EFFICIENT CHANNEL REDUCTION AND FEATURE EXTRACTION SCHEMES FOR ANALYZING MENTAL AND COGNITIVE TASK BASED EEG SIGNALS

by

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CANDIDATE’S DECLARATION

I, do, hereby declare that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

Signature of the Candidate

Kaniz Fatima

Kaniz Fatima

Dedication

To my parents.

Acknowledgements

In the name of Allah, the most Gracious, the most Compassionate.

I would like to express my sincere gratitude to my Creator for giving me the chance to work with my supervisor Dr. Shaikh Anowarul Fattah, whose support and guidance during the span of this research was extraordinary. I also want to thank Dr. Fattah for his dedication and love for his craft, which is contagious and inspires his students for greater achievements. It was him who motivated me to incite my own aptitude for knowing the unknown, encouraged me to the utmost and gave rise to the confidence in me that in an underdeveloped country like ours, it is possible to conduct research of superior quality. I also want to express my unbound respect and thankfulness to him for affording me so much time in exploring new areas of my research and new ideas and improving the writing of this dissertation. Then, I would like to thank the rest of the members of the thesis committee. Prof. Dr. Md. Shafiqul Islam, Prof. Dr. Mohammed Imamul Hassan Bhuiyan, and Prof. Dr. Khawza Iftekhar Uddin Ahmed, for their encouragement and insightful comments.

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Abstract

In view of recent increase in awareness of workplace safety, improved productivity, and social security, the importance of efficient channel reduction and feature extraction scheme for analyzing and classifying alcoholics from non-alcoholics has increased prodigiously nowadays. Most of the reported approaches use complex algorithm for channel reduction and feature extraction technique with a large feature dimension. Moreover, the channel reduction techniques have no physiological or neurological correspondence, hence, differ from person to person and trial to trial. Therefore, all the channels are to be used for the collection of EEG data which, when fed to a network or algorithm, result in a reduced set of channels. In this thesis, some channel reduction techniques are proposed based on extensive analysis on neurological behavior of different location of human brain, such as: lobe-based scheme, cortical function-based scheme, hemispheric lateralization based-scheme, Brodmann's localization theory-based scheme, and weighted score-based scheme. Through extensive study of different brain functions, it is shown that different regions of the brain as well as various channels can be discarded which results in a significant reduction in number of channels to be used. The proposed methods in this study even allow to use only one sixth of the total channels to precisely capture mental and cognitive tasks. In the process of selection, apart from biological concept, EEG signal characteristics are also taken into consideration. It is shown that the proposed weighted scoring method offers the highest number of channel reduction where both quantitative and qualitative weighting of various brain functions and scoring of channels are proposed based on similarity of the brain functions with the mental and cognitive task and proximity of the spatial areas with respect to the active functional zone. In order to classify alcoholic and nonalcoholic, two different feature sets are proposed. Reflection coefficient of gamma band visual evoked potential is proposed as a feature extraction scheme and further reduction of channels is achieved by analyzing the feature. Next, variance of spatially distributed EEG is proposed as another feature extraction technique with the lowest feature dimension. Extensive simulation is carried out on publicly available datasets where different types of cross validation techniques are used by different classifiers such as k-nearest neighbor and support vector machine. It is found that both the feature extraction schemes can offer very high classification accuracy even with the proposed reduced set of channels. The proposed method offers EEG-based classification of alcoholic from healthy persons with very small number of channels which is expected to reduce time and complexity of computation.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Electroencephalogram (EEG) signal which is electrical activity of brain, exhibits significant complex behavior with dynamic properties. In general, the analysis of EEG signal has been the subject of several studies, because of its ability to yield an objective mode of recording brain stimulation which is widely used in brain-computer interface researches with application in medical diagnosis and rehabilitation engineering [1]. EEG helps in monitoring the modes of consciousness, like emotions [2], [3], and unconsciousness, like sleep or coma [4], [5] as well as in analyzing different diseases, such as sleep disorders, epilepsy [6], alcoholism [7], [8] Alzheimer's disease [9], attention deficit hyperactivity disorder (ADHD) [10], and Parkinson's disease [11], [12]. Among these diseases, alcoholism is getting special attention because of its direct influence in increasing road accidents and violent behavior. Alcoholism is detected as creating many short-term and long-term impacts on the subject's EEG. Thus, EEG can be an effective way in analyzing the behavioral changes of an alcoholic as well as a tool for identifying such a person from healthy individual. However, it is very difficult to get useful information from these nonlinear and non-stationary EEG signals in time domain just by observing them [13]. Various EEG analysis methods have been proposed in the literature and some of these methods achieved good performance in specific application [14]. Nevertheless, most of the techniques in application are very complex, time consuming and laborious and a majority of them results in poor classification accuracy. A typical EEG signal, measured from the scalp, will have amplitude of 10μV to 100μV and frequency of 10 Hz to 100 Hz. To extract important information from the electrical activity of the brain, many electrodes can be used. But applying a large number of EEG channels may include noisy and redundant signals that degrade the performance of a classifier [11]. Moreover, this increases data size generated from long-term recording and makes it difficult to store or transfer these bio-signals which is essential in telemedicine or ambulatory monitoring purposes [15].

1.1 EEG

An EEG is a process used to evaluate the electrical activity in the brain. It is a direct measurement of neuronal activity with high temporal resolution [16]. Brain cells communicate with each other through electrical impulses. An EEG helps detecting this activity by measuring the voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical context, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20-40 minutes, as recorded from multiple electrodes placed on the scalp. The electrode only picks up electric signal from the brain when brain cells send messages to each other and does not affect the brain. So, this process is totally harmless and painless, in other words non-invasive. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution is required.

1.1.1 Source of EEG signal

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged or polarized by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of similar charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbors, they push their neighbors, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes of the scalp, they can push or pull electrons on the metal on the electrodes. Since metal conducts the push and pull electrons easily, the difference in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time results in the EEG signal. The electric potential generated by single neuron is far too small to be picked up by EEG. EEG activity therefore, always reflects the summation of the synchronous activity of thousands of millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signals because they are well-aligned and fire together. Because voltage fields fall off with the square of distance, activity from deep sources is more difficult to detect than currents near the skull. Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning (e.g. waking and the various sleep stages). These oscillations represent synchronized activity over a network of neurons. The neuronal networks underlying some of these oscillations are understood (e.g. the thalamortical resonance underlying sleep spindles), while many others are not (e.g. the system that generates the posterior basic rhythm). Research that measures both EEG ad neuron spiking finds the relationship between the two is complex with the power of surface EEG in only two bands (gamma and delta) relating to neuron spike activity.

1.1.2 10-20 standard EEG system

EEG test can be performed with different variation according to physician's need to fulfill the diagnostic requirement. The standard test duration will be 10 to 20 minutes which capture the brain activity snap for a particular time. The 10-20 system or International 10-20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment. The position of the electrode of the 10-20 system are shown in Fig. 1. This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The '10' ad '20' refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back and right-left distance of the skull. Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central parietal, and occipital lobes, respectively. It is to be noted that there is no central lobe; the 'C' letter is only used for identification purposes only. A 'Z' (zero) refers to an electrode placed on the midline. Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere, whereas odd numbers (1,3,5,7) refer to those on the left hemisphere.

Two anatomical landmarks are used for the essential positioning of the EEG electrodes. The first one is the nasion which is the point between the forehead and the nose; second, the inion which is the lowest point of the skull from the back of the head and is normally indicated by a prominent bump. When recording a more detailed EEG with more electrodes, extra electrodes are added utilizing the spaces in-between the existing 10-20 system. This new electrode-naming- system is more complicated giving rise to the Modified Combinational Nomenclature (MCN). This MCN system uses 1,3,5,7,9 for the left hemisphere which represents 10%, 20%, 30%, 40%, and 50% of the inion-to-nasion distance respectively. The introduction of extra letters allows the naming of extra electrode sites. These new letters do not necessarily refer to an area on the cerebral cortex. Multichannel EEG measures the voltage differences in two different electrodes. A multichannel EEG signal example is shown in Fig. 1.2.

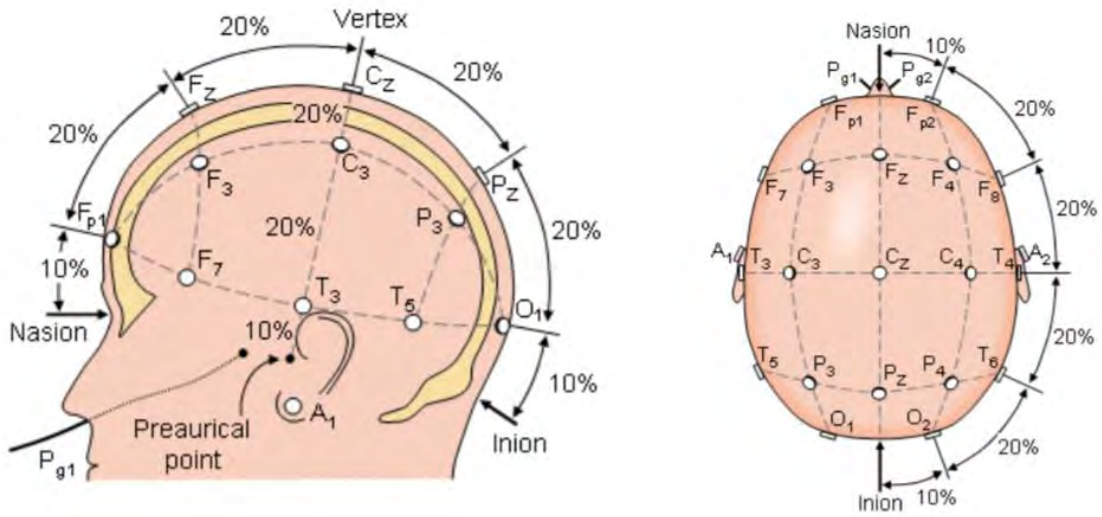


Figure 1.1: EEG electrode placement position on the scalp in 10-20 EEG recording system

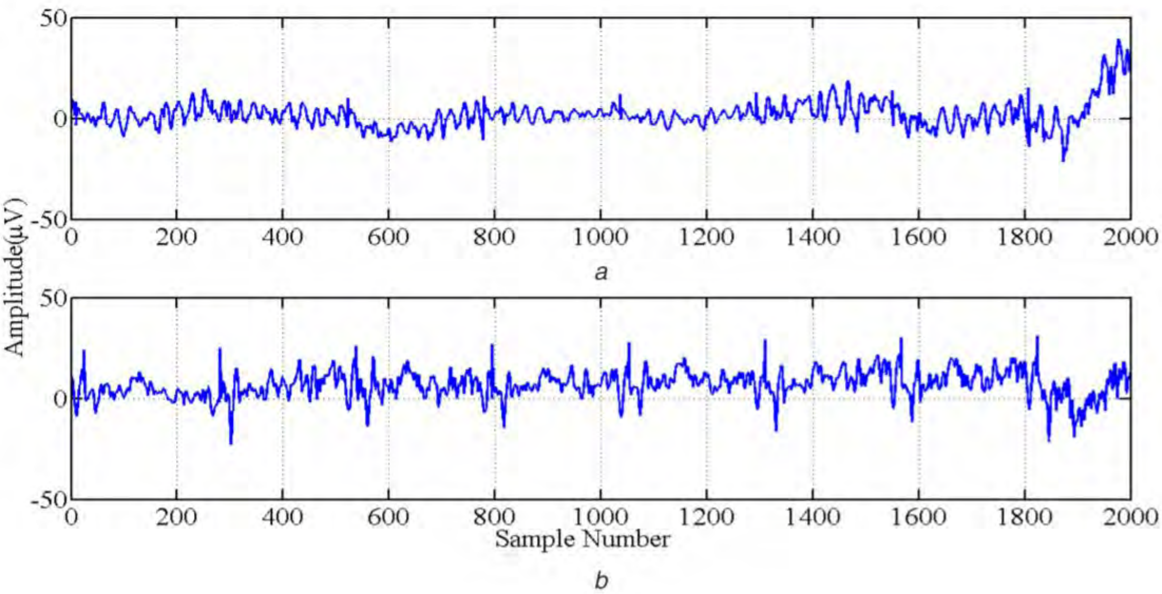


Figure 1.2: EEG signals. (a) Alcoholic (b) Control

1.2 EEG and Alcoholism

EEG contains useful information regarding different human states [17] and disorders related to disease, alcoholism etc. Alcoholism is a common disorder that leads to brain defects and associated cognitive, emotional, and behavioral impairments [18], many changes in functional and psychological behavior of the affected person. In adverse situation, alcoholism can change functioning of important part of nervous system [7], and it ranks among the top five causes of mortal abuses [8]. Diagnosis of disorders caused by alcoholism is done with the help of EEG which gets modified by the electrical activity of the brain. EEG based analysis is chosen by several researchers to obtain some correlated quantitative biological markers [19], [20].

Alcoholism has many short and long-term effect in human body and mind. Short-term effects include impaired judgment, aggressiveness, dizziness, nausea, stomach dysfunction etc. and long-term effects include high blood pressure, damage to vital organs, cancer, impaired memory, cognition and many more. All of these lead to detectable changes in the EEG of the alcoholic persons. Chronic alcoholics have been shown to have problems with memory, cognition, attention and decision-making even after a period of abstinence [21]. These eventually result in loss of productivity, poor performance, bad behavior, poor discipline, adverse impact on company image and customer relations, lateness along with negative effect on team morale and employee relations in workplace. In short, alcoholics increase the risks of accidents while putting themselves and others at risk. Therefore, in several industries like armed forces, police, prison service, public transport, testing and identifying alcoholics in the workplace is deemed very essential. Detection of alcoholics could be of great importance during the job recruitments that require certain skill set of the employees, or in those jobs that include driving, machine operation [22], [8] and above all, to ensure workplace safety for all. Thus, automatic detection of alcoholics can play important role not only in medical applications but also in reducing the number of road accidents, accidents or unwanted incidents in the workplace, and social violence.

The effects of alcohol on the central nervous system of people have been studied using evoked response. Evoked potential (EP) is typically generated by the nervous system in response to visual, auditory, motor, or somatosensory stimulus. Visual stimulus gives rise to visual evoked potential (VEP), which has become very useful for neurophysiological studies and clinical purposes over the years [23] .

1.3 Literature Review

Various EEG analysis methods have been proposed in the literature and some of these methods achieved good performance in specific applications. In response to visual, auditory, motor, somatosensory or sensory stimulation, our nervous system typically generates Evoked Potential (EP). Analysis of EP significantly contributed in the area of neurophysiological studies as well as clinical purposes. Specifically, evoked responses have been used in the study of the effects of alcohol on the central nervous system of humans [18], [7], [24] and to determine genetic predisposition toward alcoholism [25]. [26] have reported that alcohol increases the latency of Visual Evoked Potential (VEP) in humans. Nevertheless, a problem encountered in analyzing small evoked potentials is the signal to noise ratio of the waves is very low. Therefore, useful information is not perceivable about the subject's neural reaction to different stimuli [27]. The first established method to reduce this problem is signal averaging from a large number of trials to extract Event-Related-Potential (ERP) [26]. This process helps the study of time domain properties like latency, amplitude etc. Averaging ERPs, amplitude and latency were measured in [28] and [29]. It was demonstrated in [28] that ERP can reflect object recognition process. Furthermore, it was investigated in [29] that ERP mnemonic effect difference between the control and alcoholic groups may reflect working memory deficit due to long term alcohol abuse. However, signal averaging requires many trials resulting system complexity and higher computational time [30]. Thus, single trial extraction of ERPs was introduced and investigated in [22], [30], and [31].

In [22], the intricacy and inefficiency of signal averaging technique over many trials are overcome by extracting gamma band signal from single trial visual evoked potential (VEP). Gamma band VEP was extracted using a bandpass filter with a center frequency of 40 Hz. Neural Network (NN) was used to classify alcoholics and non-alcoholics who were exposed to single stimuli, using spectral power of the filtered signal. Moreover, single trial of VEP signals was used to select optimal channels using genetic algorithm to maximize the classification accuracy. This process ended up with eight optimum channels, however, not having neurophysiological significance, rather based on the classification accuracy obtained from iterations of Fuzzy ARTMAP (FA) classifier until reaching the maximum, which was trained by Genetic Algorithm (GA) generated set of population representing random binary strings to indicate active or inactive channels. 61 channel configurations resulted in a classification accuracy of 95.10% while the optimum channels yielded accuracy level of 94.30%, both averaged over 5 different sets of hidden nodes of Multilayer Perceptron-Backpropagation (MLP-BP) classifier.

The work in [30] was to investigate the feasibility of using neural network (NN) and late gamma band (LGB) EEG for identifying individuals. Here, principal component analysis (PCA) was used to extract single trials of EEG. Zero phase Butterworth filter and Parseval's time-frequency equivalence theorem were used to compute LGB EEG features. These features were classified using MLP-BP and Simplified Fuzzy ARTMAP Neural Network (SFA-NN) into different categories that represent the individuality of subjects. The results using a 10-fold cross validation scheme gave a maximum of 97.33% when tested on 800 LGB features from 40 non-alcoholic subjects using BP-NN. SFA yielded a maximum of 85.59% accuracy.

Gamma (γ) band (30-50 Hz) spectral power ratio of VEP signals, computed using a zero-phase Butterworth digital filter and Parseval's time frequency equivalence theorem, is used to train a Back Propagation Neural Network (BP- NN) to identify individuals perceiving a single picture in [32]. The VEP signals were collected from all 64 channels including the 3 reference channels. NN classification gives an average of 99.06% across 400 test VEP patterns from 20 individuals using 10-fold cross validation scheme, ensuring the method's potential to be used as a biometric identification system. However, no information is provided regarding whether the subjects under study were from alcoholic or control group. The purpose of the study was basically to design biometric individual -identification system since VEP signals carry genetically specific information.

Peak power spectral density (PSD) derived from the coefficients of a second order autoregressive (AR) model was proposed to discriminate alcoholics from control group using single trial γ-band VEP using three different classifiers: Simplified Fuzzy ARTMAP (SFA) neural network (NN), Multilayer-perceptron-backpropagation (MLP-BP) NN and Linear Discriminant (LD) in [31]. The VEP signals were recorded from 20 subjects (10 alcoholic and 10 control) in 40 trials and were high pass filtered using a 5th order Elliptic filter with a 3-dB cutoff frequency at 30 Hz. The averaged discrimination errors are 2.6%, 2.8% and 11.9% given by LD, MLP-BP and SFA classifiers respectively in 4-fold cross validation method.

Energies of EEG signals in multiple γ-band, namely low- (20-30 Hz), mid- (30-50 Hz) and high- (50-70 Hz) were used as features by an MLP-BP neural network to detect alcoholic subjects from control ones in leave one out (LOO) cross validation scheme in [33]. A 5th order zero phase Elliptic bandpass filter was used to extract the γ- bands. This work revealed a maximum accuracy of 94.55%.

Several advances in the feature extraction and classification stages of the method in [32] by performing spatial data or sensor fusion were proposed in [34]. In this paper, the component relevance was investigated by selecting maximum informative EEG electrodes selected by Davies-Bouldin index (DBI). Elman neural network (ENN) was employed to classify normalized γ -band EEG energy features in hold-out classification strategy on an ensemble of 1600 raw EEG signals, and 35 maximum informative channels. γ -band EEG was extracted using a 4th order Elliptic filter (20-50) Hz. The simulation achieved the maximum recognition rate of $98.56 \pm 1.87\%$.

Another work on biometric authentication using one class classification is done in [35], where 8 occipital electrodes are used based on the assumption that EEG signals have more correlation with the stimuli in this scalp area. Energy of differential EEG signals of these 8 channels is utilized as biometric features to extract formation about the subjects. 3 types of composition of the features single, pair and trio are used to train four types of classifiers namely, KNN, SVM, Data Description and two more classifiers resulting from the combination of the previously mentioned ones are used for classification purpose.

Differences in spectrum, coherence, and phase synchrony of topical EEG between alcohol-dependent individuals and healthy participants was assessed in [36]. Parametric spectral and coherence estimates were generally lower for alcoholics than for controls while evaluated for low EEG rhythms and after surface currents were mitigated by a common spatial filter. Phase synchrony computed for 2.34 s long EEG fragments was lower for alcoholics than for controls while evaluated in α_2 and β_1 rhythms and for specific electrode pairs. The data was collected from 77 hospitalized male alcoholic subjects and 45 male controls. Average power, average magnitude squared (MS) coherence and phase synchrony were computed for short consecutive, non-overlapping EEG fragments for each electrode and or electrode pair in [36]. Phase synchrony was found to be lower for alcoholics than for controls while evaluated in α_2 and β_1 rhythms and for specific electrode pairs. C4 was selected as analysis reference for the calculation of MS coherence and averaged within the seven EEG rhythms namely δ, θ, α_1, α_2, β_1, β_2, γ. Between the group differences were considerably higher for the low EEG rhythms - δ, θ, α_1- when evaluated for the electrode pairs C4AF8, C4F8, C4FT8, C4T8, C4TP8, C4P8, C4PO8, C4T7, C4TP7, C4PO7. This paper also concluded that more pronounced differences in EEG spectrum and coherence were observed in the right hemisphere. EEG power in δ

through β_1 rhythms was significantly different between alcoholics and non-alcoholics. Particularly, for δ rhythm, more pronounced differences are found in left Central, and right Centro-Parietal regions; for θ rhythm, in left Front-Central, Central, Parietal, right Temporal and right Temporo-Parietal; for α_1, in the left Front-Central, and right Parietal and Occipital regions; for α_2 and β_1, in the right Occipital regions.

γ -band spectral entropy was used as feature in [37] for the detection of alcoholics. Here, γ -sub-band (30-50 Hz) signals were extracted using a 6th order Elliptic filter. The PSD of the extracted γ -band was calculated using periodogram and the γ -band spectral entropy was determined. Spectral entropy coefficients were used to separate control persons from their alcoholic counterparts using an MLP-BP-NN and probabilistic neural network (PNN) classifiers. NN yielded a maximum of 93% and PNN yielded~99% accuracy (for a spread factor < 1).

A procedure based on the combined framework of time and frequency domain features, third order Nonlinear Autoregressive Model (NAR-3) and Power Spectral Density (PSD) along with the computational classifiers Support Vector Machine (SVM) and Fuzzy C- Means (FCM) clustering has been applied to detect chronic alcoholism in [38]. The analysis of EEG data and its further classification showed maximum average classification of 87% with NAR-3 feature model coefficients using SVM classifier for the EEG data of frontal cortex followed by central and partial zones with 72% and 71%, respectively. While, with FCM, the maximum average classification accuracy was 80% from the frontal zone. Conversely, the maximum accuracy of 90% was obtained from FZ focal area from both classifiers with NAR-3 features. On the other hand, using PSD feature in SVM, maximum average classification accuracy (77.6%) was obtained from ß2 band power in the central zone. The results also indicate that the maximum accuracy (80%) has been found in FZ electrode position in both ß1 and ß2 bands. With FCM the maximum average accuracy of only 53.6% was obtained from the electrodes of central zone in d bands. However, C3 electrode position showed the maximum accuracy 73% among the focal areas of EEG recording.

A methodology to estimate the differences in the status of the brain based on EEG data of normal subjects and data from alcoholics by computing many parameters stemming from effective network using Granger causality is proposed in [39]. Ten parameters were chosen as final candidates and by the combination of ten graph-based parameters, alcoholics and normal subjects were classified by a support vector machine classifier with best classification performance of 90%.

A tunable -Q Wavelet Transform (TQWT) decomposition of EEG and extracted Centered Correntropy (CC) from the fourth decomposed detail sub-band is used to extract feature from alcoholic and control EEG in [40]. The Principal Component Analysis (PCA) is used for feature reduction followed by Least Squares-Support Vector Machine (LS-SVM) for classifying normal and alcoholic EEG signals. 10-fold cross validation scheme is proposed and average classification accuracy obtained is 97.02%.

Sample entropy, approximate entropy, mean and standard deviation of raw EEG data collected from frontal polar, frontal and central electrodes are utilized to examine how the EEG signals get affected by consumption of alcohol in [41]. These features of the alcohol-affected EEG have been used to detect alcoholic from non-alcoholic using a quadratic support vector machine. The highest accuracy obtained is 95%.

[8] proposed a dual-tree complex wavelet transform (DTCWT) -based features and sequential minimal optimization support vector machine (SMO-SVM), least square support vector machine (LS-SVM), and fuzzy Sugeno classifiers (FSC) for the automatic identification of alcoholics. EEG was collected from a total of 120 trials of 122 subjects and several sub-bands decomposed from the EEG are fed to the classifiers to evaluate the best performing classifiers. Highest classification accuracy achieved was 97.91%.

1.3.1 Location-based channel selection

In [35], 8 occipital electrodes are used based on the assumption that EEG signals have more correlation with the stimuli in this scalp area.

EEG data was collected from frontal polar, frontal and central electrodes in [41] under the assumption that these areas of brain show significant changes on excessive consumption of alcohol.

1.3.2 Current approach of channel selection

[42] presents a survey for the recent developments in channel selection in the processing of EEG signals. During the last decades, EEG-based processing has become a highly attractive research field and due to the availability of low-cost interfaces, large number of channel recordings led to the evolution of channel selection algorithms. Improving model performance, providing faster response, and dimensionality reduction as well as identifying brain area that generates class-event activity are the main objectives of channel selection. Among various techniques, one is the feature selection algorithm for EEG channel selection. For a set of EEG

channels, a subset is generated where, this subset generation step is a heuristic search process to present a candidate for evaluation based on a search strategy such as complete search, sequential search, or random search. In some applications, a trained specialist selects a subset of channels based on his/her experience. Five main categories are there for candidate evaluation strategies, such as filtering, wrapping, embedded, hybrid, and human-based techniques. The process of channel subset generation and evaluation is terminated when a stopping criterion is satisfied i.e. search is completed or a threshold is reached. In the last step, the selected channel subset is validated via prior knowledge about the data.

Filtering techniques:

Filtering techniques use an independent evaluation criterion such as distance measure, information measure, dependency measure, and consistency measure to evaluate the candidate channel subsets, which are generated using a search algorithm. Filtering techniques suffer from the low accuracy, since they do not consider the combinations of different channels.

Wrapper techniques:

In case of wrapper techniques, a classification algorithm is used to evaluate the candidate channel subsets, which are generated by a search algorithm. The evaluation of every candidate is obtained by training and testing a specific classification algorithm. Consequently, they are more computationally expensive than filtering techniques and they are more prone to overfitting.

Embedded techniques:

In the embedded techniques, the channels are selected based on criteria generated during the learning process of a specific classifier because the selection is included into the classifier construction. They are computationally less expensive and less prone to overfitting. They are based on recursive channel elimination to keep only channels with appreciated magnitude.

Hybrid techniques:

A hybrid technique is a combination of a filtering technique attempting to take advantage of both in avoiding the pre-specification of a stopping criterion. Generally, hybrid techniques utilize both an independent measure and a mining algorithm for evaluation of the available channel subsets. Two threshold values are evaluated: one corresponding to the case with a classifier and another corresponding to the case without a classifier.

Human-based techniques:

A well-trained observer evaluates the outcome of a specific application, like seizure detection, on the selected channels with any of the abovementioned subset generation techniques based on his experience. Thus, the finding of the human-based techniques can be used in a feedback manner to refine the channel selection process.

This section incorporates a brief literature survey of the state-of-the-art feature extraction and classification techniques used on the EEG signal of human beings. Some works were intended toward the classification of alcoholics from non-alcoholics while, some were dedicated only to biometric identification. The two-class classification studies only utilized VEP data when subjects were shown single picture. However, simpler signal processing technique could be able to serve the purpose if VEP signals were collected from the persons while they were engaged in activities that require not only cognition but also memory retention, attention, and decision making. Feature extracted from such VEP signals could have been more useful in containing useful information that could discriminate the two groups of people with less complexity and computational burden. Furthermore, if the analysis could be performed on a reduced channel domain selected on the basis of biological significance rather than being empirically selected, then the process would be superior in feature consistency and more universal in application.

1.4 Motivation

EEG recording is needed to capture the changes that are going on in the scalp or brain wave while a subject is performing particular tasks. This recording can be stored for further diagnosis, treatment and classification. In general, many electrodes are used for this purpose to capture the most useful information from the EEG signal. However, the usage of many channels is inefficient because it takes long preparation time and the collection process itself is also very time consuming. Furthermore, the storage or transmission of the EEG recording for remote use in telemedicine or for ambulatory monitoring, which is very common today, also become very difficult with potential chance of degrading the performance of the signal to perform the desired action. In addition, use of many channels can eventually lead to poor performance in accomplishing the specific objective by including noise, redundancy, and difficulty in handling to extract the suitable features. Hence, a method capable of reducing the channels that are most active and correlated or mapped to the brain regions associated while a person is performing a particular task is very essential. Many such methods are already in use, but they are actually unable to reduce the channels needed for the collection of the EEG. Rather those methods can identify active channels through complex algorithms from all 64 or 128 channels during feature extraction for classification purpose. Thus, the complexity of collecting, storing, and transferring those large number of signals from so many electrodes are not eliminated. Henceforth, development of a neurophysiologically significant and efficient channel reduction technique that will remove the necessity of using numerous channels to collect EEG data for a special purpose has been a motivation for the current study. The channel reduction technique is efficient in a sense that for a particular purpose, for example, in this study, analyzing and classifying alcoholics from the nonalcoholic persons while they are performing a special mental and cognitive task, the same channel sets can be used for the collection of EEG data. Moreover, for another purpose, the same scheme can be applied by little modification or adjustment of the emphasis level on various functions. The second part of the thesis deals with extraction of an efficient feature to classify alcoholic persons from control or non-alcoholic persons. For such classification also many methods are used in practice. However, a combination of very simple feature extractor and classifier that can ensure the highest possible classification accuracy very quickly while reducing the size of the feature vector is not reported yet. Thus, development of a combination of simple feature extraction and classification scheme that has significantly small feature vector size and that also works well or even better in the reduced channel domain has been another motivation for this research.

