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OPTIMIZATION OF ELECTROENCEPHALOGRAPH-BASED CLASSIFICATION
FOR IMAGINARY MOTION BRAIN COMPUTER INTERFACE STUDY

by

SYLVIA BHATTACHARYA

(Under the Direction of Rami J. Haddad)

ABSTRACT

Using Electroencephalography (EEG) to detect imaginary motions from brain waves, is a very nascent and challenging field that started developing rapidly in the past few decades. EEG involves having some electrodes attached on the scalp of the patient to capture the brain signals generated through the patients thought process and record them in a computer. This technique of human and computer interfacing is called Brain Computer Interface (BCI). Disability is a serious problem of our nation and hence BCI can play an important role in facilitating the lives of people who are incapable of communicating due to spinal cord injuries. This technique uses the brain signals to make decisions, control objects and communicate with the world using brain integration with peripheral devices and systems. This requires some intelligence to classify these motions. Neural network have been used as a mean to classify motions, however, the accuracy of classification for certain motions was limited. The novelty of the proposed approach is in using a majority vote system for a network of artificial neural networks (ANNs) that is used to optimally classify imaginary motions performed by individual or multiple subjects. Three kinds of imaginary motions were classified which are imaginary left hand movement, imaginary right hand movement, and imagination of words starting with the same letter. Using an optimized set of electrodes, classification accuracy was optimized for the three users as a group and also individually. The optimization procedure was based on the ranking of the electrodes according to their

classification accuracy, electrodes with the lowest accuracies were eliminated to achieve the optimal accuracy. The group optimization of 3 subjects altogether resulted in an electrode structure consisting of 15 electrodes with a relatively high classification accuracy of almost 80%. The individual optimization for each subject resulted in structure of 20 electrodes for subject 1 and subject 3 with classification accuracies of 63.63% and 84.33%, respectively, and a single electrode structure for subject 2 with an accuracy of 94.01%. The overall average classification accuracy of all the users with the individual optimization of electrodes was as high as 82.32%.

Index Words: Artificial Neural Network, Brain Computer Interface, Majority Vote, Electroencephalography

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SYLVIA BHATTACHARYA

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Major Professor: Rami J. Haddad

Committee: Mohammad Ahad
Rocio Alba-Flores

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May 2016

DEDICATION

To my mentor and my parents, I couldn't have done this without you. Thank you for all your support all along the way.

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TABLE OF CONTENTS

	Page
DEDICATION	2
ACKNOWLEDGMENTS	3
LIST OF TABLES	6
LIST OF FIGURES	7
 CHAPTER	
1 Introduction	9
2 BACKGROUND AND LITERATURE REVIEW	12
2.1 The Human Brain	12
2.2 Electroencephalography (EEG)	14
2.3 EEG Electrode Positioning	15
2.4 Brain Computer Interface (BCI)	16
2.5 Literature Review	18
3 Individual user BCI using EEG electrode optimization	21
3.1 Data Set Used	21
3.2 Proposed Technique	23
3.3 Result For Individual Subject Analysis	25
4 Multiuser BCI using EEG electrode optimization	30
4.1 Result For Individual Subject Analysis	30
4.2 Result For Multiuser Subject Analysis	31

5 Conclusion and Future Work 37

REFERENCES 39

LIST OF TABLES

Table	Page
3.1 10-20 system electrodes used in experiments	22
3.2 Optimization of Electrodes for Individual Subjects	29
4.1 Optimization of Electrodes	33
4.2 Result Comparison	35

LIST OF FIGURES

Figure	Page
1.1 Brain Waves	10
1.2 Taxonomy of Imaginary Motions	11
2.1 Parts of the Brain	12
2.2 Characteristics of left brain and right brain	14
2.3 EEG Electrodes	16
2.4 EEG Electrodes	17
2.5 Means of conducting Imaginary Motions	18
2.6 EEG Classifier Taxonomy	20
2.7 ANN Algorithms	20
3.1 A Single Artificial Neural Network	24
3.2 ANN Architecture	24
3.3 Optimization of electrodes for individual user	26
3.4 Individual Electrode Classification Accuracy for a) Subject 1, b) Subject 2, c) Subject 3	27
3.5 Optimal set of electrodes for a) Subject 1, b) Subject 2, c) Subject 3	28
3.6 Classification Accuracy vs. No. of Channels for a) Subject 1, b) Subject 2, c) Subject 3	29
4.1 Structure of ANN	31

4.2	Optimization of Electrodes for Multiusers	32
4.3	Individual Channel Classification Accuracy	33
4.4	The Optimal Electrode Sets using a) 17 Channels, b) 16 Channels, c) 15 Channels	34
4.5	Classification accuracy of each subject versus sessions for 17, 16, 15, and 14 electrode structures	35
4.6	Classification accuracy of each subject versus channel structure for 3 different sessions	36

CHAPTER 1

INTRODUCTION

The World Health Organization (WHO) reported that about 15% of the world population (more than 1 billion persons) live with some form of disability with 110-190 million people having very significant difficulties in functioning. In the United States of America, at least 70% of adults with physical disabilities require some form of assistance to conduct their daily activities which culminates to restricted social and economical implications [1]. In severe cases such as spinal cord injuries, body paralysis is induced and Brain Computer Interface (BCI) is used to provide a non-muscular output for communication and control using raw signals from the human brain that reflects the user's intention [2, 3, 4]. Hence, signal processing is used to translate brain signals directly into specific actions [5]. The machine used to record the electrical signals from the brain is called an Electroencephalograph and the method used to record these signals is called Electroencephalography (EEG).

EEG is a non-invasive electrophysiological monitoring method that records the brain's analog electrical signals. This method comprises of several sets of electrodes, in which the 10-20 electrode system is regarded as the standard international electrode system with 32 electrodes. These 32 electrodes are positioned in specific locations all over the scalp according to the standard positioning system accepted internationally to record brain signals across different parts of the brain [6]. EEG is still considered the best known tool for BCI in terms of portability and cost benefit [7]. BCI using EEG is used to help facilitate the mobility of individuals who have severe disabilities like spinal cord injury or tetraplegia, brain stem stroke, and amyotrophic lateral sclerosis.

Brain signals are dynamic in nature and also vary across different people which tends to hinder the application of BCI. The human brain generally generates five different waves namely Alpha, Beta, Gamma, Delta and Theta waves. The bandwidth for the all the five waves combined is 1 to 70 Hz. Alpha waves have a frequency between 7 to 13 Hz and

are generated when a subject is relaxed and in an awakened state. Beta waves are present only when a subject is awake and it is always associated with one of the other four waves. Beta waves range from 13 to 30 Hz in frequency and are associated with attentiveness and concentration in mental activity. The frequency of Delta wave is between 1 to 4 Hz and is generated when a subject is in a deep sleep state [8]. The frequency of Gamma wave is 30 to 70 Hz and it is generated when processing various visual, auditory and touch responses. Frequency of Theta wave is 4 to 7 Hz and it is generated during deep meditation, and hypnosis. The Theta stage is called the twilight stage when a person is neither fully awake nor asleep. The various types of brain waves and their frequencies are illustrated in Figure 1.1

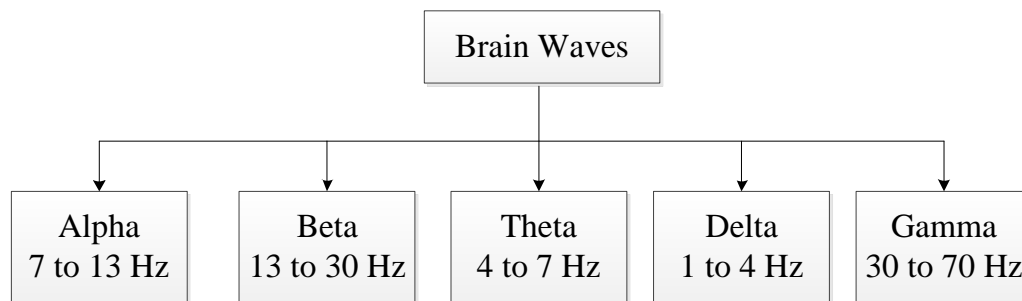


Figure 1.1: Brain Waves

When sensing these signals, there can be more than one wave generated at any time depending on the thought process. Every mental task generates a particular wave and the strength of each wave varies depending on the individual [9]. This study deals with imaginary tasks without any actual physical movement. This is only one type of EEG-based signals used in BCI. Among the various EEG-based signals used in BCI (e.g. intentional change of brain rhythms, evoked potentials, anticipatory potentials, cognitive potentials, and imaginary movement). The brain signals become more complex when more than one signal is generated at the same time which might overlap, therefore, classifying these signals is a very difficult task.

To help study brain signals, researchers classified imaginary tasks into small groups of simple two or three tasks each time brain signals are recorded. The main types of motions includes imaginary motion of hand, leg, finger, tongue, and imaginary word structure. The various types of imaginary motions used in this research field are listed in the taxonomy in Figure 1.2.

