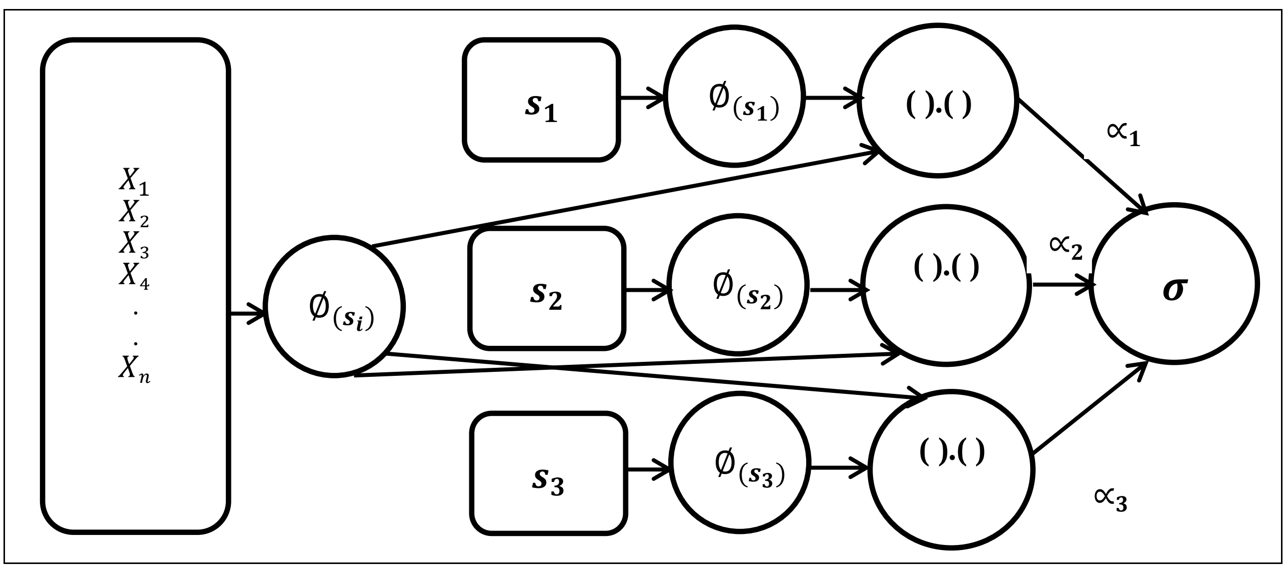

Figure 5.2: Support Vector Machine architecture

The main advantage of using support vector machine is that it shows good generalization. It is insensitive to the over training of data. It can handle higher dimensional data or curse of dimensionality. Regularization parameter is quiet flexible and user defined. Training of data set using SVM is relatively easy. It scales comparatively well to high dimensional data. It can explicitly control the error and tradeoff between complexities of classifier. While training and testing of data the limitations of SVM are the choice of kernels, speed and size. Support vector machine learning algorithms are characterized by the choice of its kernels.

5.3.1. LINEAR SUPPORT VECTOR MACHINE:

The base of linear support vector machine is a linear discriminant function. Its linear hyperplane tries to minimize the margins (distance from nearest data set used for training) by adjusting its weight. Linear function used by SVM is in the form:

$$\emptyset(s_i . x) = W^T X + b = 0 \tag{5.3.15}$$

"W" is the weight vector and "b" is its bias, which provides upper bound for error in training. If training data set will be labeled as $\{X_n, Lable_n\}$ where *n = {1,2.....N}*. $Lable_n \in$ {Upper limb extension, Upper limb flexion} represented by {1,-1} and $X_n$will be the feature vector of EEG signals. Then the point which satisfies the activation function $W^T X + b = 0$, lies on the separating hyperplane. $W^T$is perpendicular to the separating plane. Thus perpendicular distance from origin to the separating plane is $\frac{|b|}{\|w\|}$. $\|w\|$ is norm of W^T. We know that EEG data is noisy and irregular that is why error in training of data set (samples on the wrong side of separating hyperplane) is in evitable.

5.3.2. QUDRATIC SUPPORT VECTOR MACHINE:

Whenever we are dealing with nonlinear data, it is possible to create nonlinear hyperplane to better classify data. It can be done by using kernel tricks though it may enhance the complexity of classifier. It consists of independent and absolute mapping of data to another space, generally in higher dimensionality using a higher order kernel.

$$\emptyset(s_i . x) = e^{-\|s_i - x\|^2} \tag{5.3.16}$$

The corresponding support vector machine uses quadratic kernel. Where s_i the support vector and x is feature vector.

5.3.3. RADIAL BASED FUNCTION SUPPORT VECTOR MACHINE:

Just like quadratic support vector machine, RBF SVM is another approach to separate the data by using nonlinear decision boundaries. It uses the higher order kernels which have better capability of separation of vector by transforming data in higher dimensional feature space. Thus the radial based function is given by.

$$\emptyset(s_i . x) = (s_i . x + r)^2 \qquad \text{Where} \quad r \geq 0 \tag{5.3.17}$$

r is the quadratic function parameter needed to be select carefully for better classification. Support vector machine has been widely used in brain computer interfacing, because it is a simple classifier that performs robustly and insensitive to the curse of dimensionality.

It means that a large number of training data set is not required for better performance of classifier, even with very high dimensional feature vectors. These advantages come at the expense of execution speed. Nevertheless, SVM requires less computational cost for real-time BCI.

5.4. Multi-Layer Perceptron:

Multilayer perceptron is consists of several layers of neurons which consists of an input layer, possibly one or several hidden layers, and an output layer. Each neuron's input is connected with the output of the previous layer's neurons whereas the neurons of the output layer determine the class of the input feature vector.