1.5 Objectives and Scope

1. Developing neurophysiologically significant and efficient channel reduction scheme to lessen computational complexity and burden to analyze and classify alcoholics from non-alcoholics.
2. Developing feature extraction and classification schemes that offer significant performance improvement of classification over conventional methods to analyze EEG signals containing VEP from people engaged in some form of mental and cognitive tasks to distinguish alcoholic persons from nonalcoholic group.

3. Evaluating the performance improvement of the feature extraction and classification scheme in analyzing mental and cognitive task- based EEG signals while using the reduced set of channels.

The outcome of this thesis is an efficient channel reduction and feature extraction scheme for analyzing mental and cognitive task- based EEG of a group of alcoholic and control persons in order to classify these two groups. This is not the method for detecting alcoholics under the influence of alcohol like using alcohol levels in blood e.g. the breath analyzer test. Rather, this approach identifies alcoholic individuals when they are sober. This system can be utilized for screening or detection of alcoholics in specific jobs that require good memory, attention, strong cognitive and decision-making power of the employees. This can also be used for identifying alcoholics in workplace to avoid accidents, injury and ensure workplace safety.

1.6 Organization of the Thesis

In the first Chapter, a brief introduction to EEG, source of EEG, and its acquisition technique utilizing electrodes is presented. Moreover, it discusses about alcoholism, effects of alcoholism, and importance of classifying alcoholics from the non-alcoholic group. In addition, this Chapter depicts the motivation and objectives of the thesis by providing the past and current research scenarios in the use of various channel reduction, feature extraction and classification techniques. The rest of the thesis is organized as follows.

In Chapter 2, a description about the data characteristics, format and acquisition process along with the details of the participants are provided.

Chapter 3 discusses about step-by-step ways of channel reduction technique with an attempt to select those channels that have proper biological significance. At first, the channels of a specific lobe of a brain are identified. Then, neurophysiological knowledge gained by extensive study has been utilized to identify the specific regions of the brain that are mostly involved in the processing of the specific mental and cognitive tasks that relate to the current study. In this approach, initially, based on the correlation of functional areas of cerebral cortex with Brodmann's areas, those channels or regions are eliminated from consideration which are not directly involved in the special tasks or more precisely, which are responsible for different types of activities not related to the study. Next, channel reduction scheme depending on the concept of hemispheric lateralization is proposed. After that, the problems of this method of channel reduction are removed by a fourth approach where specific areas taking part in cognitive and mental tasks are dealt with. From the selected channel set, channels that produce the same minimum and maximum level of amplitude are discarded. However, channels that yield high fluctuations in the peak and trough and larger deviations in the pattern of EEG waveform between the two groups of subjects are selected. After that, a weighted scoring method has been implemented to rank all the channels. Taking into consideration of the ranking and each channel's functional activities, finally, the desired reduced channel domain is obtained.

In Chapter 4, a classification scheme utilizing the reflection coefficient of gamma band visual evoked potential (VEP) is proposed. This part describes the preprocessing, feature extraction and classification techniques alongside the associated classification accuracy for each of them. Furthermore, the effect of varying the Autoregressive (AR) model order, using different classifier and validation scheme, and the effect of channel reduction are observed on classification accuracy. The feature extraction and classification scheme are applied on different reduced channel domain to observe which one is more successful in solving the classification problem. In addition, based on the capability of reflection coefficient to distinguish alcoholic persons from control persons, two more reduced channels sets are proposed here. All the techniques are repeated for three different visual stimuli and the results are recorded.

In Chapter 5, a second feature extraction and classification scheme based on spatial filtering of EEG are proposed along with the effect of different classifier, channel reduction and trial number reduction. A comparative analysis of time required for the two proposed techniques when all channels are used and when the selected reduced channel domain is used, is done.

Chapter 6 summarizes the outcome of the thesis with some concluding remarks and possible future works.

Chapter 2

Data Description

EEG signals are electrical potentials exhibited by neuronal excitations in the cortex [26]. In this study the used data [43] are multiple electrode time series EEG recordings of two groups of subjects: control and alcoholic.

2.1 Data Characteristics

This data arises from a large study to examine EEG correlation of an individual to have genetic affectation to alcoholism. It contains measurements for 1 second from 64 electrodes placed on the subject's scalp which were sampled at 256 Hz. Each subject was exposed to either a single stimulus (S1) or to two stimuli (S1 and S2) which were pictures of objects chosen from the 1980 Snodgrass and Vanderwart picture set [44]. When two stimuli were shown, they were presented in either a matched condition where S1 was identical to S2 or in a non-matched condition where S1 differed from S2.

2.1.1 Data format

EEG data were collected from 10 alcoholic and 10 control subjects, with 10 trials per subject per paradigm. Three stimulus conditions generate three paradigms 'single', 'S2 match', and 'S2 non match'. There are 256 samples per electrode. The sensor values are in micro volt (V).

2.1.2 Data acquisition

The EEG signals were recorded non-invasively from 61 active plus 3 reference channels from the scalp. The subject was seated in a reclining chair located in a sound-attenuated RF shielded room and fixated a point in the center of a computer display located 1m away from his or her eyes. Each subject was fitted with a 61-lead electrode cap (ECI, Electrocap International). The positions of 19 electrodes were in conjunction with the 10/20 international montage and additional electrodes were placed in between these to obtain a total of 61 electrodes covering most of the electrical activity of the brain. According to standard electrode position nomenclature 1990, of American electroencephalographic association, additional 41 sites are as follows: FPZ, AFZ, AF1, AF2, AF7, AF8, F1, F2, F5, F6, FCZ, FC1, FC2, FC3, FC4, FC5, FC6, FT7, FT8, C1, C2, C5, C6, CPZ, CP1, CP2, CP3, CP4, CP5, CP6, TP7, TP8, P1, P2, P5, P6, POZ, PO1, PO2, PO7 and PO8. The electrode positions are shown in Figure 2.1. All scalp electrodes were referred to CZ. Subjects were grounded with a nose electrode, and the electrode

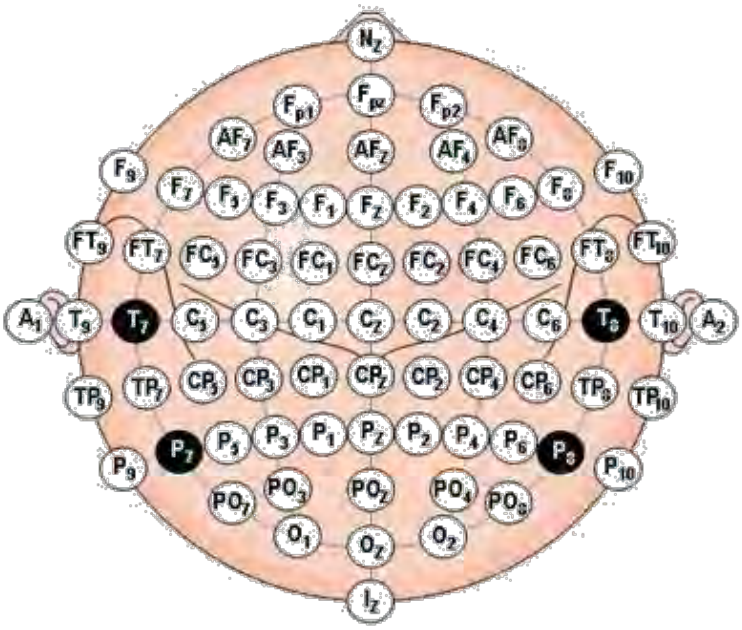


Figure 2.1: Electrode placement on scalp for 64-channel EEG

impedance was always below 5kΩ. Two additional electrodes were used to record the EOG. Therefore, in this study, the remaining 61 active electrodes are considered only.

The stimuli were composed of 90 pictures of objects. These pictures are common black and white line drawings like an airplane, a banana, a ball, etc. These pictures, as shown in Fig. 2.2, represent different concrete object. These were chosen according to a set of rules that provides consistency of pictorial contents. They have been standardized based on the variables of central relevance to memory and cognitive processing. These objects have definite verbal labels, i.e. they could be named. Details of data collection are described at [10]. The stimuli were presented on a white background at the center of a computer monitor and were 5-10 cm in height and 5-10 cm in width. For trials with two stimuli, the duration for the first (S1) and second (S2) picture in each test trial was 300 ms. The interval between two trials were fixed to 3.2s.

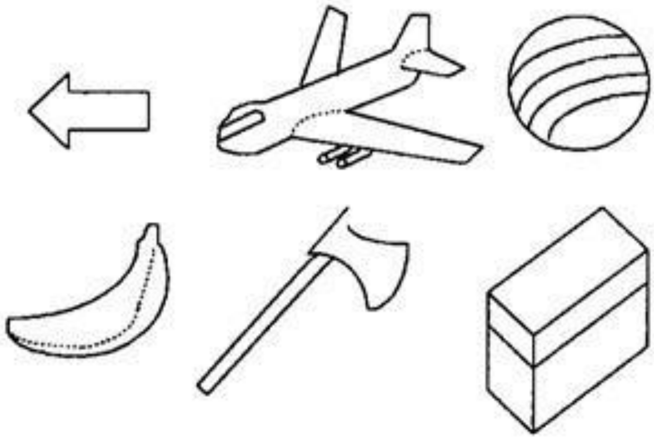


Figure 2.2: Some objects from Snodgrass and Vanderwart picture set

In the matching condition, the S2 was repeated as S1. In the non-matching condition, the S1 was followed by a picture that was completely different from S1. No S1 was repeated as S1. The presentation of the matching and non-matching trials was randomized. On half of the trials, the test stimuli (S2) were identical to S1; on the other half of the trials, the S2s were different from S1.

2.2 Participants

Majority of the alcoholic group have been drinking heavily for at least 15 years. All alcoholics have been abstinent for a minimum period of one month. As a result, no short-term effects of alcohol might be observed. Most of them were drinking heavily for a minimum duration of 15 years and started drinking at the age of approximately 20. The control subjects had no history of personal or family alcohol or drug abuse and also no record of known neurological or psychiatric disorders. All control subjects were right handed and had normal or corrected to normal vision. Individuals with history of severe alcohol or drug dependence were not included in the study.

All the subjects were asked to remember or recognize the stimulus. The subjects' task was to decide whether the second picture (S2) was the same as the first stimulus (S1).

2.3 Conclusion

The study basically aims at detecting alcoholics who have been drinking heavily for many years, however, are sober while being tested for alcoholism. That is why this particular data set has been chosen.

Chapter 3

Channel Reduction Schemes with Neurophysiological Significance

3.1 Introduction

A problem encountered in analyzing visual evoked potential (VEP) is the determination of channels, or electrodes, that carry significant information for classification purposes. Although modern VEP measuring instruments provide many electrodes for measuring data, in general not all are necessary to study the particular task. Moreover, using a large number of EEG electrodes involves a prolonged preparation time. Different tasks such as auditory or visual may require different channel configurations to capture the information from the brain. Prior knowledge of the configuration of these channels will allow a reduction in the required hardware, memory of the storage device, and computation time [22]. Most of the available methods of VEP signal analysis either use a large number of electrodes or use selective channels based on heuristic selection without considering any biological significance [11], [22], [45]. It is shown in [21] and [29] that alcoholics who have been drinking heavily for many years, have shown to have problems with memory, attention and decision making even after a period of abstinence. Furthermore, [36] has shown that when compared to healthy persons, alcoholism related alterations are found in spectrum, coherence, and phase synchrony of the topical EEG of alcoholics. Therefore, specific channels located on particular spatial location on the scalp must contain distinctive information that can greatly lessen the requirement of complex preprocessing, feature extraction and classifier to distinguish alcoholics from control group. Selecting the least number of channels that yield the best or required accuracy can balance both needs for performance and convenience. Hence, an attempt has been taken in this chapter to develop some channel reduction techniques that incorporate proper biological reasoning and efficiently classify alcohol dependent individuals from healthy participants while they are engaged in some form of mental and cognitive tasks.

3.2 Proposed Method

The proposed EEG channel reduction method is based on electrode mapping to brain regions that actively take part in the actions that are performed while a subject is shown visual stimulus to perceive and recognize that, keep in memory and use the memory to identify a second picture and make decision whether they match or not.

3.2.1 Lobe-based scheme

The cerebral cortex is the most complex component of the human brain, as a result of its complex and widespread connections. It functions in the planning and initiation of motor connectivity, perception and conscious awareness of sensory information, learning, cognition, comprehension, memory, conceptual thinking, and awareness of emotion. The cerebral cortex consists of 50-100 billion nerve cell bodies arranged into a three to six layered sheet that laminates the brain surface. In humans the brain surface is convoluted displaying prominent, alternating grooves and elevations as a result of the folding of the cerebral cortex, which occurs during development. The elevations are referred to as gyri, whereas the grooves are referred to as sulci or fissures [46] as shown in figure 3.1.

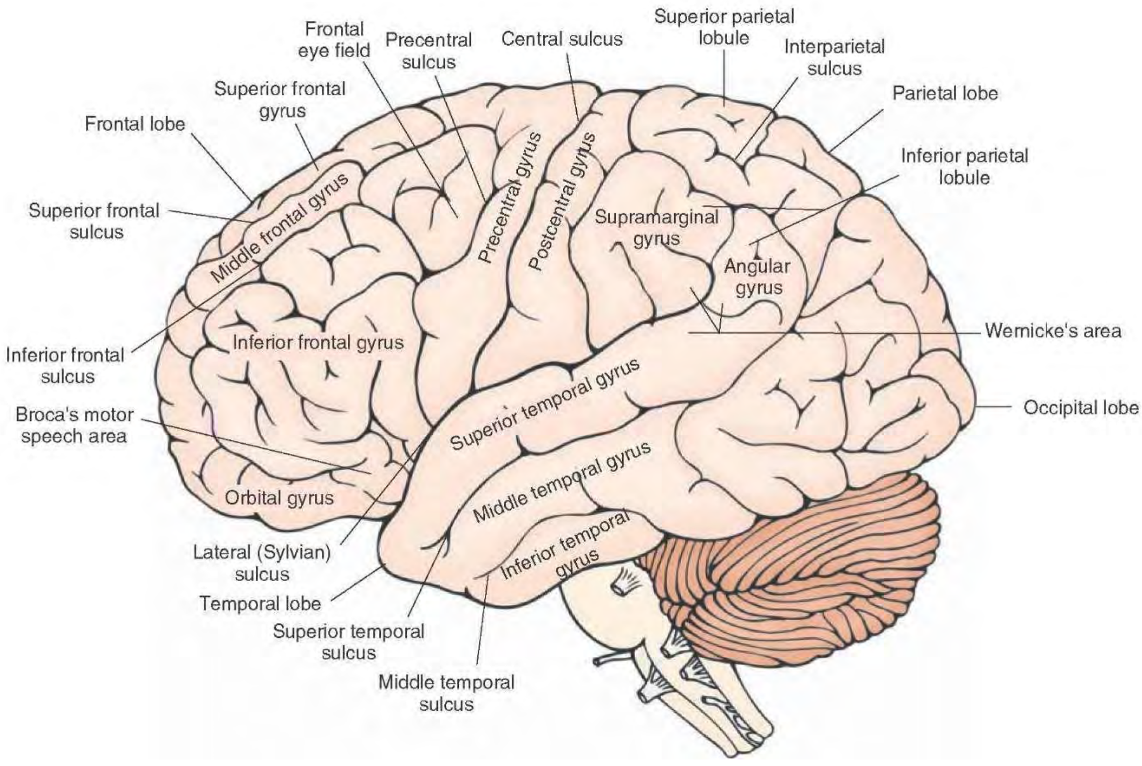


Figure 3.1: Lateral view of the cerebral hemisphere showing the principal gyri and sulci of the cerebral cortex

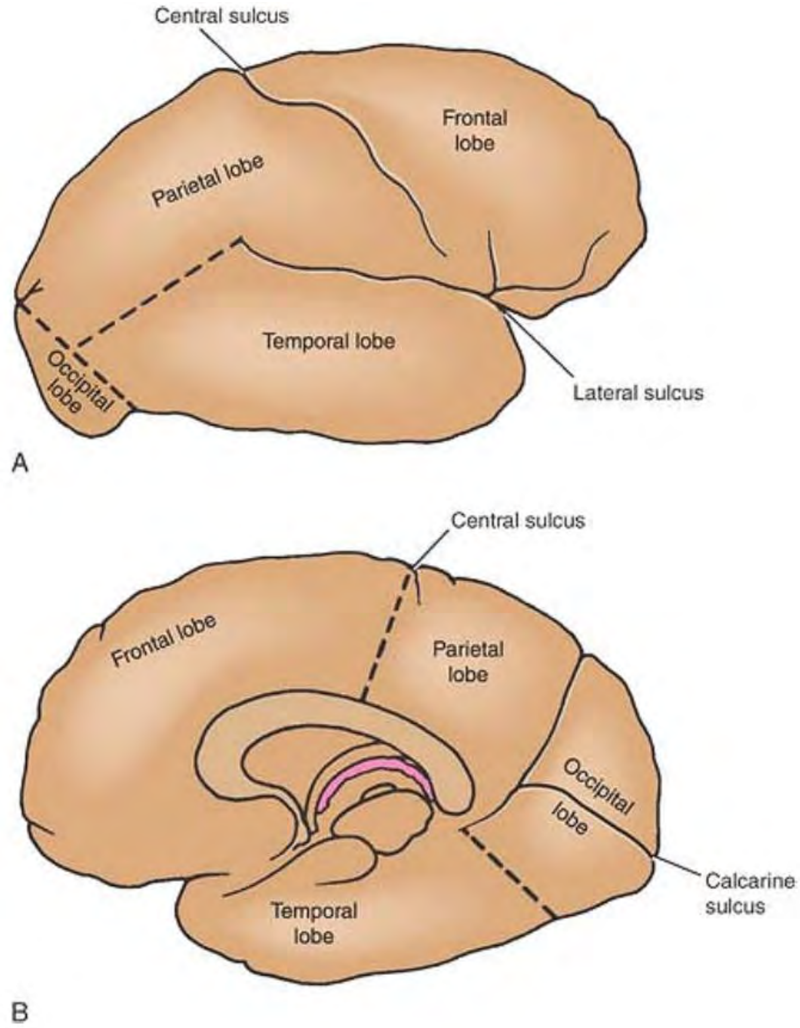


Figure 3.2: A: A lateral view of the right cerebral hemisphere showing the lobes

B: Medial view of the right cerebral hemisphere showing the lobes [47].

The appearance of sulci and gyri increases the surface are for the neurons many times without increasing the size of the brain [48]. The cerebral hemispheres coordinate the highest level of nervous function, the anterior half dealing with executive 'doing' functions and the posterior half constructing a perception of the environment [49]. Each cerebral hemisphere has four functionally specialized lobes namely Frontal, Parietal, Temporal, and Occipital. During collection of EEG signal, electrode is placed on the central part of the scalp too. Based on that, an additional lobe is defined in the study of brain electrical activity which is called central lobe. Basically, it is a hypothetical lobe. From the perspective of neurology, this is motor cortex division which is divided into three areas: Primary motor cortex, Premotor cortex, and Supplementary motor area (SMA) [48]. This part actually incorporates part of the frontal lobes. Different parts of the brain engage in different types of functions.

Frontal lobe:

The cortex of the frontal lobe may be divided for convenience into two main regions, precentral and the prefrontal. The frontal lobes are concerned with executive function, movement, behavior, and planning. In addition to the primary and supplementary motor cortex, there are specialized areas for the control of eye movements, speech (Broca's area) and micturition.

Parietal lobe:

The parietal lobes integrate sensory perception. The primary sensory cortex lies in the post-central gyrus of the parietal lobe. Much of the remainder is devoted to 'association' cortex, which processes and interprets input from the various sensory modalities. The non-dominant parietal lobe is concerned with spatial awareness and orientation.

Temporal lobe:

Temporal lobes contain the primary auditory cortex and primary vestibular cortex. On the inner medial sides lie the olfactory cortex, which is involved in memory function.

Occipital lobe:

The occipital lobes are responsible for visual interpretation.

Table 3.1 represents the major functions of different lobes and table 3.2 shows the channel sets on each lobe. In this case, only the channels located in a particular lobe are used to collect EEG data and the effect of such reduction on classification accuracy is examined. In this way, five different channel sets are obtained for the five major lobes of the brain. For example, seventeen channels on the frontal lobe, fourteen channels on the central lobe, ten channels on the parietal lobe, eight channels on the occipital lobe, and finally, twelve channels on the temporal lobe. Effects on accuracy of these five electrode sets are investigated to seek whether any particular zone of electrodes can capture significant information to better classify alcoholics from control group or at least perform the classification with the same accuracy as obtained by using all the channels.

Table 3.1: The major functions of different lobes of the brain

Lobe/Region	Functions
FRONTAL LOBE Primary motor cortex	Voluntary control of skeletal muscle
PARIETAL LOBE Primary sensory cortex	Conscious perception of touch, pressure, pain, vibration, taste, and temperature
OCCIPITAL LOBE Visual cortex	Conscious perception of visual stimuli
TEMPORAL LOBE Auditory cortex and olfactory cortex	Conscious perception of auditory and olfactory stimuli
ALL LOBES Association areas	Integration and processing of sensory data; processing and initiation of motor activities

Table 3.2: Five Lobe-Wise Channel Sets

Lobe	Channel Number	Channels
Frontal	17	FP1, FP2, F7, F8, AF1, AF2, FZ, F3, F4, AF7, AF8, F5, F6, FPZ, F1, F2, AFZ
Central	14	FC1, FC2, FC3, FC4, FC5, FC6, FCZ, C1, C2, C3, C4, CZ, C5, C6
Parietal	10	CP1, CP2, CP3, CP4, CPZ, P1, P2, P3, P4, PZ
Occipital	8	PO1, PO2, POZ, PO7, PO8, O1, O2, OZ
Temporal	12	P5, P6, P7, P8, CP5, CP6, TP7, TP8, T7, T8, FT7, FT8

3.2.2 Cortical function-based scheme

Functional or Cortical areas of Cerebral Cortex:

There are three basic functional division of cerebral cortex as shown in Fig. 3.3.

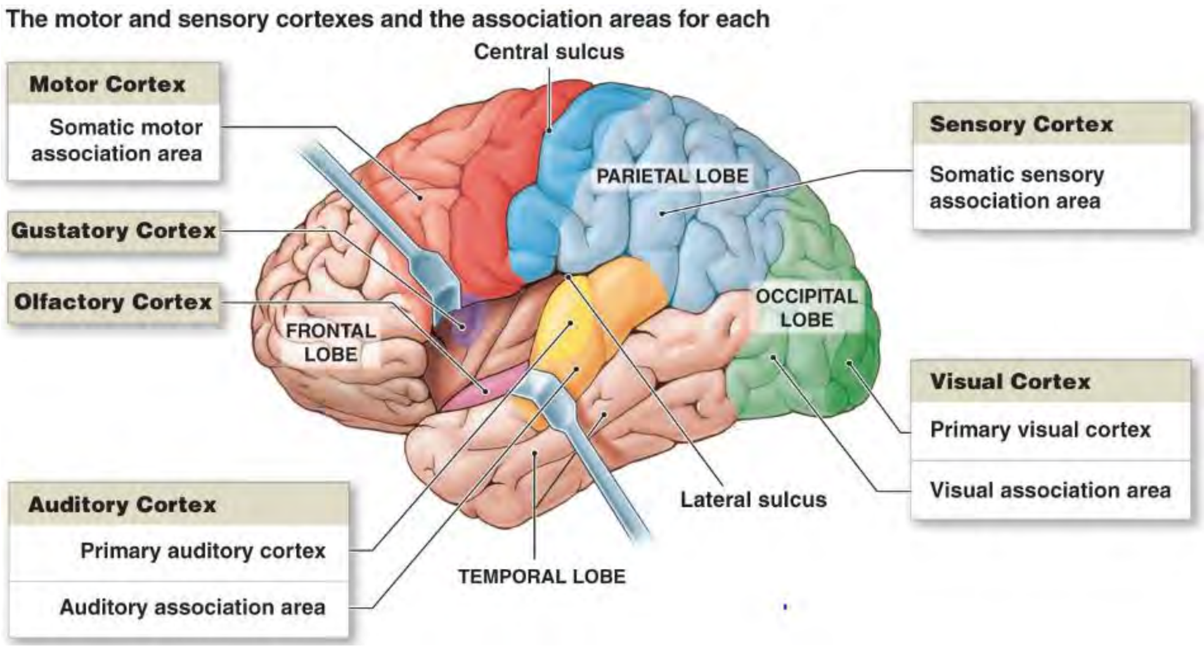


Figure 3.3: Motor and sensory cortices and association areas for both

1. Motor areas: These are the specific areas of the cerebral cortex, diencephalon, cerebellum, brain stem and spinal cord which generate impulses which innervate all effectors in the body, e.g., voluntary skeletal muscles, involuntary muscles, and glands, both endocrine and exocrine. The primary motor area has been identified on the basis of evocation of motor responses at a low threshold of electric stimulation which gives rise to contraction of skeletal musculature [48].
2. Sensory areas: Specific areas of the cerebral cortex which receive and interpret somatic sensory impulses, e.g., olfaction in the frontal lobe, cutaneous sensations in the parietal lobe, visual sensations in the occipital lobe, taste, hearing, and equilibrium in the temporal lobe belong to sensory areas. Visceral sensory impulses are received and interpreted in the diencephalon, cerebellum, and brain stem. In these areas, electrical activity can be recorded if appropriate sensory stimulus is applied to a particular part of the body [48].
3. Association areas: Specific areas of the cerebral cortex which integrate sensory information with emotional states, memories, learning and rational thought processes constitute the association areas. In these regions, the direct sensory or motor responses are not elicited rather, these areas integrate and analyze the responses from various sources [48].

***Brodmann's areas**:*

Early in the 20th century, numerous researchers attempted to describe and classify regional differences in the histological organization of the cerebral cortex. They hoped to correlate the patterns of cellular organization with specific functions. By 1919, at least 200 patterns had been described, but most of them were abandoned. However, the cortical map prepared by Korbinian Broadmann in 1909 has proved useful to neuroanatomists [50].

Brodmann areas have been discussed, debated, refined, and renamed exhaustively for nearly a century and remained the most widely known and frequently cited cytoarchitectural organization of the human cortex. Brodmann's localization theory stands on a solid basis for localization within a brain, a knowledge of variability, and a means to identify same brain areas in different individuals. A Brodmann area is a region of the cerebral cortex, in the human or other primate brain, defined by cytoarchitecture, or histological structure and organization of cells. Brodmann areas were originally defined and numbered by the German anatomist Korbinian Brodmann. Based on the cytoarchitectural organization of neurons he observed in the cerebral cortex using the Nissl method of cell staining. Brodmann published his maps of cortical areas in humans, monkeys, and other species, along with many other findings and observations regarding the general cell types and laminar organization of the mammalian cortex. He described 47 patterns of cellular organization in the cerebral cortex [50]. A similar, but more detailed cortical map was published by Constantin von Economo and Georg N. Koskinas in 1925 [51].

Many of the areas Brodmann defined based solely on their neuronal organization have since been correlated closely to diverse cortical functions. For example, Brodmann areas 1, 2 and 3 are the primary somatosensory cortex; area 4 is the primary motor cortex; area 17 is the primary visual cortex; and areas 41 and 42 correspond closely to primary auditory cortex. Higher order functions of the association cortical areas are also consistently localized to the same Brodmann areas by neurophysiological, functional imaging, and other methods (e.g., the consistent localization of Broca's speech and language area to the left Brodmann areas 44 and 45) [48]. These regions of the brain and Brodmann's functional areas are shown in Fig. 3.4. An attempt has been taken in this study to use only the electrodes located on the specific Brodmann's functional areas that are assumed to take part in the cognitive and mental tasks required for the subjects in this study.

Relevant activities while observing visual stimuli:

As described in Chapter 2, the dataset used in this study is obtained from a group of alcoholic and non-alcoholic persons while they are exposed to some visual stimuli. They are asked to recognize the picture, keep it in memory, and compare with a second piece of stimuli to decide whether the two objects were same or not. Thus, the proposed activities performed by a human brain when this kind of mental and cognitive tasks are going on are listed in table 3.3.

