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I, Shweta Sahu, hereby submit this original work as part of the requirements for the degree of Master of Science in Computer Science.

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Channel Selection in Unicorn Headset

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Channel Selection in Unicorn Headset

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by

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Abstract

Brain-computer interface (BCI) allows the human brain to connect directly with the outside world using electroencephalogram (EEG) signals, due to this it has received a lot of interest in recent years. These EEG signals are generated through the electrode placed on the head which captures brainwave activity while performing different motor imagery task, these electrodes are also known as EEG channels which generates EEG signals. In the further processing of these EEG signals, commands are generated that are used to control equipment such as wheelchairs, robotic arms, etc. In the proposed work we are interested in selecting the optimal number of EEG channels from the available unicorn channels without much affecting the system accuracy.

To my Dearest Parents

Acknowledgment

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Chapter 1

Introduction of Brain-Computer Interface

1.1 Brain-Computer Interface

Brain-computer interface (BCI) read the signals from the brain, analyze the brain signals, and convert those raw signals into meaningful information or actions that are carried out by output devices [6] [7]. BCI has reached the general interest of the public over the past few years, but the people have been working on it for the last 20-30 years. BCI are devices or systems which respond to the neural processes in the brain that generate or modify movement. So, the signal which BCI use are the signal from the neuron or the scalp. The signal coming from the brain just before any movement is process by signal processing unit and pass to the output device, the action perform by output device is based on the signal that picks up from the brain [6].

1.1.1 Goal of BCI

The goal of BCI is to create an environment that enables people with damaged neural pathways to control their environment. Brain signals are used to control devices rather than paralyzed limbs, control device could be robotic arm or any other device [6]. BCI systems are predicted to have great societal impact, and there is a growing interest from industry to commercialize and market BCI system for medical and non-medical applications [6].

BCI allow disable people to control a wheelchair, robotic prosthesis or a computer cursor. Many research are going on but nothing has been widely deployed they still are in pilot stages. There is still a huge opportunity in this field to make a BCI device which is cost effective and reliable [6]. The current trend in worldwide BCI is extensive and is rising rapidly BCI and is approaching the level of first-generation medical practice, and clinical trial of invasive BCI technologies [6].

1.1.2 BCI system

There are two types of systems P300 and Gtec. Suppose you have a patient with stroke, to rehabilitate them or help them to communicate you can use these systems. P300 stimulus has different alphabets being flashed on the screen [6]. Suppose the subject wants to say "hello," he has different alphabets being scalped, the first letter of the word hello is “H,” it has P300 signal and 6 instances of this it will get the alphabet “H,” similarly alphabet “e” and then followed by the other word. As the transfer rate is slow, it is hard to communicate, but still helpful for a person who has difficulty in communicating. Figure 1.1 is the classical P300-based spelling paradigm, it is developed by Dochin [6].

Figure 1.1: The classical P300-based spelling paradigm [1]

.

1.1.3 Implications of BCI

1. Closed-loop system

2. Real time system

1.2 Brain Activity Detection

The phenomenon known as neuronal activity is due to the motion of electric charges in the brain, which produces both electric and magnetic fields. Brain-computer captures this change in electric and magnetic field that occurs as a result of certain tasks performed by the brain.

1.2.1 Invasive

Invasive BCI have multi-electrode arrays of tens to hundreds of electrode implanted in brain cortical tissue from which movement intent is decoded. It is not painful to create the recording. However, it can be painful to perform surgery and there are risks involved with recovery [3]. Animals such as monkeys and rats are typically used for invasive recordings. Animals (for example monkey) can be recorded for weeks and months, while humans can be recorded for as little as a few minutes in a clinical setting [3].

We worked on noninvasive BCI because for invasive BCI it is not possible unless you are a neurosurgeon and have access to patient brains [8].

1.2.2 Non-invasive

Non-invasive BCI use the scalp signal and record the changes in EEG stage, follow through the signal conditioning unit to control output devices. The recorded signals are electrical signals range between 5 to 10 microvolts, this could be motor potentials [3] [9].

1.3 Thesis Outline

This thesis is organized as follows:

Chapter 1 (the current chapter) covers a basic introduction of the BCI.

Chapter 2 includes the different non-invasive techniques and brief description about electrode positioning.

Chapter 3 introduces the related work and contribution as per topic. which involves BCI, EEG signals, channel selection and unicorn headset.

Chapter 4 covers the introduction of the bootstrap fusion scheme and proposed method to select optimum channel in unicorn headset.

Chapter 5 covers the channel selection algorithm in unicorn headset.

Chapter 6 describes the experiment set up which includes data-set and procedure, then presents the simulation results and discussions.

Chapter 7 conclude the paper giving future research directions.

Chapter 2

Noninvasive Techniques

2.1 Noninvasive Techniques

Noninvasive recording techniques employ sensors placed on the scalp, or machinery surrounding the whole skull [10]. Noninvasive techniques are broadly categorized into two types of:

1. Direct techniques
2. Indirect techniques

Direct techniques measures the electrical activity or the magnetic activity of the brain, examples: Electroencephalography, Magnetoencephalography [10]. Indirect techniques measures brain function that reflect metabolism, examples: Functional magnetic resonance imaging, Functional near infrared imaging [10].

2.1.1 Electroencephalography

EEG (Electroencephalography) is a method of recording brain signals non-invasively using electrodes placed on the head [3] [11]. The high temporal resolution of EEG is advantageous because it is a low-cost procedure for an experiment design and data collection that can be used for brain data collection [12]. Figure 2.1 shows the image of the electroencephalography signal.