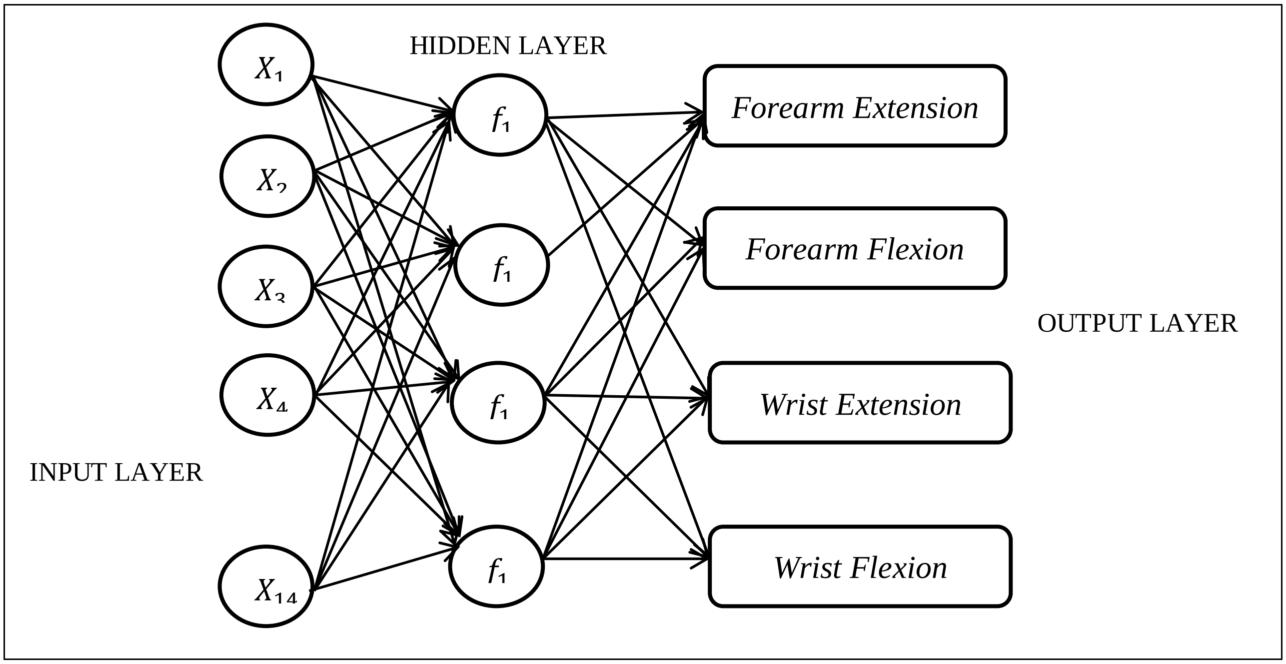

Figure 5.3: Multilayer perceptron architecture

Multi-layer perceptron, are universal approximators, i.e. when composed of enough neurons and layers, they can approximate any continuous function. Added to the fact that they can classify any number of classes, this makes neural network very flexible classifiers that can be used to solve variety of problems. Consequently, MLP, which are the most popular NN used in classification, have been applied to almost all BCI problems such as binary or multiclass, synchronous or asynchronous BCI.

However, MLP are universal approximator that is why these classifiers are sensitive to overtraining, especially with such noisy and non-stationary data as EEG. Therefore, careful architecture selection and regularization is required. Let us suppose that we have input feature vector *X* and weight vector *W* as shown below.

$$X_i(t) = [x_1, x_2, x_3, x_4, x_5, x_6 \ldots \ldots \ldots x_n]$$

$$W_i(t) = [w_1, w_2, w_3, w_4, w_5, w_6 \ldots \ldots \ldots w_n]$$

$y = f(X)$ represents the output from perceptron for an input feature vector *X*. b is bias and $Tran = \{(X_1, T_1), (X_2, T_2), \ldots \ldots .. (X_s, T_s)\}$ is data set used for training, it consists of *s* samples which is randomly chosen for training. X_s represents the training data while T_s is class labels. α is the learning rate. First of all weights and threshold are initialized, weight is to be multiplied by the i^{th} input feature. Now calculate the actual output by the following equation.

$$y_i(t) = f[W(t).X_i] = f[w_o(t) + w_1(t)x_1 + w_2(t)x_2 + w_3(t)x_3 + \cdots + w_n(t)x_n] \quad (5.4.1)$$

In the second phase we will get weights. Initially weights are set to zero and learning rate will be $0.1 \leq \gamma \leq 1$. if Out_{desire} is desired output, the error signal $e_t$can be calculated by.

$$e_t = Out_{desire} - y_i(t) \quad (5.4.2)$$

Multilayer perceptron learning law is used to update the weights.

$$w_{t+1} = w_t + \Delta w_t \quad (5.4.3)$$

Where

$$\Delta w_t = \alpha\, e_t\, X_i(t) \quad (5.4.4)$$

In Figure 5.3 single layer perceptron architecture is shown. In this figure, input vector $X_i(t)$ is connected to each neuron through weight matrix W. b is the bias vector. *f* is the hidden layer and last one is output layer. By this output we can get classification result. Figure 4.4 shows learning law of multilayer perceptron.

However, MLP are universal approximator that is why these classifiers are sensitive to overtraining, especially with such noisy and non-stationary data as EEG. Therefore, careful architecture selection and regularization is required. Let us suppose that we have input feature vector *X* and weight vector *W* as shown below.

$$X_i(t) = [x_1, x_2, x_3, x_4, x_5, x_6 \ldots \ldots \ldots x_n]$$

$$W_i(t) = [w_1, w_2, w_3, w_4, w_5, w_6 \ldots \ldots \ldots w_n]$$

$y = f(X)$ represents the output from perceptron for an input feature vector *X*. b is bias and $Tran = \{(X_1, T_1), (X_2, T_2), \ldots \ldots .. (X_s, T_s)\}$ is data set used for training, it consists of *s* samples

which is randomly chosen for training. X_s represents the training data while T_s is class labels. α is the learning rate. First of all weights and threshold are initialized, weight is to be multiplied by the i^{th} input feature.

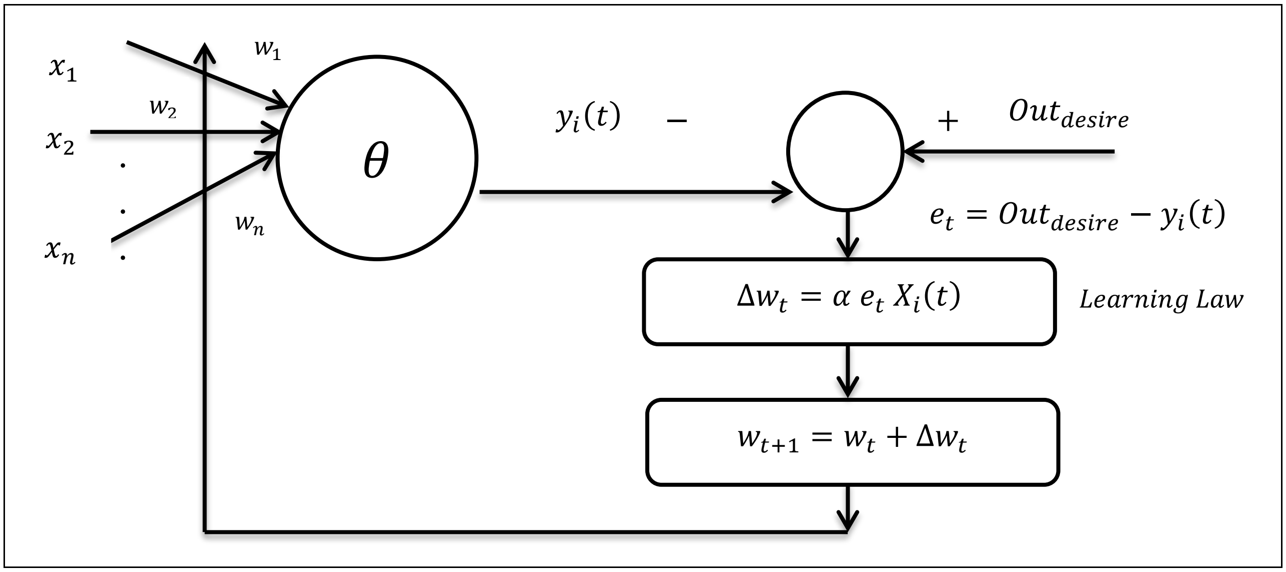

Figure 5.4: Learning law of multilayer perceptron.