Table 3.3: Actions and activities while performing mental and cognitive tasks in response to visual stimuli

1.	Eye movement	18.	Visuospatial and visuomotor attention
2.	Saccades	19.	Memory retrieval
3.	Working memory	20.	Short-term memory
4.	Action planning	21.	Recency
5.	Multitasking	22.	Recognition
6.	Topographic memory	23.	Recall
7.	Eye guidance	24.	Joint attention
8.	Object naming	25.	Verbal memory
9.	Inhibit response	26.	Visual attention
10.	Same or different	27.	Visual priming
11.	Goals	28.	Visual memory
12.	Error detection	29.	Monitor color and shape
13.	Imageability	30.	Visual memory recognition
14.	Visuospatial attention	31.	Visual fixation
15.	Stereopsis	32.	Visual categorization
16.	Executive control	33.	Visual discrimination
17.	Perceptual priming	34.	Picture memory

Cortical function and electrode mapping to reduce channels:

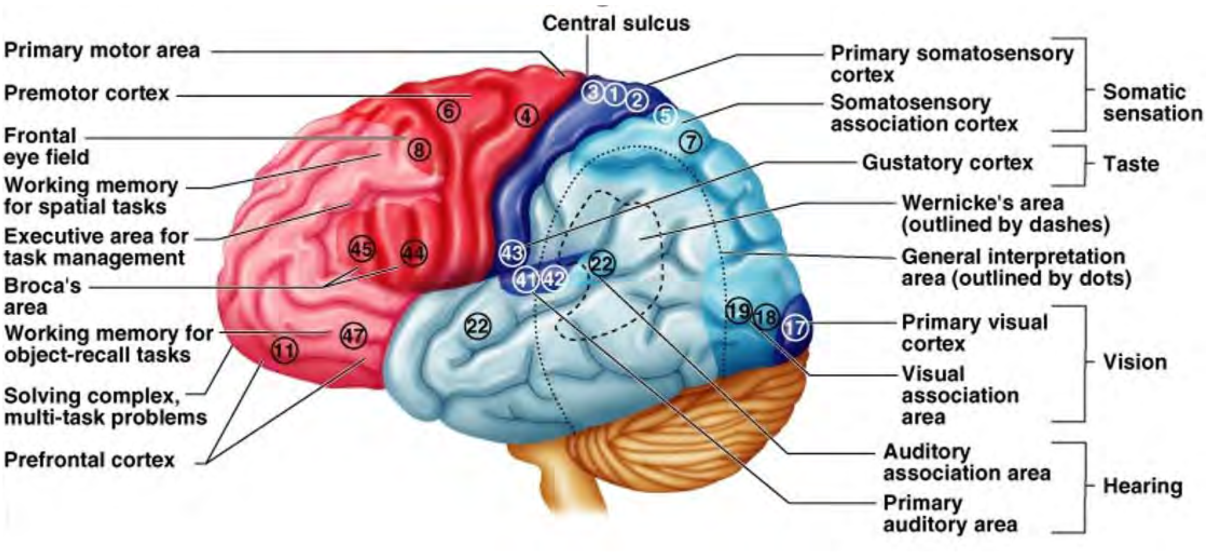


Figure 3.4: Functional areas of cerebral cortex

The major cortical regions of the brain over which EEG electrodes are placed are shown in Fig. 3.4. The two gyri immediately neighboring the central sulcus are the

- Primary motor cortex (in frontal direction), and
- Primary sensory cortex (in occipital direction).

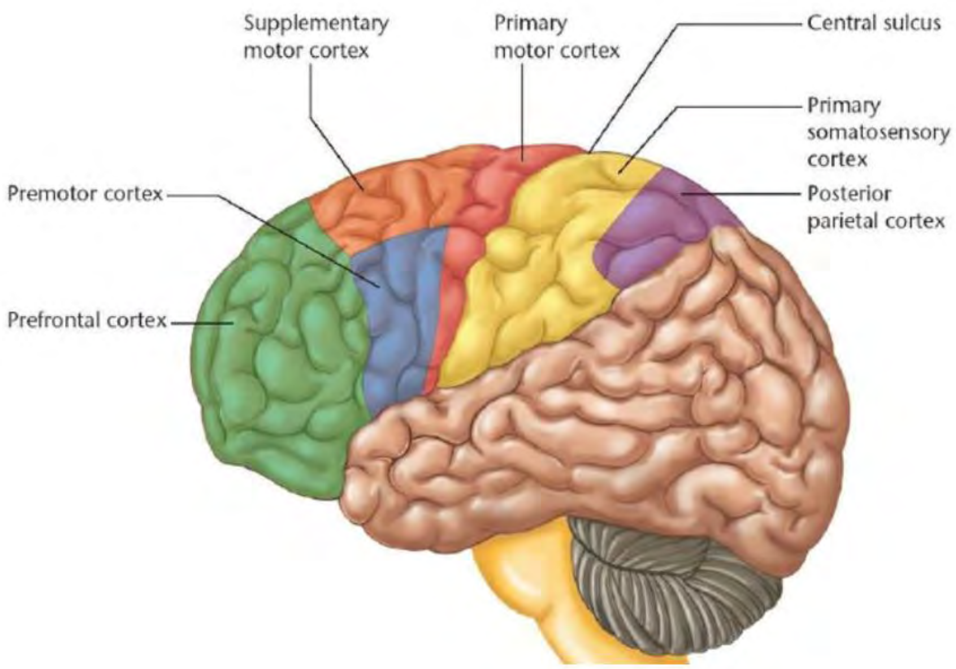


Figure 3.5: The major cortical regions of the brain over which EEG electrodes were placed

The central sulcus (Rolandic fissure) separates the frontal lobe from the parietal lobe [Fig. 3.2 & 3.5]. Its course corresponds to the thin lines touching CPZ-C2-C4 and CPZ-C1-C3 respectively as indicated by Fig. 3.5. The course of the lateral sulcus corresponds to the lines C6-FT8-FT10 and C5-FT7-FT9. It separates the temporal lobe from the remaining part of the brain.

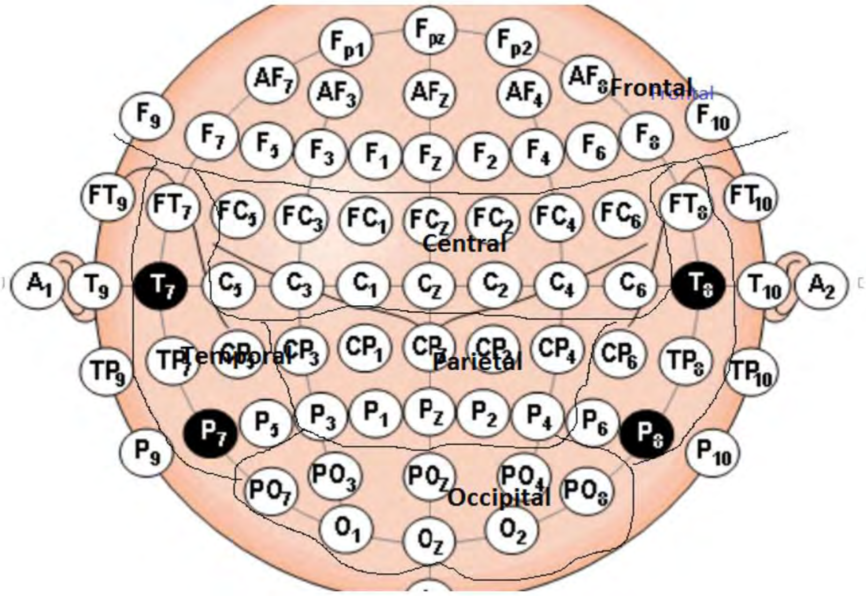


Figure 3.6: EEG electrodes in different location of the brain

Thus, the electrodes corresponding to the Central sulcus are located at C3-C1-CPz-C2-C4. In front of it, primary motor cortex area 4 [Fig. 3.4] lies which coincides with FC5, C3, C1, CZ, C2, C4, FC6 [Fig. 3.6]. This area controls voluntary activities of the opposite half of the body [48]. In alcoholic database, there is no use of this motor cortex area. So, we can eliminate 7 channels (FC5, C3, C1, CZ, C2, C4, FC6) associated with this area.

In front of primary motor cortex area, there is premotor cortex or motor association area 6 [Fig. 3.4] which controls extrapyramidal system [48] and coincides with FC3, FC1, FCZ, FC2, FC4 [Fig. 3.6]. Therefore, we can discard these 5 channels also.

Brodmann area (BA) 3,1,2 [Fig. 3.4] represents primary somatosensory cortex and 5,7 [Fig. 3.4] represents somatosensory association cortex, which coincide with CP3-CP1-CPZ-CP2-CP4. BA 3,1,2 is in charge of perception of exteroceptive (touch, pain, and temperature) and proprioceptive impulses. Similarly, BA 5,7 is for stereognosis and sensory speech [48]. Furthermore, BA 43 [Fig. 3.4] is gustatory cortex for taste sensation coinciding with C5, C6.

BA 41 and 42 [Fig. 3.4] are auditosensory areas that coincide with CP5, CP6. On the other hand, BA 22 [Fig. 3.4] is Auditopsychic or Wernicks sensory speech area that coincides with P5, P3, P4, P6. We can eliminate these channels as well.

Association areas (prefrontal and parietal-temporal-occipital) are where different modalities combine, attention is shifted, planning occurs, and memories are stored. PTO (parietal-temporal-occipital) is formed by connection of P1-PZ-P2 with PO3-POZ-PO4 and P7-TP7-T7 in one side and P8-TP8-T8 on the other side.

We can eliminate total 25 channels plus 2 reference and 1 ground electrode. Thus, the remaining channels are 64-28=36 channels. The cortical functions of the areas that are excluded are listed in table 3.4 and the channels that are selected are presented in table 3.5.

Table 3.4: Cortical functions of areas being eliminated

<table>
<tr><td>Cortical functions</td><td>Cortical area</td><td>Brodmann’s area</td><td>Channels</td></tr>
<tr><td>Controlling voluntary activities of the opposite half of the body</td><td>Primary motor cortex</td><td>BA 04</td><td>FC5, C3, C1, CZ, C2, C4, FC6</td></tr>
<tr><td>Controlling extrapyramidal (involuntary) system</td><td>Premotor cortex or motor association area</td><td>BA 06</td><td>FC3, FC1, FCZ, FC2, FC4</td></tr>
<tr><td>Perceiving exteroceptive (touch, pain, and temperature) and proprioceptive (self-movement and body position) impulses</td><td>Primary somatosensory cortex</td><td>BA 01, 02, & 03</td><td rowspan="2">CP3, CP1, CPZ, CP2, CP4</td></tr>
<tr><td>Stereognosis (perceiving solid object by touch) and sensory speech (comprehending spoken and written words)</td><td>Somatosensory association cortex</td><td>BA 05 & 07</td></tr>
<tr><td>Sensing taste</td><td>Gustatory cortex</td><td>BA 43</td><td>C5, C6</td></tr>
<tr><td>Processing sound</td><td>Auditosensory areas</td><td>BA 41 & 42</td><td>CP5, CP6</td></tr>
<tr><td>Reflexive mimicking of words and their syllables that are associated to the sensory and motor images of spoken words.</td><td>Auditopsychic or Wernicks sensory speech area</td><td>BA 22</td><td>P5, P3, P4, P6</td></tr>
</table>

Table 3.5: Channels selected based on cortical functions

Lobe	Channel Number	Channels
Frontal	17	FP1, FP2, F7, F8, AF1, AF2, FZ, F4, F3, AF7, AF8, F5, F6, FPZ, F2, F1, AFZ
Parietal	3	PZ, P2, P1
Occipital	8	PO2, PO1, O2, O1, PO7, PO8, POZ, OZ
Temporal	8	T8, T7, P8, P7, FT7, FT8, TP8, TP7

3.2.3 Hemispheric lateralization-based scheme

Each cerebral hemisphere receives sensory information from and sends motor commands to the opposite side of the body. The two hemispheres have different functions even though they look almost identical [50]. In right-handed individuals the left hemisphere is almost always dominant, while around half of the left-handers have a dominant right hemisphere [49]. Thus, each of the two cortical hemisphere is responsible for specific functions that are not ordinarily performed by the opposite hemisphere. This regional specialization has been called hemispheric lateralization. Left-handed people represent 9% of the human population [50]. This indicates that for majority of the population, left hemisphere is the most active and area-wise brain functions of a right-handed individual represent majority of samples.

In most people, the left hemisphere contains the general imperative and speech centers and is responsible for language-based skills. For example, reading, writing, and speaking are dependent on processing done in the left hemisphere. In addition, the premotor cortex involved with the control of hand movements is larger on the left side for right-handed individuals than for left-handed ones. The left hemisphere is also important in performing analytical tasks, such as mathematical calculations and logical decision making. For these reasons, the left cerebral hemisphere has been called the dominant hemisphere, or the categorical hemisphere [50].

On the other hand, the right cerebral hemisphere analyzes sensory stimulations or information and relates the body to the sensory environment. Interpretive centers in this hemisphere permit people to identify familiar objects by touch, smell, sight, taste, or feel.

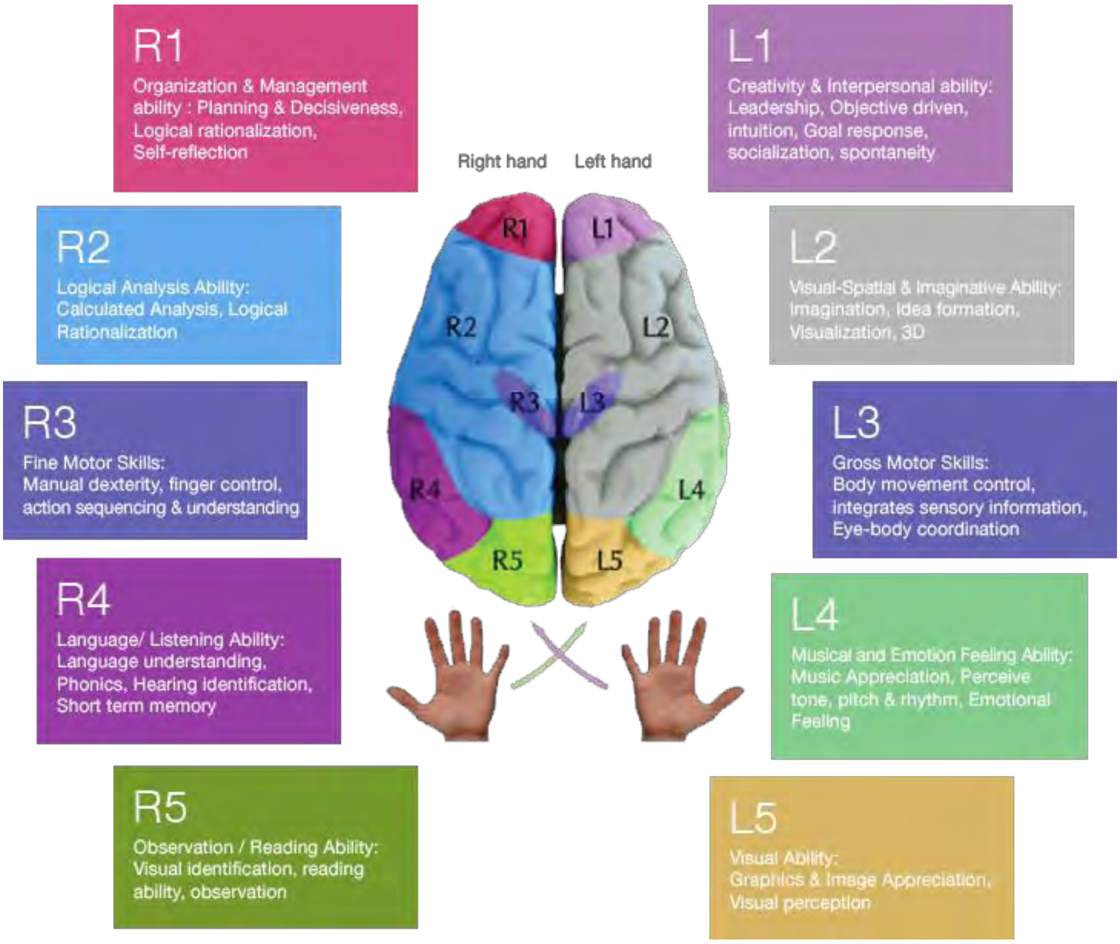


Figure 3.7: Cortical lobar functions (dominant and non-dominant)

Table 3.6: Channels selected based on Cortical lobar function

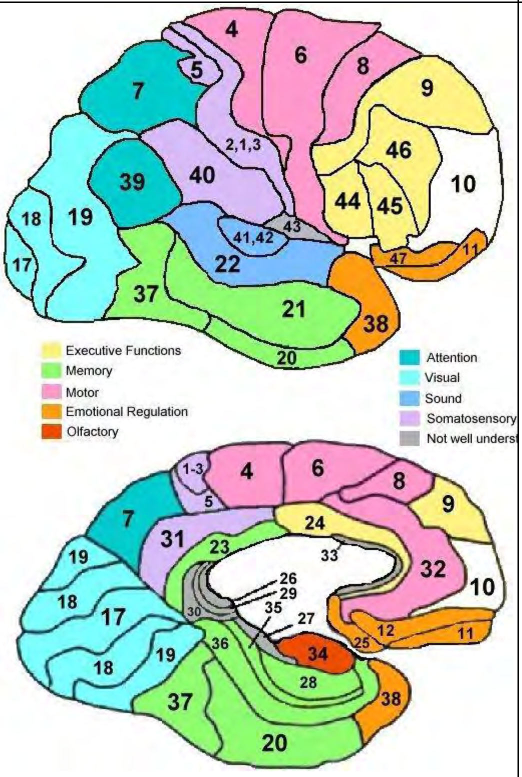
Lobe	Channel Number	Channels
Pre-Frontal Right, (R1) Planning, decisiveness, logical rationalization	3	FP2, AF2, AF8
Frontal Left, Central Left, Parietal Left (L2) Visuo-spatial, imaginative ability, visualization	14	F7, F5, F3, F1, FC5, FC3, FC1, C5, C3, C1, CP3, CP1, P3, P1
Temporal Right (R4) Short-term memory	6	CP6, TP8, T8, P6, P8, FT8
Occipital Right (R5) Visual identification, observation	3	PO2, PO8, O2
Occipital Left (L5) Visual ability	3	PO1, PO7, O1

According to Fig. 3.7, R1 or prefrontal right is associated with decision making. Whereas, frontal left, central left, and parietal left (L2) deals with visualization. Furthermore, temporal right (R4) controls short term memory, Occipital right R5 controls observation and visual identification. Occipital left (L5) corresponds to visual perception. In this way, we can select 29 channels. However, a problem associated to this scheme is that, whether the subjects were right-handed or left-handed, this information is unknown in the current study and while this scheme will be applied in practical purposes, this additional information about the subject is to be known.

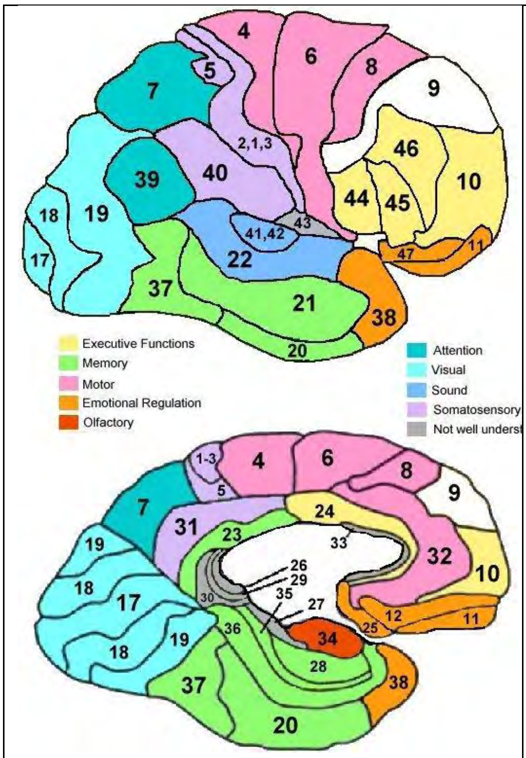
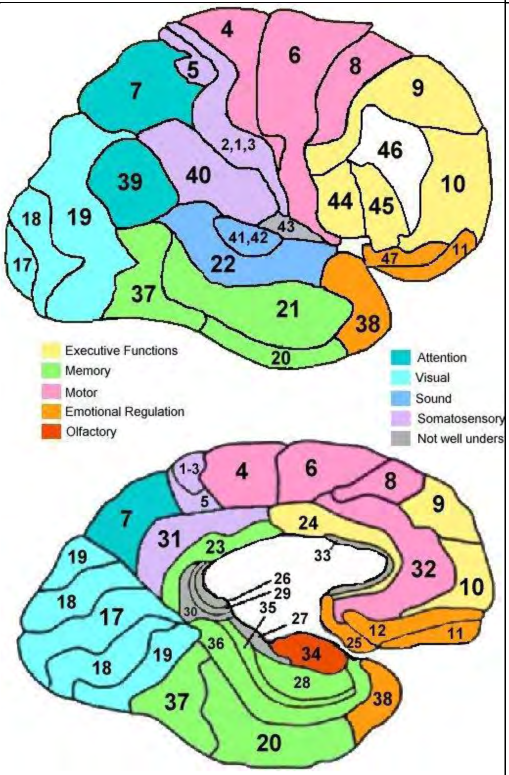
3.2.4 Brodmann's localization theory-based scheme

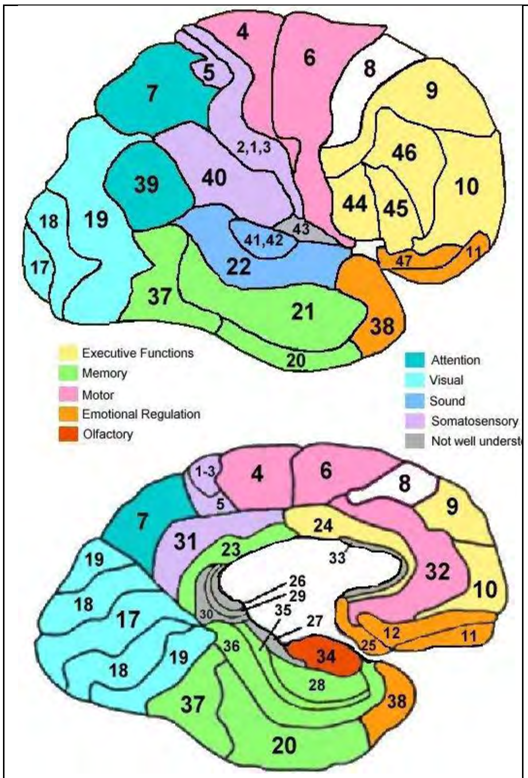
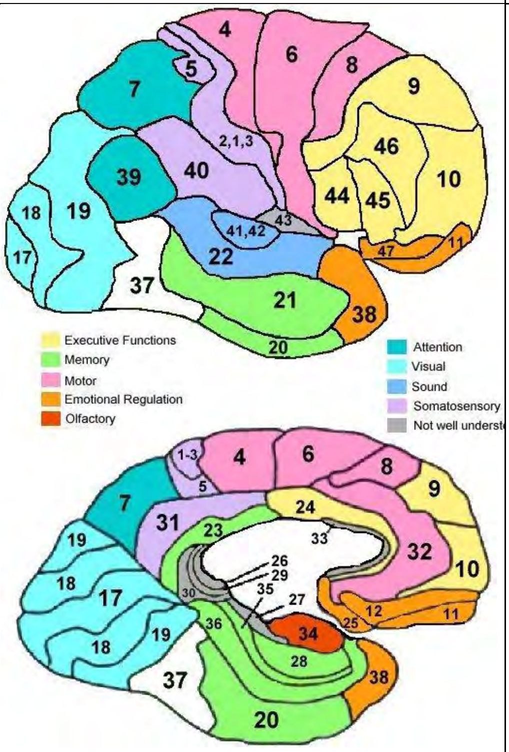
Functions associated with Brodmann areas are represented in [52] and locational descriptions are available in [53]. Moreover, the mapping of electrodes in 10-10 system on the Brodmann's areas are presented in [54], [55]. Based on the mapping of electrodes on the region of brain that are supposed to be more active during such mental and cognitive tasks mentioned in this study, we can arrive at Table 3.7.

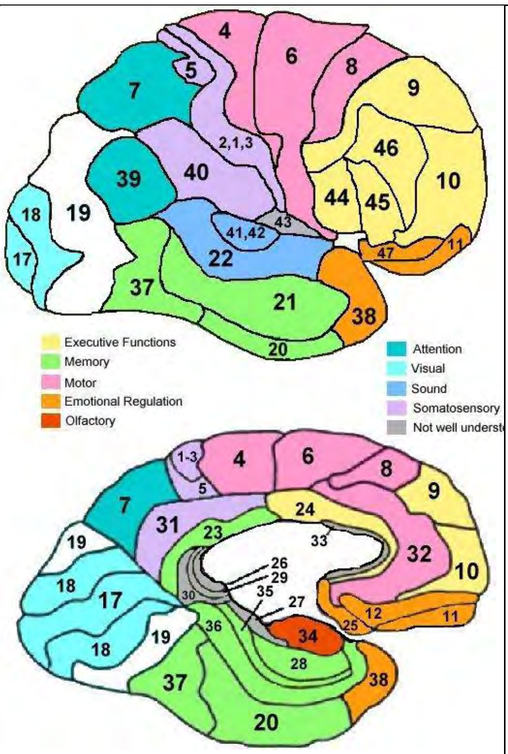
Table 3.7: Selection of EEG electrode based on BA and functional activity of brain

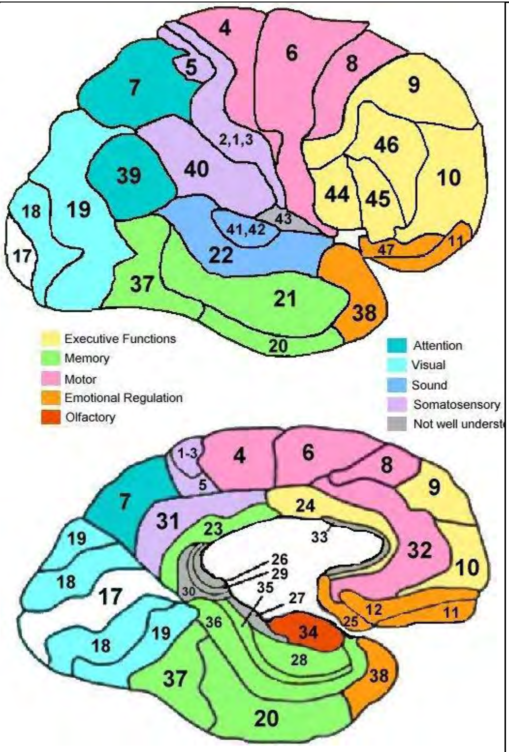
<table>
<tr><td>Selected region in the brain</td><td>EEG electrode</td><td>Brodmann’s area and function</td><td>Left</td><td>Right</td></tr>
<tr><td>

Frontal pole</td><td>FP1 (10L),
FP2 (10R),
FPZ (10L)</td><td>10
Govern executive functions
- Working memory [56], [57]
- Spatial memory
- Recognition
- Recall
- Joint attention</td><td>10L</td><td>10R</td></tr>
</table>

 Middle frontal gyrus	AF1 (9L), AF2 (9R), AFZ (9L)	9 Govern executive functions - Short-term memory	9L	9R - Working memory - Spatial memory - Recogniti on - Recall
 Medial frontal gyrus	AF7 (46L), AF8 (46R) F5 (46L) F6 (46R)	46 - Memory recognition - Working memory - Categorizati on - Monitor - Strategy	46L	46R

 Lateral and medial supplementary motor area	F3 (8L), F1 (8L), FZ (8L) F2 (8R) F4 (8R)	8 Governance of eye movements Executive control Working memory Topographic memory Perceptual priming Saccades	8L	8R - Memory retrieval
 Posterior inferior temporal gyrus, middle temporal gyrus, and fusiform gyrus	P7 (37L) P8 (37R)	37 Visual analysis and association - Visual fixation	37L - Visual categorization of item as natural or manmade	37R

 Secondary visual cortex - Inferior occipital gyrus; extrastriate/peristriate	PO7 (19L) PO8 (19R)	19 Visual association area: feature-extraction, shape recognition, attention, and multimodal integration. Likely differentiation point of 'what' (ventral) and 'where' (dorsal) visual pathways **Receive** - Visual patterns **Organize** - Visual memory recognition - Feature based attention - Visual priming - Visual memory recognition - Spatial working memory	19L	19R - Visuo-Spatial memory - Visual priming - Visual memory recognition - Spatial working memory - Visual imagery - Saccades

 Primary visual cortex	POz (17L) Oz (17R)	17 Process visual information **Organize** - Visual attention - Visual priming	17L	17R - Visuo-spatial

Thus, we end up with selecting 21 channels which are expected to be located on the BA regions which are heavily involved in cognitive and mental tasks. For example, channels FP1, FP2, and FPZ belong to BA10 which is involved in governing executive functions, working memory, spatial memory, recognition, recall, joint attention etc. these functions are more likely to be executed while a person is exposed to visual cue. AF1, AF2, and AFZ belongs to BA09 and this area is also responsible for governing executive functions, working memory, spatial memory, recalling, recognition, planning and so on. AF7, AF8, F5, F6 are in BA45. This area is involved in handling working memory, memory recognition, categorization and monitoring. F1, F2, F3, F4, and FZ fall under BA08 which area’s tasks include governance of eye movement and memory retrieval. PO7 and PO8 are in BA19 and responsible for visual association like: feature extraction, shape recognition, attention, visual patterns, visual memory recognition that are highly likely activities when a person is exposed to visual stimuli. POZ, OZ are in BA17 and relevant activities include processing visual stimuli and visual attention. BA37 embeds P7, P8. This area corresponds to visual analysis and association, visual fixation, and visual categorization.