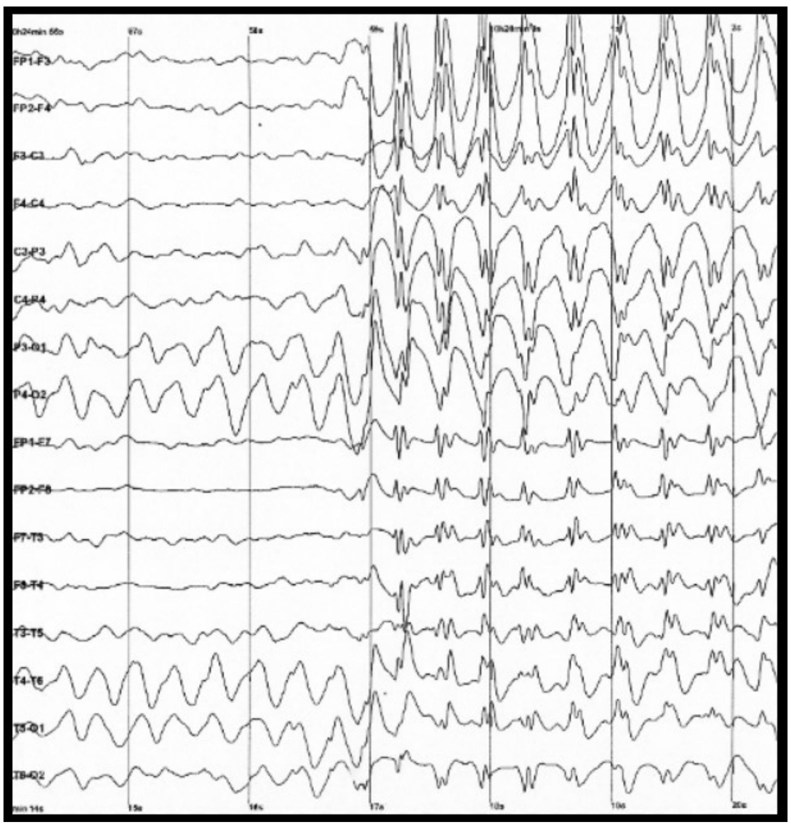

Figure 2.1: Electroencephalography [2]

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Figure 2.2 shows a subject wearing headset containing an EEG cap with three electrodes - a recording electrode, reference electrode, and ground electrode to record EEG signals [10]. A differential amplifier is used to amplify the EEG, which is the core of the measurement. For the EEG waveform to be accurately captured, this impedance should be as low as possible.

Figure 2.2: Subject wearing EEG cap [3]

EEG signals consist of different types of oscillations called rhythms or frequency. The spatial and spectral localization of these rhythms can differ [13]. There are five major bands in an EEG recording, corresponding to frequencies of 0.5Hz to 40z [12]. Table 2.1 [13] shows the name of rhythms with their frequency range and amplitude.

Table 2.1: EEG rhythms

Rhythm	**Frequency in Hertz**	**Amplitude in μV**
Delta	$1-4$	$100-200$
Theta	$4-7$	$5-10$
Alpha	$8-12$	$20-80$
Beta	$13-30$	$1-5$
Gamma	$30-40$	$0.5-2$

In the delta wave, the frequency ranges from 1 to 4 Hz [13]. Waves in this group tend to have the highest amplitude and the slowest waves. This is the pattern seen normal in slow-wave sleep in adults and also in infants [2]. Figure 2.3 shows the waveform of Delta waves.

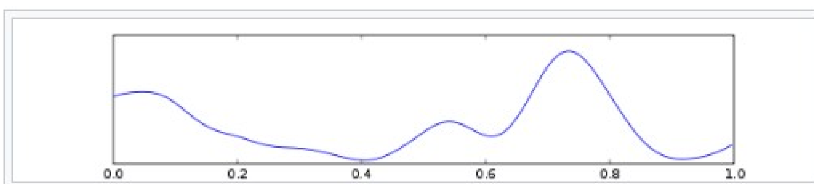

Figure 2.3: Waveform of Delta wave [2]

Theta waves have a frequency range of 4 Hz to 7 Hz [13]. In young children, theta is commonly observed. Children and adults may show signs of drowsiness or arousal, and it may be evident during meditation as well. An excessive amount of theta indicates abnormal activity [2]. Figure 2.4 shows the waveform of Theta waves.

The frequency range of an alpha wave is 8 Hz to 12 Hz [13]. The wave occurs on both sides of the head, but its amplitude is greater on the dominant side. In this state, it arises when the eyes are closed and relaxing, and recedes when the eyes are opened or when mental effort is exerted. This rhythm is actually lower than 8 Hz in children [2]. Figure 2.5 shows the waveform of Alpha waves.

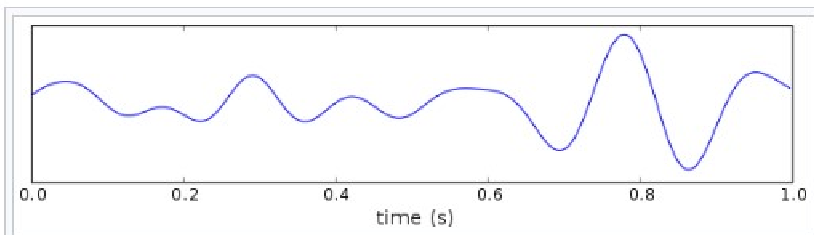

Figure 2.4: Waveform of Theta wave [2]

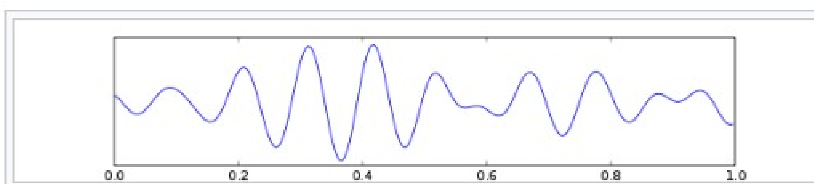

Figure 2.5: Waveform of Alpha wave [2]

The beta wave oscillates between 13 Hz to 30 Hz [13]. Most frequently, it appears frontally and is symmetrically distributed on both sides. During movements, the beta activity is generally attenuated and is linked closely to the motor behavior. An active, busy, or anxious mindset is often accompanied by a low-amplitude beta signal with multiple and varying frequencies [2]. Figure 2.6 shows the waveform of Beta waves.