Now calculate the actual output by the following equation.

$$y_i(t) = f[W(t).X_i] = f[w_o(t) + w_1(t)x_1 + w_2(t)x_2 + w_3(t)x_3 + \cdots + w_n(t)x_n] \quad (5.4.1)$$

In the second phase we will get weights. Initially weights are set to zero and learning rate will be $0.1 \leq \gamma \leq 1$. if Out_{desire} is desired output, the error signal $e_t$can be calculated by.

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Multilayer perceptron learning law is used to update the weights.

$$w_{t+1} = w_t + \Delta w_t \quad (5.4.3)$$

Where

$$\Delta w_t = \alpha\, e_t\, X_i(t) \quad (5.4.4)$$

In Figure 5.3 single layer perceptron architecture is shown. In this figure, input vector $X_i(t)$ is connected to each neuron through weight matrix W. b is the bias vector. *f* is the hidden layer and last one is output layer. By this output we can get classification result. Figure 4.4 shows learning law of multilayer perceptron.

Table 5.1: Summary of machine learning algorithms.

Classification Algorithm	Properties
Linear Discriminant Analysis	a. It uses linear hyperplane to separate data. b. It requires less computational power. c. Quiet easy to use. d. It required generalization.
Quadratic Discriminant Analysis	a. It can be used to classify nonlinear complex data. b. Quiet easy to use. c. Insensitive to outlier.
Naïve Bayes	a. It is generative classifier. b. It produces nonlinear decision boundaries. c. Assigns the data to the labeled class to which it has the highest belonging probability.
Linear SVM	a. It uses linear hyperplane to separate data. b. Require less computational power. c. It tries to maximize the perpendicular distance between nearest training data and separating hyper plane. d. Fails in case of strong noise. e. It is insensitive to over training of data. f. Regularization parameter is user define. g. It shows good generalization property.
Quadratic SVM	a. It uses nonlinear decision boundary to separate data. b. It tries to maximize the perpendicular distance between nearest training data and separating hyper plane. c. It is speedy classifier and require less computational power d. Regularization parameter is user define. e. It is insensitive to over training of data. f. It shows good generalization property.
RBF SVM	a. It uses linear hyperplane to separate data. b. It tries to maximize the perpendicular distance between nearest training data and separating hyper plane. c. It can handle curse of dimensionality. d. Regularization parameter is user define. e. It is insensitive to over training of data. f. It shows good generalization property.
Multilayer Perceptron	a. Flexible classifier. b. Multi class c. For higher dimensional and complex data it requires high computational cost.

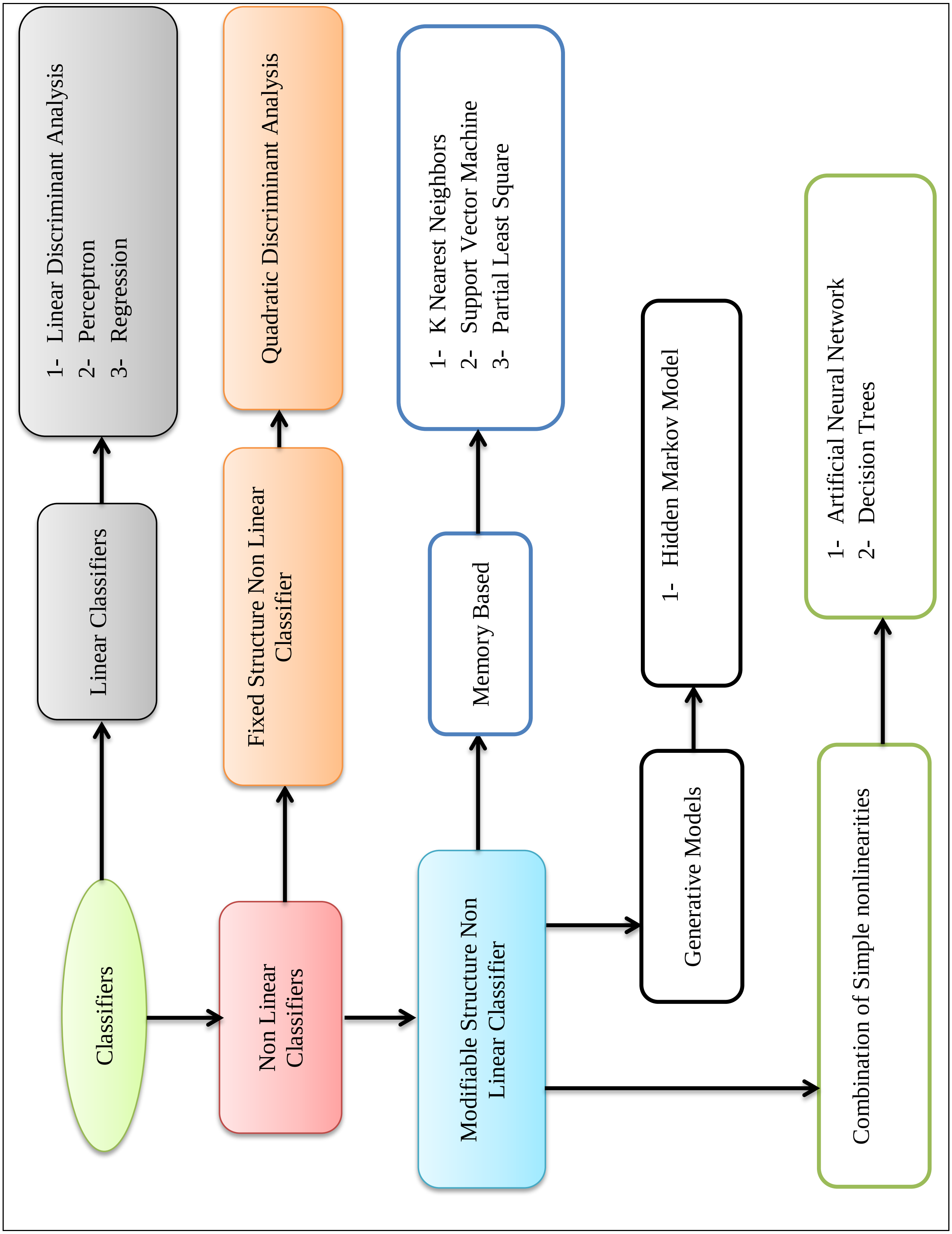

Figure 5.5: Flow chart shows the families of Classifiers depending upon their properties.