Table 3.8: Channels selected based on EEG electrode mapping on selected Brodmann's areas

Lobe	Channel Number	Channels
Frontal	15	FP1, FP2, FPZ, AF1, AFZ, AF2, AF7, AF8, F5, F6, F1, F2, F3, F4, FZ,
Occipital	4	PO7, PO8, POZ, OZ
Temporal	2	P8, P7

Table 3.9: Brodmann Areas with anatomical gyrus of the selected 19 channels and their weights based on relevant tasks to total tasks

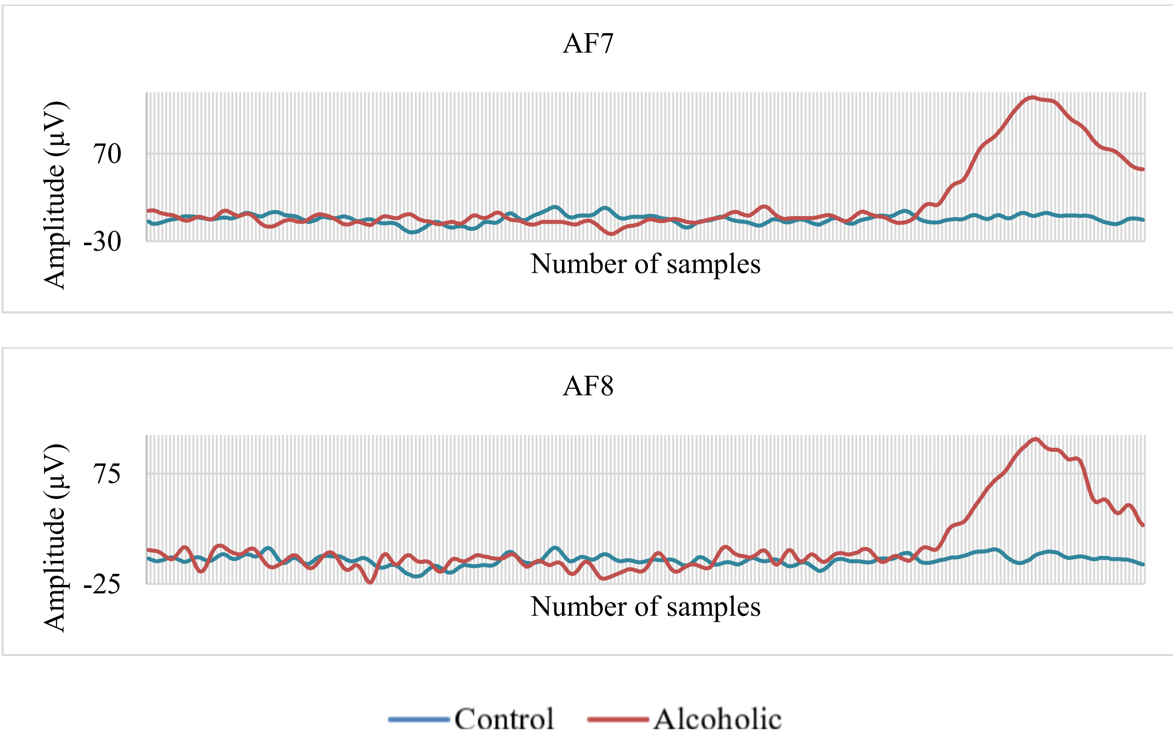
Channels	Brodmann Area	Anatomical Gyrus (Functional Names)	Total activities	Relevant activities	Weight
FP1, FP2, FPZ	BA10	Frontopolar (Dorsolateral Prefrontal Cortex, DLFC)	22	5	23%
AF1, AFZ, AF2	BA09	Granular frontal (DLFC)	24	5	21%
AF7, AF8, F5, F6,	BA46	Middle frontal	15	5	33%
F1, F2, F3, F4, FZ	BA08	Intermediate frontal	25	7	8%
PO7, PO8	BA19	Peristriate (Tertiary or associative visual cortex, V3)	25	8	32%
POZ, OZ	BA17	Striate (Primary visual cortex, V1)	10	3	30%
P8, P7	BA37	Occipitotemporal	17	2	12%

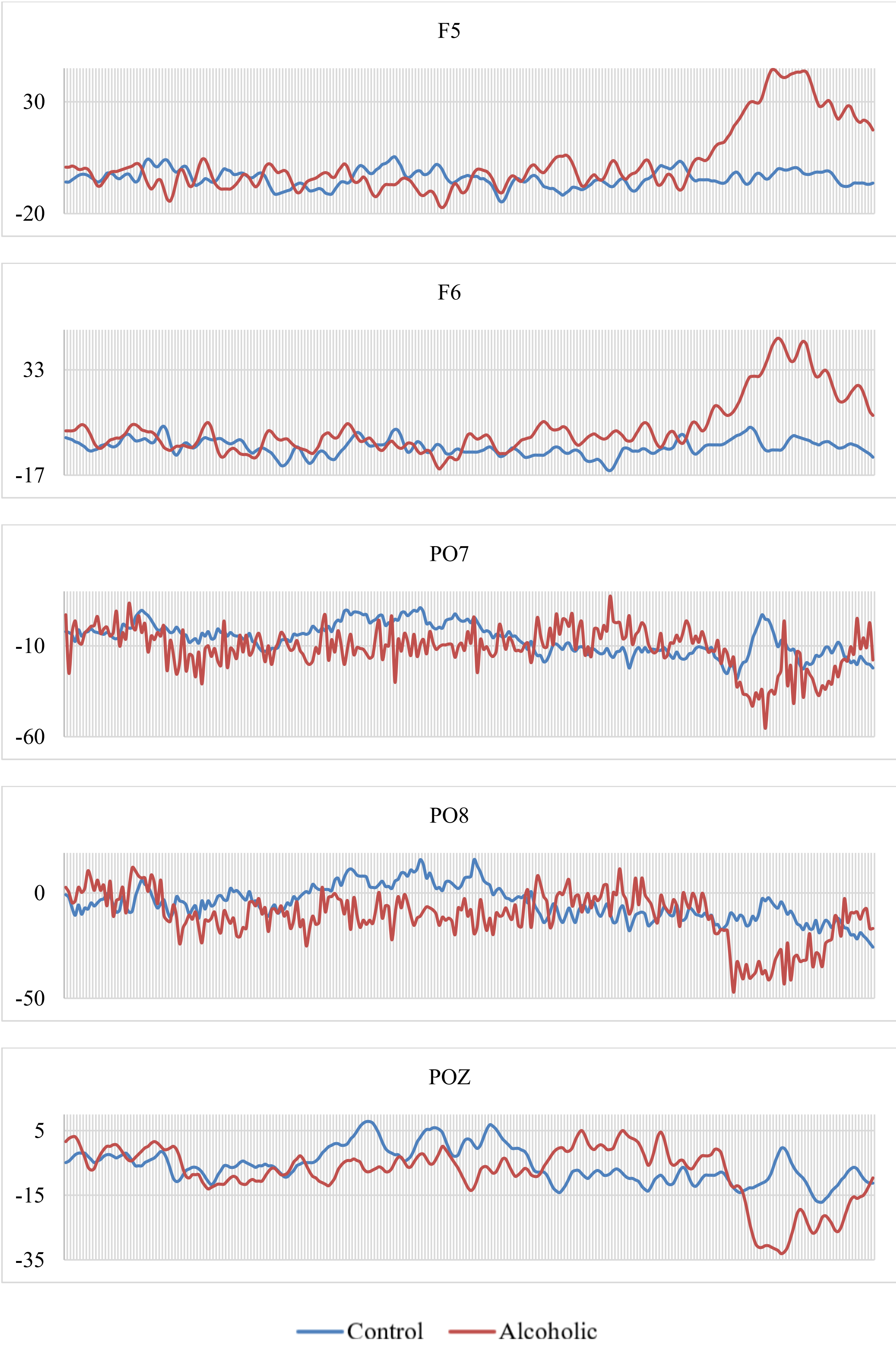
If these 21 channels are categorized according to the lobes on which they are positioned, then we get that broadly only 3 lobes: frontal, occipital and temporal are associated to these 21 channels. Whereas, a total of 7 Brodmann's areas are incorporated with these channels. These 7 BAs perform many other functions as well. As such, if we observe the relative weights of relevant activities performed while observing, recognizing, and recalling visual cue to total activities, of each set of channels on a particular Brodmann's area, we arrive at table 3.9. If the channels sets are ranked based on the weights, then BA19 from occipital lobe scores the highest position while BA08 from frontal lobe scores the lowest as shown in table 3.10.

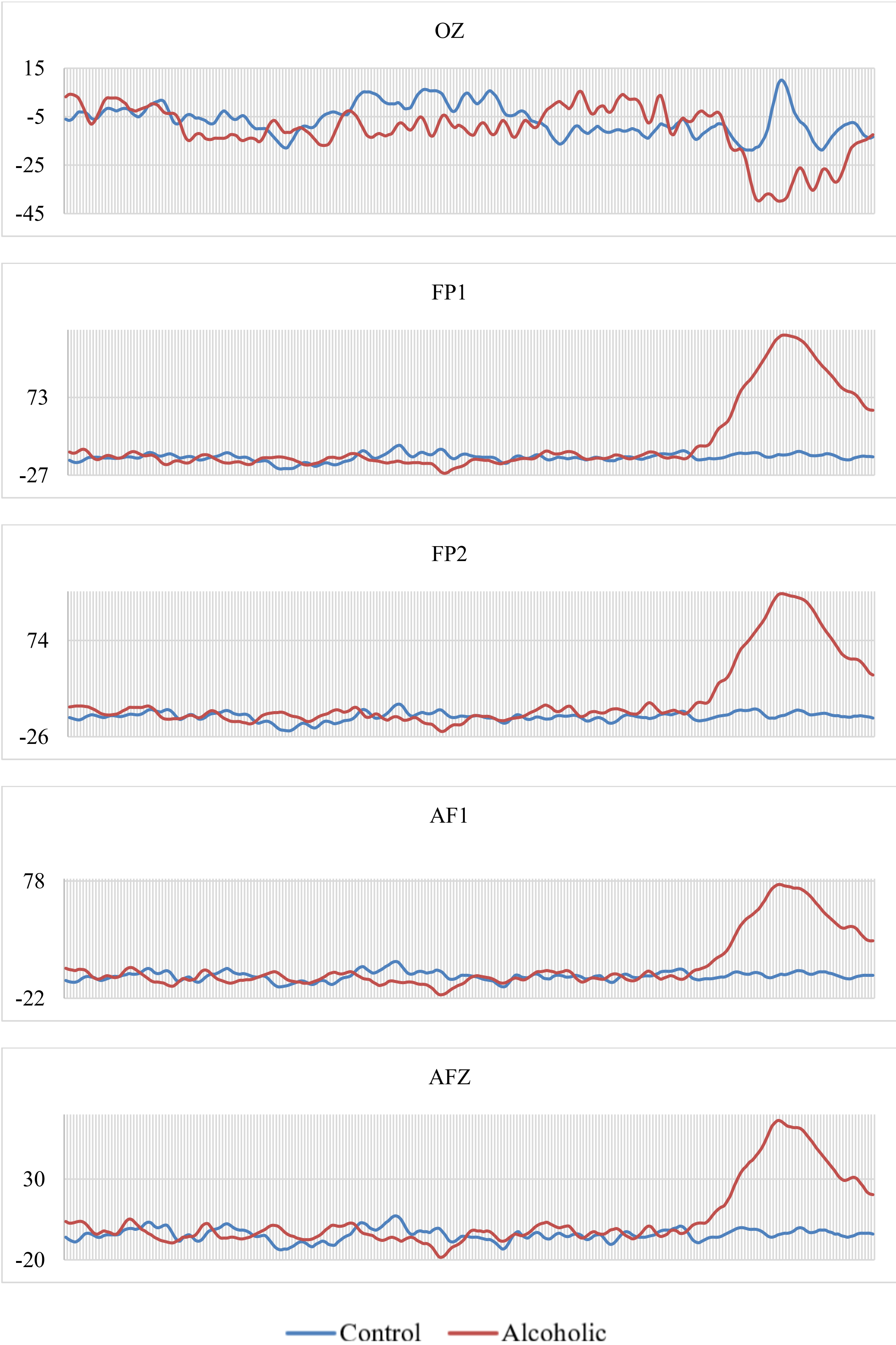
Table 3.10: Ranking of the channel sets based on weights

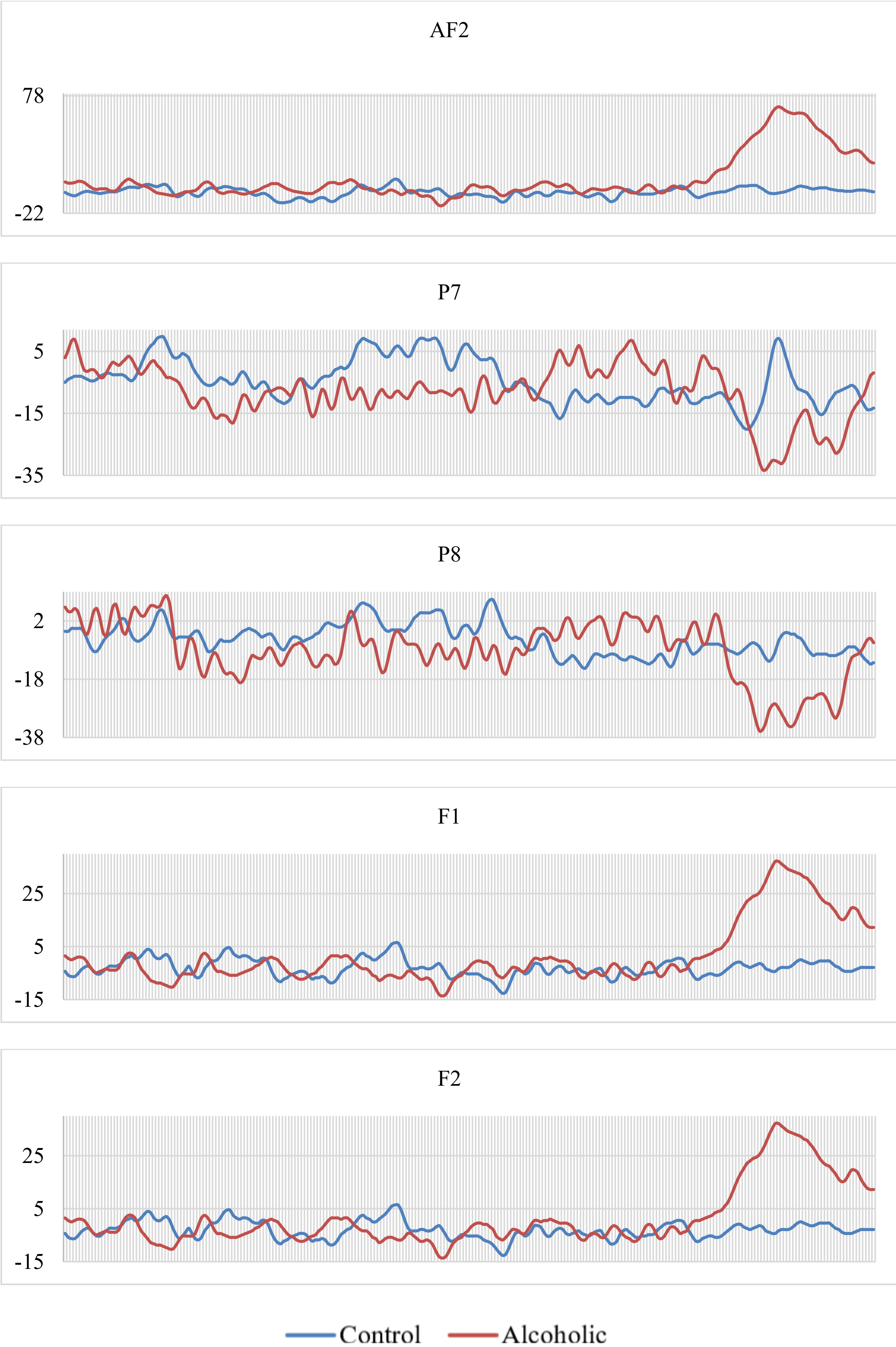
Channels	Brodmann Area	Lobe	Weight	Rank
AF7, AF8, F5, F6,	BA46	Frontal	33%	1
PO7, PO8	BA19	Occipital	32%	2
POZ, OZ	BA17	Occipital	30%	3
FP1, FP2, FPZ	BA10	Frontal	23%	4
AF1, AFZ, AF2	BA09	Frontal	21%	5
P8, P7	BA37	Temporal	12%	6
F1, F2, F3, F4, FZ	BA08	Frontal	8%	7

Among these 21 channels, 15 are from frontal, 4 are from occipital, and the remaining 2 are from temporal lobe. Fig. 3.8 presents the magnitude of raw EEG collected from all these 21 channels of a control and an alcoholic person under match visual cue.




F5
30
-20
F6
33
-17
PO7
-10
-60
PO8
0
-50
POZ
5
-15
-35
Control
Alcoholic


OZ
15
-5
-25
-45
FP1
73
-27
FP2
74
-26
AF1
78
-22
AFZ
30
-20
Control
Alcoholic


AF2
78
-22
P7
5
-15
-35
P8
2
-18
-38
F1
25
5
-15
F2
25
5
-15
Control
Alcoholic

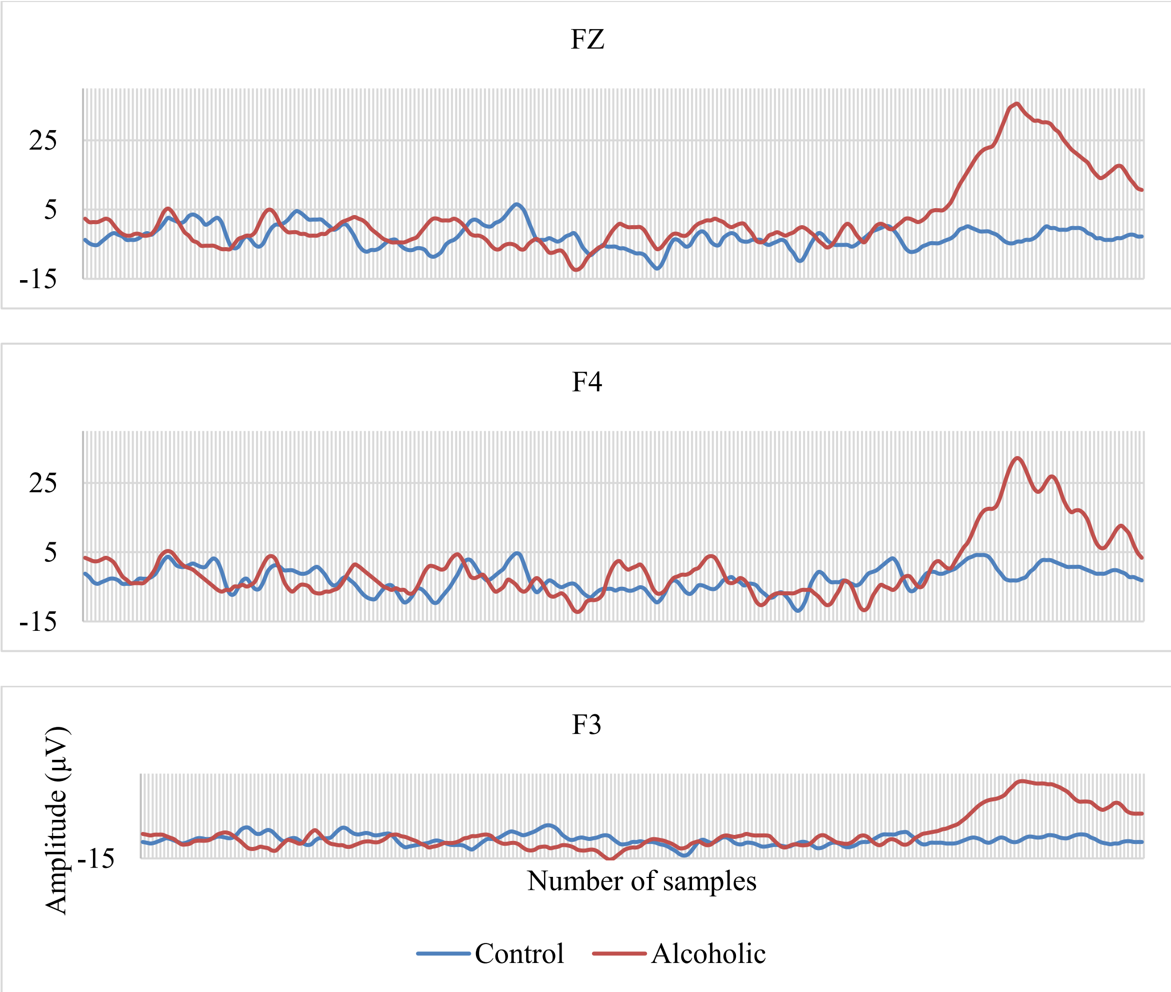


Figure 3.8: Raw EEG collected from the 21 channels

Table 3.11: Selected 16 channels

Channels	Brodmann Area	Lobe	Anatomical Gyrus (Functional Names	Weight	Rank
AF7, AF8, F5, F6,	BA46	Frontal	Middle frontal	33%	1
PO7, PO8	BA19	Occipital	Peristriate (Tertiary or Associative visual cortex, V3)	32%	2
POZ, OZ	BA17	Occipital	Striate (Primary visual cortex, V1)	30%	3
FP1, FP2, FPZ	BA10	Frontal	Frontopolar (Dorsolateral prefrontal cortex, DLFC)	23%	4
AFZ, AF2	BA09	Frontal	Granular frontal (DLFC)	21%	5
P8, P7	BA37	Temporal	Occipitotemporal	12%	6
FZ	BA08	Frontal	Intermediate frontal (includes Frontal eye fields)	8%	7

From Fig.3.8, we observe that all the 5 channels (F3, F4, FZ, F1, F2) from BA08 in frontal lobe generate almost similar form of signal. There is no significant variation in the amplitude level of these 5 channels. Thus, any one from these 5 can be selected. We are selecting FZ. Similarly, AF1 and AF2 from BA 09 produce similar waveforms. We can select any one from them. Since, right side of BA09 performs more relevant tasks, thus, we can select AF2. As a result, in this method, we can select 16 channels- AF7, AF8, F5, F6, PO7, PO8, POZ, OZ, FP1, FP2, FPZ, AF2, AFZ, P7, P8, FZ. The BA sites are recorded in table 3.11.

An important point is that the reduced channel domain is dominated by frontal lobe electrodes. Among these selected 16 channels, 10 are form that lobe, while, 4 are from occipital and 2 from trmporal lobe.

3.2.5 Weighted scoring scheme

According to [50], the correspondence between a specific function and a specific region of the cerebral cortex is imprecise. Because the boundaries are indistinct and have considerable overlap, one region may have several functions. Some aspects of cortical function cannot easily be assigned to any single region. Moreover, the persons under consideration might be involved in some other activities during the time when the data collection process will be ongoing. Based on the proposition, a weighted scoring method is proposed to select channels and reduce channel dimension. For this purpose, a total of 287 brain activities of a normal person are identified. Now these 287 activities are weighted on a scale of 0-10 divided in 7 discrete segments or levels depending on their relevance in attention, observation, identification, recognition, memory retention, memory retrieval or recall, decision making i.e. all activities that are supposed to take place while a subject is involved in cognitive and mental tasks as mentioned in table 3.3. The levels of the weights are shown in table 3.12.

Table 3.12: Levels of task relevance and weights assigned to them

Level	Weight
Essential	10
Most likely	9
More likely	7
Likely	5
Less likely	3
Least likely	1
Irrelevant	0

For example, identification of objects whether they are same or different, executive control, memory retrieval, short term memory etc. are essential tasks in this study. Thus, these activities are assigned the highest level of weight, 10. Eye movement, blinking, joint attention are most likely to occur but would not persist for long. These tasks are assigned 9. Perceptual priming, visuospatial and visuomotor attention, remembering after delay, recency, etc. are more likely to occur but are not essential. Thus, are assigned 7. Monitoring color and shape, feature based attention, visuospatial challenge, etc. are likely to happen and thus, assigned 5. Error awareness, motivated reasoning, self-calm, etc. are less likely to occur and thus assigned 3. Familiar odor, sequence learning, line bisection judgment, etc. are least likely to occur, hence, are assigned 1. Muscle learning, muscle imagery, speech programs, express fear or disgust are irrelevant and assigned 0.

After the weights are assigned to different activities, each channel is scored out of 10. This scoring is done based on brain electrode mapping on Brodmann's areas. The channels on a particular Brodmann area will score 10 for the activities that are performed by that particular location. Since, other nearby regions and their activities can also have impact on this definite zone's activities, that is why, for the activities that according to Brodmann are actually done by the nearby areas, this particular channel is assigned a score. Activities of the closest zone get 9, and in this way, the further the distance the lower become the scores. For example, FP1 belongs to BA10. This region is responsible for working memory, spatial memory, recognition, recall, intentional forgetting, nonspeech sound, recognition of emotions, calculation, pain, joint attention, syntax, metaphor, lexical resources, verbs, self-reflection, self-appraisal, inferences during reading, recalling episodes, nonspeech sound, familiar odors, reward vs. conflict, and risk vs. benefit. For all these activities, FP1 scores 10 since it is in this area. However, for activities that are not performed by BA10 but by BA09 which are adjacent to BA10, FP1 scores 9. For activities that are performed by BA46, which are more distant from BA10 than that from BA09, FP1 gets score of 7. For simplicity, left and right positions are not separately scored. The distance among a particular BA site and other nearby BA sites are collected from [55]. Following the process, all 61 channels are scored and finally, weighted sum is calculated for each channel. This method excludes the bias of hemispheric lateralization and incorporates the interferences created by other brain regions and electrodes. Hence, can be claimed to be a robust one. Using the weighted sum, the channels are ranked. The final rank is shown in table 3.13.

Table 3.13: Ranking of channels and BA site based on weighted scoring method

Electrode	Site	Weighted sum	Rank
F3, F1, FZ, F2, F4	BA08	2387	1
FC3, FC1, FCZ, FC2, FC4,	BA06	2361	2
FP1, FPZ, FP2	BA10	1977	3
AF1, AFZ, AF2	BA09	1879	4
P7, P8	BA37	1772	5
POZ, OZ	BA17	1609	6
O1, O2	BA18	1533	7
PO7, PO8,	BA19	1516	8
P1, PZ, P2,	BA07	1290	9
C4	BA01,03	1164	10
C1, CZ, C2, CP1, CPZ, CP2,	BA05	1138	11
AF7, AF8, F5, F6	BA46	1099	12
T7, C5,	BA42	1059	13
F7, FT7, FT8,	BA47	1057	14
C3, CP3	BA 02	996	15
C6,	BA41	987	16
P5, P3, P4, P6,	BA39	904	17
FC6,	BA44	844	18
F8,	BA45	832	19
CP5, CP4, CP6,	BA40	826	20
T8, TP7, TP8,	BA21	800	21

From this weighted average ranking, we select first 10 BA zones and analyze them. The weighted scoring method particularly takes into account the effects of all possible activities that are ongoing during a mental and cognitive task. Thus, taking final decision regarding mostly active channels is a bit complex and difficult. Therefore, this process should not be done solely based on the ranks obtained by the weighted summation rather it should be done by superimposing all previous schemes on it to arrive at a stronger decision.

It is expected that for a particular mental and cognitive task, only a certain part and nearby regions of brain will be highly active and it will not be a scattered event distributed in multiple locations. The first four upper ranked zones namely BA 08, 06, 10 and 09 are located together. BA06 is typically responsible for motor activities which is typically not required in this case. However, some involuntary motor actions are always running and therefore, BA06 is ranked high by the weighted score. Thus, we can select the central FCZ channel from this site. From the previous section, we selected only one channel from BA08, which is FZ. After these 4 sites, comes BA37. Based on the activities done by 37R and 37L, we can exclude P8 from 37R. Later, comes BA17, 18, and 19 from occipital lobe. Interestingly, all these sites are in common with the previously discussed method except for BA18. BA17 and 19 include 4 of the total 8 occipital channels. Thus, including BA18 will include redundancy. That is why, BA18 is excluded. Next, 3 channels, P1, PZ, P2 of BA07 and C4 from BA01, 03 rank 9th and 10th respectively. Figure 3.12 delineates the amplitude of raw EEG data collected from these 4 channels of a control and alcoholic subject.