Gamma wave refers to the frequency range between 30 Hz to 40 Hz.

It is generally believed that Gamma rhythms represent the co-ordination of different populations of neurons in order to carry out certain cognitive functions. Figure 2.7 shows the waveform of Gamma waves.

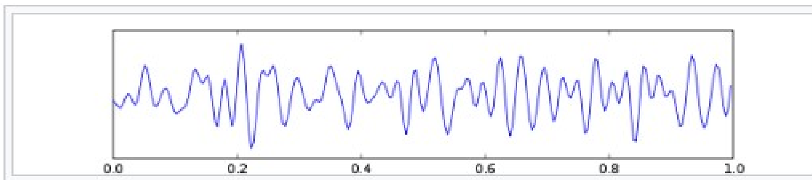

Figure 2.6: Waveform of Beta wave [2]

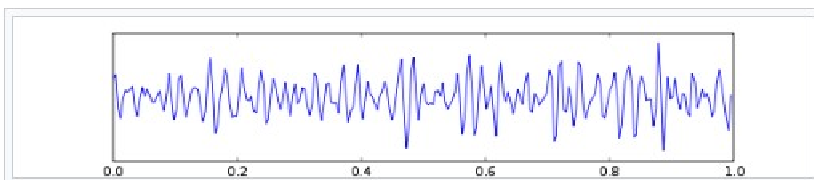

Figure 2.7: Waveform of Gamma wave [2]

2.1.2 Magnetoencephalography

Magnetoencephalography (MEG) technique is a noninvasive technique that records the magnetic fields generated by neurons in the brain [3]. Magnetic fields cannot be detected by a single neuron, but they can be detected when numerous neurons fire together, creating a much larger and more visible magnetic field. Anatomical images such as magnetic resonance imaging, as well as the functional information obtained from magnetic field recordings, are combined in the MEG [10].

2.1.3 Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging (fMRI) is used to measure the neuronal activity of the brain, it identifies a hemodynamic response to blood oxygen levels dependent also known as BOLD [10]. A fundamental principle of magnetic resonance imaging is the coupling of neuronal activity with regional cerebral blood flow and oxygenation [3]. For detailed BCI tasks, fMRIs could provide highly accurate spatial information, but compared to other techniques such as EEG or MEG, their temporal resolution is relatively slow [10].

2.1.4 Functional Near Infrared Imaging

Functional Near Infrared Imaging (fNIR) monitors the blood flow in the cerebral cortex for changes in oxygenated and deoxygenated blood. Light is absorbed at different rates by oxygenated and deoxygenated blood [3]. fNIRS has a slower temporal resolution than EEG or invasive approaches due to the latent nature of the blood flow response to neuronal activations in the cerebral cortex. It can only detect surface changes in the brain, as it doesn't penetrate into deeper areas[10].

2.2 Electrode positions

Electrodes need to be positioned in a standard manner to obtain multichannel EEGs. The international 10–20 system is the most common electrode arrangement. In the current EEG studies, higher density systems such as 10-10 and 10-5 systems are used, specifically in the 64 electrodes and 128 electrodes measurements [10] [14]. Figure 2.8 shows positioning of electrodes used for measurement of EEG signals.

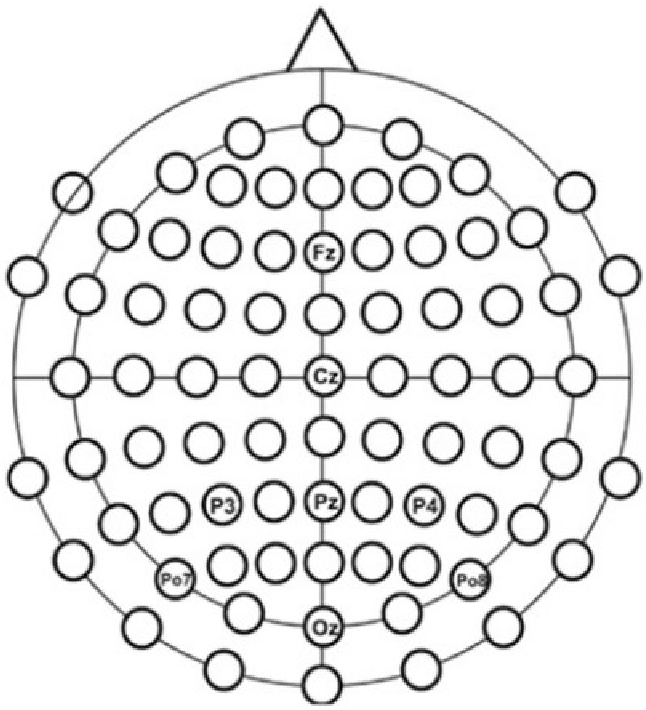

Figure 2.8: Electrode positions used for the EEG measurements [4]

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Chapter 3

Literature Survey

3.1 Related work and contribution

Gaur et al. [7] presents a method for reducing the number of channels with minimal computational complexity and sufficient accuracy, by utilizing an automatic subject-specific channel selection method based on Pearson correlation coefficient. In their work, EEG correlations are computed to select highly discriminating EEG signals. Jianli Yu et al. [15] proposed a quantitative assessment and ranking criterion, providing a practical method to assess EEG channels during MI tasks. When calibrating MI BCI systems, the ranked channels are selected, by reducing the complexity of computing and configuration. Between the traditional work of feature extraction and channel selection, Jiuqi Han et al. [16] proposes feature compression and normalized signal representation, classifying a single EEG trial with selected channels is performed with a linear discriminant analysis(LDA) model. Mahnaz Arvaneh et al. [17] worked on an optimization problem, that selects the fewest channels within a constraint of accuracy; by removing noisy and irrelevant channels, the algorithm can yield the best accuracy.