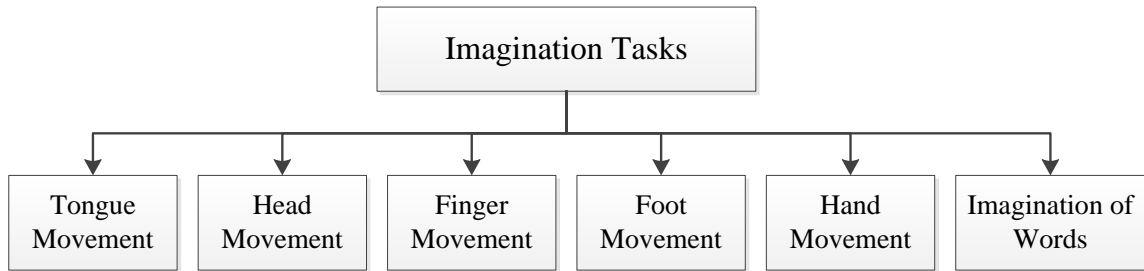


Figure 1.2: Taxonomy of Imaginary Motions

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 The Human Brain

The human brain is a very vital and complex organ of our body. It is the source of human intelligence. The weight of a normal human brain is about 3 pounds [10]. It controls behavior and body movement. The brain is protected inside a brain cage and brain fluid surrounding it. Our identities, qualities, and decisions are defined by our brain. The brain is divided into three parts namely Cerebrum, Cerebellum, and Brain Stem among which the Cerebrum is the largest part which controls various important brain functions including our thought process. The Cerebrum consists of four lobes. The names of these lobes are Frontal lobe, Occipital lobe, Parietal lobe, and Temporal lobe [11]. The function of the various lobes are highlighted in the Figure 2.1.

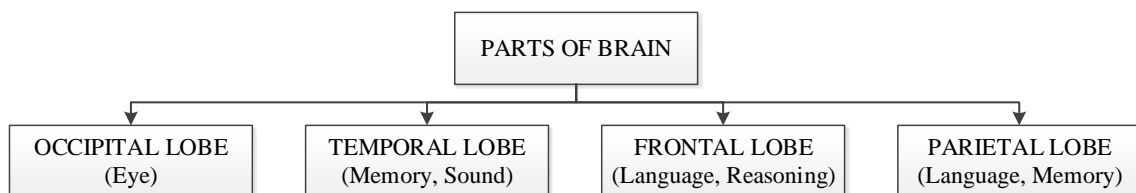


Figure 2.1: Parts of the Brain

Each lobe has a specific function among which Frontal lobe is responsible for language, reasoning, higher level recognition, and motor skills [12]. The location of this lobe is at the front part of the brain. Any injury to the frontal lobe leads to change of socialization, attention, sexual habits etc. The Parietal lobe processes the information sent to the brain by the sense organs and it makes us feel pain, pressure, and touch. The Parietal lobe is located at the center of the brain. Injury to the Parietal lobe disturbs language, ability of controlling eye gaze, and verbal memory. The Occipital lobe is responsible for interpreting the signals sent by the eyes to the brain. Occipital lobe is located at the back of the brain. Any damage

to the occipital lobe affects the visual ability and hampers the recognition power of colors, words, and objects. The Temporal lobe is associated with memories and it processes the sounds that is received by the ears. It is located at the bottom of the brain. Temporal damage can cause problem with language skills, speech perception, and memory [13].

The human brain is divided into two halves. These halves are commonly called the right side and the left side of the brain or hemispheres. It is known that the right and left hemispheres control the opposite sides of the human body i.e, the right hemisphere controls the left side and possess the vision of left eye and controls our left hand and leg while the left hemisphere controls the right side of the body and possesses the right eye vision and controls right hand and leg. The concept of the left and right brain developed in the late 1960s of an psychobiologist Roger W. Sperry [14]. The human brain has two different ways of processing. The right side of the brain focuses on the overall image of an object first, then goes into the details of that image. While the left brain is analytical and hence captures every part of the image sequentially and then joins them altogether. The use of each of the brain sides varies from one person to another. Some people use their left brain while some use their right brain and it is involuntarily controlled. The difference in usage makes the personality of each person unique. The left brain is also called the digital brain as it notes minute details. It also controls reading and writing, calculation, and logical thinking. The right brain is known as the analog brain [15]. It controls 3D sense, creativity, and artistic senses [16]. The functionality of the left and right brain sides is summarized in Figure 2.2.

In general, the left hemisphere of our brain conducts imaginative logical tasks [17]. The right hemisphere performs all creative tasks. The left brain is said to be more functional in hand motion and language in about 92% of people [18].

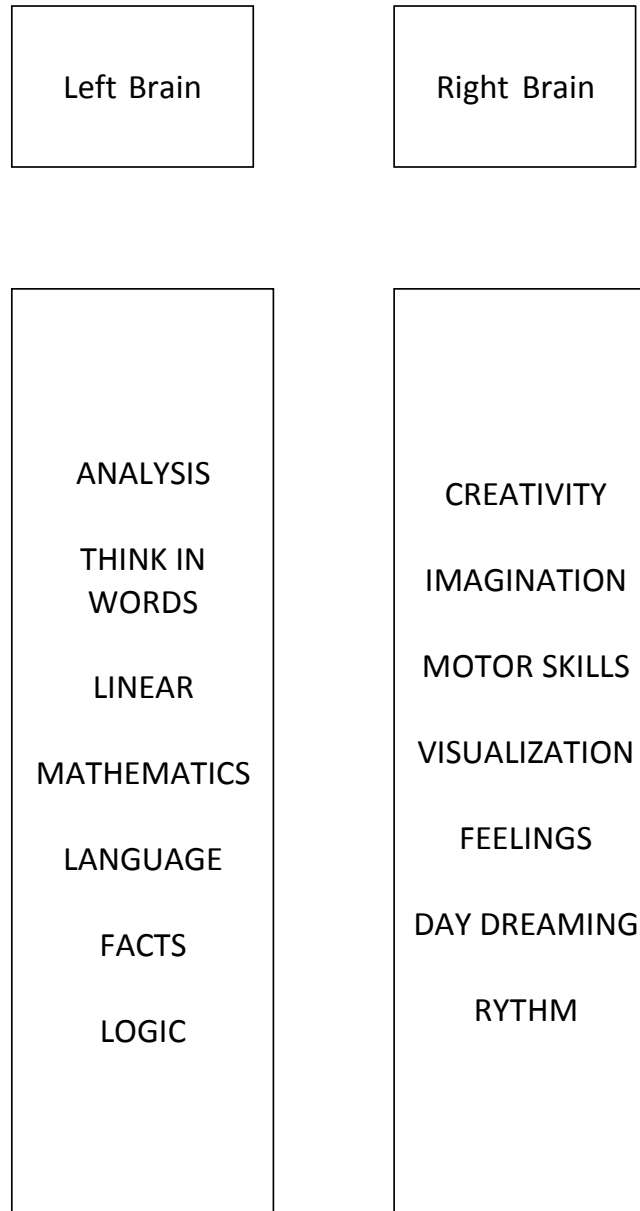


Figure 2.2: Characteristics of left brain and right brain

2.2 Electroencephalography (EEG)

An electroencephalogram (EEG) is a medical diagnostic test which is used to evaluate the electrical activity within the brain. These electrical impulses connect the brain cells with each other. EEG is effective in detecting the abnormalities in brain activity of a

person. The test identifies and records the pattern of the brain wave. Small, flat metal discs called electrodes are used to capture the signals by placing them on the scalp. The electrodes capture the signals and transmit it to the computer to record. Any irregularity in the pattern of the signals is the reason of some brain disorder such as seizure disorders (Such as epilepsy), a head injury, encephalitis (an inflammation of the brain), a brain tumor, encephalopathy (a disease that causes brain dysfunction), memory problems, sleep disorders, stroke, and dementia. Magnetic Resonance Imaging (MRI) is another imaging technique used to detect brain disorder but they are more expensive to operate than EEG. EEG is a non-invasive and a very safe medical diagnostic test which has no side effects. An epileptic patient's stimuli causes a seizure while doing the EEG. The technician who performs EEG on patients are specially trained to manage these kinds of situations.

2.3 EEG Electrode Positioning

EEG requires the placement of a large number of electrodes placed on the scalp at specific positions. Based on the physiology of the brain, depending on the function of the specific brain regions scientists came up with a standard positioning system of EEG electrodes. This electrode positioning system is called 10-20 system which is adopted internationally [19]. This system comprises of 32 electrodes each of which is named according to the region of the brain it is placed on. F, T, C, P, and O are the letters used which represents Frontal, Temporal, Central, Parietal and Occipital lobes respectively. The letter 'z' is used to denote the center of each lobe. 'Cz' represents the center of the scalp. Along with letters, numbers are also designated for naming. Odd numbers are used to denote the electrodes on the left side of the brain and even numbers are used to name the electrodes on the right side of the brain [20]. The 10-20 electrode positioning system is shown in Figure 2.3.