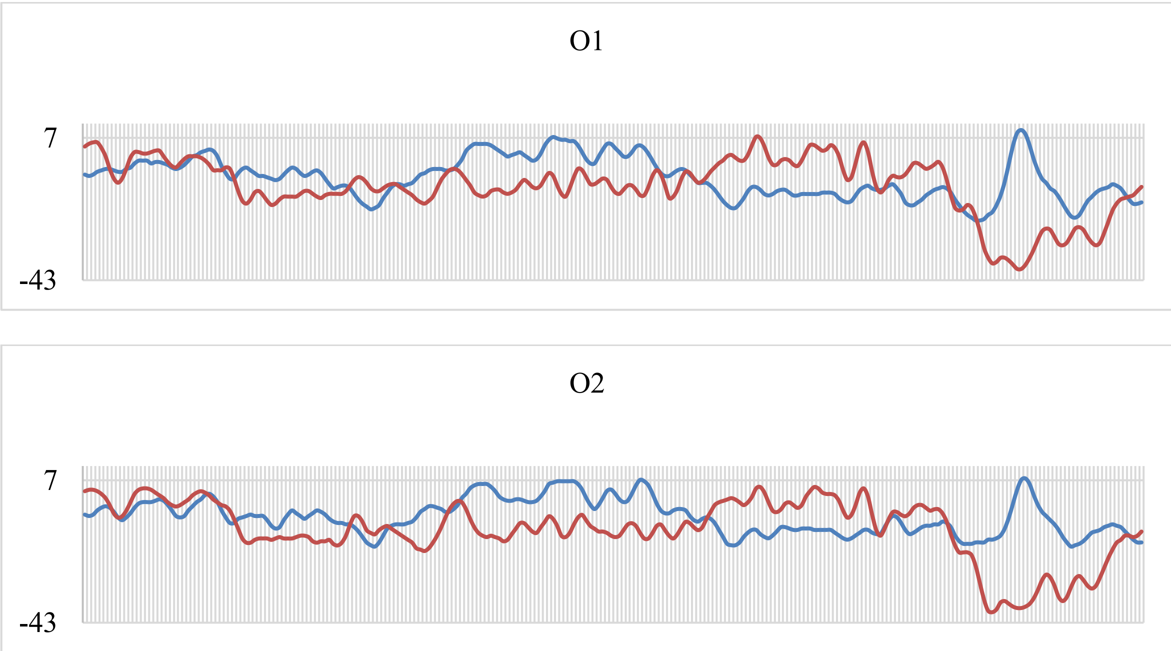
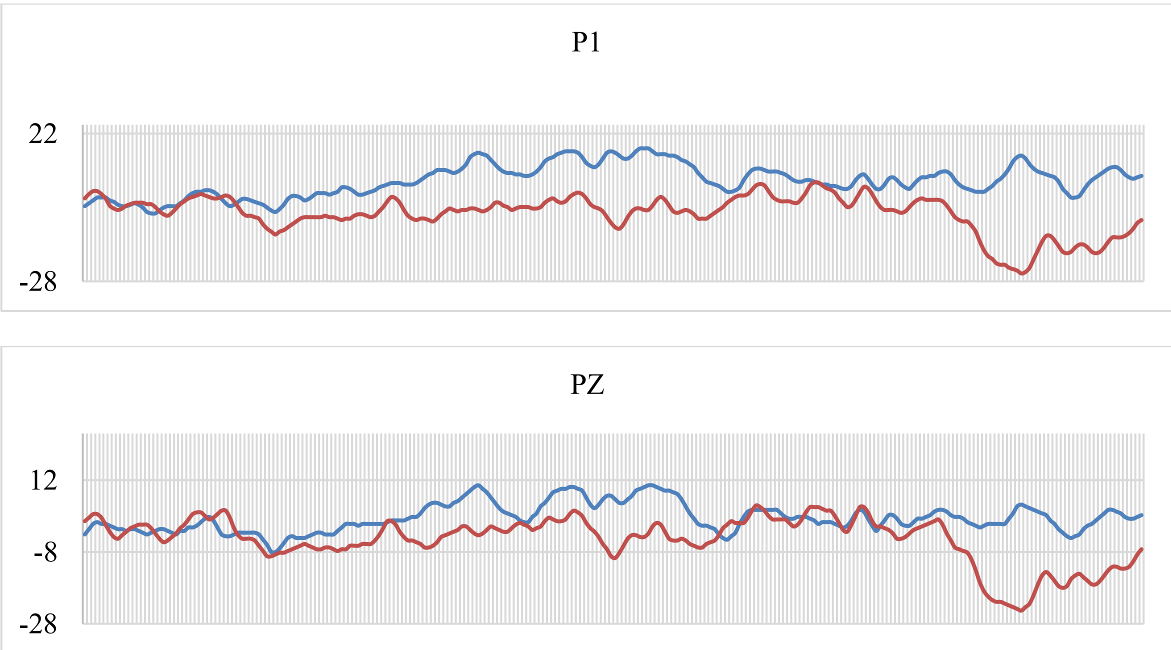


Figure 3.9: Raw EEG collected from BA18



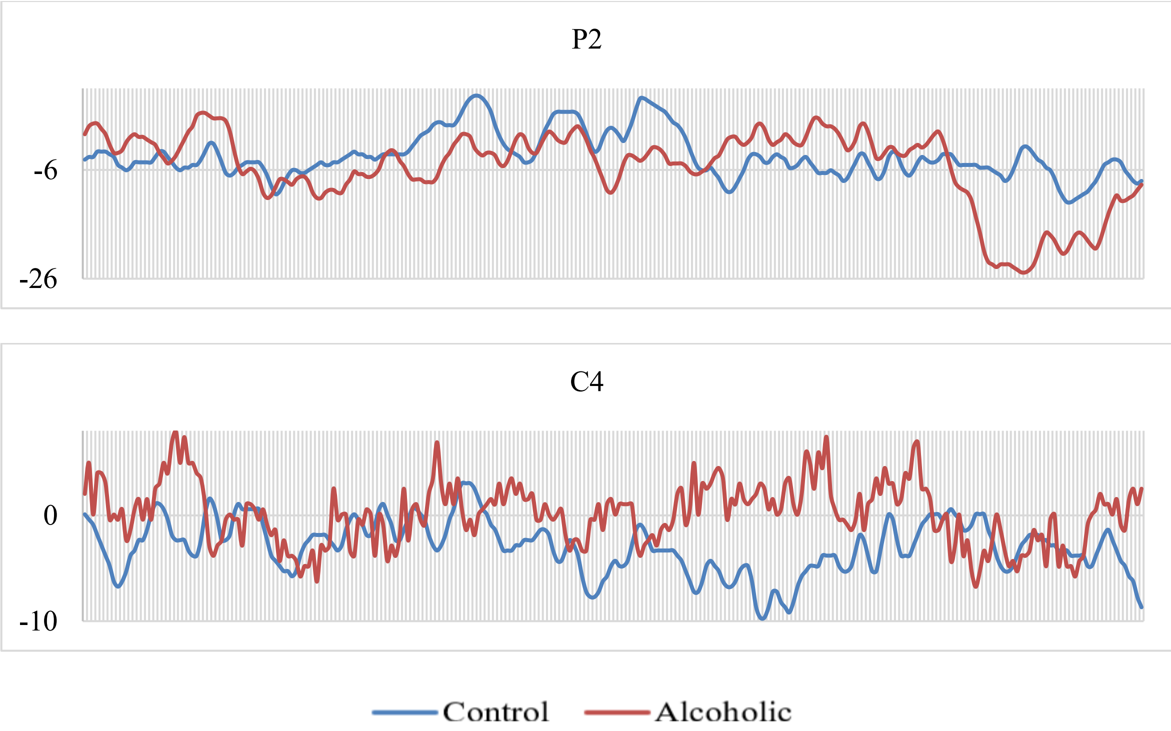


Figure 3.10: Raw EEG collected from BA07, BA01,03

Thus, combining the weighted score and these assumptions, a set of 16 channels is proposed as depicted in table 3.14.

From table 3.14 it is obvious that weighted scoring method includes channels from all lobes of the brain. This is because this method assumed that while a person is performing the specific task assigned to him, some other task or thinking might be ongoing in his/her mind and that may have impact in the EEG signal. Method 4 and 5 have 12 channels in common. The previous method includes 4 channels from BA46 which is replaced in weighted scoring by 3 channels of BA07 and 1 channel of BA01 & 03.

Table 3.14: Selected 16 channels in weighted scoring method

Electrode	Site	Lobe	Anatomical Gyrus (Functional Names)	Weighted sum	Original Rank
FZ	BA08	Frontal	Intermediate frontal	2387	1
FCZ	BA06	Central	Agranular Frontal (Premotor cortex and supplementary motor cortex)	2361	2
FP1, FPZ, FP2	BA10	Frontal	Frontopolar (Dorsolateral prefrontal cortex, DLFC)	1977	3
AFZ, AF2	BA09	Frontal	Granular frontal (DLFC)	1879	4
P7	BA37	Temporal	Occipitotemporal	1772	5
POZ, OZ	BA17	Occipital	Striate (Primary visual cortex, V1)	1609	6
PO7, PO8	BA19	Occipital	Peristriate (Tertiary or Associative visual cortex, V3)	1516	8
P1, PZ, P2	BA07	Parietal	Superior parietal (Somatosensory Association Cortex)	1290	9
C4	BA01,03	Central	Intermediate, caudal, and rostral postcentral (Primary Somatosensory Cortex)	1164	10

3.3 Conclusion

This Chapter includes five proposed approaches to reduce the channel required to collect EEG signal of a group of alcoholic and non-alcoholic persons who perform some mental and cognitive tasks. The methods are basically a sequential procedure to closely investigate the functional activities of different areas of the brain and their relation or relevance with the tasks under consideration in order to extract the most relevant channel sets to analyze the visual information carried out by the them. The underlying assumption is that the channels reduced from a large set based on neurophysiologic knowledge and bearing strong discriminating pattern between the two classes will be able to classify the groups with high classification accuracy. Neurophysiological knowledge is essential for initial screening out of the most relevant channel sets and leads to the ease of analyzing the signals. First of all, the activities captured by the channels on different lobes of the brain are investigated. Then, correlation of functional areas of cerebral cortex with Brodmann's areas are utilized to narrow down the options. The third approach is based on hemispheric lateralization which deals with the relevant activities from the dominant and non-dominant parts of the brain and selects all the channels of a particular area supposed to be engaged in certain tasks. The problems of this third approach is overcome in the next approach where more specific Brodmann's areas are selected irrespective of left- or right-hand domination unless they are otherwise significant. In this fourth approach, the amplitude and pattern of the waveforms of the raw EEG signals captured by the channels are observed to further reduce the channels not showing significant discriminating behavior. However, since many researchers claim that a specific region of the brain performing a certain task has little significance; rather other nearby regions may have some influences on them and a person may be multi-tasking and some other mental processes may be ongoing in the background simultaneously, the 5th method is an attempt to address all these claims. A total of 287 tasks of the brain are identified and weighted under seven discrete levels according to the degree of relevance of the activities to the tasks under consideration. To take into account of the interference of the activities performed by the nearby regions of a specific zone, the channels adjacent to a certain channel are also scored. In this way, all the channels are ranked in a weighted scoring method and the most relevant channels within the first 10 levels are chosen as the reduced channel sets. The relevance is decided in line with the convergence of activities with the tasks of the current study and differentiating criteria of the amplitude levels of the signals.

Chapter 4

Proposed Autoregressive Reflection Coefficient Feature Based Classification Scheme

4.1 Introduction

Designing a feature set which is capable of extracting distinguishable information to detect alcoholics or genetic predisposition of people to alcoholism from a mixture of normal and alcohol affected EEG signal is not an easy task. Recently, a variety of methods have been widely used to extract the features from EEG signals, among these methods are time frequency distributions (TFD), fast Fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT), auto regressive method (ARM), and so on. However, none of the methods in practice could achieve 100% accuracy in detecting alcoholic from nonalcoholic group of people. Moreover, all the proposed methods depend on a large volume of feature set that increases the complexity of data collection, feature extraction, and classification.

In this chapter, we introduce a time domain feature extracted from a simple signal processing technique applied after a minor preprocessing is done on the EEG data of the two groups of people – alcoholic and control. The feature vector set is then used to train the classifier. Different classifiers and validation techniques are used to find out the accuracy of classification of the proposed method.

4.2 Proposed Method

The proposed EEG based alcoholic and non-alcoholic person detection and classification method consists of some major steps, namely, pre-processing, time domain analysis, feature extraction and classification. The raw EEG data is high pass filtered and modeled through Autoregression. After that, reflection coefficient of the AR model is used as feature to classify the two groups of people. K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) classifiers are used for classification tasks. Leave one out cross (LOO) and 10-fold cross validation techniques are used to find out the classification accuracy.

AR model order is varied to observe the effect of that on classification accuracy. In addition, the effect of the five reduction schemes is observed on classification accuracy.

4.2.1 Preprocessing

The dominant frequency bands in EEG signals correspond to δ (0-3 Hz), θ (4-7 Hz), α (8-13 Hz), β (14-30 Hz) and γ (>30Hz) components or waves [41]. δ waves occur in very deep sleep, in infancy, and in serious organic brain disease. θ waves occur during emotional stress in some adults, particularly, during disappointment and frustration. α waves are found in the EEGs of almost all normal adult people when they are awake in a quiet, resting state of cerebration, whereas, during deep sleep, α waves disappear. When the awake person's attention is directed to some specific type of mental activity, α waves are replaced by asynchronous, higher frequency but lower voltage β waves. γ band oscillations are evoked especially during visual perception when a stimulus is recognized and these oscillations contribute to feature binding process, which is necessary during stimulus perception [58]. Study in [58] speculated that the function of γ band oscillation is to provide a reference clock to control the firing of the excitatory neurons during different mental activity.

In general, filtering is performed as a pre-processing step to extract a band from the raw EEG data [59], which is useful for a particular application. Since this work attempts to classify alcoholic and non-alcoholic persons based on EEG signal in response to visual stimuli, signals in the γ band region are found more useful in comparison to that in the lower frequency bands. To extract the γ band oscillations from the raw data, filtering is required. Since, according to [58], γ band may range from 20-70 Hz, in this work, frequency response in the region beyond 20 Hz is taken into consideration while performing filtering operation. For such a filtering operation, a digital Butterworth band-pass filter is used in [32], and a digital Elliptic high-pass filter is employed in [31]. Although an obvious idea can be obtained about the lower cut-off region for the γ band oscillations, it is difficult to predict about the upper cut-off because there is a general correlation between the degrees of cerebral activity and the average frequency of the EEG rhythm, the average frequency increasing progressively with higher degrees of activity

[60]. That is why a high pass filter is preferred in the present work. In order to design a suitable HPF, instead of FIR, IIR filter is used which offers an advantage of reduced filter order and higher controllability. However, unlike the method proposed in [31], in this paper a Butterworth filter is used—which offers lower ripples in the pass band. In order to remove the complexity associated with higher orders, the high-pass filter of order 5 is chosen with a 3-dB cut off frequency at 20 Hz. Forward and reverse filtering are used for removing the non-linear phase effect of Butterworth filter. After filtering in the forward direction, the filtered sequence is then reversed and run back through the filter thus resulting precisely zero phase distortion and modifying the magnitude by the square of the filter's magnitude response. Measures are taken to minimize start up and ending transients by matching initial conditions.

4.2.2 Time domain analysis

Electroencephalogram (EEG) is a natural signal that provides information about the activity of the brain. Technically, a feature represents a distinguishing property, a recognizable measurement, and a functional component obtained from a section of a pattern. Extracted features are meant to minimize the loss of important information embedded in the signal. In addition, they also simplify the amount of resources needed to describe a huge set of data accurately. This is necessary to minimize the complexity of implementation, to reduce the cost of information processing, and to cancel the potential need to compress the information [1]. EEG signals are information bearing signals that evolve as a function of a single independent variable, time [61]. Thus, modeling in time domain to extract useful feature from EEG is the simplest, easiest, and most convenient method.

In this work, an attempt has been taken to extract effective and efficient features from time domain model of EEG and evaluate the performance of the features in representing the characteristic difference between EEG of two different classes of people – alcoholic and nonalcoholic, while they are performing a mental and cognitive task. The effectiveness and efficiency of the feature extraction scheme lie on how accurately the two groups can be separated from each other using simple feature with a very small feature vector size. The search for appropriate feature is carried on until 100% precision is achieved.

4.2.3 Feature extraction

In order to classify alcoholic and non-alcoholic (control) persons, we propose a pattern recognition approach based on a set of features, namely reflection coefficients extracted from EEG signal in response to visual stimuli or visual evoked potential (VEP). Unlike conventional approaches, we focus to analyze the total power distribution of a pre-processed EEG data over frequency based on spectral estimation. The concept of reflection coefficients comes from the spectral estimation of EEG data.

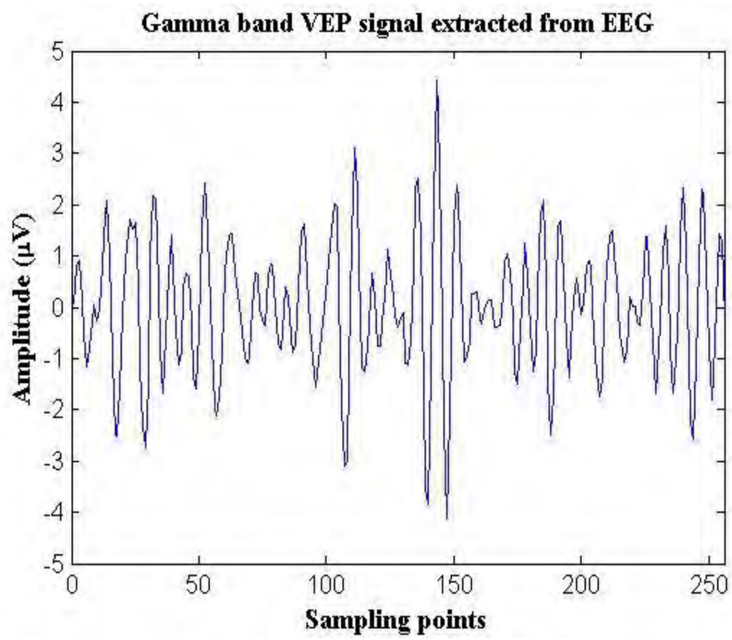


Figure 4.1: Extracted γ (gamma) band VEP from EEG

According to [31], γ band VEP exhibits pseudo-periodic behavior as seen in Fig. 4.1. It is reported in [62] that, autoregressive (AR) model is able to provide high resolution spectral estimates from short EEG intervals, even in cases where intervals contain less than a full period of a cyclic waveform. Moreover, EEG fragments of 1s duration can be deemed as locally stationary [11]. Therefore, an AR model can be used to model the EEG dataset of either an alcoholic or a non- alcoholic person under any stimulus condition.

Thus, a given frame of EEG data can be effectively modeled as the output of an AR system excited by white Gaussian noise [63]. A real valued, zero mean, stationary, non-deterministic, AR model of order p is given by,

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \tag{4.1}$$

where, p is the model order, x(n) is the data of the signal at sampled point n, $\{a_k\}$ are the real valued AR coefficients, commonly known as the linear prediction coefficient (LPC) and $e(n)$ is assumed to be white Gaussian noise excitation with zero mean and variance σ_e^2. LPC or AR parameters are most commonly employed as a feature in speech recognition. The AR parameters $\{a_k\}$ can be estimated using the Yule-Walker equations as-

$$r_x(m) = -\sum_{k=1}^{p} a_k r_x(m-k) + \sigma_e^2 \delta(m), m \geq 0 \tag{4.2}$$
$$= r_x(-m), m < 0$$

where $r_x(m)$, the ACF of x(n), can be estimated as

$$r_x(m) = \frac{1}{N} \sum_{n=0}^{N-1-m} x(n)x(n+m), m \geq 0 \tag{4.3}$$

and $\delta(m)$ is the Kronecker delta function. To determine the AR parameters using (4.2), one can consider m = 0, 1, 2, .… , P. Because the last part of the equation (4.2) is non-zero only if m=0, the equation is usually solved by representing it as a matrix for, m > 0, thus getting equation,

$$\begin{bmatrix} r_x(1) \\ r_x(2) \\ \vdots \\ r_x(p) \end{bmatrix} = -\begin{bmatrix} r_x(0) & r_x(-1) & \cdots & r_x(1-p) \\ r_x(1) & r_x(0) & \cdots & r_x(2-p) \\ \vdots & \vdots & \vdots & \vdots \\ r_x(p-1) & r_x(p-2) & \cdots & r_x(0) \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} \tag{4.4}$$

Equation 4.4 can be written as $\boldsymbol{r} = -\boldsymbol{R}A$, where **R** is a p ×p matrix of elements $r(m,k) = r(|m,k|), (1 \leq m, k \leq p)$, **r** is a column vector $[r_x(1), r_x(2), r_x(p)]^T$, and A is a column vector of AR coefficients $[a_1, a_2, a_{p]})^T$. **R** is also called Toeplitz matrix where all elements along a given diagonal are equal. Solving for all the AR coefficients $\{a_k\}$requires inversion of the matrix **R** and multiplication of the resultant p × p matrix with the **r** vector. For all m=0,

$$r_x(0) = \sum_{k=1}^{p} a_k r_x(-k) + \sigma_e^2 \tag{4.5}$$

from which σ_e^2 can be solved. The error e_n can be written as

$$e_n = x(k) + \sum_{k=1}^{p} a_k(n)x(n-k) \tag{4.6}$$

Let, E be the error energy

$$E = \sum_{n=-\infty}^{\infty} e_n^2 = \sum_{n=-\infty}^{\infty} \left[x(k) + \sum_{k=1}^{p} a_k x(n-k) \right]^2 \tag{4.7}$$

From 4.2 and 4.3, minimum prediction error E_p for a p-pole model is

$$E_p = r_x(0) + \sum_{k=1}^{p} a_k \, r_x(k) \tag{4.8}$$

where $r_x(0)$ is the energy of the signal x(n).

AR parameters have already been used as features for EEG signal classification. For example, in [63], sixth-order AR parameters are used for EEG-based mental task classification. One major problem in using AR parameters as features is the wide range of variation in parameter values, which does not have any boundary. As an alternate to the AR parameters, in this work, reflection coefficients are proposed as representative features.

The m-th reflection coefficient computes the correlation between $x(n)$ and $x(n-m)$ after filtering the intermediate observations from x(n−1) to x(n−m+1). It can be obtained directly from ACF values of given signal $x(n)$ by utilizing the Levinson–Durbin recursion formulas [33], [34] in which the following set of ordered equations are solved recursively for i=1,2, …, p,

$$k_i = \frac{r_x(i) + \sum_{j=1}^{i-1} a_{i-1}(j) r_x(i-j)}{E_{i-1}}, \tag{4.9}$$

$$a_i(i) = k_i,$$

$$a_i(j) = a_{i-1}(j) + k_i a_{i-1}(i-j), \qquad \text{For } 1 \le j \le (i-1)$$

$$E_i = (1 - k_i^2) E_{i-1}, \qquad m \ge 1$$

where initially, $E_0 = r_x(0), a_0 = 0$.

In summary, use of reflection coefficients as features provides following advantages in comparison with the AR parameters:

1. As described above, the reflection coefficients can be directly obtained from autocorrelation values of given EEG data by utilizing simple recursive formula. Complicated AR parameter estimation method involving matrix inversion is not necessary for obtaining reflection coefficients.
2. One problem in AR parameter values is that there is no certain limit for the value of an AR parameter. A feature value without a specific bound may create problem in feature -based classification problem. On the other hand, the value of a reflection coefficient (k_m) is bounded for stable AR systems, which is $|k_m| < 1$. Given EEG data is modeled as the output of stable AR system.

3. It is found that the effect of different types of external noises, such as power line noise, load noise and muscle noise can cause less variation in reflection parameters in comparison with AR parameters. This may occur due to the process of computing reflection coefficients which involves a very few arithmetic operations using few ACF values in comparison with the case of AR parameter estimation. For example, to obtain first two reflection coefficients, only following operations are required.

$$k_1 = \frac{r_x(1)}{r_x(0)}, \tag{4.10}$$

$$k_2 = \frac{r_x(2) - k_1 r_x(1)}{(1 - k_1^2) r_x(0)} = \frac{1}{1 - k_1^2} \left(\frac{r_x(2)}{r_x(0)} - k_1^2 \right) \tag{4.11}$$

4. Reflection coefficients offer localization of spectral errors for small deviation in coefficient values.
5. The reflection coefficients are computed recursively by using autocorrelation values. Unlike AR parameters, increase in number of reflection coefficients from P to $P + 1$ will only produce one new coefficient instead of completely new $P + 1$ number of coefficients.

Thus, reflection coefficients acquired from the temporal domain autocorrelation function of the EEG signal have the potential to form a distinctive feature vector for cognitive task- based classification. In other words, these reflection coefficients extracted from the EEG signal have the potential in forming an effective feature vector for classification of alcoholics and non-alcoholics.

To extract the appropriate feature based on which classification can be done, an autoregressive (AR) model is fitted to both of the datasets each consisting of 10 alcoholic and 10 control persons for each of the three stimulus conditions: single, S2 match and S2 non match.

One major concern is the number of reflection coefficients to be computed for feature extraction. In fact, it is a common problem in the AR modeling of EEG signal to find the model order that is appropriate for the given data. Considering different model order will provide AR parameters those are completely different. However, with the increase in model order by one for a given signal, only the value of the last (highest order) reflection coefficient will be changed. Considering the size of the feature vector, only first few reflection coefficients can be chosen.

A second order AR model was proposed as the optimal order to represent the pseudo-periodic behavior of gamma band VEP in [31]. In [36], sufficient AR model order was evaluated to be 3 using the Minimum Description Length (MDL) criterion. However, 5th order AR model was implemented because of the tendency of MDL criterion to produce underestimated results. In this work, a four-step approach has been used to find out the most suitable AR model order. The steps are described below:

At first, the pre-processed gamma band VEP is fit to a 15 order AR model. Then the reflection coefficients returned are used to compute the partial autocorrelation sequence. The partial autocorrelation sequence is plotted along with the large sample 95% confidence intervals with the idea that, if the gamma band VEP generated by each channel are fit to an AR process of order p, the values of the sample partial autocorrelation sequence for lags greater than p follow a N(0,1/N) distribution, where N is the length of the channel data. The number of lags on which, the values of the partial autocorrelation sequence lie outside the 95% confidence bound will determine the correct model order.

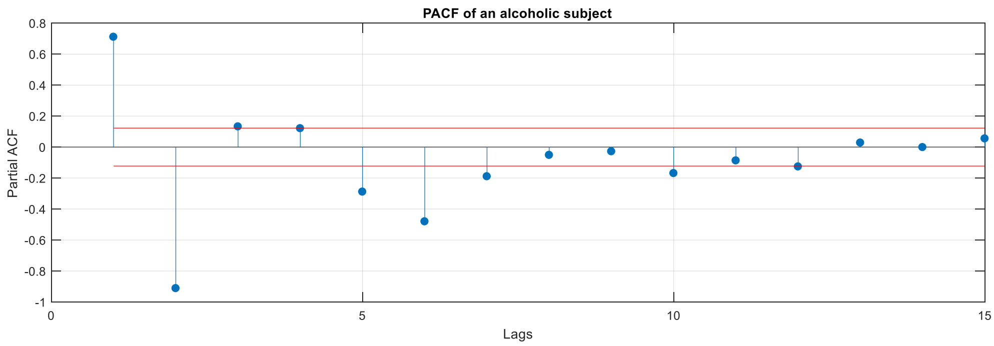


Figure 4.2: PACF of a sample trial of an alcoholic subject

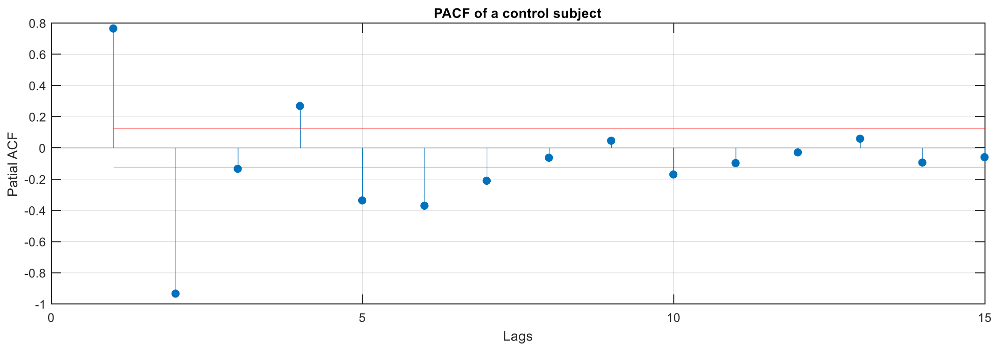


Figure 4.3: PACF of a sample trial of a control subject

For 65% of the cases of the total of 2×10×10×61 samples, the number of lags on which, the values of the partial autocorrelation sequence lie outside the 95% confidence bound are found to be 7.

Next, the model order is varied from 1 to 6, and average estimated variance of white noise input to the AR models of the preprocessed EEG over the 10 trials, are plotted for all the channels of the subjects as shown in Fig. 4.4 and 4.5. It is observed that the error tends to reduce with the increase of model order. The lowest error for all the channels occurs at model order 6.

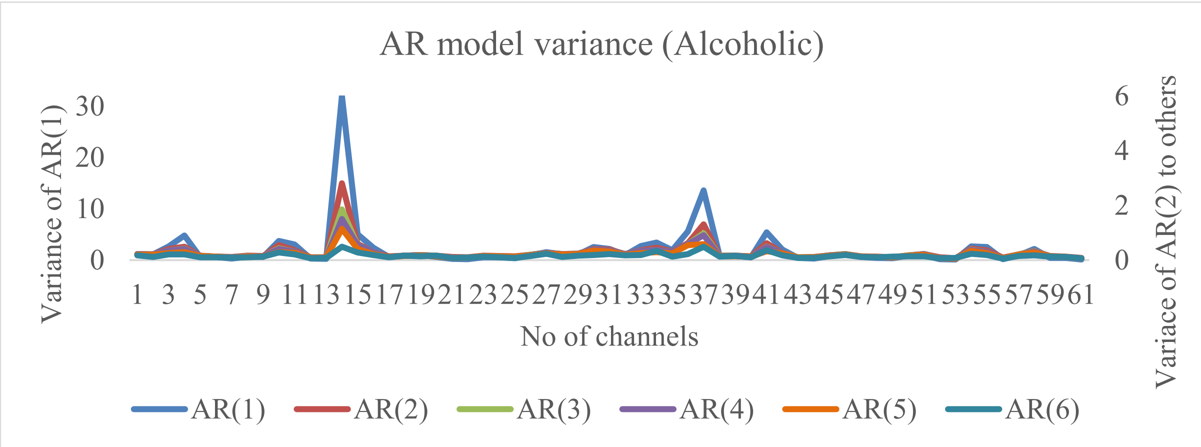


Figure 4.4: Estimated variance for alcoholic subject

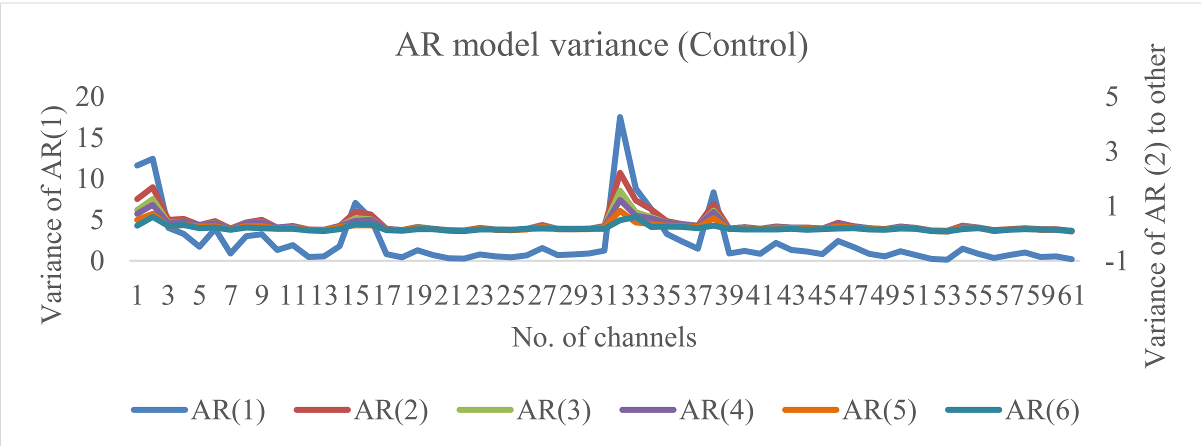


Figure 4.5: Estimated variance for control subject

Table 4.1: Results of regression analysis of a sample trial of a control person

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0040	0.0395	0.1001	0.92034702
X Variable 1	1.9096	0.0511	37.3673	3.5778E-103
X Variable 2	-1.6749	0.1210	-13.8437	1.3808E-32
X Variable 3	-0.0456	0.1618	-0.2818	0.778368524
X Variable 4	0.8432	0.1211	5.9619	3.06278E-11
X Variable 5	-0.5980	0.0511	-11.7095	1.90878E-25

Some sample channel data of alcoholic and control persons are fit to AR(5) process and the p-values of the 5th coefficients are compared with α=0.05. 50 samples of alcoholic and 50 samples of control were checked. For control, 100% of the cases, the 5^{th} coefficient of the independent variable is found to be statistically significant, i.e. we reject the null hypothesis that this coefficient is equal to 0. However, for alcoholic, in 70% of the cases it is found to be statistically significant. Table 4.1 and 4.2 show the result of regression analysis.