CHAPTER 6: RESULTS AND DISCUSSION

Once the raw EEG data is filtered and after extracting important features in term of feature vector using hjorth parameters and average band power (PSD). The feature vectors are then fed in to the classifier to classify forearm and wrist (Extension/Flexion). The classification algorithms are applied in two steps as illustrated in Figure 6.1.

- First Classifier is trained with known data set to discriminate between aforementioned upper limb movements.
- Second one is the testing of classifier.

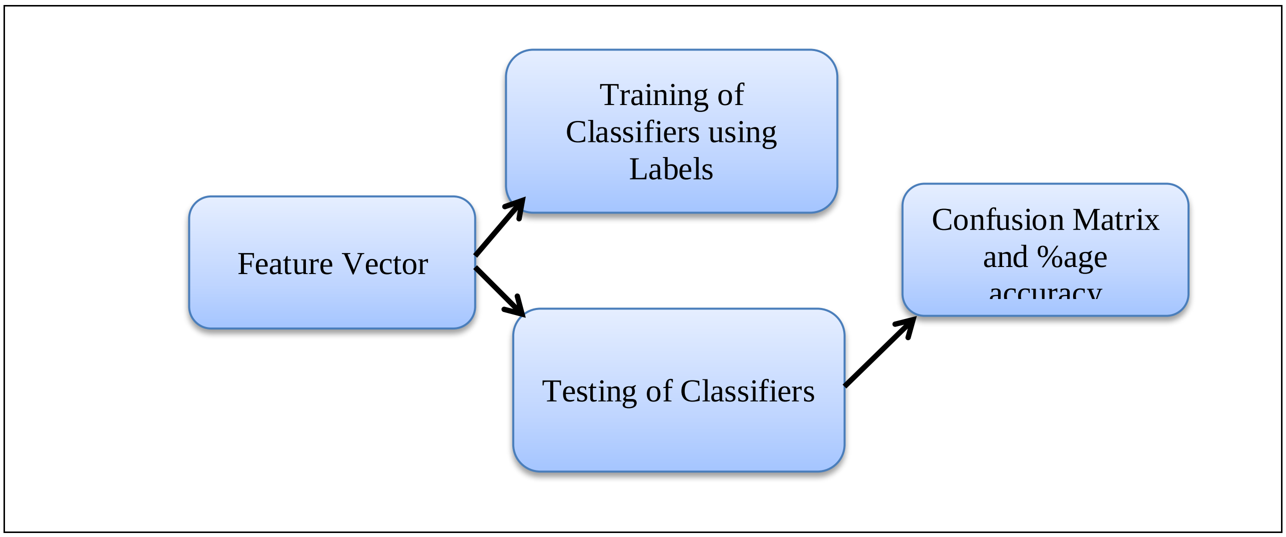

Figure 6.1: Classification approach used in this work

Six different types of linear and nonlinear classifiers are used as mentioned in the previous chapter. Codes for the classifiers used in this study are presented in Appendix C. The classification approach and results obtained from different classifiers are discussed below.

6.1. DISCRIMINANT ANALYSIS:

In our thesis two types of discriminant analysis is used for training and validation of data set.

6.1.1. LINEAR DISCRIMINANT ANALYSIS:

Linear Discriminant Analysis (LDA) has been employed for classification of extension/flexion of forearm and wrist movements in our study owing to its comparatively low computational complexity. Since features extracted from EEG signals tend to be highly dimensional along with noise and outliers, LDA may not be able to exhibit higher classification accuracies however it has been included in our study to define a baseline case of classification.

Table 6.1: Decoding accuracy of forearm movements using Linear Discriminant Analysis

Linear Discriminant Analysis		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 68 & 6 & 11 & 19 \\ 14 & 62 & 20 & 8 \\ 11 & 19 & 61 & 13 \\ 16 & 10 & 19 & 59 \end{bmatrix}$	60.19%
Activity	$\begin{bmatrix} 61 & 9 & 16 & 18 \\ 14 & 62 & 18 & 10 \\ 9 & 18 & 46 & 31 \\ 10 & 9 & 17 & 68 \end{bmatrix}$	56.88%
Complexity	$\begin{bmatrix} 46 & 18 & 17 & 23 \\ 25 & 40 & 19 & 20 \\ 19 & 14 & 50 & 21 \\ 17 & 23 & 18 & 46 \end{bmatrix}$	43.65%
Mobility	$\begin{bmatrix} 58 & 21 & 22 & 9 \\ 20 & 56 & 11 & 17 \\ 11 & 16 & 48 & 29 \\ 17 & 13 & 24 & 50 \end{bmatrix}$	50.85%

The LDA classifier was trained and validated by using the CLASSIFY function in the Matlab 2013 environment. A ten-fold cross validation method has been applied in the LDA classifiers for validation of the feature sets. The classifier was trained with known data. The result of LDA classifier are shown.

6.1.2. QUADRATIC DISCRIMINANT ANALYSIS:

Quadratic Discriminant Analysis is a generalized version of LDA, however the underlying assumption in QDA is that the covariance of each class is not identical. This fundamentally alters that accuracy of classifying data at the cost of increased computational complexity.

Table 6.2: Decoding accuracy of forearm movements using Quadratic Discriminant Analysis

Quadratic Discriminant Analysis		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 81 & 3 & 10 & 10 \\ 4 & 94 & 1 & 5 \\ 9 & 4 & 66 & 25 \\ 8 & 1 & 19 & 76 \end{bmatrix}$	80.20%
Activity	$\begin{bmatrix} 85 & 3 & 10 & 6 \\ 4 & 95 & 1 & 4 \\ 5 & 5 & 71 & 23 \\ 5 & 2 & 20 & 77 \end{bmatrix}$	79.75%
Complexity	$\begin{bmatrix} 73 & 5 & 19 & 7 \\ 5 & 75 & 16 & 8 \\ 10 & 4 & 72 & 18 \\ 9 & 13 & 17 & 65 \end{bmatrix}$	68.41%
Mobility	$\begin{bmatrix} 69 & 8 & 12 & 15 \\ 9 & 62 & 19 & 14 \\ 10 & 7 & 64 & 23 \\ 13 & 14 & 19 & 58 \end{bmatrix}$	60.72%

Since Quadratic discriminant analysis draws a nonlinear decision boundary to classify data, it is found to be quite useful for classification of highly random nonlinear data without being oversensitive to outliers. Consequently QDA has been included in our study for classification of EEG signals.