In order to study some more advanced and detailed features of the brain waves, it is not sufficient to only use 32 electrodes. In such cases, more than 32 electrodes are used

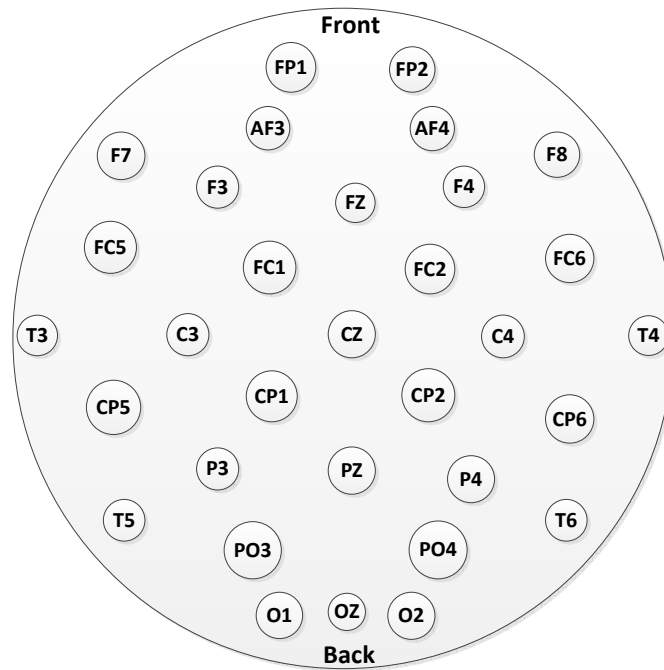


Figure 2.3: EEG Electrodes

and these extra electrodes are placed in between the spaces of these 32 major positioned electrodes. This new system that added extra electrodes to the 10-20 system is called Modified Combinatorial Nomenclature (MCN) [21].

2.4 Brain Computer Interface (BCI)

BCI is an interface system which utilizes the captured brain signal to control objects such as controlling a devices or prosthetic limbs [22]. This helps a paralyzed person to control a wheel chair, play video game or write a book. For controlling these objects, the brain signal are processed and then classified with the help of a classifier [8]. Traditionally, BCI was associated with implants but now the technique is completely non-invasive [23]. It was the scientists from Europe who first came up with the idea of using non-invasive electrode caps on the scalp of a human being to capture signals [24]. One of the area of that is still being investigated is how to increase the classification accuracy of this technique. An increased

accuracy would improve the overall performance, hence it is very important to find out the optimal classifier to classify a particular task. An overview of the overall BCI system is shown in Figure 2.4.

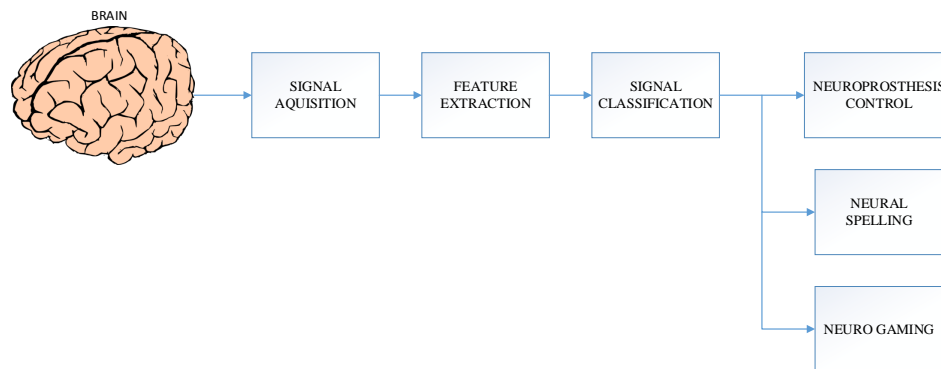


Figure 2.4: EEG Electrodes

BCI system is almost always associated with EEG due to its high temporal resolution and its ease of use [25]. However, EEG signal tends to pick up noise which limits its usability. To overcome such limitation, EEG signals are usually pre-processed raw to eliminate this noise [26]. Pre-processing of raw EEG signals involve many techniques among which is P300 [27].

Presently, the work of Bin He [28] fused the imaging and signal processing together with BCI in order to get more detailed information to be utilized to control objects [29]. He used advanced functional neuroimaging including functional MRI and EEG source imaging. His work identified the co-variation and co-localization of electrophysiological and hemodynamic signals induced by motor imagination [30]. Using neuroimaging approach and applying a training protocol, the ability of a non-invasive EEG based brain-computer interface to control the flight of a virtual helicopter in 3-dimensional space, based upon motor imagination was demonstrated [31].

For BCI to work, the EEG signals are processed and then classified into different imaginary motions using pattern recognition based classifiers. When a subject performs

such imaginary motions, these motions are either self paced or changed according to the operator's instruction. In the self-paced instructions, the subject proceeds from one imaginary task to the next based on his/her own pace. So it is completely based on the subject's response and does not require any immediate instruction from an operator. As for the operator instructed tasks, the subject will have to respond to what imaginary task the operator is currently instructing. Hence, the means of recording imaginary motions are summarized in Figure 2.5.

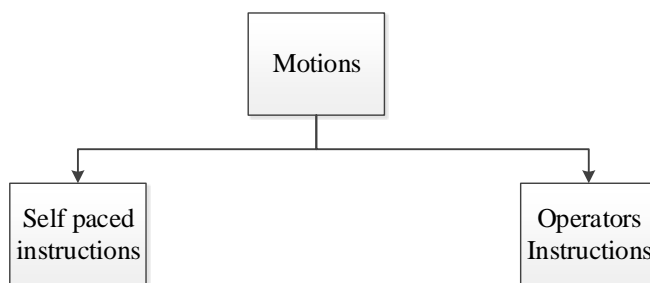


Figure 2.5: Means of conducting Imaginary Motions

2.5 Literature Review

A study using BCI data with two features classifier (right and left hand movement at operator's instruction) shows better performance when using Artificial neural network (ANN) compared to Hidden Markov Model (HMM) [32] [33]. The study also concludes that reducing the number of electrodes used in the BCI setup gives a much better accuracy. A similar study compared between Linear Discriminant Analysis (LDA), ANN, and Decision Trees also showed that ANN outperformed the other classifiers with an accuracy of 81.6% [34, 35].

A different study was conducted to compare the performance of classifying imaginary motions such as hand, foot, and tongue. In this study, a nonlinear K-nearest neighbor algorithm based Support Vector Machine (KNN-SVM) was compared with two linear

classifiers; LDA and Naive Bayesian. The nonlinear SVM was reported to outperform the other classifiers with an accuracy of 82.14% [36]. Additionally, it was reported that when the size of the data set is reduced, then KNN-SVM accuracy increases by 5%. Fuzzy particle swarm optimization was also used with neural network to classify BCI data of imaginative head movement and it has achieved an accuracy of 84.4% [37, 38].

P300 classification which is based on Independent Component Analysis (ICA) and Wavelet Transform proves to be a very good approach in selecting optimal features from the time domain and frequency domain. Based on specific subjects and it reduces the amount to data to improve the speed of classification but at the same time it increases the accuracy. This algorithm was tested on imagination of characters from words defined by the operator [36].

The University of Barcelona used Statistical Discriminator with the preprocessed EEG data samples to classify three types of imaginary motions that were conducted by the subjects in a self paced repetitive fashion. The imaginary motion classified were left-hand, right-hand movements, and the generation of words beginning with same random letter. Data was preprocessed offline at first and then processed using a statistical discrimination classifier [39]. The three mental tasks are classified after normalizing and then transforming the normalized data using canonical variate transform. This algorithm achieved an average accuracy of nearly 71%. Another interesting study was conducted by the Computer Vision and Multimedia Lab. at the University of Geneva, Switzerland. They tested four different classifiers which are Support Vector Machine (SVM), decision tree, Learning Vector Quantization (LVQ), and Naive Bayes classifier. Each of the datasets was used to train these classifiers and the results generated showed that SVM gives better accuracy than the rest of the three classifiers with a margin of 8% [40]. The dataset used in these studies was chosen to be used in this study. The reason behind choosing this particular dataset is the relatively low reported classification accuracy. However, we used a different method than what was

used by the University of Barcelona.

Imaginary movements can be classified using classifiers, linear and nonlinear [41]. Linear classifiers are said to be more suitable for this kind of data. Linear classifier is again broadly divided into two models namely generative and discriminative models. The various types of classifiers are illustrated in the Figure 2.6.

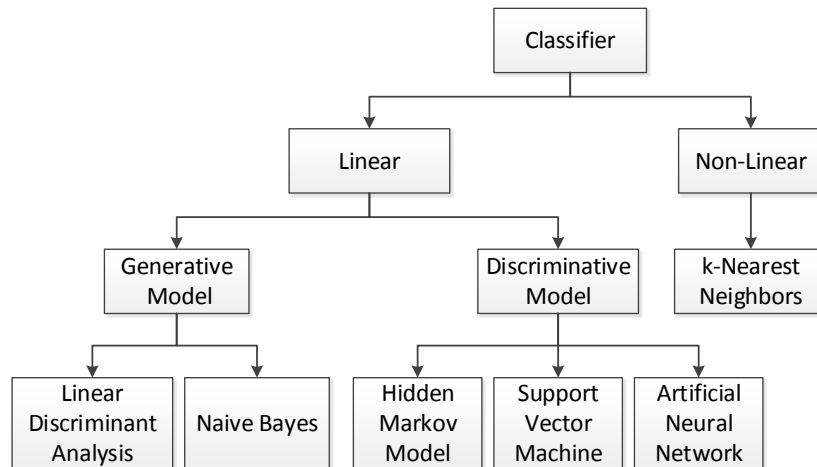


Figure 2.6: EEG Classifier Taxonomy

Most of the studies in this field showed that certain algorithms like Elman recurrent, wavelet transform, Fuzzy logic, and Principal component analysis are used along with ANN in order to classify the imaginary motions accurately. Some of the common algorithms that are used along with ANN are shown below in the Figure 2.7.