Table 4.2: Results of regression analysis of a sample trial of an alcoholic person

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.0014	0.0310	-0.0443	0.964724
X Variable 1	1.7743	0.0524	33.8454	2.41E-94
X Variable 2	-1.3607	0.1107	-12.2895	2.31E-27
X Variable 3	-0.3091	0.1393	-2.2192	0.02739
X Variable 4	0.9012	0.1109	8.1284	2.16E-14
X Variable 5	-0.5730	0.0524	-10.9289	5.59E-23

The final approach is selecting the model order to be used for the whole study based on classification accuracy, which is discussed under section 4.3.1.

Excluding the reference and EOG electrodes, the remaining 61 active electrodes are used for the study. For each trial of one class, 61 reflection coefficients are found. In this way, a matrix of size 10×61 is found for each person of each class from a dataset of 256×61 for AR model order 1. So, for 10 persons of each class, for each stimulus condition, a matrix of size 100×61 is obtained when AR model order is 1. The size of training data set, for AR model order 1, 2, 3, 4, 5 and 6, for 10 alcoholic and 10 control persons, is 200× 61, 200×122, 200×183, 200× 244, 200×305, and 200×366 respectively.

4.2.4 Classification

Classifier section is essential to obtain satisfactory result while performing test validation of the proposed method. In this chapter, we employ two different classifiers to determine the efficacy of the feature vector in classifying alcoholic and control persons.

k-nearest neighbor (KNN) classifier:

The k-nearest neighbor (KNN) is the simplest linear classifier [64]. Here, an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors, where k is typically small positive integer. If k=1, then the object is simply assigned to the class of its nearest neighbor. In a KNN classifier, different types of mathematical distances are used to rate all neighbors. Among them, KNN classifier with Euclidian distance is attractive in the sense of reducing the processing time.

In the Euclidian distance-based classifier, the classification task is carried out based on the Euclidian distances between the feature vectors of the training EEG and the feature vectors of the testing EEG. Given the q-dimensional feature vector for the f -th training EEG belonging to the class ψ be {$\alpha_{\psi f}$ (1), $\alpha_{\psi f}$ (2), … , $\alpha_{\psi f}$ (q)} and a υ-th test EEG with a feature vector {βυ(1), βυ(2),… βυ(q)}, Euclidian distance is measured between the test EEG υ and the training EEG f belonging to class ψ as

$$ED_{\psi f}^{v} = \sqrt{\sum_{i=1}^{q} \left|\alpha_{\psi f}(f) - \beta_{v}(i)\right|^{2}} \tag{4.12}$$

Considering total Γ training EEG data belonging to class ψ minimum Euclidian distance is obtained from

$$ED_{\psi}^{v} = min_{f=1}^{\Gamma} ED_{\psi f}^{v} \tag{4.13}$$

Therefore, test EEG beat will be classified as ψ class among Ψ number of classes if it satisfies the condition

$$ED_{\psi}^{v} < ED_{a}^{v}, \qquad \forall\psi \neq a, \forall a \in 1,2, \dots, \Psi \tag{4.14}$$

In this work, we are interested to handle a two-class problem (Ψ=2).

Support vector machine (SVM) classifier:

In the proposed method, kernel based SVM classifier is chosen to effectively classify cognitive task-based EEG of alcoholic and control persons. SVM classifier has wide acceptability as a supervised classifier. To generate an N dimensional decision vector **w**= $[w_1\, w_2\, \cdots\, w_N\,]^T$, reflection coefficient feature extracted from the γ-band EEG signal are provided into the classifier instead of raw EEG data. The extracted features from the training dataset are converted from the original space to a new representative vector space to discriminate the two classes more efficiently. A class label is provided for each N_i dimensional frame $\boldsymbol{x_i} = x_i(n), n = 1, \cdots, N_i$. For two class problem with two class label +1 and -1, each frame $\boldsymbol{x_i}$ fulfill the following inequalities:

$$\begin{aligned} \boldsymbol{w^T x_i} + b &\geq +1, for\ all\ positive\ x_i \\ \boldsymbol{w^T x_i} + b &\leq -1, for\ all\ negative\ x_i \end{aligned} \tag{4.15}$$

In kernel based SVM classifier, to match with class label of the training data set, the following discriminant function $f(x)$ is utilized to form the decision vector, which can be expressed as,

$$f(x) = \sum_{i=1}^{P} c_i k(x_{i,}x) + b \tag{4.16}$$

Here, c_i is an empirical vector and kernel matrix K is given by

$$\boldsymbol{K} = \begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) & \cdots & k(x_1, x_P) \\ k(x_2, x_1) & k(x_2, x_2) & \cdots & k(x_2, x_P) \\ \vdots & \vdots & \cdots & \vdots \\ r_x(x_P, x_1) & k(x_P, x_2) & \cdots & k(x_P, x_P) \end{bmatrix} \tag{4.17}$$

In calculation of the reported classification accuracies, leave one out (LOO) cross validation scheme is employed in case of KNN classifier to generate classification result. However, 10-fold cross validation scheme is used for both of the classifiers to determine the classification accuracy.

In LOO technique, each frame is tested one by one, i.e. when a frame is left out for testing, remaining frames are used for training. Let us consider total $N_A + N_B$ number of frames where N_A number of frames belong to class A and N_B number of frames belong to class B. In the LOO cross validation scheme, when one of those $N_A + N_B$ frames is left out for testing, remaining $N_A + N_B - 1$ frams are used for training. This process is repeated for $N_A + N_B$ times. Finally, classification accuracy is defined as the percentage of correctly identified class of each frame. Among total $N_A + N_B$ number of frames if N_t number of frames are correctly classified, the classification accuracy can be expressed as

$$Accuracy = \frac{N_t}{(N_A + N_B)} \times 100\% \tag{4.18}$$

In K-fold cross validation technique, data set is divided into *k* subsets. Then, the training and testing are repeated for *k* times. Each time, one of the *k* subsets is used as the test set and the other *k-1* subsets are put together to form a training data set. Then the average error across all *k* trials is computed. The advantage of this method is that it matters less how the data gets divided. Each data point gets to be in the in a test set exactly once, and gets to be in a training data set *k-1*times. The variance of the resulting estimate is reduced as *k* is increased.

4.3 Simulation and Results

In this section, performance of various feature extraction methods is investigated considering classification accuracy obtained under different conditions, such as varying the feature dimension, using different classifiers and reducing number of electrodes to collect EEG data.

A comparative analysis on classification performance between the proposed method and some other methods are presented as well.

In the proposed method, instead of directly using channel data, reflection coefficients of γ-band EEG signal are used to train and test data. The preprocessing, feature extraction, and classification tasks are repeated under three different stimulus condition and classification accuracy is observed under each. Unless otherwise specified, KNN classifier is employed in leave one out cross validation manner to obtain classification accuracy.

4.3.1 Effect of varying model order

The AR model order is varied from one to six to find out the optimum model order such that the reflection coefficient extracted from the model yields in the best classification accuracy. KNN classifier is used to classify the two classes of people in leave one out cross validation technique. Since it is a two-class problem, three nearest neighbors are selected, because two nearest neighbors can result in a tie and number of nearest neighbors cannot be multiple of two.

From the results of classification of the KNN classifier, it is observed that for all three stimuli, classification accuracy increases with model order up to the 5^{th} order as shown in table 4.3 and Fig. 4.5. If model order is increased further, classification accuracy does not improve for match and non-match conditions. As a matter of fact, after model order 3, accuracy remains the same for match and nomatch stimulus condition, However, for single visual cue, it is maximum for model order 4 and 5 and starts decreasing after order 5. In order to design a common order AR model optimum for all cases, model order 5 is chosen to be the optimum one and used in general for this study.

Figure 4.6 depicts the effect of AR model order variation on classification accuracy under all three stimuli condition. Another thing that is quite obvious is that, match stimulus yields in the highest classification accuracy which is 99.5% while, that resulted by no-match stimuli is 99% as opposed to only 97% obtained under single stimuli.

Table 4.3: Effect of model order variation in classification accuracy

	Stimulus Condition	AR Model Order					
		1	2	3	4	5	6
Classification Accuracy (%)	Single	92	95.5	95.5	97	97	95.5
	Match	93	98	98.5	99.5	99.5	99.5
	No-match	89	97	98.5	99	99	99

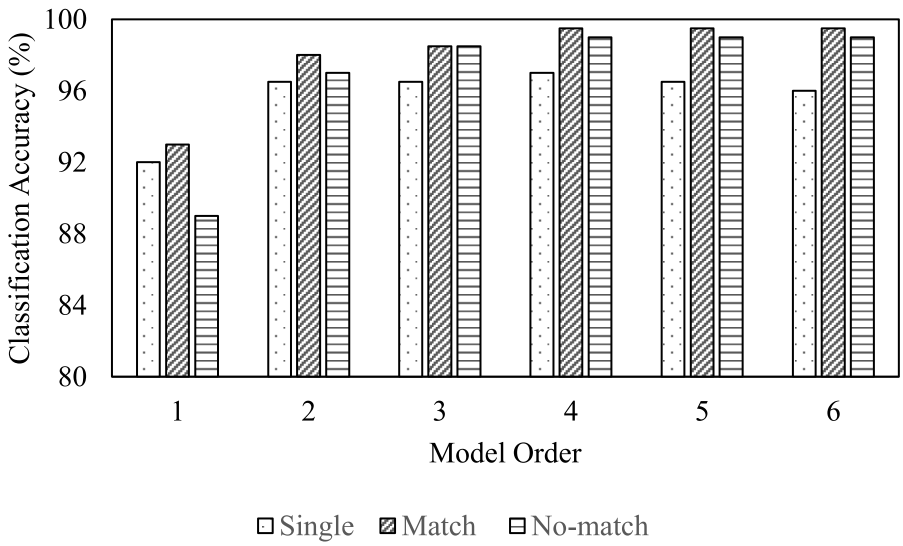


Figure 4.6: Effect of AR model order variation on classification accuracy

4.3.2 Effect of using different classifiers and validation techniques

In the previous section, the effect of AR model order variation was analyzed in search for finding out the optimal order that best classifies the two classes of people and fifth order was selected. Now effect of different classifiers namely KNN and SVM is observed on the classification accuracy where fifth order AR model is used to extract features based on reflection coefficients.

For both of the classifiers, 10-fold cross validation technique is employed to compare the test data with the training data set. The results are summarized in figure 4.7 and table 4.4.

Table 4.4: Effect of classifier and validation techniques on classification accuracy

		Classifier	
	Stimulus Condition	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	97	94.92
	Match	99.5	94.95
	No-match	99	95.97

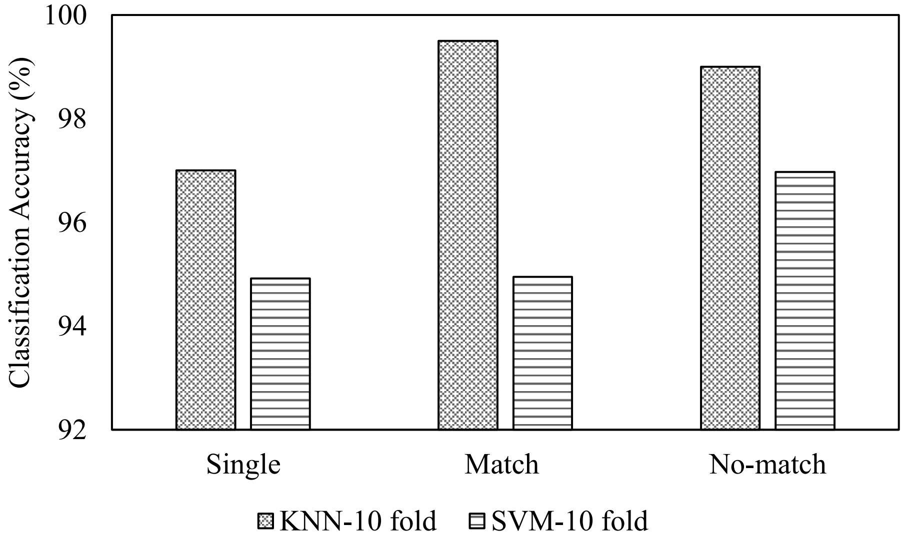


Figure 4.7: Effect of different classifiers on classification accuracy

Figure 4.7 illustrates that classification accuracy significantly reduces in case of SVM classifier. Whereas, accuracy remains the same in case of both of the cross-validation techniques employed in KNN classifier. It is also noteworthy that match and no-match stimuli conditions lead to the higher classification accuracies (99.5% and 99% respectively) compared to only single stimulus (97%) in all of the cases. KNN classifier can best classify VEP (with 99.5% accuracy) under match stimulus paradigm whereas, SVM can do the same for no-match (95.97%). Consequently, it is evident that γ-band VEP, collected while subjects are involved in multiple mental tasks like attention, cognition, memory retention, and decision making, is superior in withholding useful discriminative information of the two groups of people.

4.3.3 Effect of channel reduction

(i) Accuracy in lobe-based scheme

The cerebral cortex is the most complex component of the human brain, as a result of its complex and widespread connections. It functions in the planning and initiation of motor connectivity, perception and conscious awareness of sensory information, learning, cognition, comprehension, memory, conceptual thinking, and awareness of emotion. In this case, only the channels located in a particular lobe are used to collect EEG data and the effect of such reduction on classification accuracy is examined. In this way, five different channel sets are obtained for the five major lobes of the brain. For example, seventeen channels on the frontal lobe, fourteen channels on the central lobe, ten channels on the parietal lobe, eight channels on the occipital lobe, and finally, twelve channels on the temporal lobe. Effects on accuracy of these five electrode sets are investigated to seek whether any particular zone of electrodes can capture significant information to better classify alcoholics from control group or at least perform the classification with the same accuracy as obtained by using all the channels.

Results of classification accuracy using the five channel sets are presented in table 4.5, 4.6, and 4.7 and Fig. 4.8, 4.9 and 4.10 correspondingly for single, match and no-match stimuli conditions. Reflection coefficients from a 5th order AR model are used as feature.

Table 4.5: Effect of lobe-based channel reduction scheme on classification accuracy under single stimulus

Classification Accuracy (%) in Single Stimulus Condition			
Lobe	KNN-LOO	KNN- 10 fold	SVM-10 fold
Frontal	97	93	83
Central	95	93	87.82
Parietal	75	69.5	70.5
Occipital	89.5	86	75.5
Temporal	97	95.5	85.5

Table 4.6: Effect of lobe-based channel reduction scheme on classification accuracy under match stimuli

Classification Accuracy (%) in Match Stimulus Condition			
Lobe	KNN-LOO	KNN- 10 fold	SVM-10 fold
Frontal	98	97.5	83.5
Central	97	97	91.96
Parietal	75.5	76	78.5
Occipital	89.5	87.5	84.92
Temporal	98.5	98	82.5

Table 4.7: Effect of lobe-based channel reduction scheme on classification accuracy under nomatch stimuli

Classification Accuracy (%) in Nomatch Stimulus Condition			
Lobe	KNN-LOO	KNN- 10 fold	SVM-10 fold
Frontal	97	95.5	86
Central	97	97.5	89.9
Parietal	79.5	78.5	70
Occipital	88.5	86	80
Temporal	97	97	92.93

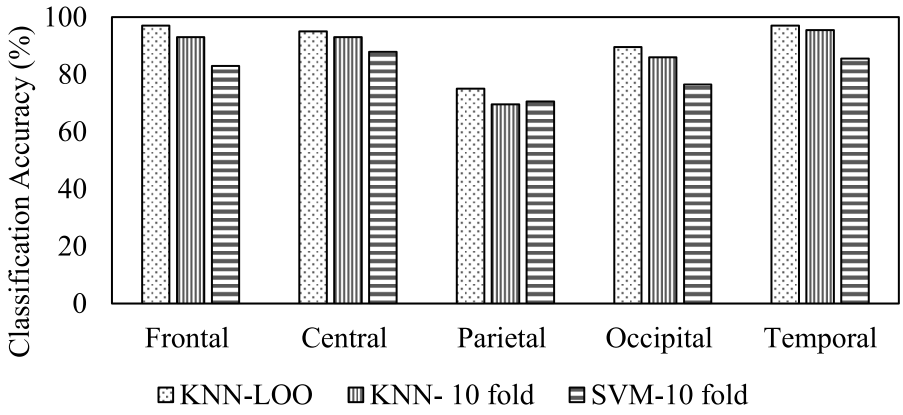


Figure 4.8: Effect of lobe-based channel reduction scheme on classification accuracy under single stimulus condition

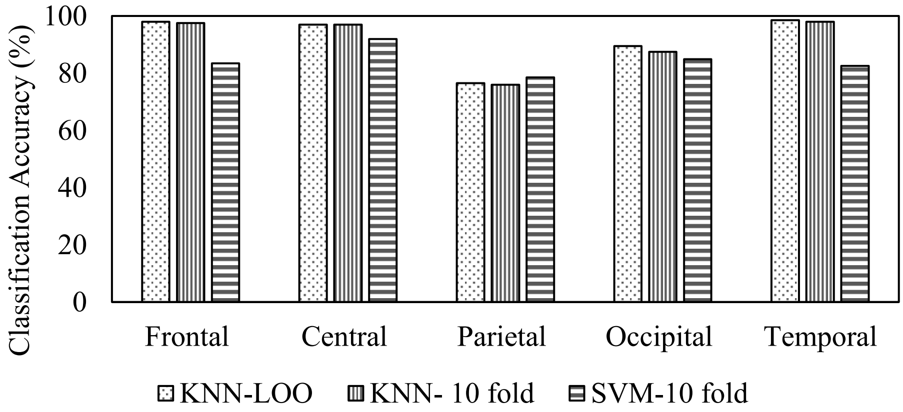


Figure 4.9: Effect of lobe-based channel reduction scheme on classification accuracy under match stimulus condition

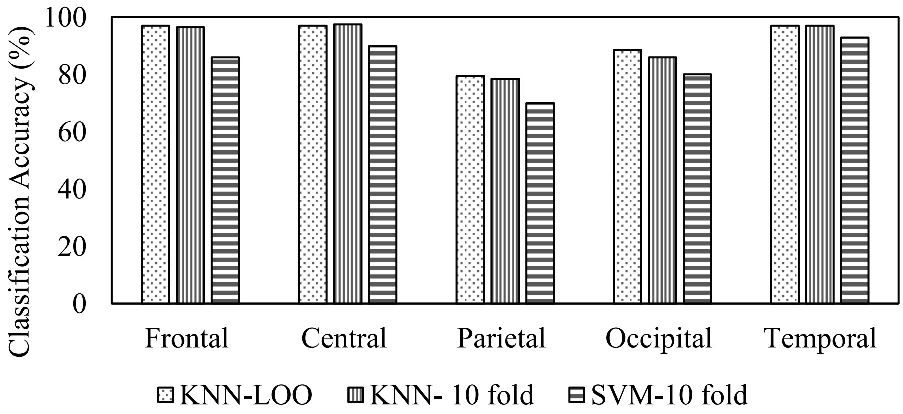


Figure 4.10: Effect of lobe-based channel reduction scheme on classification accuracy under nomatch stimulus condition

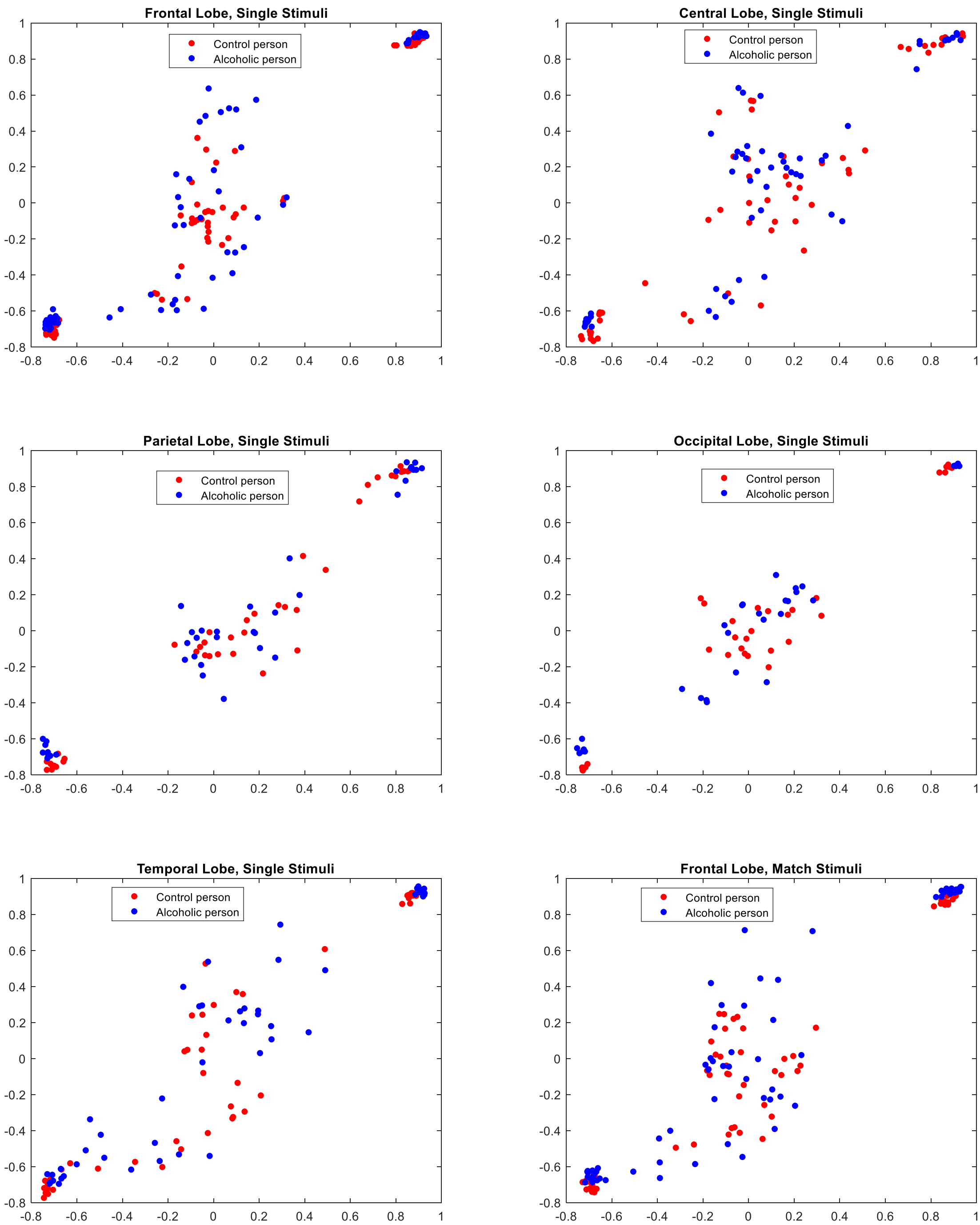
The effect of lobe wise channel reduction on classification based on reflection coefficients of γ -band VEP under single stimulus paradigm is shown in Fig. 4.8 from which it is clear that, frontal 17 channels and temporal 12 channels individually yield the same accuracy level (97%) as found in using all the 61 channels when KNN classifier and LOO validation technique is employed. However, the level reduces for other lobes, SVM classifier and other validation techniques.

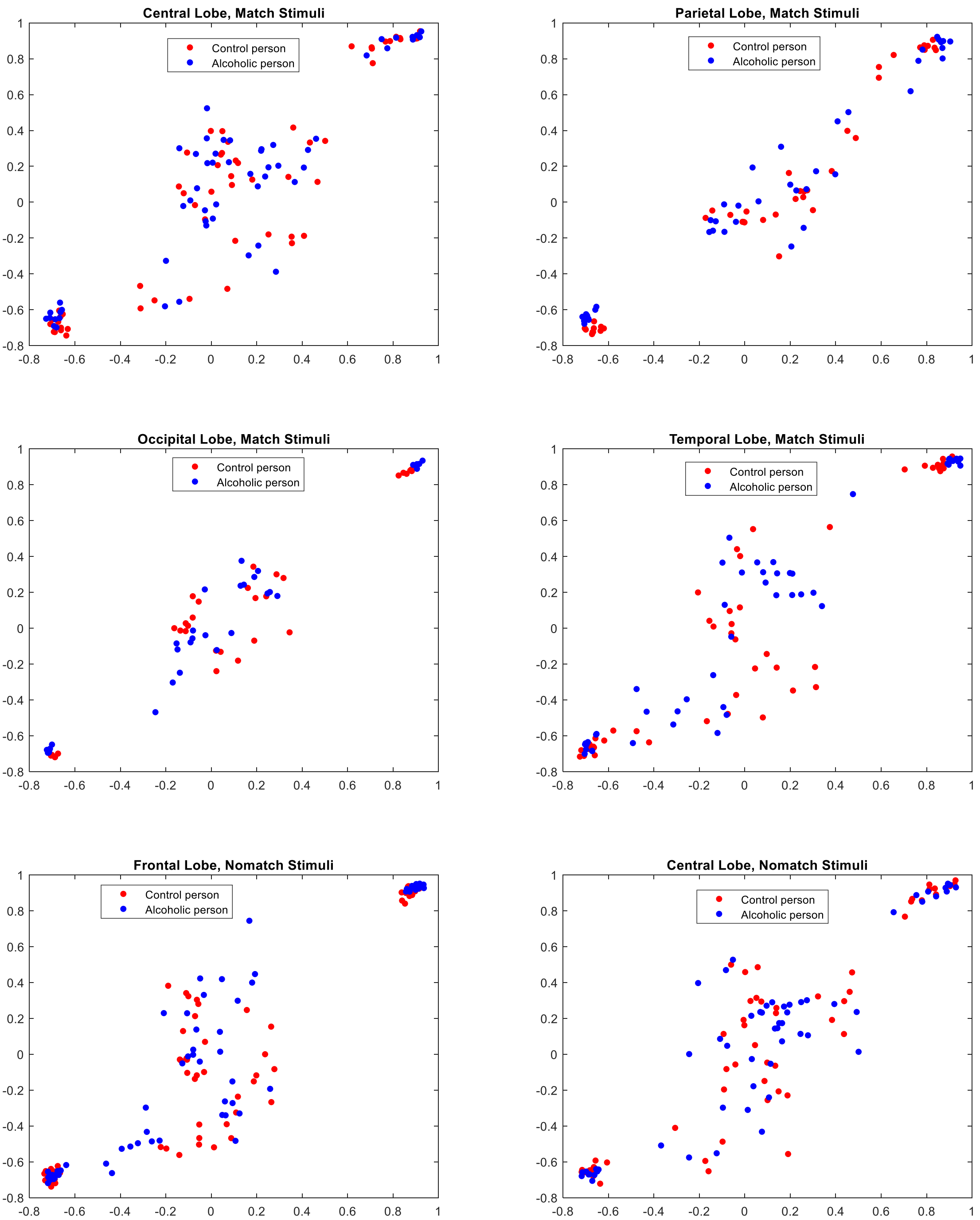
The classification accuracies obtained by lobe wise channel selection criteria for match stimuli as depicted in Fig. 4.9 suggest that, temporal channels can successfully classify the two groups using KNN classifier under both of the cross-validation techniques – 98.5% in LOO strategy while 98% in 10-fold cross validation strategy. The accuracies obtained using these 12 channels are in close proximity to that obtained by using 61 channels. However, the highest accuracy (91.96%) is obtained in SVM classifier for central 14 channels, which is remarkably lower than that obtained by using all 61 channels (94.95%).

According to Fig. 4.10, under nomatch stimulus condition, the highest accuracy is obtained for central channels under both LOO and 10-fold cross validation strategy in KNN classifier (97% & 97.5% respectively). However, for SVM classifier, feature extracted from temporal lobe channels yielded the best results (92.96%).

Thus, KNN classifier proved to be the appropriate one in using all 61 channels as well as in the reduced channel domain irrespective of all types of stimuli. However, this channel reduction technique may be feature dependent. That is, for different feature different region of the brain may show significant difference in characteristic of the same person under the same group and therefore, desired accuracy might not be obtained.

The scatter plots of the features (reflection coefficients of 5th order AR model) of one sample trials of two different alcoholic and two different control persons in cases where channels are placed on only a single lobe, are shown in Fig. 4.11.