The QDA classifier was trained and validated by using the CLASSIFY function in the Matlab 2013 environment. A ten-fold cross validation method has been applied in the QDA classifiers for validation of the feature sets. The classifier was trained with known data. The result of QDA classifier are shown.

6.2. NAÏVE BAYES RULE:

Naïve Bayesian Rule is a classification algorithm which ignores interaction between attributes within individuals of the same class. Naïve Bayesian Rule is a generative classifier and therefore possesses capabilities that are distinct from linear and nonlinear classifiers. In our study the Bayesian classifier does not hold much promise in delivering accurate classification results which may be attributed to large dimensionality of our data set.

Table 6.3: Decoding accuracy of forearm movements using Naïve Bayes classifier

Naïve Bayes Rule		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 49 & 11 & 10 & 34 \\ 14 & 75 & 1 & 14 \\ 8 & 9 & 42 & 45 \\ 7 & 5 & 19 & 73 \end{bmatrix}$	57.45%
Activity	$\begin{bmatrix} 55 & 12 & 12 & 25 \\ 14 & 78 & 2 & 10 \\ 9 & 8 & 46 & 41 \\ 11 & 3 & 17 & 73 \end{bmatrix}$	60.58%
Complexity	$\begin{bmatrix} 45 & 10 & 21 & 18 \\ 10 & 56 & 29 & 9 \\ 20 & 19 & 49 & 16 \\ 24 & 14 & 37 & 29 \end{bmatrix}$	43.03%
Mobility	$\begin{bmatrix} 32 & 19 & 38 & 15 \\ 16 & 45 & 37 & 6 \\ 11 & 16 & 64 & 13 \\ 11 & 20 & 12 & 61 \end{bmatrix}$	48.56%

6.3. SUPPORT VECTOR MACHINE:

A Support Vector Machine classification algorithm optimally separates data into two or more categories by generating an N-dimensional hyperplane. Support Vector Machines are known to less prone to overtraining but highly sensitive to noise. Many past studies have used SVM classifiers to decode various limb movements.

Some of the key reasons for such an extensive use of SVM in studies related to EEG data are:

1. SVM classifiers are insensitive to overtraining.
2. SVM classifiers are less prone to the curse of dimensionality that is associated with EEG signals.
3. SVM classifiers require comparatively less regularization to prevent overfitting.

Due to the above mentioned advantages of SVM classifiers they have been included in our study for classification of four upper limb movements.

The SVM-classifier was trained and validated by using the SVMTRAIN and SVMCLASSIFY function in the Matlab 2013 environment. were trained and tested using the four individual feature vectors. 66% of the data of each feature vector were labeled and randomly used for training the classifier whereas the remaining 33% data was used to predict class labels i.e. identify a particular movement of the forearm and wrist.

6.3.1. LINEAR SUPPORT VECTOR MACHINE:

Table 6.4: Decoding accuracy of forearm movements using Linear support vector machine

Linear Support Vector Machine		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 64 & 12 & 12 & 16 \\ 32 & 44 & 16 & 12 \\ 0 & 4 & 60 & 40 \\ 20 & 16 & 28 & 40 \end{bmatrix}$	50.00%
Activity	$\begin{bmatrix} 64 & 8 & 12 & 20 \\ 32 & 44 & 20 & 8 \\ 4 & 4 & 56 & 40 \\ 20 & 12 & 28 & 44 \end{bmatrix}$	50.00%
Complexity	$\begin{bmatrix} 40 & 24 & 12 & 20 \\ 20 & 40 & 32 & 12 \\ 16 & 32 & 48 & 8 \\ 36 & 16 & 32 & 20 \end{bmatrix}$	37.50%
Mobility	$\begin{bmatrix} 28 & 20 & 32 & 24 \\ 28 & 40 & 36 & 0 \\ 44 & 4 & 56 & 0 \\ 32 & 12 & 44 & 16 \end{bmatrix}$	33.65%

6.3.2. QUADRATIC SUPPORT VECTOR MACHINE:

Table 6.5: Decoding accuracy of forearm movements using Quadratic support vector machine

Quadratic Support Vector Machine		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 92 & 0 & 4 & 8 \\ 8 & 84 & 0 & 12 \\ 8 & 12 & 40 & 44 \\ 8 & 4 & 16 & 76 \end{bmatrix}$	70.19%
Activity	$\begin{bmatrix} 96 & 0 & 4 & 4 \\ 12 & 84 & 4 & 4 \\ 8 & 4 & 56 & 36 \\ 8 & 4 & 8 & 84 \end{bmatrix}$	76.92%
Complexity	$\begin{bmatrix} 88 & 8 & 8 & 0 \\ 14 & 61 & 17 & 12 \\ 21 & 12 & 53 & 18 \\ 6 & 14 & 29 & 55 \end{bmatrix}$	61.77%
Mobility	$\begin{bmatrix} 64 & 8 & 8 & 24 \\ 20 & 68 & 12 & 4 \\ 28 & 8 & 52 & 16 \\ 12 & 24 & 24 & 44 \end{bmatrix}$	54.81%

6.3.3. RADIAL BASED FUNCTION SUPPORT VECTOR MACHINE:

Table 6.6: Decoding accuracy of forearm movements using RBF support vector machine

Radial Based Function Support Vector Machine		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 80 & 16 & 4 & 4 \\ 8 & 92 & 4 & 0 \\ 8 & 8 & 60 & 28 \\ 8 & 12 & 36 & 48 \end{bmatrix}$	67.31%
Activity	$\begin{bmatrix} 84 & 16 & 4 & 0 \\ 4 & 100 & 0 & 0 \\ 12 & 0 & 52 & 40 \\ 0 & 16 & 20 & 68 \end{bmatrix}$	73.08%
Complexity	$\begin{bmatrix} 76 & 8 & 8 & 12 \\ 26 & 56 & 14 & 8 \\ 20 & 22 & 58 & 4 \\ 36 & 0 & 24 & 44 \end{bmatrix}$	56.23%
Mobility	$\begin{bmatrix} 64 & 20 & 8 & 12 \\ 36 & 52 & 12 & 4 \\ 32 & 16 & 48 & 8 \\ 14 & 24 & 20 & 46 \end{bmatrix}$	50.42%

6.4. MULTILAYER PERCEPTRON:

The multilayer perceptron (MLP) was trained using newp function of the Matlab environment. The input vector and the target vectors are given. The perceptron network trained with that inputs. The network trained with train function.