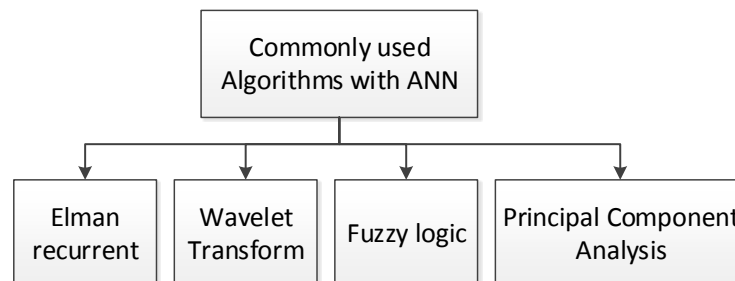


Figure 2.7: ANN Algorithms

CHAPTER 3

INDIVIDUAL USER BCI USING EEG ELECTRODE OPTIMIZATION

Although the physiology of the brain is same for every human being, still there is a big difference between each person by the way they use their brain. Some people use their left side of the brain during their thought process while some use their right side of the brain. General tendency of any human being is to use both left and right side of the brain and this usage of brain is completely involuntary [42]. So, in order to get a good accuracy for object controlling, it is required to design the electrode positioning of each individual separately. Keeping this in mind, we tried to find out the best set of probes of a person and study the difference of probes used across individuals. Our objective was also to study the brain usage pattern across different subjects.

3.1 Data Set Used

For the purpose of their work, the BCI Competition III dataset V were used as the experimental dataset. This dataset is generated by the IDIAP research institute in Switzerland [40]. In this dataset, data of 3 healthy subjects were recorded, with 3 sessions for each of them performing 3 Imaginary mental motion tasks (Imagination of Left hand movement, Right hand movement and word generation starting with the same letter). All of these 3 sessions for each subject were recorded on the same day. Each session lasted for 4 minutes with a break of 5-10 minutes in between each session. In each session, a subject performed all three kinds of Imaginary motions with each motion lasting for about 15 seconds and then switching to another motion at the operator's request. The EEG potentials were recorded at 512 Hz sampling rate using a portable Biosemi EEG machine with 32 electrodes placed on the scalp according to 10-20 system of standard electrode positioning. Each electrode was assigned a channel number to simplify the experimentation as shown in Table 3.1.

Recorded EEG data were provided in two formats, 1) raw EEG potentials and 2)

Table 3.1: 10-20 system electrodes used in experiments

Channels	Electrode	Channels	Electrode
1	FP1	17	O2
2	AF3	18	PO4
3	F7	19	P4
4	F3	20	T6
5	FC1	21	CP6
6	FC5	22	CP2
7	T3	23	C4
8	C3	24	T4
9	CP1	25	FC6
10	CP5	26	FC2
11	T5	27	F4
12	P3	28	F8
13	PZ	29	AF4
14	PO3	30	FP2
15	O1	31	FZ
16	OZ	32	CZ

precomputed Power Spectral Density (PSD). In this thesis, the raw data (without any pre-processing) with over 288 data samples were used for training and testing of the proposed system of ANNs. This dataset is previously used by other universities during BCI competition and University of Barcelona is ranked first for classifying the dataset with an accuracy of 71%. This accuracy was used as the benchmark to the performance of the proposed classifying technique.

3.2 Proposed Technique

To classify this dataset of imaginary motions, ANN was the classifier of choice. Although, ANN was used in BCI Competition before by the University of Essex, they only ranked eighth with a reported accuracy of 63.91%. The goal of this work, is not only to improve the reported accuracy by the University of Essex, but also exceed the best reported accuracy of 71%. The proposed model involves using, separate ANN for each channel (electrode) and then combine all classification using a majority vote. Artificial neural networks are network models that are created with motivations from biological neural networks. These networks use an approximation function that assimilates a wide variety of inputs and targets and provides an output. The model uses a system of neurons that are interconnected to learn the patterns underlying a large array of inputs. An artificial neural network operates by creating connections between many different processing elements, each analogous to a single neuron in a biological brain. These neurons may be physically constructed or simulated by a digital computer [43]. The proposed neural network consists of two hidden layers of 10 and 20 neuron in size to maintain a high classification accuracy for the network. The number of neurons in each layer is selected based on various experimentation. Back propagation method was used to train this network. Artificial neural networks have proved useful in a variety of real-world applications that deal with complex data such as visual pattern recognition and speech recognition. In addition, recent programs for text-to-speech have utilized ANNs. Many handwriting analysis programs are powered by ANNs [44]. The ANN structure used in this study for individual user accuracy classification is shown in Figure 3.1.

The novelty of this proposed system lies in using the Majority Vote system in conjunction with a network of ANNs. Using majority vote system along with the network of ANNs improved the ability of the system to successfully detect motions since it was based voting which didn't require high accuracy per channel. The structure of our proposed system is

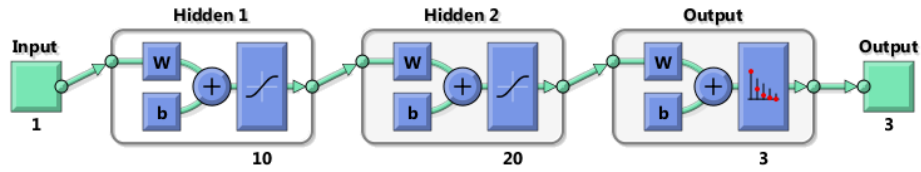


Figure 3.1: A Single Artificial Neural Network

detailed below 4.1. The process of classification utilizes the data acquired from an electrode and categorizes these values into three imaginary task categories or classes. This is done using the target specifications in the data-set.

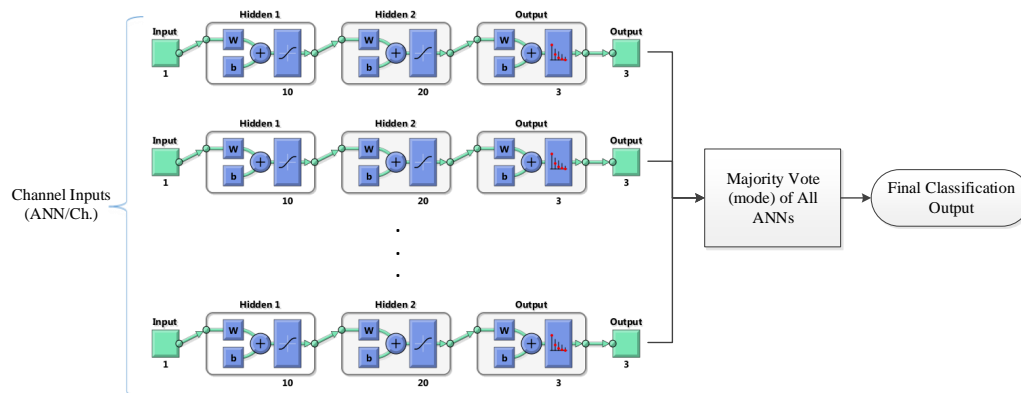


Figure 3.2: ANN Architecture

Majority vote is the concept which chooses the decision of more than half hence, majority [45]. Majority voting is a very powerful tool in case of odd number of classes in any pattern recognition process [46]. It is seen that majority voting is a much faster way of decision making than other algorithms like Genetic Algorithm. In this study, hence we implemented the concept of majority voting to classify motions into three classes namely Class 7, Class 3, Class 2. The ANNs are trained with with the data of all the 32 channels as the first step. Then the outputs for the individual channels are combined using a majority vote system in order to find the final voted classification [47]. The outputs of the classes are represented in the form of bits(1 or 0) and the class which gets the highest number of

votes the final classification. To validate the results obtained, the final classifications are compared with the original motions recorded in the target files. If two of the classes have the same vote then the previous vote is also considered to break the tie.

The implementation of majority vote has been the key factor in enhancing the accuracy of the EEG classification. Besides, increasing the classification accuracy using the majority vote, the set of electrodes were optimized to get the optimal accuracy. For the process of optimization, the 32 ANNs for each subject were used. Based on the accuracy of each channel, all the channels were ranked to optimize the electrodes. The optimization process is shown in Figure 3.3. An optimized set of electrodes was obtained for every subject since human in general differ in the way they use their brains. But for each subject the brain behaves differently and there is no consistency and it is necessary to find optimized electrodes for each user. The electrodes were optimized for each user separately and then used to obtain the individual classification accuracy. finally these accuracies were averaged out to obtain the overall accuracy. To optimize the set of electrodes, first the EEG raw inputs of three session for every subject were used to train and test the 32 ANNs with 50% of data for training and 50% for testing. The accuracies of the 32 electrodes across three sessions are averaged and the channels are ranked then according to their accuracies. Using this rank, we eliminated the worst electrodes were eliminated one at a time to obtain the new accuracy of the majority vote. The process continues until the classification accuracy obtained is the maximum. The resulting set of electrodes that obtain the maximum classification accuracy is the optimal set of electrodes.