Frontal Lobe, Single Stimuli
Central Lobe, Single Stimuli
Parietal Lobe, Single Stimuli
Occipital Lobe, Single Stimuli
Temporal Lobe, Single Stimuli
Frontal Lobe, Match Stimuli
Control person
Alcoholic person



Central Lobe, Match Stimuli
Parietal Lobe, Match Stimuli
Occipital Lobe, Match Stimuli
Temporal Lobe, Match Stimuli
Frontal Lobe, Nomatch Stimuli
Central Lobe, Nomatch Stimuli
Control person
Alcoholic person

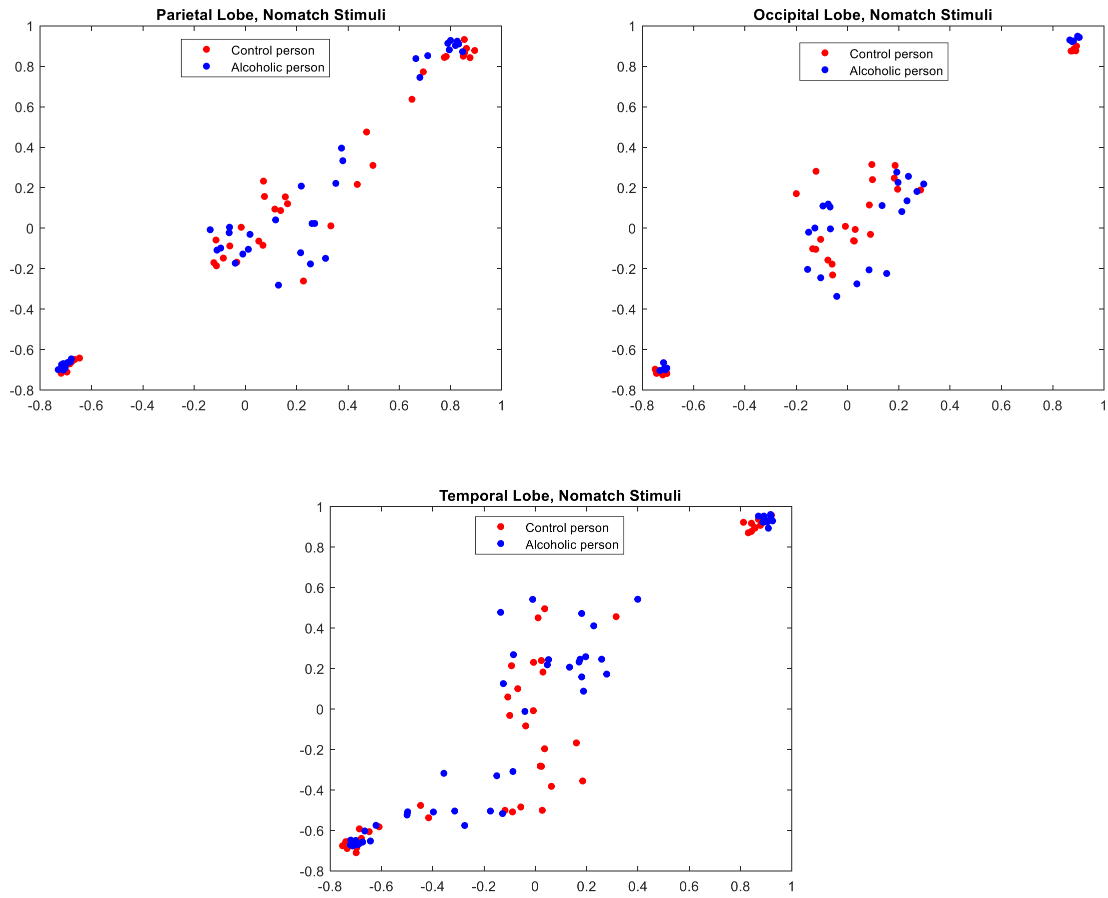


Figure 4.11: Reflection coefficients of two sample trials for control and alcoholic persons of different lobes

(ii) Accuracy in cortical function-based scheme

By utilizing the correlation between the functional areas of cerebral cortex and Brodmann's areas, a total of 36 electrodes were identified. Classification accuracy by using those 36 channels are presented in Fig. 4.12, from which it is evident that using only these 36 channels gives even better result than using all channels for single and match stimuli which are 99% and 100% correspondingly compared to 97% and 99% using all channels in LOO strategy applied to KNN classifier. This is true for 10-fold cross validation strategy in KNN as well (98% and 100%). However, for nomatch stimuli, accuracy slightly decreases from that using all channels (from 99% to 98.5% in LOO and from 99% to 97% in 10-fold cross validation). Accuracy decreases for all stimuli in case of SVM classifier. Thus, it is clearly understood that, match stimuli condition can best classify these two groups of people even in reduced channel domain.

Table 4.8: Classification accuracy using 36 channels selected by cortical functions

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	99	98	90.5
	Match	100	100	92.96
	No-match	98.5	97	87

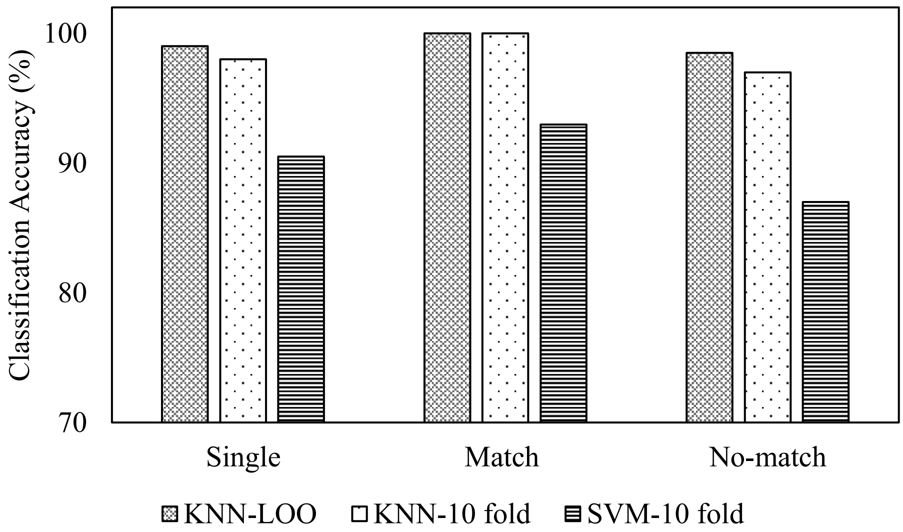


Figure 4.12: Effect of channel reduction based on cortical functions on classification accuracy

Fig. 4.13 delineates the difference between using all 61 channels to extract features and using only selected 36 channels for the same under single, match, and nomatch visual cue. The rest 25 channels are excluded basically for the reason that they are not expected to play significant role in cognitive and mental task induced by visual stimuli. The result of such selection in separating the two groups of people proves highly accurate in single and match visual stimuli. However, the case is opposite under nomatch stimuli.

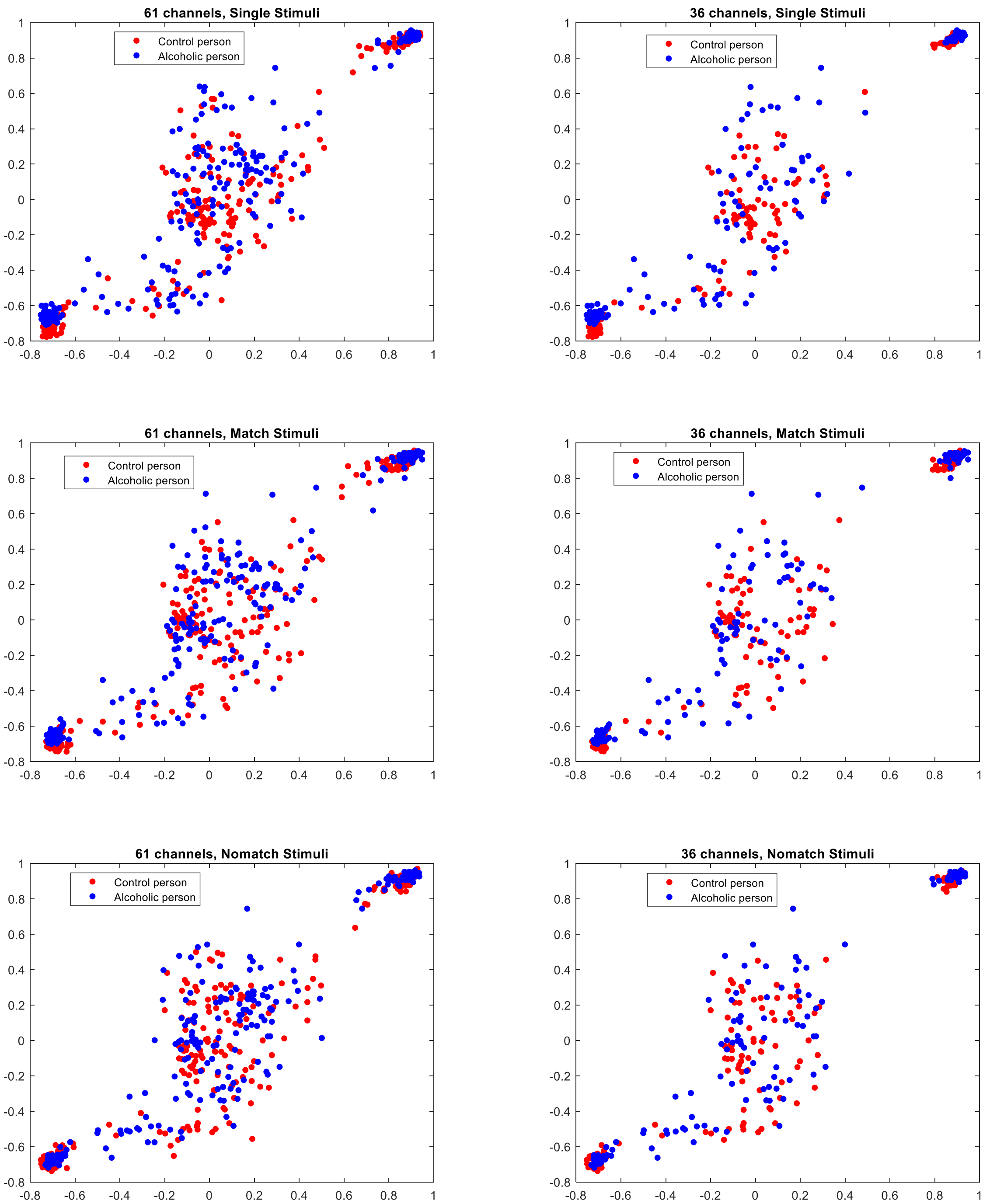


Figure 4.13: Reflection coefficients of single trial of two different control and two different alcoholic persons (Left: Using 61 channels; Right: Using 36 channels)

(iii) Accuracy in hemispheric lateralization-based scheme

According to this method of channel reduction, 29 different channels are selected. Effect of these 29 channels on classification accuracy of alcoholic and control individuals is reflected in table 4.9 and Fig. 4.14. It is conspicuous from the figure that this technique yields better accuracy in both match and nomatch stimuli. However, accuracy slightly deceases for single stimulation from 99% to 98% and 98% to 97.5% in KNN-LOO and KNN-10fold cross validation technique respectively, compared to the previous 36-channel strategy. Accuracies have improved than the 36-channel situation in all cases when SVM classifier is used.

Table 4.9: Classification accuracy using 29 channels selected by hemispheric lateralization

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	98	97.5	92.5
	Match	100	100	95.48
	No-match	100	99.5	92.5

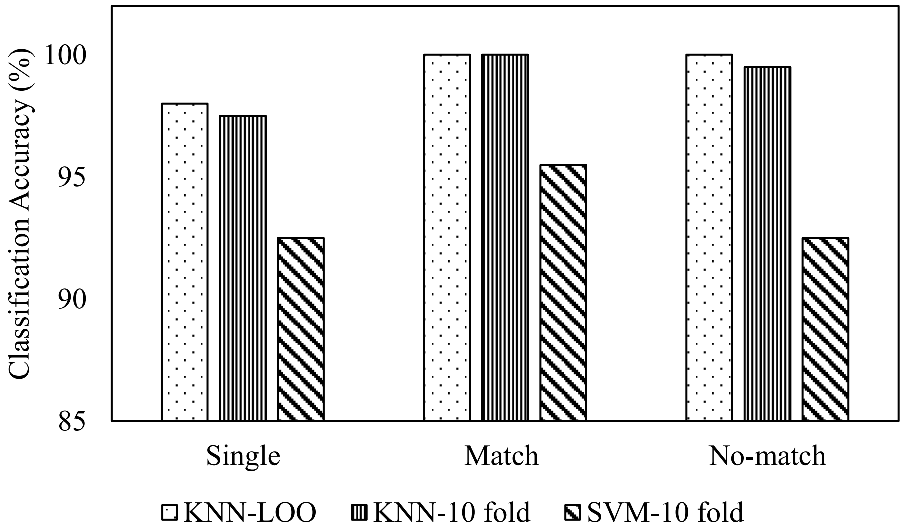


Figure 4.14: Effect of channel reduction based on hemispheric lateralization on classification accuracy

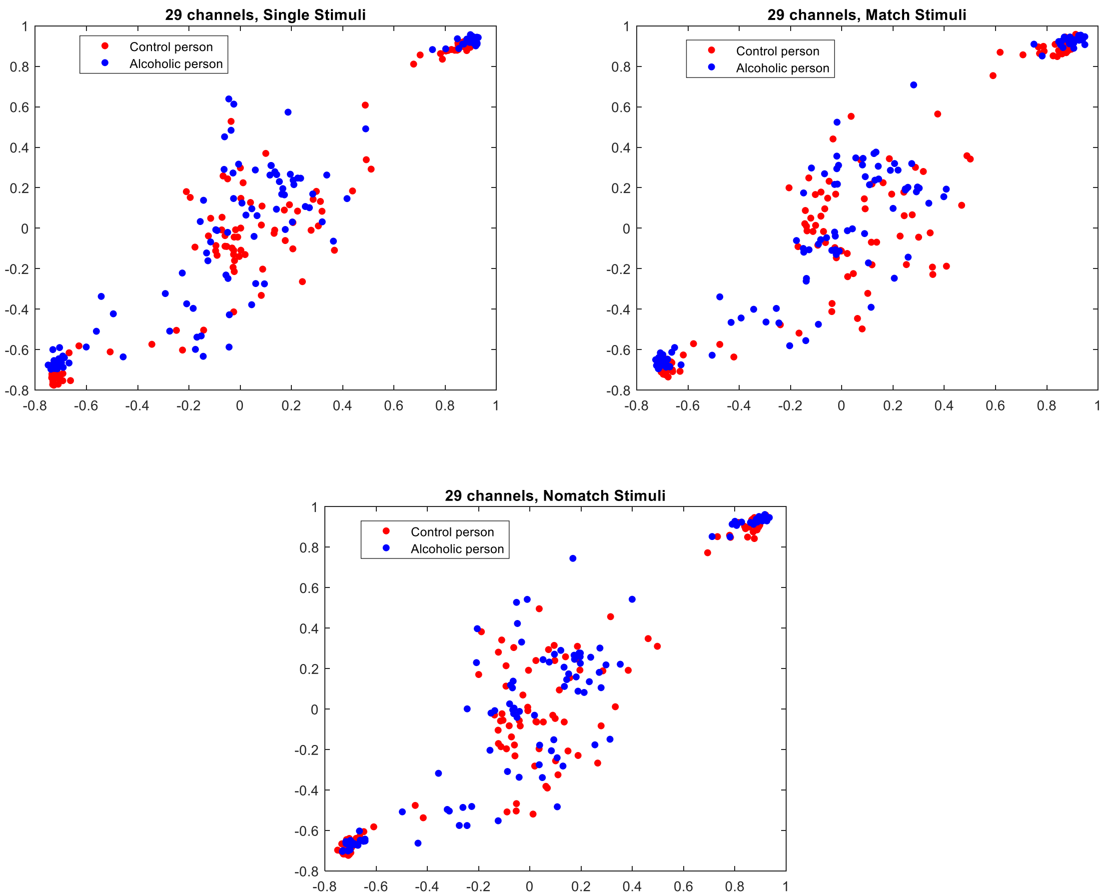


Figure 4.15: Reflection coefficients of single trial of two different control and two different alcoholic persons using 29 channels

(iv) Accuracy in Brodmann's localization theory-based schemes

In this method 16 channels were selected. Now the classification performance of these 16 channels are presented in table 4.10 and Fig. 4.16 in response to 3 visual stimuli.

Table 4.10: Classification accuracy using 16 channels

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	98	97.5	87
	Match	99	97.5	82
	No-match	99	98.5	83.5

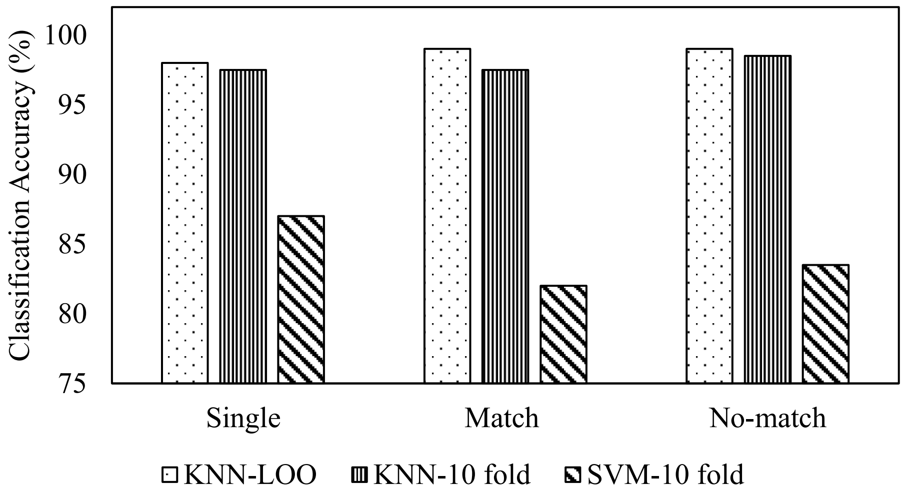
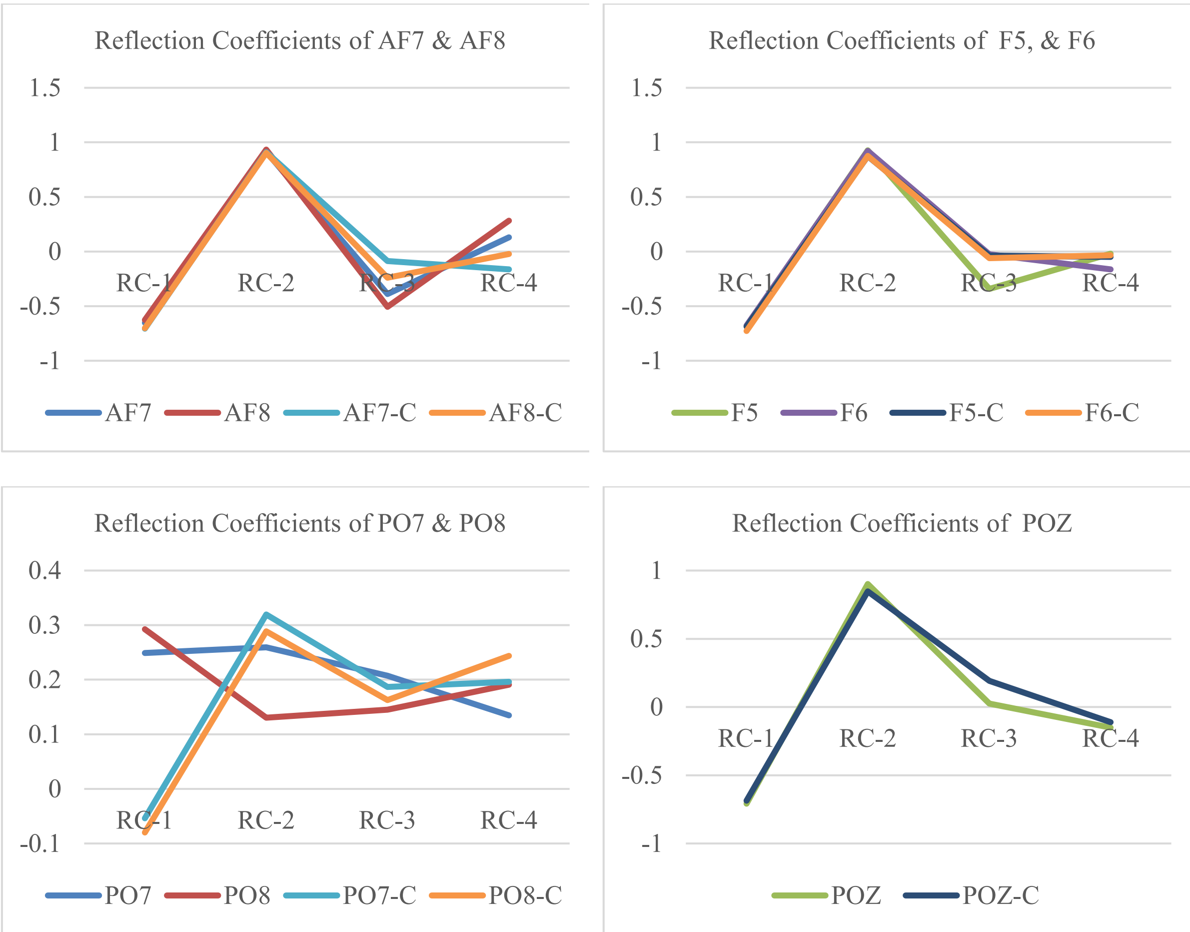
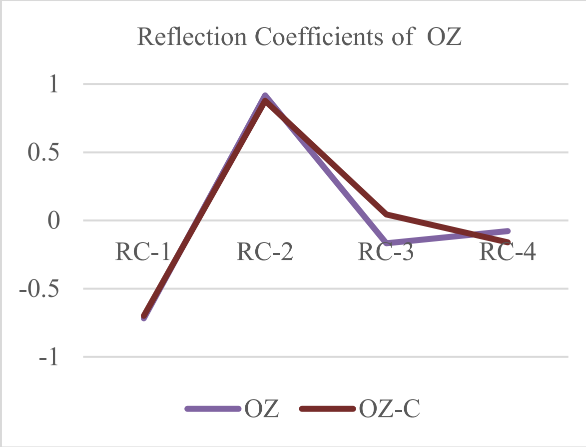
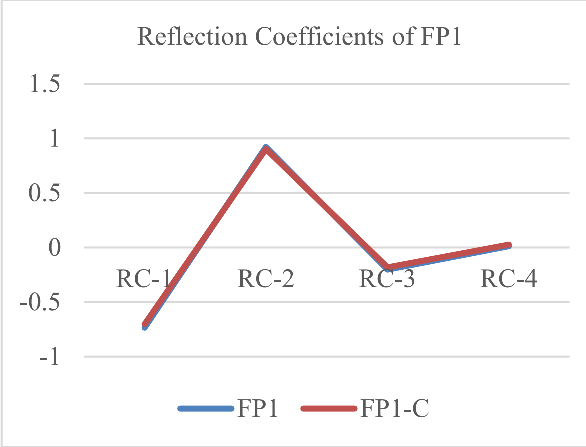
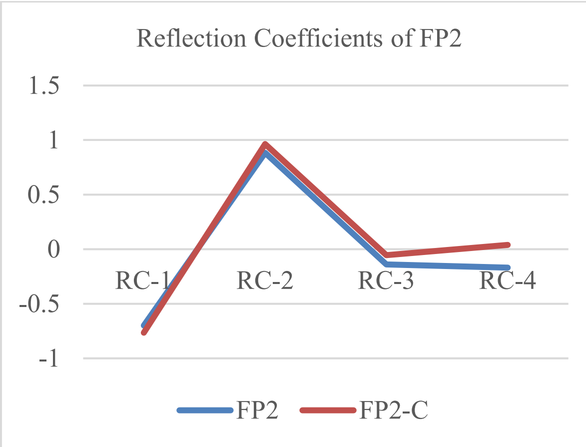


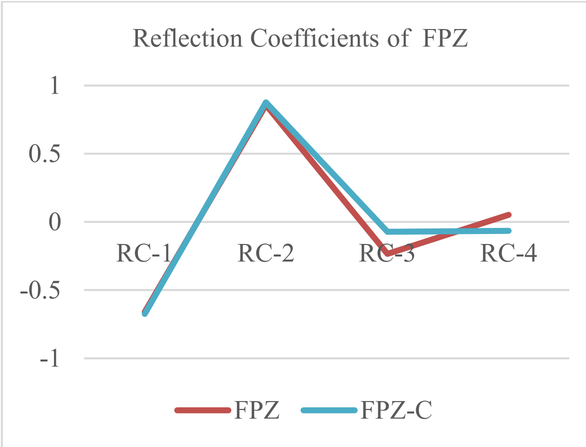
Figure 4.16: Effect of channel reduction based on Brodmann's localization theory




Reflection Coefficients of OZ
1
0.5
0
-0.5
-1
RC-1
RC-2
RC-3
RC-4
OZ
OZ-C


Reflection Coefficients of FP1
1.5
1
0.5
0
-0.5
-1
RC-1
RC-2
RC-3
RC-4
FP1
FP1-C


Reflection Coefficients of FP2
1.5
1
0.5
0
-0.5
-1
RC-1
RC-2
RC-3
RC-4
FP2
FP2-C


Reflection Coefficients of FPZ
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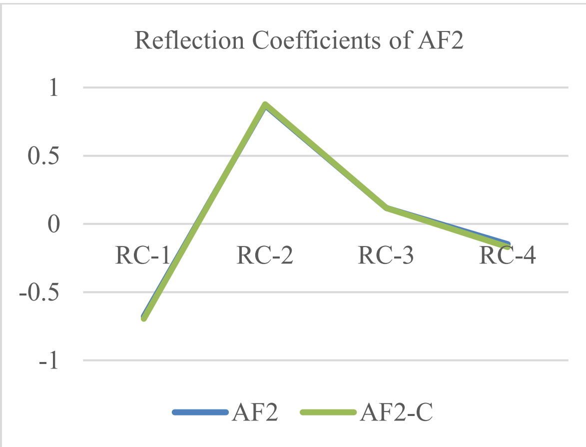
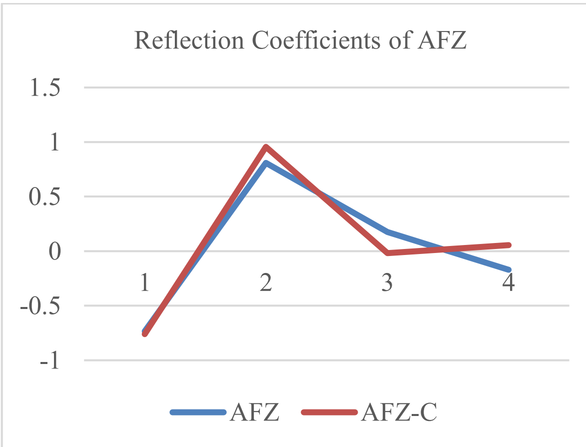
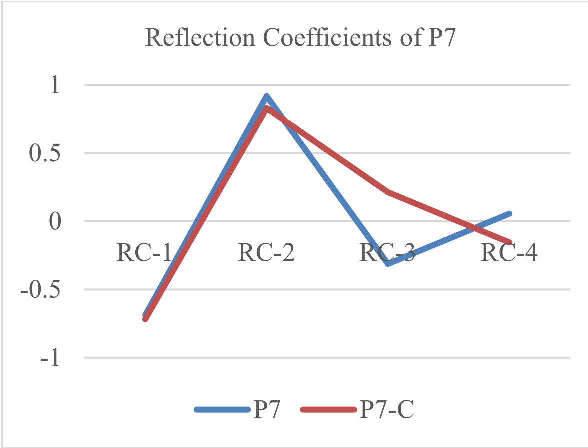
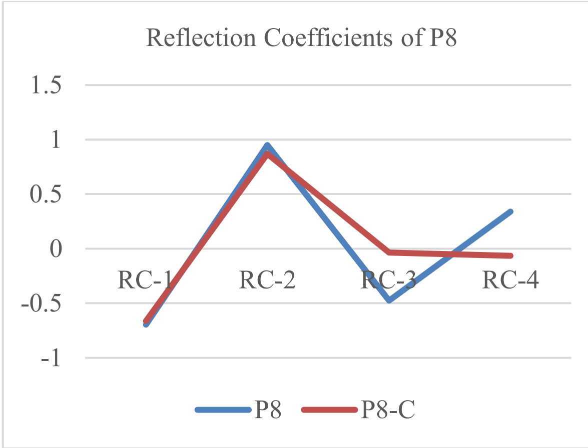
0.5
0
-0.5
-1
RC-1
RC-2
RC-3
RC-4
FPZ
FPZ-C


Reflection Coefficients of AF2
1
0.5
0
-0.5
-1
RC-1
RC-2
RC-3
RC-4
AF2
AF2-C


Reflection Coefficients of AFZ
1.5
1
0.5
0
-0.5
-1
1
2
3
4
AFZ
AFZ-C





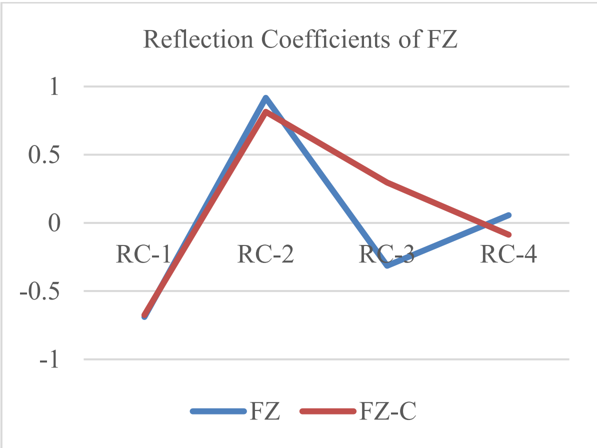


Figure 4.17: Reflection coefficients of the 16 channels selected by Brodmann's localization theory- based scheme

By observing the reflection coefficients of the 16 channels for several trials of different control and alcoholic persons, it is found that for most of the cases, reflection coefficients of FP1 and AF2 of control and alcoholic persons do not present much differences. Thus, eliminating these 2 channels, we find 14 channels that can best discriminate the 2-classes. The 14 channels are listed in table 4.11 and the details of the classification accuracies for these 14 channels are reflected in table 4.12 and Fig. 4.18.