Table 6.7: Decoding accuracy of forearm movements using Multilayer Perceptron

Multilayer Perceptron		
Features	Confusion Matrix	% age Accuracy
Average Band Power	$\begin{bmatrix} 93 & 1 & 5 & 5 \\ 3 & 92 & 5 & 4 \\ 12 & 2 & 52 & 38 \\ 10 & 4 & 28 & 62 \end{bmatrix}$	73.49%
Activity	$\begin{bmatrix} 92 & 4 & 4 & 4 \\ 4 & 89 & 3 & 8 \\ 11 & 1 & 56 & 36 \\ 5 & 7 & 27 & 65 \end{bmatrix}$	73.59%
Complexity	$\begin{bmatrix} 67 & 7 & 13 & 17 \\ 23 & 51 & 19 & 11 \\ 22 & 5 & 51 & 26 \\ 25 & 6 & 22 & 51 \end{bmatrix}$	52.88%

Table 6.8: Stratified cross validation results and weighted average accuracy by class

Multilayer Perceptron (MLP)	Kappa Statistic	Mean Absolute error	Relative Absolute error	Coverage of Class (0.95 level)	Mean rel. Region Size (0.95 level)	True Positive (Weighted Avg.)	False Positive (Weighted Avg.)
Band Power	0.6453	0.189	50.38%	98.79%	61.14%	0.735	0.089
Activity	0.6346	0.168	44.80%	95.67%	50.18%	0.726	0.091
Complexity	0.4033	0.279	74.60%	98.79%	84.03%	0.554	0.151

In this chapter we presented the classification accuracies for decoding the extension/flexion movement of wrist and forearm using synchronous BCI, through different combinations of classifiers and feature vectors. As highlighted in Tables shown above, the most promising results were obtained by training a QDA classifier with PSD feature vector. Earlier research in decoding other upper limb movements has reported similar results. [31]employed PSD feature vector in conjunction with LDA classifier to decode hand v/s arm and right limb v/s left limb movements with accuracies of 83.69% and 67.95% respectively. [33] Performed a similar study of classifying the elbow, finger and shoulder movement of each hand with a classification accuracy of 80.11% for elbow movement and 81.12% for shoulder movement. A PSD feature vector was used to train a RBF SVM classifier in that study. The highest classification accuracies exhibited in the previously mentioned studies are in close with agreement with our classification accuracy value of 77.37% for the classification of extension/flexion movement of wrist and forearm. [68][69]pointed out that the number of electrodes used to record the evoked potential of brain has insignificant impact on the classification accuracy. In fact the number of electrodes used in various studies ranges from 2 [33] to over 128 [45] In our study, 14 electrodes were used to record EEG signals that were generated in response to motor activities such as extension of forearm or flexion of wrist. Electrodes were placed over the test subject’s scalp according to the

10-20 electrode placement system[70]. An interesting aspect of our study is illustrated in Figure 3.5 (B), where it is evident that the evoked potential generated in response to movement of forearm and wrist is being recorded in other areas beside the sensorimotor area. This can be explained by the fact that as a result of volume conduction [71], local EEG field activity also produces a far-field potential[72] and consequently the evoked potential will not only be recorded directly above the sensiromotor area but will also appear as a function of current spreading over the skull and scalp [68]. Much of the earlier work on decoding upper limb movements was performed by studying the mu and beta rhythms of EEG signals. However in view of the findings by [73] [74] that suggest that gamma rhythm contains useful information about motor activity, we have applied feature extraction to analyze Event Related Synchronization (ERS) in gamma rhythm. These past studies and our study confirm that gamma rhythm of EEG signals can be successfully utilized for decoding upper limb movements with significant accuracy.

Table 6.9: Mean Classification accuracy of four upper limb movements (wrist extension, wrist flexion, forearm extension and forearm flexion).

% age Classification accuracy of four upper limb movements					
Sr. No.	**Classifiers**	**Mobility**	**Complexity**	**Activity**	**PSD (Band Power)**
1	Linear Discriminant Analysis	50.85%	43.65%	56.88%	60.19%
2	Quadratic Discriminant Analysis	60.72%	68.41%	79.75%	80.20%
3	Naïve Bayes	48.56%	53.03%	60.58%	67.45%
4	Quadratic Support Vector Machine	58.08%	61.77%	76.92%	70.19%
5	RBF Support Vector Machine	50.42%	56.23%	75.96%	69.31%
6	Multilayer Perceptron	NaN	52.22%	73.59%	73.49%

CHAPTER 7: CONCLUSION

In our study, QDA and Quadratic SVM have been shown to exhibit the highest level of accuracy for classifying or decoding forearm and wrist movements. The higher classification accuracy of these two classifiers can be attributed to the fact that both classifiers create a second order decision boundary in the kernel space to cater for unstable and low variance features of EEG signals[75]. Furthermore, QDA and Quadratic SVM are recognized to be highly robust against the curse of dimensionality[26][76] and overfitting owing to their enhanced regularization capabilities[75]. The poor classification accuracy of Naïve Bayes can be explained by its inability to cater for biased and high dimensionality feature vectors whereas the poor performance of LDA is attributable to a linear decision boundary. Apart from the careful selection of classifier, feature extraction plays a vital role in deciding the classification accuracy. In several studies, various features of EEG signals have been studied and used to decode upper and lower limb movements as illustrated in chapter 2.

In our study, a new combination of classifier and feature vector has been proposed to decode flexion/extension of forearm and wrist. Improving the accuracy of classifying or decoding various limb movements has garnered considerable attention in recent years. However little attention had been paid to the classification of forearm and wrist movements which otherwise form the basis many activities of daily life. The aim of this study was to advance our knowledge regarding the classification of forearm and wrist movements by presenting a comparative performance analysis of various classifiers and feature extraction techniques. In our further scope of our work, we will focus on detecting the ocular and eye blink artifacts that are inadvertently included in our data set and in later stages developing a FPGA based online BCI system that are inadvertently included in our data set and in later stages developing a FPGA based online BCI system.

This study investigated the performance of five classifiers with four different feature extraction techniques for decoding extension/flexion of forearm and wrist. The performance metric for this study was the classification accuracy of each classifier with the four different feature extraction techniques. LDA, QDA, Naïve Bayes, Quadratic SVM and RBF SVM were used as classifiers whereas Hjorth Parameters and PSD were used to extract features from the gamma rhythm of EEG signals that were generated in the test subject’s brain.

At the culmination of our study, it was shown that Quadratic SVM and PSD feature extraction technique can be accurately used to decode the extension/flexion of forearm and wrist which are some of the fundamental limb movements behind activities of daily life.

APPENDIX A

Questionnaire for Movement experiment

Form No. …………………. Date: ………………….