Yongkoo Park et al. [18] used method to optimize channel in which, channels are grouped based on an analysis of their correlations, and the Fisher scores are computed by utilizing the filter-bank CSP (FBCSP) exclusively applied to those channels. Ian Daly et al. [19] refer that during motor imagery tasks of the hands and feet, there was a significant difference between the event-related desynchronization and phase locking value strength of individuals with cerebral palsy and healthy individuals. Cerebral palsy patients had significantly lower event-related desynchronization strengths and phase locking values.

Yongkoo Park et al. [20] select the discriminative H channels and target channel of the EEG and configure several sub-channels to get the optimal selection using the channel covariance matrix and cross-combining region. Using the statistical characteristics of the available channels EEG signal, a channel selection method is proposed by Venkata Phanikrishna Balam et al. [21] for a single-channel EEG-BCI system.

Xiaorong Gao et al. [22] design a system that is intended to enable people with motion disabilities to control household appliances. The hardware has been redesigned and advanced signal processing techniques have been used.

Chapter 4

Channel Selection in Unicorn Headset

4.1 Motivation

The motivation behind the approach is to find an optimum subset of unicorn headset channels without compromising the performance. Classifiers are used to to analyze the accuracy. One way to select the optimum subset of channels is to analyze each channel present in unicorn headset and select channels with high performance.

The proposed method aims to select a channel for unicorn headsets while maintaining an acceptable accuracy level.

4.2 Unicorn Headset

Unicorn headset is a device used to capture brain waves perfectly. It is a high-quality wearable EEG headset. Brain activity can be recorded with or without the help of gel in the headset, enabling the device to be used for all kinds of BCI applications. Unicorn headset has eight electrodes placed in the cap, which corresponds to eight unicorn channels name Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 [5]. Figure 4.1 [5] shows eight channel unicorn headset.

Figure 4.1: Unicorn headset [5]

.

4.3 Proposed Method

Unicorn headset contains eight channel named Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8. Consider $u[k]$ as received signal at unicorn headset for $k = 1, 2, \ldots, 8$, where k represents the number of channel. The distribution of the signal depends upon the number of samples taken in a particular time interval. If the number of samples are few, they follow the Chi-square distribution; on the other hand, if a significant number of samples are taken ($n \geq 250$), they follow the Gaussian distribution [23]. The mathematical modeling for Gaussian distributed signal is done quite easily. In the proposed work, we select the motor imagery data set. This data set consists of one- and two-minute EEG recordings, obtained from 109 subjects. This data set consist of mainly four different task:

- Task-1 represents opening and closing of left fist or right fist.
- Task-2 represents imagine opening and closing of left fist or right fist.
- Task-3 represents opening and closing of both fists or both feet.
- Task-4 represents imagine opening and closing of either both fists or both feet.

Out of these activities we have selected the Task-4 activity in which the EEG signals are recorded when the subject imagines opening and closing of either both fists or opening and closing of both feet, and then the subject goes to idle state. In the proposed work, we consider large number of samples, which can significantly help to increases the probability of classification accuracy. It may be noted here that other choices of task from the data set are also possible such as task-1, task-2 or task-3. The outputs of each channel in the unicorn headset are the samples obtained from the unknown distribution of EEG signals. Here, we are interested in calculating mean of the unknown distribution with the help of data samples through bootstrapping [24].

Let $V = [V_1, V_2, \ldots, V_M]$ be the data samples obtained from the output of the unicorn headset for each channel. Assuming each of the observed values V_j for $j = 1, 2, \ldots, M$, equiprobable, the bootstrap samples are obtained by random sampling with replacement from the data set. Let $V^{*1}, V^{*2}, \ldots, V^{*B}$ denote the B sets of independent bootstrap samples each consisting of M data values, where $V^{(*)}$ indicates that it is not the actual data set but a re-sampled version of V.

The expected mean values of all the bootstrap samples are calculated next, which are given by $E[V^{*1}]$, $E[V^{*2}]$, $\ldots$, $E[V^{*B}]$, where

$$E[V^{*m}] = \frac{1}{M} \sum_{i=1}^{M} V_i^{*m} = \gamma_m \qquad m = 1, 2, \ldots, B \tag{4.1}$$

We designate these mean values ($E[V^{*m}]$) as γ_{mN} and γ_{mS} for the fists movement and the feet movement respectively. We further use γ_N to represent the set of mean values of bootstrap samples when the fists movement is present, and γ_S when the feet movement is present. Thus, we have

$$\gamma_N = [\gamma_{1N}, \gamma_{2N}, \dots, \gamma_{BN}] \tag{4.2}$$

$$\gamma_S = [\gamma_{1S}, \gamma_{2S}, \dots, \gamma_{BS}] \tag{4.3}$$

In general, we use γ to denote the EEG signals. If the data samples are large enough, then according to the central limit theorem, a Gaussian distribution of the mean values of the bootstrap samples is obtained [25].

Let Γ_N and Γ_S represent the random variables corresponding to γ_N and γ_S with mean μ_0 and μ_1, and variance σ_0^2 and σ_1^2, for the fists movement and the feet movement, respectively. Thus, we have

$$\Gamma_N \sim \mathcal{N}(\mu_0, \sigma_0^2) \tag{4.4}$$

$$\Gamma_S \sim \mathcal{N}(\mu_1, \sigma_1^2) \tag{4.5}$$

where $\mathcal{N}$ denotes the normal distribution.