3.3 Result For Individual Subject Analysis

At first, the classification accuracy was recorded for each electrode and subject. Figures 3.4- (a, b, c) illustrate the accuracies of all the electrodes for subject 1, subject 2, and subject 3, respectively.

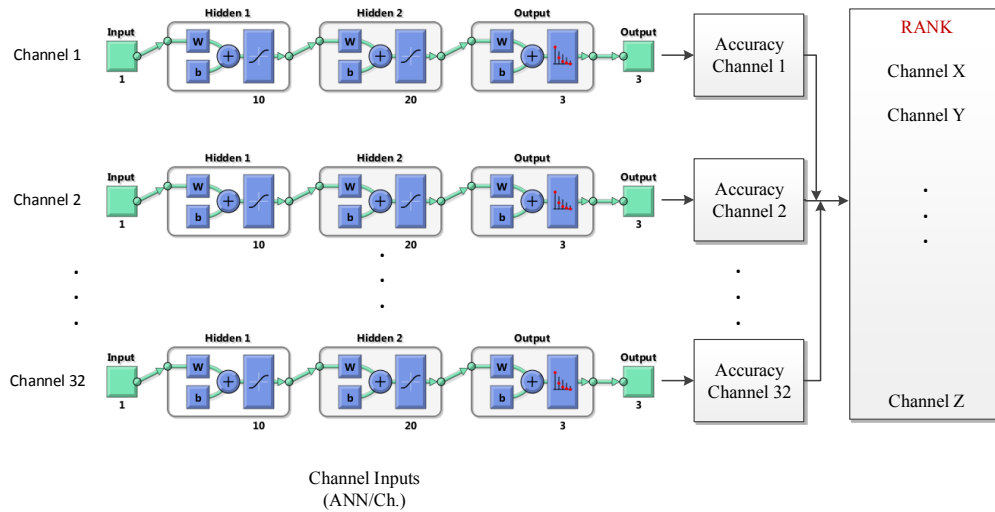
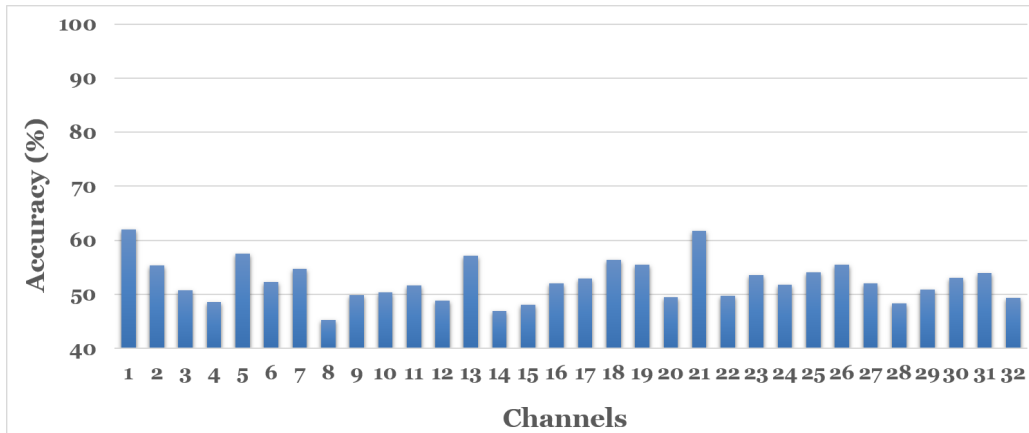


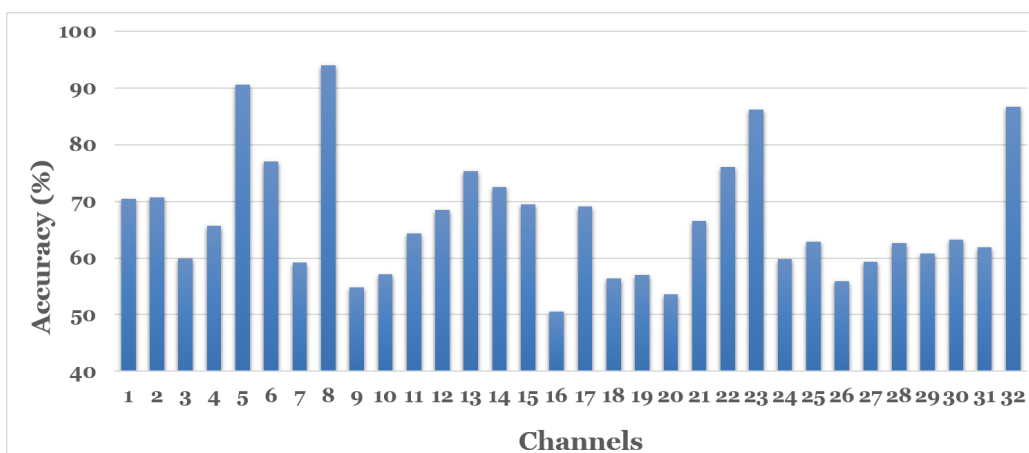
Figure 3.3: Optimization of electrodes for individual user

Based on the average classification accuracy of each individual electrode for each subject, the electrodes were optimized. For the dataset used in this experiment, subject 1 had a set of 20 electrodes as the optimized electrode set which resulted in a classification accuracy of 63.33%, while subject 2 had a set of only 1 electrode with a classification accuracy of 94.01%. Subject 2 had only one electrode since this electrode classification accuracy was significantly higher compared to the rest of the electrodes. Finally, subject 3 optimal set of electrodes consisted of 14 electrodes with a classification accuracy of 84.33%. Figure 3.5-(a, b, c) illustrate the placement of the optimal set of electrodes for subject 1, subject 2, and subject 3, respectively. It is obvious from these results, that each subject utilized a different set of electrodes to obtain the optimal classification accuracy. For two subjects (subject 1 and 3), both sides of the brain worked together through Corpus Callosum, while subject 2 was left lateralized, since the left side of the brain is known for critical thinking. It is worth noting that subject 2 performed the best among all three.

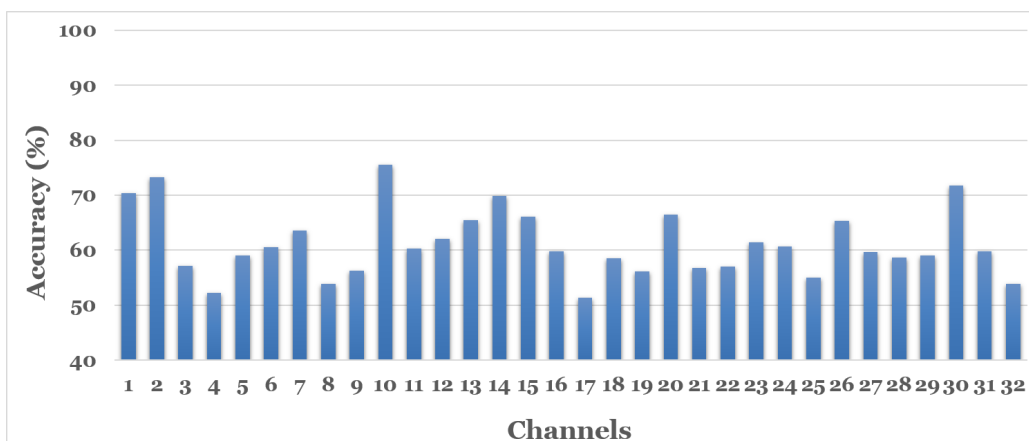
Figure 3.6 illustrates the overall classification accuracy results of the optimization process as a function of the number of electrodes used for subject 1, subject 2, and subject



(a) Subject 1



(b) Subject 2



(c) Subject 3

Figure 3.4: Individual Electrode Classification Accuracy for a) Subject 1, b) Subject 2, c) Subject 3