Name:

Age:

Sex (Male/Female):

Vision:

Mention Your Test Protocol:

Medical History (Specifically related to the orthopedics and psychology):

APPENDIX B
Emotiv Head set Specifications

EEG Head set	
Number of Channels	14 Channels (plus CMS/DRL references, P3/P4 locations)
Channel names (International 10-20 locations)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling. Single ADC
Sampling rate	128 SPS (2048 Hz internal)
Resolution	14 bits 1 LSB = 0.51μV (16 bit ADC, 2 bits instrumental noise floor discarded)
Bandwidth	0.2 - 45Hz Digital notch filters at 50Hz and 60Hz
Filtering	Built in digital 5th order Sinc filter
Dynamic range (input referred)	8400 μV (pp)
Coupling mode	AC coupled
Connectivity	Proprietary wireless 2.4 GHz band
Power	LiPoly
Battery life (typical)	12 hours
Impedance Measurement	Real time contact quality using patented system

APPENDIX C
PROGRAMS

1. DATA ACQUISITION IN MATLAB:

(Reading EDF File from Emotiv Test BenchV1.5.1.2)

```
function [data, header] = readEDF(filename)
fid = fopen(filename,'r','ieee-le');
%%% HEADER LOAD
% PART1: (GENERAL)
hdr = char(fread(fid,256,'uchar')');
header.ver=str2num(hdr(1:8));
% 8 ascii : version of this data format (0)
header.patientID  = char(hdr(9:88));
% 80 ascii : local patient identification
header.recordID  = char(hdr(89:168));
% 80 ascii : local recording identification
header.startdate=char(hdr(169:176));
% 8 ascii : startdate of recording (dd.mm.yy)
header.starttime  = char(hdr(177:184));
 % 8 ascii : starttime of recording (hh.mm.ss)
header.length = str2num (hdr(185:192));
 % 8 ascii : number of bytes in header record
reserved = hdr(193:236);
% [EDF+C] % 44 ascii : reserved
header.records = str2num (hdr(237:244));
% 8 ascii : number of data records (-1 if unknown)
header.duration = str2num (hdr(245:252));
% 8 ascii : duration of a data record, in seconds
header.channels = str2num (hdr(253:256));
% 4 ascii : number of signals (ns) in data record
%%%% PART2 (DEPENDS ON QUANTITY OF CHANNELS)
header.labels=cellstr(char(fread(fid,[16,header.channels]
,'char')'));
% ns * 16 ascii : ns * label (e.g. EEG FpzCz or Body temp)
header.transducer=cellstr(char(fread(fid,[80,header.channels],
```

```
'char')'));
% ns * 80 ascii : ns * transducer type (e.g. AgAgCl electrode)
header.units =
cellstr(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * physical dimension (e.g. uV or degreeC)
header.physmin =
str2num(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * physical minimum (e.g. -500 or 34)
header.physmax =
str2num(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * physical maximum (e.g. 500 or 40)
header.digmin =
str2num(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * digital minimum (e.g. -2048)
header.digmax =
str2num(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * digital maximum (e.g. 2047)
header.prefilt =
cellstr(char(fread(fid,[80,header.channels],'char')'));
% ns * 80 ascii : ns * prefiltering (e.g. HP:0.1Hz LP:75Hz)
header.samplerate =
str2num(char(fread(fid,[8,header.channels],'char')'));
% ns * 8 ascii : ns * nr of samples in each data record
reserved = char(fread(fid,[32,header.channels],'char')');
 % ns * 32 ascii : ns * reserved
f1=find(cellfun('isempty', regexp(header.labels, 'EDF
Annotations', 'once'))==0);
% Channels number with the EDF Annotations
f2=find(cellfun('isempty', regexp(header.labels,
'Status', 'once'))==0);
% Channels number with the EDF Annotations
f=[f1(:); f2(:)];
%%%%%% PART 3: Loading of signals
%Structure of the data in format EDF:
```

```
%[block1 block2 .. , block N], where N=header.records
% Block structure:
% Ch = header.channels
% d = header.duration
Ch_data = fread(fid,'int16'); % Loading of signals
fclose(fid); % close a file
%%%%% PART 4: Transformation of the data
if header.records<0, % If the quantity of blocks is not known
R=sum(header.duration*header.samplerate); % Length of one block
header.records=fix(length(Ch_data)./R);
 % Quantity of written down blocks
end
% Separating a read signal into blocks
Ch_data=reshape(Ch_data, [], header.records);
% establishing calibration parametres
sf = (header.physmax - header.physmin)./(header.digmax –
header.digmin);
dc = header.physmax - sf.* header.digmax;
data=cell(1, header.channels);
Rs=cumsum([1; header.duration*header.samplerate]);
% separating of signals of everyone the channel from blocks
% and recording of signals in structure of cells
for k=1:header.channels
data{k}=reshape(Ch_data(Rs(k):Rs(k+1)-1, :), [], 1);
if sum(k==f)==0 % non Ànnotation
% Calibration of the data
data{k}=data{k}.*sf(k)+dc(k);
end
end
% PART 5: ANNOTATION READ
header.annotation.event={};
header.annotation.starttime=[];
header.annotation.duration=[];
header.annotation.data={};
```

```
if sum(f)>0
try
for p1=1:length(f)
Annt=char(typecast(int16(data{f(p1)}), 'uint8'))';
% separate of annotation on blocks
Annt=buffer(Annt, header.samplerate(f(p1)).*2, 0)';
ANsize=size(Annt);
for p2=1:ANsize(1)
% search TALs starttime
Annt1=Annt(p2, :);
Tstart=regexp(Annt1, '+');
Tstart=[Tstart(2:end) ANsize(2)];
for p3=1:length(Tstart)-1
A=Annt1(Tstart(p3):Tstart(p3+1)-1); % TALs block
header.annotation.data={header.annotation.data{:} A};
% duration and starttime TALs
Tds=find(A==20 | A==21);
if length(Tds)>2
td=str2num(A(Tds(1)+1:Tds(2)-1));
if isempty(td), td=0; end
header.annotation.duration=[header.annotation.duration(:); td];
header.annotation.starttime=[header.annotation.starttime(:);
str2num(A(2:Tds(1)-1))];
header.annotation.event={header.annotation.event{:}
A(Tds(2)+1:Tds(end)-1)};
Else
header.annotation.duration=[header.annotation.duration(:); 0];
header.annotation.starttime=[header.annotation.starttime(:);
str2num(A(2:Tds(1)-1))];
header.annotation.event={header.annotation.event{:}
A(Tds(1)+1:Tds(end)-1)};
end
end
end
```

```
end
% delete annotation
a=find(cell2mat(cellfun(@length, header.annotation.event,
'UniformOutput', false))==0);
header.annotation.event(a)=[];
header.annotation.starttime(a)=[];
header.annotation.duration(a)=[];
end
end
header.samplerate(f)=[];
header.channels=header.channels-length(f);
header.labels(f)=[];
header.transducer(f)=[];
header.units(f)=[];
header.physmin(f)=[];
header.physmax(f)=[];
header.digmin(f)=[];
header.digmax(f)=[];
header.prefilt(f)=[];
data(f)=[];
```