4.3.1 Bootstrap fusion scheme

In the proposed work, the channel selection is done through bootstrap method. Bootstrap is a computer based simulation method to estimate some statistical properties of an unknown distribution. It is quite advantageous when the empirical distribution is unknown, but the samples of the distribution are available. The output signals of the unicorn headset are considered as the data samples of the unknown distribution. The sets of bootstrap samples are created through re-sampling with replacement. After this, the mean value of each set of the bootstrap samples is calculated. This mean value is compared with the threshold, which is set as per the majority rule and then the decision is made.

4.3.2 Channel selection

In the proposed work channel selection is done in two steps, in the first step we calculate the standard error for the mean values of the bootstrap samples obtained at the individual channel. The standard error is an estimate of the standard deviation of the sampling distribution of the mean. The higher values of standard error shows that the sample means are more spread around the population mean, so there is a greater chance that any given mean is an inaccurate representation of the true population mean, whereas low value of standard error shows that sample means are closely distributed, so there is a higher chance that, the chosen sample mean is a more accurate reflection of the actual population mean.

In the second step, we arrange all the standard error values obtained in the previous step in the increasing order. Let's say now out of eight channel we have to select six channels, for this purpose we will select top six channel having lower value of standard error. This process is repeated for N number of patients. It may be noted that for all the patients there may not be similar channels consisting of lower values of standard error out of eight any six values can be selected depending upon strength of EEG signal, task done, and the sample taken at that instant, therefore after repeating the process for N number of patients we apply the majority rule for channel selection. In majority rule, we count the number of times a particular channel has been occurred then select top six channels.

Chapter 5

Channel Selection Algorithm

5.1 Channel Selection Algorithm in Unicorn Headset

In the proposed work, bootstrap method is used for channel selection in unicorn headset. We explained two scenario for selecting the unicorn channel.

1. Six unicorn channel selection algorithm

2. Four unicorn channel selection algorithm

5.1.1 Six unicorn channel selection algorithm

The steps for the proposed six channel selection bootstrap fusion scheme is summarized in Table 5.1.

Table 5.1: Six unicorn channel selection through bootstrap fusion scheme

Steps	**Description**
Step 1	Obtain M data samples $[V_1, V_2, \ldots, V_M]$ from the output of unicorn headset.
Step 2	Select B set of independent bootstrap samples $[V^{*1}, V^{*2}, \ldots, V^{*B}]$ each comprising M independent data samples obtained with replacement.
Step 3	Calculate the mean values of B independent data sets and obtain the set of mean values $[\gamma_z = \gamma_{1z}, \gamma_{2z}, \ldots, \gamma_{Bz}]$, where $z = S, N$, depending upon the fists movement or feet movement.
Step 4	Calculate the mean $\bar{\gamma}_z$.
Step 5	Calculate the standard error (SE).
Step 6	Select six unicorn channel with lowest standard error.
Step 7	Repeat the process for all subjects.
Step 8	Count the occurrence of individual unicorn channel.
Step 9	Apply majority rule to select top six channels.

5.1.2 Four unicorn channel selection algorithm

The steps for the proposed four channel selection bootstrap fusion scheme is summarized in Table 5.2.

Table 5.2: Four channel selection through bootstrap fusion scheme

Steps	Description
Step 1	Obtain M data samples $[V_1, V_2, \ldots, V_M]$ from the output of unicorn headset.
Step 2	Select B set of independent bootstrap samples $[V^{*1}, V^{*2}, \ldots, V^{*B}]$ each comprising M independent data samples obtained with replacement.
Step 3	Calculate the mean values of B independent data sets and obtain the set of mean values $[\gamma_z = \gamma_{1z}, \gamma_{2z}, \ldots, \gamma_{Bz}]$, where $z = S, N$, depending upon the fists movement or feet movement.
Step 4	Calculate the mean $\bar{\gamma}_z$.
Step 5	Calculate the standard error (SE).
Step 6	Select four unicorn channel with lowest standard error.
Step 7	Repeat the process for all subjects.
Step 8	Count the occurrence of individual unicorn channel.
Step 9	Apply majority rule to select top four channels.

Chapter 6

Experiment Setup and Results

6.1 Experiment Setup

6.1.1 Dataset

The motor imagery data set [26] consists of EEG recordings gathered from 109 subjects. Using the BCI2000 system, subjects performed different motor imagery tasks while 64-channel EEG signals were recorded. Four experimental runs per subject were completed: two baseline runs of one minute each with eyes open and closed, and three runs of two minutes each of the four tasks.

- Baseline, eyes open
- Baseline, eyes closed
- Task 1 (open and close left or right fist)

- Task 2 (imagine opening and closing left or right fist)
- Task 3 (open and close both fists or both feet)
- Task 4 (imagine opening and closing both fists or both feet)

6.1.2 Experiment Procedure

In the proposed work, we worked on motor imagery dataset. In this dataset, experiment are performed on 109 subjects and contains recording of four different tasks. We have worked on eight unicorn channels. The name of the channels are Fz, C3, Cz, C4, Pz, PO7, Oz, PO8. Further, we calculated their classification accuracy, and compared their performance by selecting six channels and then four channels through our proposed bootstrap-based channel selection algorithm through standard error. In this motor imagery dataset, each channel has 60,000 data samples obtained from 1–2-minute recording of EEG signals.