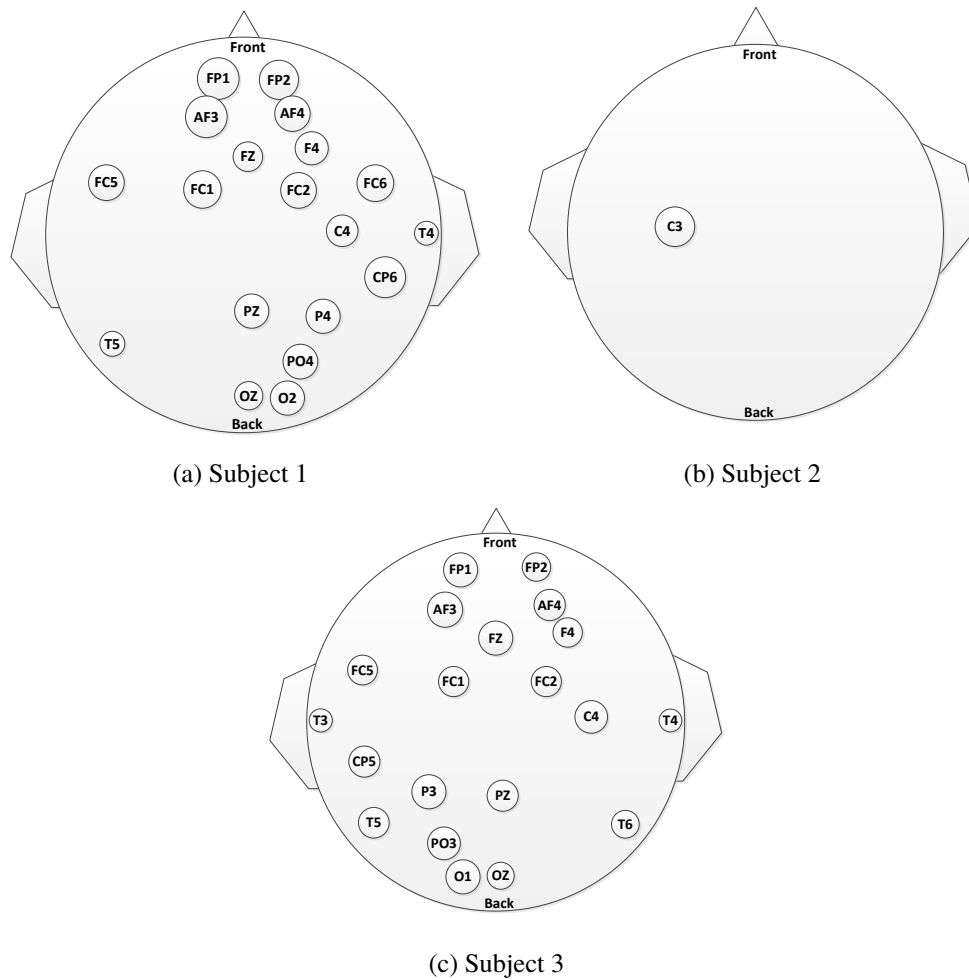
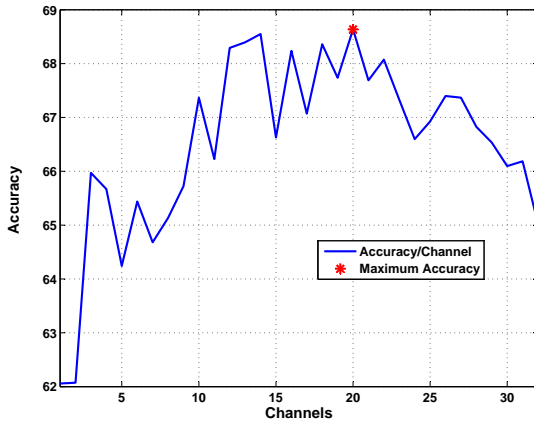


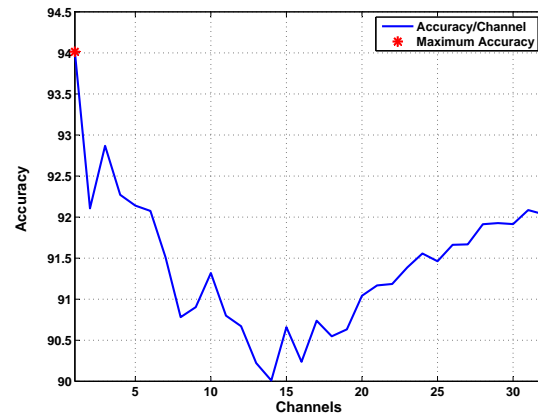
Figure 3.5: Optimal set of electrodes for a) Subject 1, b) Subject 2, c) Subject 3

3, respectively.

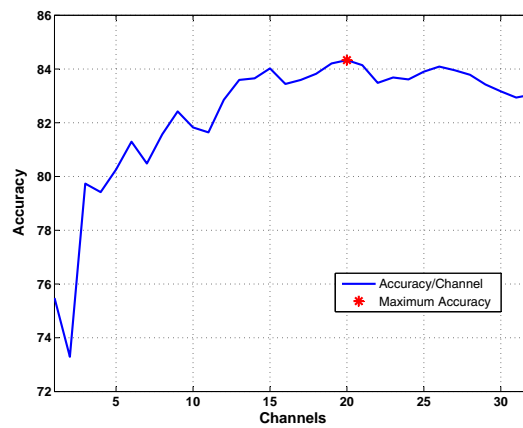
Table 3.2 summarizes all the optimized classification accuracies of all the subjects. The reported overall accuracy calculated by averaging the classification accuracy of all subjects was 82.32% which is higher than the 71% accuracy reported by the University of Barcelona. It is also observed that subject 1 and subject 3 used both the left and the right side of their brains to perform the imaginary tasks given while subject 2 used only right side of the brain to do so.



(a) Subject 1 Accuracy Optimization



(b) Subject 2 Accuracy Optimization



(c) Subject 3 Accuracy Optimization

Figure 3.6: Classification Accuracy vs. No. of Channels for a) Subject 1, b) Subject 2, c) Subject 3

Table 3.2: Optimization of Electrodes for Individual Subjects

Subject	Classification Accuracy
1	63.63%
2	94.01%
3	84.33%
Average	82.32%

CHAPTER 4

MULTIUSER BCI USING EEG ELECTRODE OPTIMIZATION

Even though human beings are unique in the way they use their brain, there are some applications where the BCI system would only be utilized for a small amount of time such as gaming. In such uses, to enhance the BCI system commercial viability and utilization a multiuser BCI system with an optimized set of electrodes can help achieve these goals. In the multiuser BCI system, multiple users will share this system at different times which help save the cost of purchasing dedicated systems for every user.

4.1 Result For Individual Subject Analysis

In this research work, a three-layer feed-forward neural network per electrode was used, with sigmoid hidden and output layers. This neural network can classify all the three different imaginary motions relatively well, given a 10 and 20 neurons in its two hidden layers. The network was trained using the scaled conjugate gradient back-propagation algorithm. The novelty of this proposed approach is in using a majority vote system for a network of artificial neural networks (ANNs) that is used to optimally classify imaginary motions performed by multiple subjects. 32 channels were used to train 32 ANNs in order to reduce the complexity of designing a single ANN with 32 inputs. The difference between the other reported studies and this one is that, they used a single ANN with 32 channels input which resulted in a complicated ANN structure and low overall accuracy. Unlike the proposed model uses a simple ANN for every channel. Figure 4.1 illustrates the proposed model.

In general, all the EEG based BCI systems will target a specific class of imaginary motions to classify. This provides a priori information about which region of the scalp will be more effective which help reduce the number of channels used. However, this approach won't be as effective when developing an optimal system for multiusers due to the individual difference among the users. Therefore, the number of electrode channels used are optimized

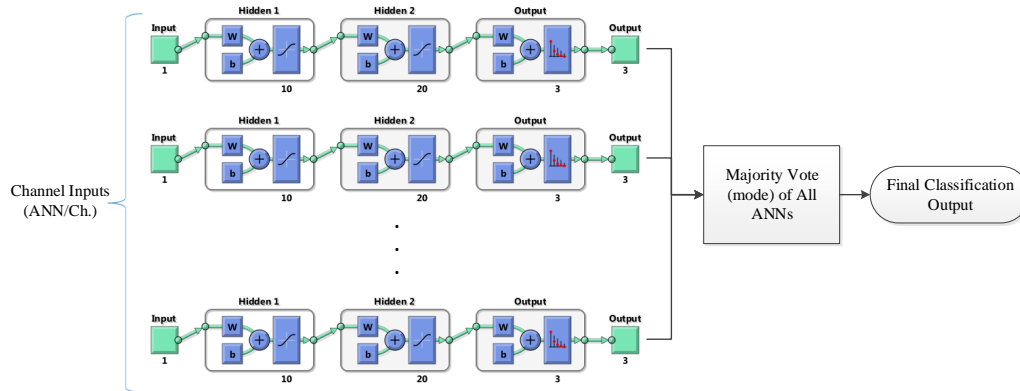


Figure 4.1: Structure of ANN

by maximizing the overall multiuser classification accuracy. The channel optimization is based on the elimination of channels with low average classification accuracy across all users. To do so, the channels are first ranked based on their average classification accuracy across all users as illustrated in Figure 4.2. The cost function for this optimization problem is to maximize the overall average classification accuracy of the system.

4.2 Result For Multiuser Subject Analysis

To validate the performance of the proposed method discussed in this chapter, the BCI Competition III dataset V was used to train and test the network of ANNs. First, we recorded the classification accuracy for each channel separately as reported in Figure 4.3. Based on the individual channel classification accuracy results obtained in the previous step, the 17 channels with the highest classification accuracies channels were chosen as the first initial optimized set of electrodes with minimum accuracy of 58.63%. The chosen electrodes are illustrated in Figure 4.4 (a). It is observed that the left side and the center of the scalp are the most effective common regions among the 3 users in this study. Most of our selected electrodes are on the left lateral frontal lobe region of the brain. This region is known to be responsible for motor functions and word generation [48].