2. Filtration of Electroencephalographic DATA:

```
function [Y1,Y2,Y3,Y4]= FILTRATION(B_dn,B_up,C_dn,C_up);
%% B_dn (Forearm Extension)& B_up (Forearm Flexion)
%% C_dn (Wrist Extension)& C_up (Wrist Flexion)
tic
[p,q]=butter(5, [0.0008 0.256],'bandpass');
[t,u]=butter(5,[0.096 0.104],'stop');%removes 48-52Hz
v=filtfilt(p,q,B_dn);
Y1=filtfilt(t,u,v);
v=filtfilt(p,q,B_up);
Y2=filtfilt(t,u,v);
v=filtfilt(p,q,C_dn);
Y3=filtfilt(t,u,v);
v=filtfilt(p,q,C_up);
```

```
      Y4=filtfilt(t,u,v);
      toc
      End
```

3. Main Code of Feature Vector using Hjorth Parameter and PSD:

```
clc;
clear all;
close all;
[B_dn,B_up] = Brachium();% Reading Forearm (Extension/ Flexion)data
[C_dn,C_up] = Carpus();% Reading Wrist (Extension/ Flexion)data
[Y1,Y2,Y3,Y4]= FILTRATION(B_dn,B_up,C_dn,C_up);
 %  Gaussian Windowing
 a = 1;
 v = [Y1 Y2 Y3 Y4];
      size(v);
      N=52;
      n = -(N-1)/2:(N-1)/2;
      alpha = 1;
      y = exp(-1/2*(alpha*n/(N/2)).^2);
      w = gausswin(N,alpha);
      w1=w';
      for i=1:51:5255;
          vv = w1*v(i:i+51,:);
          for j=1:1:56
      [ACTIVITY, MOBILITY, COMPLEXITY,m0,m1,m2] = hjorth(vv(:,j));
      %%hjorth parameters can be calculated at here
      A11(a,j)=ACTIVITY;
      %A11(a,j)  = MOBILITY;
      %A11(a,j)= COMPLEXITY;
          end
          a = a+1;
      end
      % for i=1:51:5255
      %     vv = v(i:i+50,:);
      %     vv=abs(vv);
      %   Hpsd = dspdata.psd(vv); %%PSD feature
      %   b=avgpower(Hpsd);
      %   sal(n,:)=(b);
```

```
% 	n=n+1;
%  end
A2=A11; %final save feature vector in A2
w1=A2(:,1:14); %extracting first 14 columns and saving in w1 for
%% forearm Extension
w2=A2(:,15:28); %extracting 14 columns and saving in w2 for
%% forearm flexion
w3=A2(:,29:42); %extracting 14 columns and saving in w3 for wrist
%% Extension
w4=A2(:,43:56); %extracting 14 columns and saving in w4 for wrist
%%Flexion
X=[w1;w2;w3;w4];
t1=ones(1,104); % Labels for Forearm Extension
t2=2*t1; %Labels for Forearm Flexion
t3=3*t1; %Labels for  Wrist Extension
t4=4*t1; %Labels for Wrist Flexion
YY=[t1,t2,t3,t4];
Y=YY';
```

4. Classifiers

Linear Discriminant Analysis

```
rng(0,'twister');
C = cvpartition(Y,'k',10); % dividing output y into 10 folds
yorder = unique(Y);
% FOR LDA ANLYSIS
F=@(xtr,ytr,xte,yte)confusionmat(yte,classify(xte,xtr,ytr,'linear'),'order',yorder);
cfMat = crossval(F,X,Y,'partition',C);
cfMat1 = reshape(sum(cfMat),4,4); %arranging confusion matrix in 4x4 matrix.
acc                         = 100*sum(diag(cfMat1))./sum(cfMat1(:));
fprintf('Linear Discrimenent Analysis:\naccuracy = %.2f%%\n', acc);
fprintf('Confusion Matrix:\n'), disp(cfMat1)
```

Quadratic Discriminant Analysis

```
% % FOR QDA ANALYSIS
F=@(xtrain,ytrain,xtest,ytest)confusionmat(ytest,classify(xtest,xtrain,
ytrain,'quadratic'),'order',yorder);
cfMat = crossval(F,X,Y,'partition',C);
cfMat2 = reshape(sum(cfMat),4,4);
%arranging confusion matrix in 4x4 matrix.
acc = 100*sum(1.0525*(diag(cfMat2)))./sum(cfMat2(:));
fprintf('Quadratic Discrimenent Analysis:\naccuracy = %.2f%%\n', acc);
fprintf('Confusion Matrix:\n'), disp(cfMat2);
```

Naïve Bayes Rule

```
% % FOR NAIVE BAYES WITH NORMAL DISTRIBUTION
F=@(xtrain,ytrain,xtest,ytest)confusionmat(ytest,predict(NaiveBayes.fit
(xtrain,ytrain), xtest));
cfMat = crossval(F,X,Y,'partition',C);
cfMat3 = reshape(sum(cfMat),4,4);
 %arranging confusion matrix in 4x4 matrix
acc = 100*sum(diag(cfMat3))./sum(cfMat3(:));
fprintf('NAIVE BAYES WITH NORMAL DISTRIBUTION:\naccuracy = %.2f%%\n',
acc);
     fprintf('Confusion Matrix:\n'), disp(cfMat3)
```

Support Vector Machine

```
%# classify using one-against-one approach, SVM with 3rd degree poly
Kernel. Plz see help for Linear SVM and Quadratic SVM
for k=1:numel(svmModel)
%# get only training instances belonging to this pair
idx  = trainIdx & any( bsxfun(@eq, g, pairwise(k,:)) , 2 );
%# train
svmModel{k}   = svmtrain(X(idx,:),
g(idx),'showplot',0,'Kernel_function','rbf','rbf_sigma',0.7);
```

```
%# test
    predTest(:,k) = svmclassify(svmModel{k}, X(testIdx,:));
    end
    pred = mode(predTest,2);
    % Voting: clasify as the class receiving most votes performance
    cmat                          = 4*confusionmat(g(testIdx),pred);
    acc                           = 100*sum(diag(cmat))./sum(cmat(:));
    fprintf('SVM (1-against-1):\naccuracy = %.2f%%\n', acc);
    fprintf('Confusion Matrix:\n'), disp(cmat)
```

Multilayer Perceptron

```
net = newp(P,T);
net.trainParam.epochs = 1000;
net = train(net,P,T);
Output = sim(net,P);
Error = Output-T;
% P is an R-by-Q matrix of Q input vectors of R elements each.
% T is an S-by-Q matrix of Q target vectors of S elements each.
```

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