6.2 Result

6.2.1 Scenario I: Selected six channel

In Table 6.1, we have calculated the standard error of channels, to calculate the standard error for each channel for a single subject, we took these 60,000 data samples, and resample this data set with replacement to form our bootstrap samples. The resampled dataset has been formed by randomly selecting the values from the original 60,000 samples. Since we are randomly selecting from the dataset each bootstrap sample will be different from one another and it will be different from the actual dataset. After creating 10,000 bootstrap samples where each bootstrap sample will have 60,000 values, we calculate the mean of each bootstrap sample, and thus 10,000 mean values are obtained. The distribution of these mean values follows the gaussian distribution, from this Gaussian distribution standard error for a single subject is calculated. Table 6.1 shows the standard error for subject-1. Here the

Table 6.1: Standard error of unicorn channels and standard error of selected six channels for subject-1

Unicorn Channels	**Standard Error**
Fz	$9.268e-08$
C3	$9.062e-08$
Cz	$8.954e-08$
C4	$7.965e-08$
Pz	$8.878e-08$
PO7	$9.829e-08$
Oz	$1.087e-07$
PO8	$9.448e-08$

Selected Channels	**Standard Error**
C4	$7.965e-08$
Pz	$8.878e-08$
Cz	$8.954e-08$
C3	$9.062e-08$
Fz	$9.268e-08$
PO8	$9.448e-08$

standard error for the unicorn channels Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are 9.268*e*–08, 9.062*e*–08, 8.954*e*–08, 7.965*e*–08, 8.878*e*–08, 9.829*e*–08, 1.087*e*–07, and 9.448*e*–08 respectively, out of these eight channels we selected six channels C4, Pz, Cz, C3, Fz, and PO8 having lowest standard error 7.965*e*–08, 8.878*e*–08, 8.954*e*–08, 9.062*e*–08, 9.268*e*–08, and 9.448*e*–08, respectively. A lower standard error corresponds that the value is closer to the mean, which improves the accuracy of the model.

Table 6.2 refers to the standard error calculation for subject-2. Here the standard error of the unicorn channels Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are 5.599e–08, 5.656e–08, 6.181e–08, 4.833e–08, 5.869e–08, 5.212e–08, 5.513e–08, and 5.960e–08, respectively. It may be noted that standard error values will be different for different subjects, depending upon the strength of the received EEG signal at unicorn channels. Out of eight channels we selected six channels C4, PO7, Oz, Fz, C3, and Pz having the lowest standard error 4.833e–08, 5.212e–08, 5.513e–08, 5.599e–08, 5.656e–08, and 5.869e–08, respectively. Due to the change in the values of the standard error, the selected six channels are different from the channels of other subjects.

Table 6.2: Standard error of unicorn channels and standard error of selected six channels for subject-2

Unicorn Channels	**Standard Error**
Fz	$5.599e-08$
C3	$5.656e-08$
Cz	$6.181e-08$
C4	$4.833e-08$
Pz	$5.869e-08$
PO7	$5.212e-08$
Oz	$5.513e-08$
PO8	$5.960e-08$

Selected Channels	**Standard Error**
C4	$4.833e-08$
PO7	$5.212e-08$
Oz	$5.513e-08$
Fz	$5.599e-08$
C3	$5.656e-08$
Pz	$5.869e-08$

Similar calculations are shown in table 6.3, table 6.4, and table 6.5 for subject-3, subject-4, and subject-5.

For subject-3 the standard error for unicorn channels are Fz, C3, Cz,

Table 6.3: Standard error of unicorn channels and standard error of selected six channels for subject-3

Unicorn Channels	**Standard Error**
Fz	$9.263e-08$
C3	$8.661e-08$
Cz	$8.830e-08$
C4	$8.160e-08$
Pz	$9.092e-08$
PO7	$1.025e-07$
Oz	$9.927e-08$
PO8	$8.831e-08$

Selected Channels	**Standard Error**
C4	$8.160e-08$
C3	$8.661e-08$
Cz	$8.830e-08$
PO8	$8.831e-08$
Pz	$9.092e-08$
Fz	$9.260e-08$

C4, Pz, PO7, Oz, and PO8 are 9.263e–08, 8.661e–08, 8.830e–08, 8.160e–08, 9.092e–08, 1.025e–07, 9.927e–08, and 8.831e–08, respectively, out of this we selected six channels C4, C3, Cz, PO8, Pz, and Fz having lowest standard error 8.160e–08, 8.661e–08, 8.830e–08, 8.831e–08, 9.092e–08, and 9.260e–08 respectively.

For subject-4 the standard error for unicorn channels are Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are $3.803e-08$, $3.624e-08$, $3.746e-08$, $3.510e-08$, $3.347e-08$, $3.629e-08$, $3.140e-08$, and $3.230e-08$, respectively, out of this we selected six channels Oz, PO8, Pz, C4, C3, and PO7 having lowest standard error $3.140e-08$, $3.230e-08$, $3.347e-08$, $3.510e-08$, $3.624e-08$, $3.629e-08$, respectively.

For subject-5 the standard error for unicorn channels are Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are $4.555e-08$, $4.127e-08$, $4.406e-08$, $3.892e-08$, $4.083e-08$, $4.380e-08$, $3.957e-08$, and $4.453e-08$, respectively out of this we selected six channels Oz, PO8, Pz, C4, C3, and PO7 having lowest standard error $3.892e-08$, $3.957e-08$, $4.083e-08$, $4.127e-08$, $4.380e-08$, and $4.406e-08$, respectively.