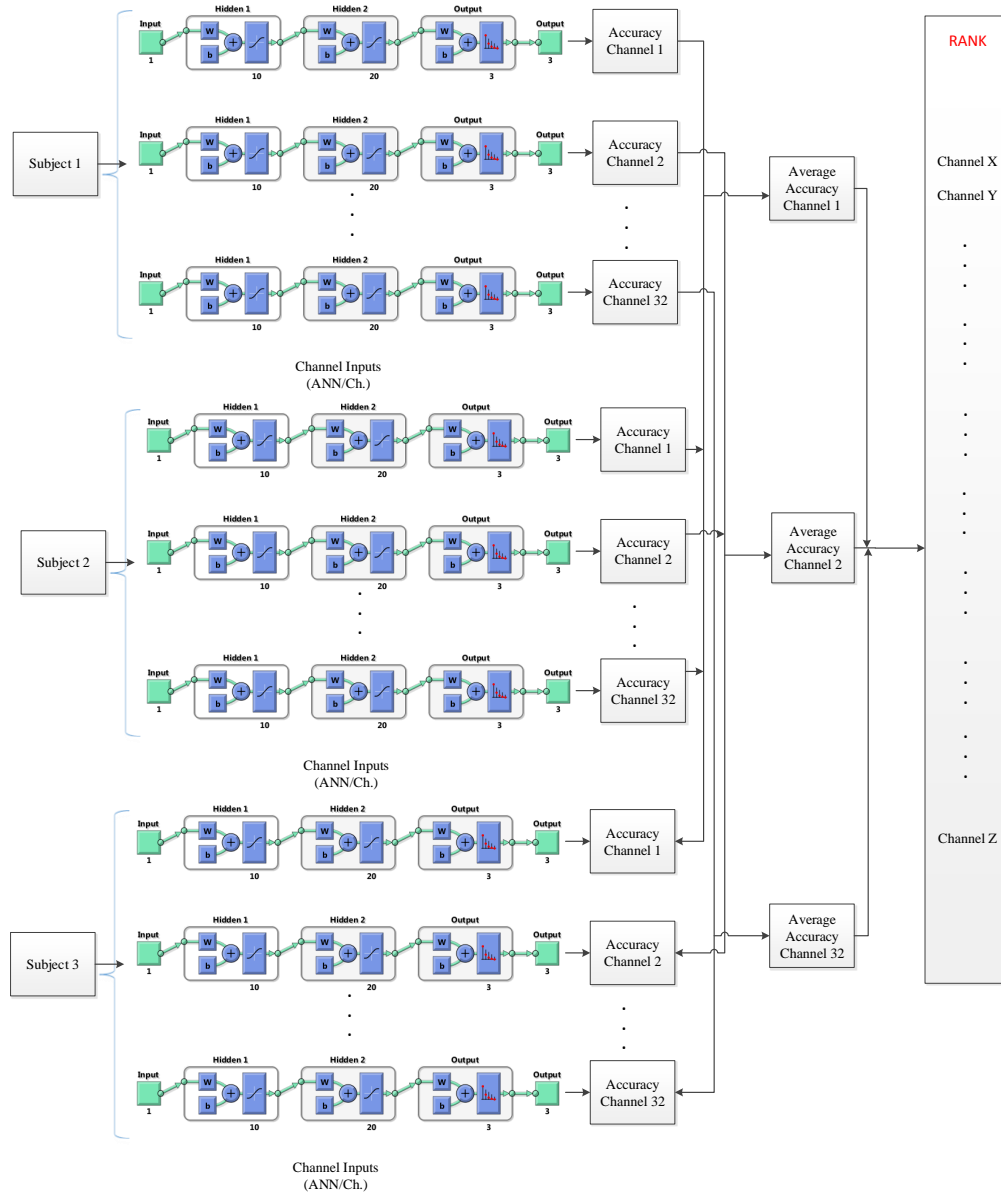


Figure 4.2: Optimization of Electrodes for Multiusers

The overall system performance using the 17 channel structure resulted in an average classification accuracy of 78.71%, which is higher than the maximum reported accuracy of nearly 71% for this dataset [39]. A fine optimization stage was implemented, by eliminating channels 15, 31, and 7, respectively. The final optimal structure consisted of 15 electrodes, as illustrated with an average classification accuracy of 79.96%. The set of 16 and 15 chosen

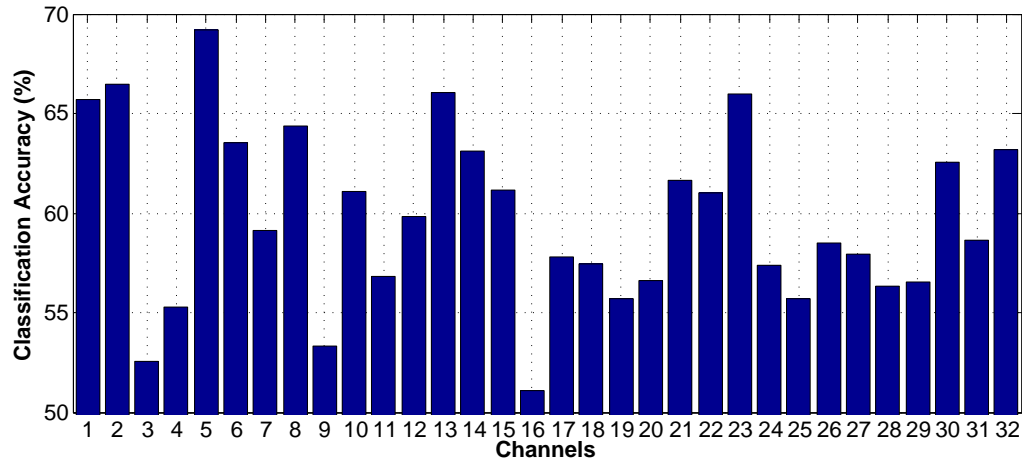


Figure 4.3: Individual Channel Classification Accuracy

electrodes are illustrated in Figures 4.4 (b) and (c), respectively. The results of optimization step is recorded in Table 4.1.

Table 4.1: Optimization of Electrodes

No. of Channels	Classification Accuracy
17	78.71%
16	79.21%
15	79.96%
14	78.91%

Figure 4.5 illustrates how the classification accuracy varies with time across sessions for the 17, 16, 15, and 14 electrode structures. It is observed that classification accuracy varies across the different users with subject 2 having the highest accuracy followed by subjects 3 and 1, respectively. In addition, it is also observed that the classification accuracy degrades with time for all users, which could be due to fatigue and lose of interest.

Figure 4.6 illustrates how the classification accuracy varies with different electrode structures in 3 different sessions. It is observed that the classification accuracy do not

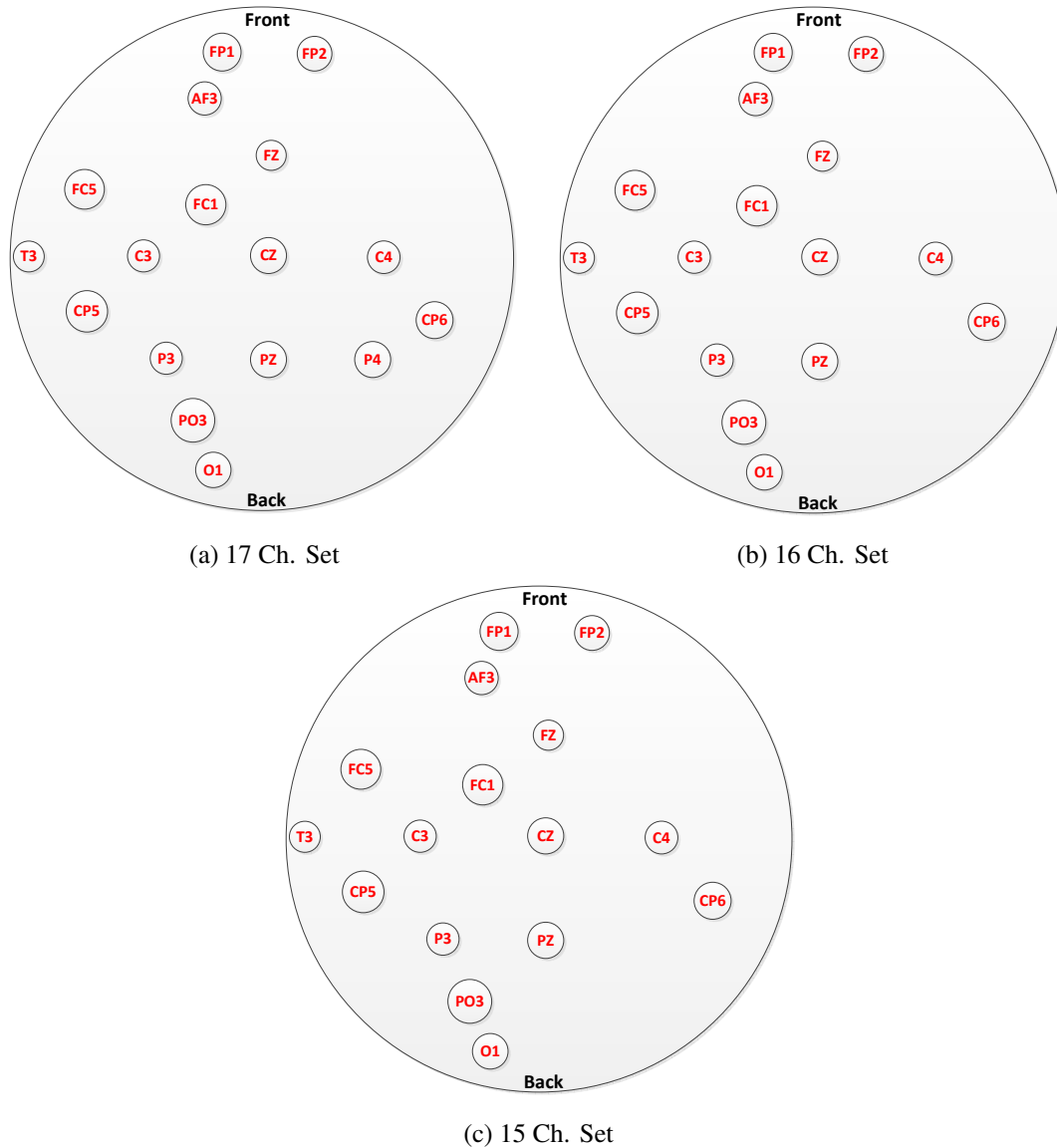


Figure 4.4: The Optimal Electrode Sets using a) 17 Channels, b) 16 Channels, c) 15 Channels

vary significantly with the structure consisting of 15 electrodes providing the best accuracy. However, it is observed that the classification accuracy per user varies differently across sessions with subject 1 having the highest variation across sessions. This emphasize that EEG based BCI is very user dependent and this makes the optimization of a specific set of EEG electrodes to serve as a unified multiuser BCI system very difficult.

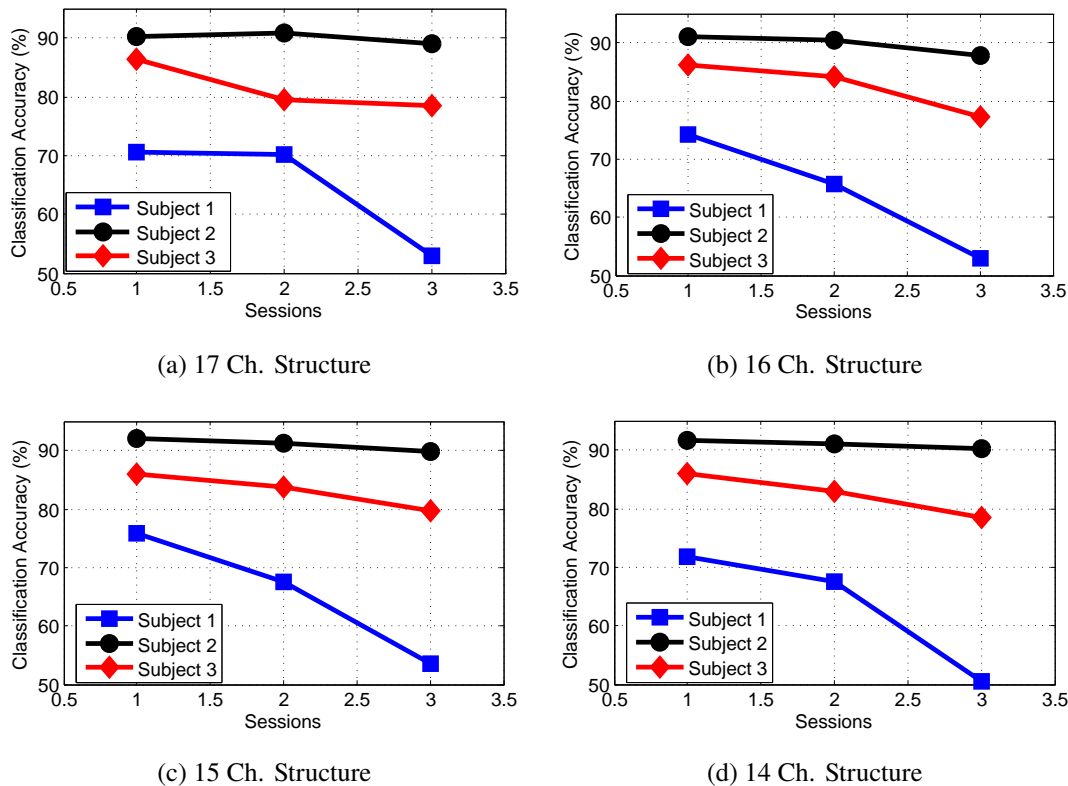


Figure 4.5: Classification accuracy of each subject versus sessions for 17, 16, 15, and 14 electrode structures

From Table 4.2, the University of Barcelona that ranked first reported an accuracy of 71.00% but our method of majority vote improved the accuracy to 79.96% for multiuser optimized BCI and 82.32% for individually optimized BCI.

Table 4.2: Result Comparison

Institution	Classification Technique	Overall Accuracy
Georgia Southern Uni.	MV with ANNs (Individual User Optimized)	82.32 %
Georgia Southern Uni.	MV with ANNs (Multiuser Optimized)	79.96 %
Uni. of Barcelona	Statistical Discriminator	71.00 %
Uni. of Essex	ANN	63.91 %

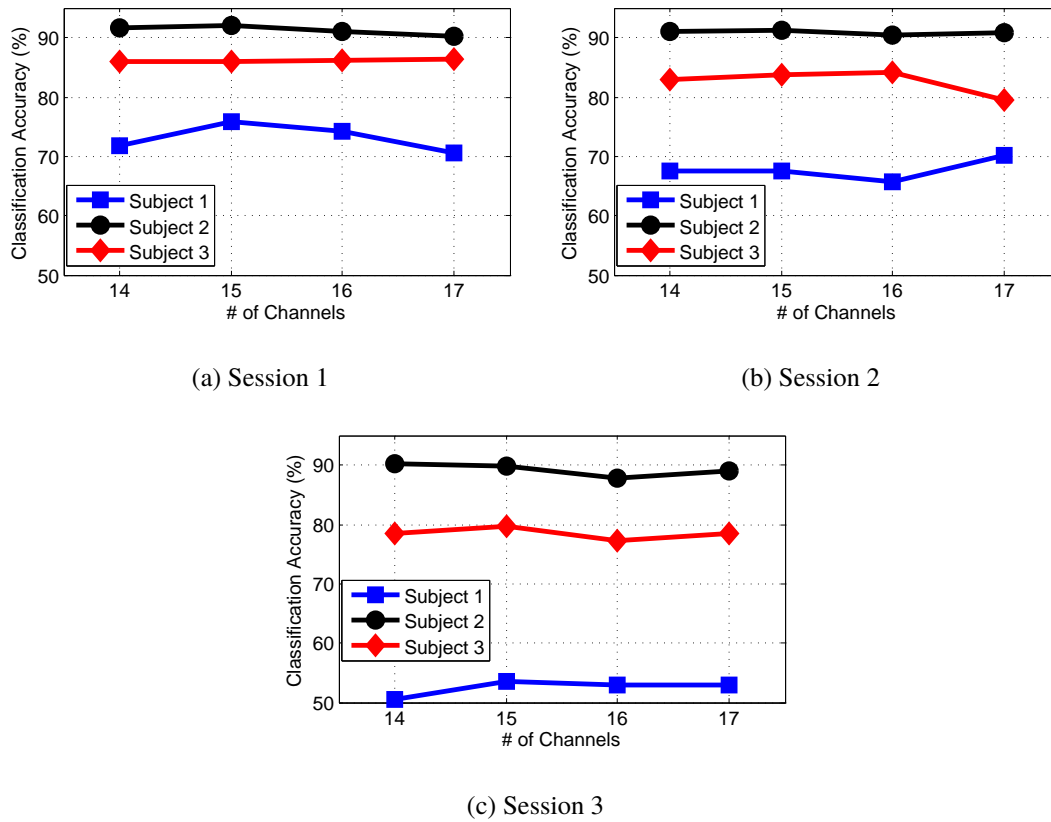


Figure 4.6: Classification accuracy of each subject versus channel structure for 3 different sessions

CHAPTER 5

CONCLUSION AND FUTURE WORK

A majority vote system for a network of artificial neural networks (ANN) to optimally classify imaginary motions performed by individual and multiple subjects were proposed. The proposed method optimizes the channels used for single user and multi-user classification by ranking the channels based on their classification accuracy. The best performing electrodes are identified with the help of some statistical analysis. The performance of the proposed method was evaluated using the BCI competition III dataset V which primarily consisted of three imaginative motions like Imaginary left hand movement, Imaginary right hand movement, Imaginaton of words starting with the same letter. It was observed that using a separate ANN for every channel coupled with a majority vote system was able to improve the average classification accuracy of such imaginary motions for all three users from a maximum 71% to almost 82.32% for individual use while maintaining a relatively simple ANN structure. In addition, the quality of the EEG signal generated by the users declined with time due to fatigue and loss of concentration. It was also concluded that the classification accuracy is user dependent in nature which limits it optimization for multiple subjects. The proposed method presented is novel in the structure of such classification network and in the optimization of its channels. It is concluded that classification accuracy is user dependent and hence each user has a different set of optimal electrodes.

Although, we reported good classification results, the study has some inherent limitations the dataset is based on three subjects only, there might be more variation when considering more subjects. Also the subjects in the dataset are of same age group and of same gender (male). The study would be even stronger if more diverse subjects are considered. As seen from the results, a change of performance in every session, was due to fatigue and loss of concentration which could be aged dependent. Therefore the limitation within the dataset prevented testing all the variables. in addition the optimization method used

was linear. Hence, in order to improve the optimization process, a nonlinear optimization technique such as genetic algorithm can be used.

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