Table 6.4: Standard error of unicorn channels and standard error of selected six channels for subject-4

Unicorn Channels	**Standard Error**
Fz	$3.803e-08$
C3	$3.624e-08$
Cz	$3.746e-08$
C4	$3.510e-08$
Pz	$3.347e-08$
PO7	$3.629e-08$
Oz	$3.140e-08$
PO8	$3.230e-08$

Selected Channels	**Standard Error**
Oz	$3.140e-08$
PO8	$3.230e-08$
Pz	$3.347e-08$
C4	$3.510e-08$
C3	$3.624e-08$
PO7	$3.629e-08$

Similar calculations are done for the remaining 104 subjects. As we have observed that the set of selected six channels may differ for different subjects, to select six channels out of eight channels we apply the majority rule. In the majority rule, we calculate the number of times a particular channel has been selected among the top six channels or has a lower standard error. For example, in table 6.1 the occurrence of channel Cz is in the third position, whereas in table 6.2 channel Cz is not present in the set of selected six channels. This indicates that the performance of channel Cz is good for subject-1, but poor for subject-2.

Table 6.6 shows the occurrence of the individual channel among all 109 subjects. Here we can observe that for each subject we have selected six

Table 6.5: Standard error of unicorn channels and standard error of selected six channels for subject-5

Unicorn Channels	**Standard Error**
Fz	$4.555e-08$
C3	$4.127e-08$
Cz	$4.406e-08$
C4	$3.892e-08$
Pz	$4.083e-08$
PO7	$4.380e-08$
Oz	$3.957e-08$
PO8	$4.453e-08$

Selected Channels	**Standard Error**
C4	$3.892e-08$
Oz	$3.957e-08$
Pz	$4.083e-08$
C3	$4.127e-08$
PO7	$4.380e-08$
Cz	$4.406e-08$

channels, but all eight channels are present in the counting. The presence of all eight is due to changes in the strength of EEG signals for individual subjects. Table 6.6 shows that out of 109 subjects channel Fz occurred 76 times in the set of top six selected channels, similarly, C3 occurred 78 times, Cz occurred 80 times, C4 occurred 101 times, Pz occurred 84 times, PO7 occurred 66 times, Oz occurred 78 times, and PO8 occurred 91 times. Out of these eight channels we selected six channels through majority rule, the selected channel are C3, Oz, Cz, Pz, PO8, and C4 having count 78, 78, 80, 84, 91 and 101, respectively.

To evaluate the performance of our bootstrap-based channel selection algorithm, we calculate the accuracy of selected six channels through a support vector machine (SVM).

Table 6.6: Number of times individual channel occur in 109 subjects, and selected six unicorn channels

Unicorn Channels	**Count**
Fz	76
C3	78
Cz	80
C4	101
Pz	84
PO7	66
Oz	78
PO8	91

Selected Channels	**Count**
C3	78
Oz	78
Cz	80
Pz	84
PO8	91
C4	101

6.2.2 Scenario II: Selected four channel

To select four channels out of eight channels of the unicorn headset, we again calculate the number of times a particular channel has occurred in the set of top four channels in standard error calculations. To create a set of top four channels we first calculate the standard error of the mean values of the set of 10,000 bootstrap samples, and then we select the lowest four values of standard error.

Table 6.7 shows the standard error calculations for subject-1. As shown in table the standard error for unicorn headset channels Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are $9.268e{-}08$, $9.062e{-}08$, $8.954e{-}08$, $7.965e{-}08$, $8.878e{-}08$, $9.829e{-}08$, $1.087e{-}07$, and $9.448e{-}08$ respectively. It can be observed that the standard error values for both cases are similar because here we are working on the set of mean values. We select the four channels with lower standard errors out of these eight values. Table 6.7 shows the names of the selected channel and their values. The selected four channels are C4, Pz, Cz, C3 and their respective standard error values are 7.965*e*–08, 8.878*e*–08, 8.954*e*–08, and 9.062*e*–08.

Table 6.7: Standard error of unicorn channels and standard error of selected four channels for subject-1

Unicorn Channels	**Standard Error**
Fz	$9.268e-08$
C3	$9.062e-08$
Cz	$8.954e-08$
C4	$7.965e-08$
Pz	$8.878e-08$
PO7	$9.829e-08$
Oz	$1.087e-07$
PO8	$9.448e-08$

Selected Channels	**Standard Error**
C4	$7.965e-08$
Pz	$8.878e-08$
Cz	$8.954e-08$
C3	$9.062e-08$

Similarly, we calculated the standard error and selected the set of four values of the lowest standard error for the remaining subjects. The standard error values and the selected channels for subject-2, subject-3, subject-4, and subject-5 are shown in table 6.8, table 6.9, table 6.10, and table 6.11.

For subject-2 the standard error for unicorn channels are Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8 are 5.599*e*–08, 5.656*e*–08, 6.181*e*–08, 4.833*e*–08, 5.869*e*–08, 5.212*e*–08, 5.513*e*–08, and 5.960*e*–08, respectively, out of this selected four channels are C4, PO7, Oz, and Fz and their standard errors are 4.833*e*–08, 5.212*e*–08, 5.513*e*–08, and 5.599*e*–08, respectively.

For subject-3 the standard error for unicorn channels are Fz, C3, Cz,

Table 6.8: Standard error of unicorn channels and standard error of selected four channels for subject-2

Unicorn Channels	**Standard Error**
Fz	$5.599e-08$
C3	$5.656e-08$
Cz	$6.181e-08$
C4	$4.833e-08$
Pz	$5.869e-08$
PO7	$5.212e-08$
Oz	$5.513e-08$
PO8	$5.960e-08$

Selected Channels	**Standard Error**
C4	$4.833e-08$
PO7	$5.212e-08$
Oz	$5.513e-08$
Fz	$5.599e-08$

C4, Pz, PO7, Oz, and PO8 are 9.263*e*–08, 8.661*e*–08, 8.830*e*–08, 8.160*e*–08, 9.092*e*–08, 1.025*e*–07, 9.927*e*–08, and 8.831*e*–08, respectively, out of this selected four channels are C4, C3, Cz, and PO8 and their standard errors are 8.160*e*–08, 8.661*e*–08, 8.830*e*–08, and 8.831*e*–08, respectively.

Table 6.9: Standard error of unicorn channels and standard error of selected four channels for subject-3

Unicorn Channels	**Standard Error**
Fz	$9.263e-08$
C3	$8.661e-08$
Cz	$8.830e-08$
C4	$8.160e-08$
Pz	$9.092e-08$
PO7	$1.025e-07$
Oz	$9.927e-08$
PO8	$8.831e-08$

Selected Channels	**Standard Error**
C4	$8.160e-08$
C3	$8.661e-08$
Cz	$8.830e-08$
PO8	$8.831e-08$

For subject-4 the standard error for unicorn channels are Fz, C3, Cz, C4,

Table 6.10: Standard error of unicorn channels and standard error of selected four channels for subject-4

Unicorn Channels	**Standard Error**
Fz	$3.803e-08$
C3	$3.624e-08$
Cz	$3.746e-08$
C4	$3.510e-08$
Pz	$3.347e-08$
PO7	$3.629e-08$
Oz	$3.140e-08$
PO8	$3.230e-08$

Selected Channels	**Standard Error**
Oz	$3.140e-08$
PO8	$3.230e-08$
Pz	$3.347e-08$
C4	$3.510e-08$

Pz, PO7, Oz, and PO8 are $3.803e-08$, $3.624e-08$, $3.746e-08$, $3.510e-08$, $3.347e-08$, $3.629e-08$, $3.140e-08$, and $3.230e-08$, respectively out of this selected four channels are Oz, PO8, Pz, and C4 and their standard errors are $3.140e-08$, $3.230e-08$, $3.347e-08$, and $3.510e-08$, respectively.

Table 6.11: Standard error of unicorn channels and standard error of selected four channels for subject-5

Unicorn Channels	**Standard Error**
Fz	$4.555e-08$
C3	$4.127e-08$
Cz	$4.406e-08$
C4	$3.892e-08$
Pz	$4.083e-08$
PO7	$4.380e-08$
Oz	$3.957e-08$
PO8	$4.453e-08$

Selected Channels	**Standard Error**
C4	$3.892e-08$
Oz	$3.957e-08$
Pz	$4.083e-08$
C3	$4.127e-08$

For subject-5 the standard error for unicorn channels are Fz, C3, Cz, C4,

Table 6.12: Number of times individual channel occur in 109 subjects, and selected four unicorn channels

Unicorn Channels	**Count**
Fz	57
C3	46
Cz	42
C4	87
Pz	43
PO7	33
Oz	56
PO8	72

Selected Channels	**Count**
Oz	56
Fz	57
PO8	72
C4	87

Pz, PO7, Oz, and PO8 are $4.555e-08$, $4.127e-08$, $4.406e-08$, $3.892e-08$, $4.083e-08$, $4.380e-08$, $3.957e-08$, and $4.453e-08$, respectively out of this selected four channels are C4, Oz, Pz, and C3, and their standard errors are $3.892e-08$, $3.957e-08$, $4.083e-08$, and $4.127e-08$ respectively.

After selecting the set of four channels for 109 subjects, we count the number of times a particular channel has occurred in the selected set of standard error values.

Table 6.12 shows the count of the occurrence of the channels. Unicorn channel Fz has occurred 57 times, C3 occurred 46 times, Cz occurred 42 times, C4 occurred 87 times, Pz occurred 43 times, PO7 occurred 33 times, Oz occurred 56 times, and PO8 occurred 72 times. On applying the majority rule, the selected four channels are Oz, Fz, PO8, and C4 and their respected counts are 56, 57, 72, and 87. Here we can observe that there is a difference in the count of the occurrence of channels in table 6.6 and table 6.12.

In both the tables, we have eight channels but the difference in the count is due to a change in the values of standard error which in turn changes the position of occurrence of a particular channel. For example, in table 6.6 Fz has occurred 76 times out of 109 subjects, whereas in table 6.12 Fz has occurred 57 times only out of 109 subjects. The difference in Fz count is due to its standard error value position. For subject-1 in table 6.1 channel Fz has occurred at sixth position, so Fz is considered for the six-channel selection method but not for the four-channel selection method.

The performance of the proposed method is measured in terms of classification accuracy. In this work, we have made use of a support vector machine (SVM) to classify different motor imagery tasks. Moreover, we have compared the accuracy of our six-channel and four-channel selection schemes with the eight channel unicorn headset. The proposed six channel selection algorithm shows an accuracy of 97.6% when compared with the eight channel unicorn headset. While the proposed four channel selection algorithm shows an accuracy of 90% when compared with the eight-channel unicorn headset.

Chapter 7

Conclusion and Future Work

In this work, we proposed a bootstrap-based channel selection algorithm in a unicorn headset. Unicorn headsets consist of eight channels, our objective is to find an optimal subset of the channel without compromising the performance. The performance of the work is measured in terms of accuracy. We calculated the accuracy by selecting six channels and then four channels out of eight channels of the unicorn headset. The proposed work is shown to exhibit a performance that is comparable to eight channels in the unicorn headset.

In this algorithm, we create a set of bootstrap samples at an individual channel and calculate the standard error of the mean values of the set of bootstrap samples. Channels having lower standard error are included in the decision-making process. The final selection of channels is done through majority rule.

It is possible in a realistic scenario for some of the channels the signal is weak. As here we are not making the decision based on actual incoming signals, we are working on the mean values of the bootstrapped signals, therefore, in such a situation when there are a considerable number of weeks signals the performance of the proposed work does not change significantly, indeed it remains almost unaffected for a range of week EEG signals.

The bootstrap-based channel selection algorithm does not make use of any feedback mechanism, it will be interesting to devise such a mechanism, through which we can assign some weight in terms of probability to individual channel to further improve the channel selection method which in turn improves the accuracy of the system.

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