Table 4.11: Selected 14 channels from the 16 channels

Channels	Brodmann Area	Lobe	Weight	Rank
AF7, AF8, F5, F6,	BA46	Frontal	33%	1
PO7, PO8	BA19	Occipital	32%	2
POZ, OZ	BA17	Occipital	30%	3
FP2, FPZ	BA10	Frontal	23%	4
AFZ	BA09	Frontal	21%	5
P7	BA37	Temporal	12%	6
FZ	BA08	Frontal	8%	7

Table 4.12: Classification accuracy using 14 channels selected from the 16 channels

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	98.5	97.5	87
	Match	99.5	97	81.5
	No-match	99.5	98.5	85

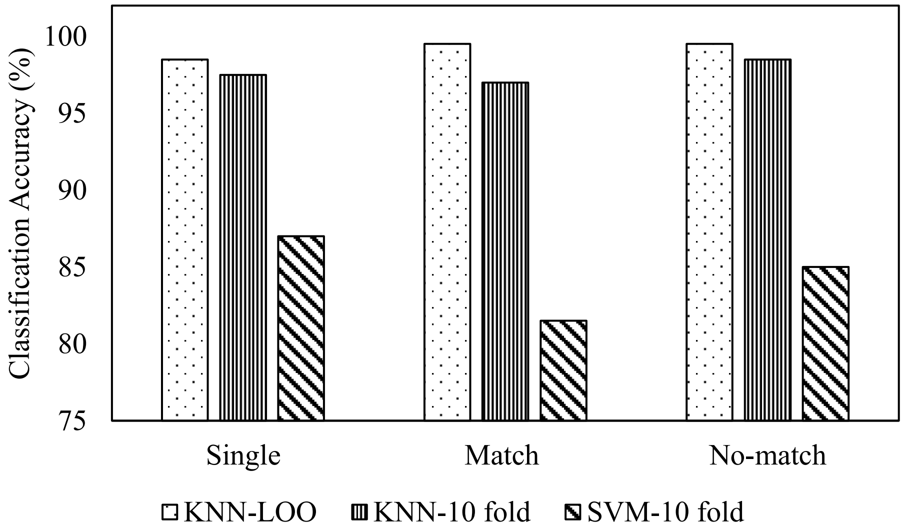


Figure 4.18: Classification accuracy using 14 channels

It is clearly understood that using only these 14 channels accuracy increases for all 3 stimuli in KNN-LOO technique. EEG of these 14 channels of the two groups of people show noteworthy differences and likewise, reflection coefficients of these 14 channels carry significant discriminating information as well. That is why, using only these 14 channels improves accuracy in all cases. For single and nomatch, this accuracy is even better than those obtained using all 61 channels. However, accuracy reduces for 10-fold cross validation technique for all classifiers.

(v) Accuracy in weighted scoring scheme

In weighted scoring method, 16 channels were selected. The classification performance of these 16 channels are depicted in table 4.13 and Fig. 4.19.

Table 4.13: Classification accuracy using 16 channels in weighted scoring scheme

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	99	99	89
	Match	99.5	98.5	90
	No-match	99.5	98	88

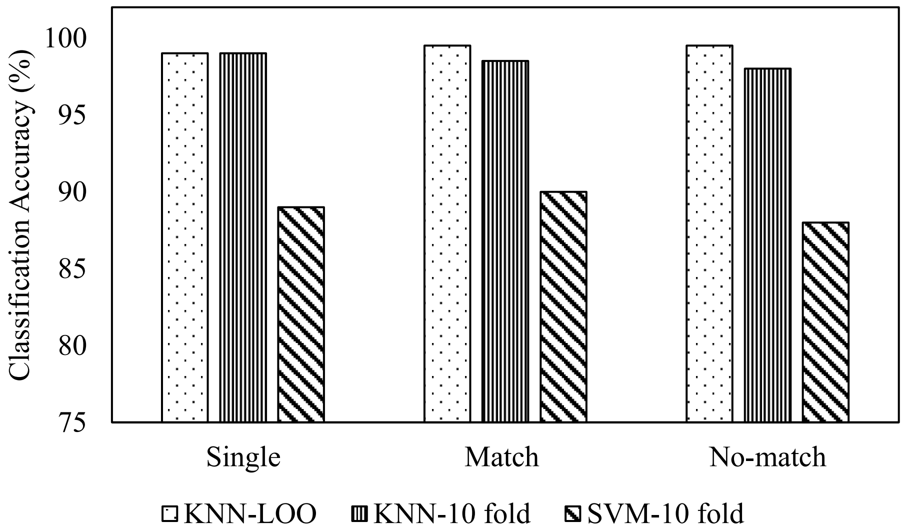


Figure 4.19: Classification accuracy using 16 channels in weighted scoring scheme

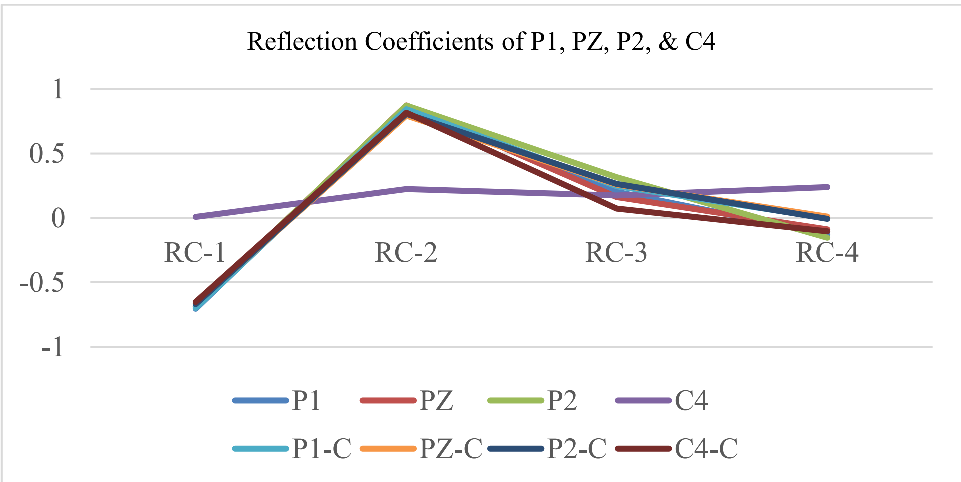


Figure 4.20: Reflection coefficients of P1, PZ, P2, & C4

These 16 -channel group can well distinguish the two groups of people with high classification accuracy. Specially, performance of SVM classifier enhances drastically. Among these 16 channels, FP1 and AF2 can be eliminated as discussed in the previous section. The 4 channels of BA46 namely, AF7, AF8, F5, and F6 are not included in this method. Instead 3 channels (P1, PZ, P2) from BA07 of Parietal lobe are included with C4 of BA01, 03. The reflection coefficients of these 4 channels are shown in Fig. 4.20. Among these 4 channels, reflection coefficients of C4 of control and alcoholic person show clearly distinguishable characteristic, while those of the rest 3 almost overlap with each other. Thus, we eliminate the 3 channels of BA07 and arrive at a total of 11 channels. These 11 channels are listed in table 4.14.

Table 4.14: List of finally selected 11 channels based on weighted scoring and feature properties of channels

Electrode	Site	Lobe	Weighted sum	Original Rank
FZ	BA08	Frontal	2387	1
FCZ	BA06	Central	2361	2
FPZ, FP2	BA10	Frontal	1977	3
AFZ	BA09	Frontal	1879	4
P7	BA37	Temporal	1772	5
POZ, OZ	BA17	Occipital	1609	6
PO7, PO8	BA19	Occipital	1516	8
C4	BA01,03	Central	1164	10

The classification performance of these 11 channels are presented in table 4.15 and Fig. 4.21.

Table 4.15: Classification accuracy using 11 channels of weighted scoring scheme

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	99.5	98.5	85
	Match	100	99.5	87
	No-match	99.5	97.5	87.5

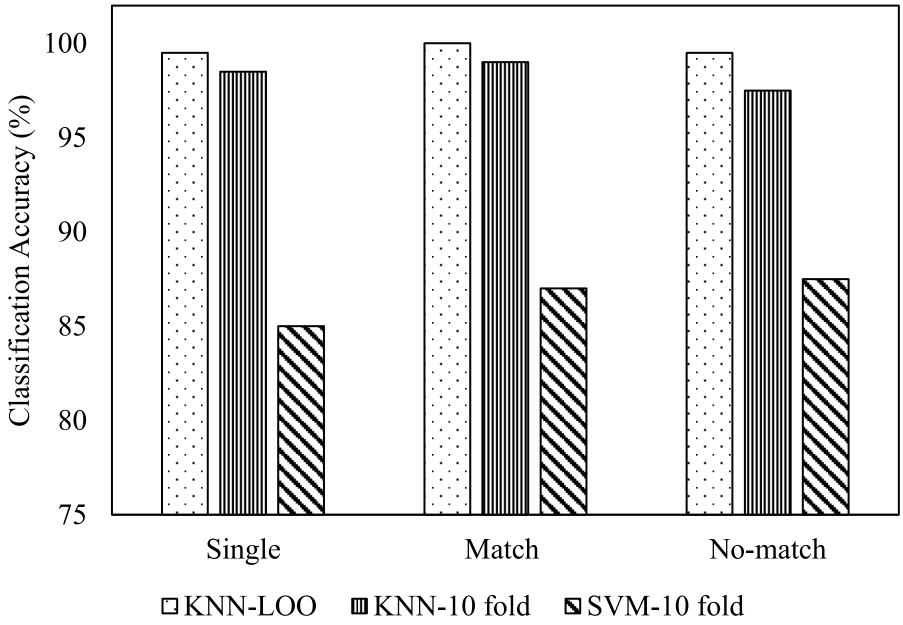


Figure 4.21: Classification accuracy using 11 channels of weighted scoring scheme

From Fig. 4.21 and table 4.15, it is clear that weighted scoring method can best select the relevant channels for a certain cognitive and mental task. This method helped in successfully sorting out only 11 channels out of 61 channels, that can identify alcoholic person from non-alcoholic group with very very high classification accuracy. The results are even better than using all 61 channels in almost all cases. For nomatch, the accuracy in KNN-LOO strategy is equal to that obtained by using all 61 channels. Most importantly, in case of using these 11 channels, performance in 10- fold cross validation also increases remarkably for both classifiers. For match condition, it reduces slightly. However, consistency prevails in all stimulus condition. In reduced channel domain, SVM classifiers performance starts to deteriorate. However, for 11 channels, it increased again to 88% in all cases.

In all of the cases, KNN works better than SVM classifier. This is because, polynomial or quadratic SVM were not chosen. From Fig. 4.11, 4.13, and 4.15 it is clear that the training sample data points are so closely situated to each other that it becomes difficult for linear SVM to find the support vectors from the hyperplane that maximizes the margin from both classes. Thus, SVM starts to sacrifice the accuracy. On the other hand, KNN uses very simple algorithm. Given a set of training vectors, KNN algorithm identifies the k-nearest neighbors of a feature vector by calculating Euclidian distance, regardless of labels. Thus, when we want to classify a test feature vector using KNN classifier, KNN looks at its K-closest or most similar neighbors and classify the test vector as the majority class in those neighbors. In this way, KNN is automatically non-linear and it tends to work very well with a lot of data points.

Accuracy improves in some cases if quadratic SVM is used. The accuracy in weighted scoring 11-channel domain for all three stimuli are shown in table 4.16 and Fig. 4.22.

Table 4.16: Classification accuracy using WS-11 channels scheme (Quadratic SVM)

		Classifier
	Stimulus Condition	SVM-10 fold (Quadratic)
Classification Accuracy (%)	Single	96
	Match	98.5
	No-match	97.5

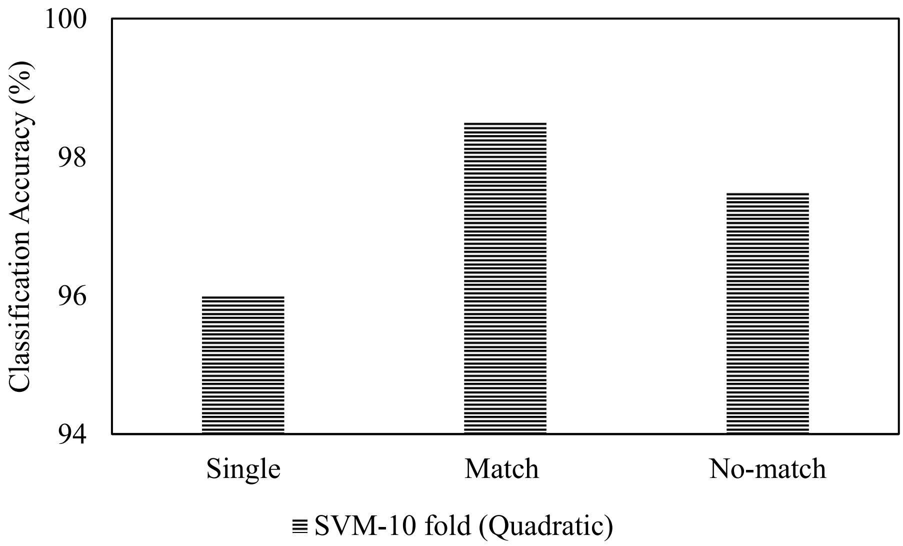


Figure 4.22: Classification accuracy using WS-11 channel in quadratic SVM classifier

4.4 Conclusion

In the proposed method, gamma band VEP is extracted and fit to an Autoregressive model. The reflection coefficient of the AR model is used as feature to analyze and classify alcoholics and non-alcoholics. To determine the model order, at the onset, the gamma band VEP is fit to an AR model of order 15 and applicable model order is selected. Then, variance of white noise input to the model while model order is varied from 1 to 6 are plotted for all 61 channels to observe effect of model order increase on that. However, in search for an optimum feature dimension without loss of originality of the signal, order 5 is chosen and the statistical significance of the 5^{th} coefficient of the independent variable is tested after the signal is fit to a 5^{th} order AR model. Effect of varying the model order and effect of different classifier with different validation technique on classification accuracy are observed under three different stimulus condition. Finally, the effect of the reduced channel sets derived under different methods are checked. Utilizing the similarity of reflection coefficient of the selected channels, some more channels are reduced from the channel set found in weighted scoring method and effect of these channels on the classification accuracy is also investigated.

Chapter 5

Proposed Spatial Filtered Feature Based Classification Scheme

5.1 Introduction

A specially designed spatial filter obtained by the method of common spatial patterns (CSP) to construct few new time-series whose variances contain the most discriminative information can be an effective way to extract suitable feature from the EEG or VEP data. The method of common spatial pattern was first applied to EEG for detection of abnormalities and later used to discriminate movement related patterns [65]. The method of CSP is based on a decomposition of the raw EEG signals into spatial patterns, which are extracted from two populations of single trial EEG. These patterns maximize the difference between the populations. Common spatial pattern considers all the electrodes simultaneously, independent of any other applied machine learning algorithm.

5.2 Proposed Method

CSP determines spatial filters that maximize the temporal variance of data recorded under one condition and minimize the temporal variance of data recorded under a second condition. It is widely used for feature dimension reduction and improvement of classification accuracy in motor imagery-based BCI [11], [66] and also for classification of event-related potential. These filters for multi -channel EEG effectively extracts discriminatory information from two populations of single trial EEG by performing the weighting of the electrodes according to their importance for the classification task [66]. The success of spatial filtering in BCI provided the motivation for using this method to spatially filter the alcoholic dataset and analyze the signal for classification. Here, spatial filtering is not used for channel dimension reduction, rather all the channel data are preserved. Each channel data of a single trial of a person is spatially filtered. In this way, the whole data set is spatially filtered. Finally, an effective statistical or frequency domain feature will be used to extract information among trials in space, time or frequency. The method actually, utilizes the variance differences between the two classes to extract a strong discriminating feature set to improve classification performance.

5.2.1 Spatial filtering

Spatial filters, estimated from a set of data by the method of common spatial patterns reflect the specific activation of cortical areas. The method used to design such filters is based on the simultaneous diagonalization of two covariance matrices.

For the analysis, the raw EEG data of a single trial is represented as an $N \times T$ matrix E, where, N is the number of channels and T is the number of samples per channel. Let, $E_a$and E_c denote the EEG matrices under two conditions alcoholic and control. The normalized spatial covariance of the EEG can be represented as

$$R_a = \frac{E_a E_a'}{trace(E_a E_a')} \qquad R_c = \frac{E_c E_c'}{trace(E_c E_c')} \tag{5.1}$$

where $'$ denotes the transpose operator that $trace(x)$ is the sum of the diagonal elements of x. For each of two groups to be separated (i.e. alcoholic and control), the spatial covariance $\bar{R}_g$, $\in [a, c]$ is calculated by averaging over the trials of each group. The composite spatial covariance is given by

$$R = \bar{R}_a + \bar{R}_c \tag{5.2}$$

R can be factored as $R = U\lambda U'$, where U is the matrix of eigenvectors and λ is the diagonal matrix of eigenvalues. Throughout this section, the eigenvalues are assumed to be sorted in descending order.

The whitening transformation

$$P = \sqrt{\lambda^{-1}}\, U' \tag{5.3}$$

Equalizes the variances in the space spanned by U, i.e. all eigenvalues of PRP' are equal to one. If $\bar{R}_a$ and $\bar{R}_c$ are transformed as

$$S_a = PR_aP' \text{ and } S_c = PR_cP' \tag{5.4}$$

Then S_a and S_c share common eigenvectors and the sum of corresponding eigenvalues for the two matrices will always be one,

$$S_a = B\lambda_a B' \quad S_c = B\lambda_c B' \quad \lambda_a + \lambda_c = I \tag{5.5}$$

where I is the identity matrix. Since the sum of two corresponding eigenvalues is always one, the eigenvector with the largest eigenvalue for $\bar{S}_a$ has the smallest eigenvalue for $\bar{S}_c$ and vice versa. This property makes the eigenvectors B useful for classification of the two groups. The projection of whitened EEG onto the first and last eigenvectors in B (i.e. the eigenvectors corresponding to the largest λ_a and λ_c) will give feature vectors that are optimal for discriminating two populations of EEG in the least square sense.

With the projection matrix $W = (B'P)'$, the decomposition (mapping) of a trial E is given as

$$Z = WE \tag{5.6}$$

The column of W^{-1} are the common spatial patterns and can be seen as time-invariant EEG source distribution vectors.

5.2.2 Feature extraction

After the raw EEG signal is spatially filtered, the variance between each signal of the two group is maximized. The benefit of this huge gap in variance, justifies the selection of a simple statistical feature as a tool for differentiating one group from the other. Hence, the variance, i.e. the average of the squared deviations from the mean of each spatially filtered EEG channel data is proposed as a feature to train the classifier.

5.2.3 Classification

For classification purpose, K-nearest neighbor (KNN) and Support Vector Machine (SVM) are used. For KNN, leave one out (LOO) cross validation and 10-fold cross validation technique both are used. Whereas, for SVM, only 10-fold cross validation technique is used.

5.3 Simulation and Results

The result of classification using spatially filtered signal's variance to train KNN-LOO classifier is summarized in table 5.1 and Fig. 5.1.

Fig. 5.2 shows the raw EEG of one alcoholic and one control person. EEG represents the EEG of an alcoholic person and EEG-C represents that of a control person. Unless any preprocessing is applied, it is very difficult to differentiate the two waveforms. On the other hand, the spatially filtered signal of the same alcoholic and control persons single trial is plotted in Fig. 5.3.

‘Spatial filtered EEG’ means spatially filtered EEG of an alcoholic person and ‘Spatially filtered EEG-C’ means that of a control person.

Table 5.1: Classification accuracy using variance of spatially filtered EEG

	Stimulus Condition	KNN-LOO
Classification Accuracy (%)	Single	100
	Match	100
	No-match	100

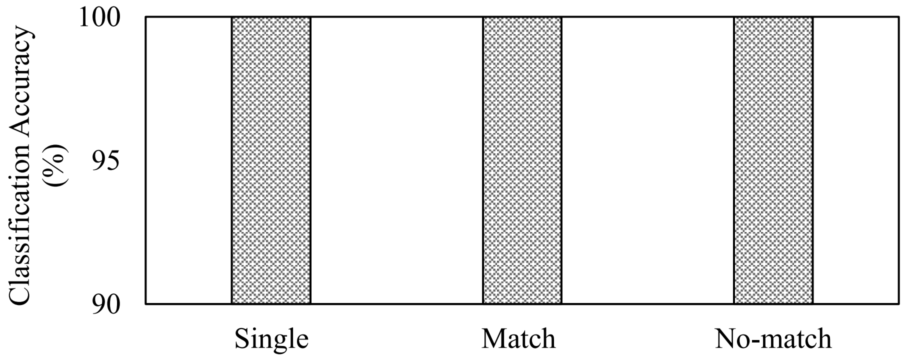


Figure 5.1: Classification accuracy using variance of spatially filtered EEG

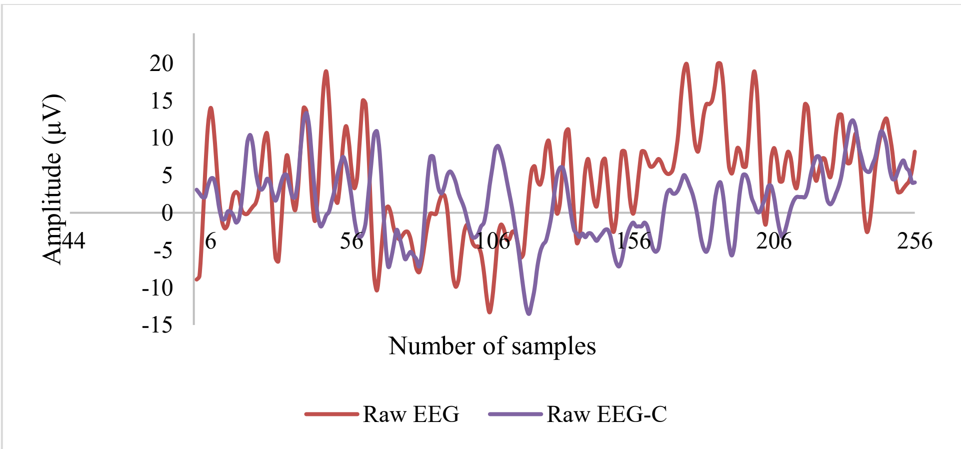


Figure 5.2: Raw EEG signal of alcoholic and control person

The differnces between the waveforms as observed form Fig. 5.2 and Fig. 5.3 justifies such high classification accuracy. The beauty of the method is that it is very simple though computationally expensive. However, the complexity of the filtering is compensated by the simplicity of the nature of the feature. Without any other preprocessing technique, this method can distinguish two groups of people with the highest possible level of precision.

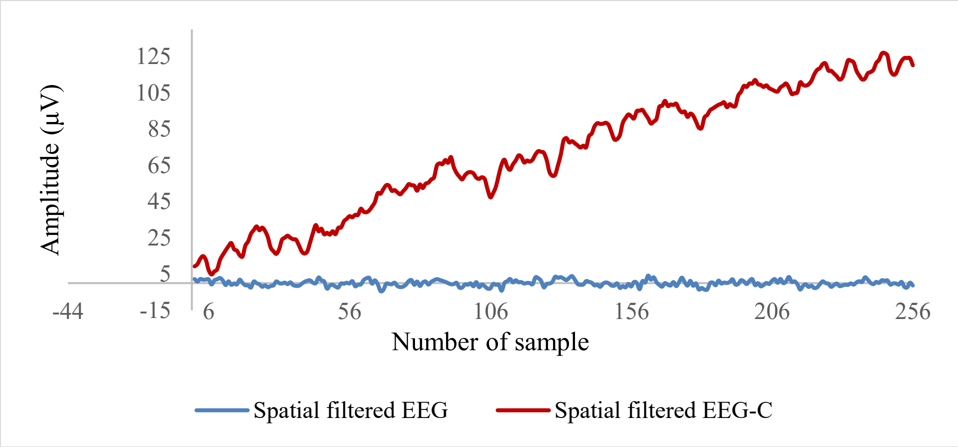


Figure 5.3: Spatially filtered EEG of alcoholic and control persons

5.3.1 Effect of using different classifier and cross validation techniques

The accuracy remains the same when KNN 10-fold and SVM 10-fold cross validation techniques are employed. The details are presented in table 5.2 and Fig. 5.4.

Table 5.2: Effect of different classifier and cross validation technique

		Classifier	
	Stimulus Condition	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	100	100
	Match	100	100
	No-match	100	100

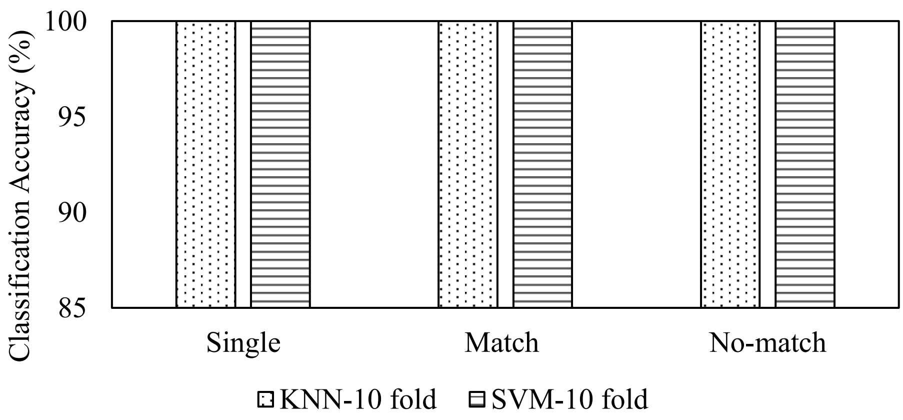


Figure 5.4: Classification accuracy in KNN and SVM classifier (10-fold cross validation technique)

5.3.2 Effect of channel reduction

(i) Accuracy in lobe-based scheme

The performance of spatially filtered EEG signals' variance of channels on a specific lobe are evaluated and listed in table 5.3 and Fig. 5.4, 5.5, and 5.6 respectively for single, match and nomatch condition.

Table 5.3: Effect of lobe-based channel reduction scheme in all 3 stimuli condition

Stimulus condition	Lobe	Classifiers		
		KNN-LOO	KNN- 10 fold	SVM-10 fold
Single	Frontal	100	100	100
	Central	100	100	100
	Parietal	99.5	99	98.5
	Occipital	99.5	99.5	99.5
	Temporal	99.5	99.5	100
Match	Frontal	99.5	99.5	100
	Central	99.5	99.5	100
	Parietal	99.5	99.5	100
	Occipital	99.5	99.5	99.5
	Temporal	100	100	100
Nomatch	Frontal	100	100	100
	Central	100	100	100
	Parietal	100	100	100
	Occipital	100	98.5	99
	Temporal	99.5	100	99.5

It is noteworthy that, when spatial filtered signal variance is used as feature, SVM classifier's performance improves remarkably. In some of the cases the accuracy obtained under SVM is even better that that in KNN-LOO, opposite to the case when reflection coefficients of gamma band VEP were used as features.

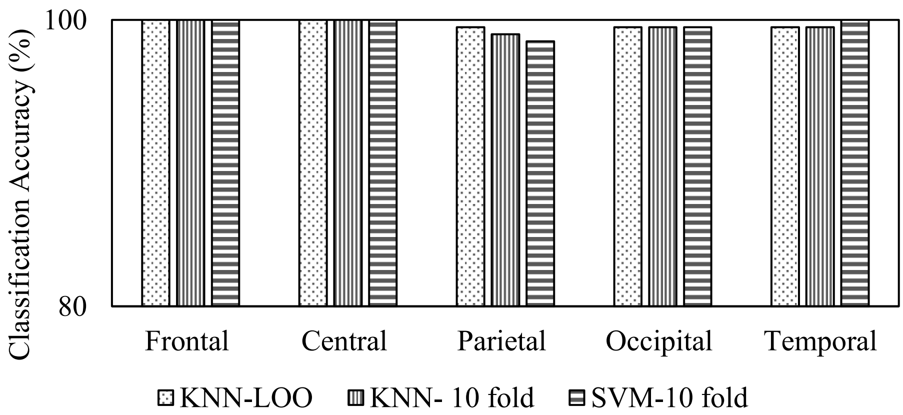


Figure 5.5: Effect of lobe-based channel reduction scheme on classification accuracy-single

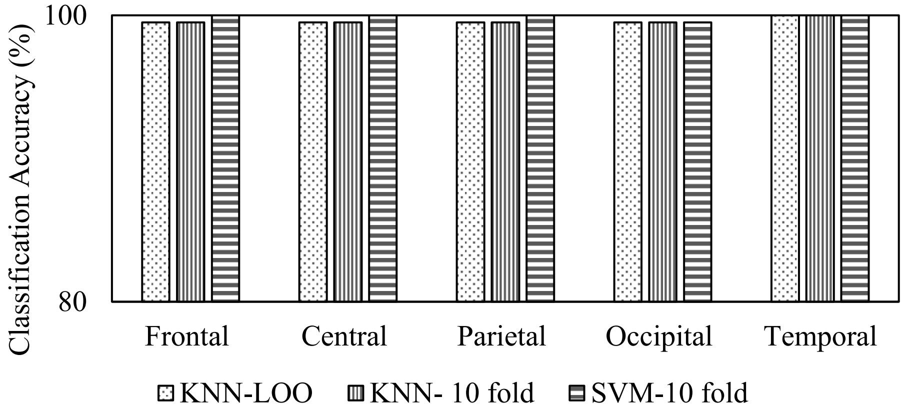


Figure 5.6: Effect of lobe-based channel reduction scheme on classification accuracy -Match

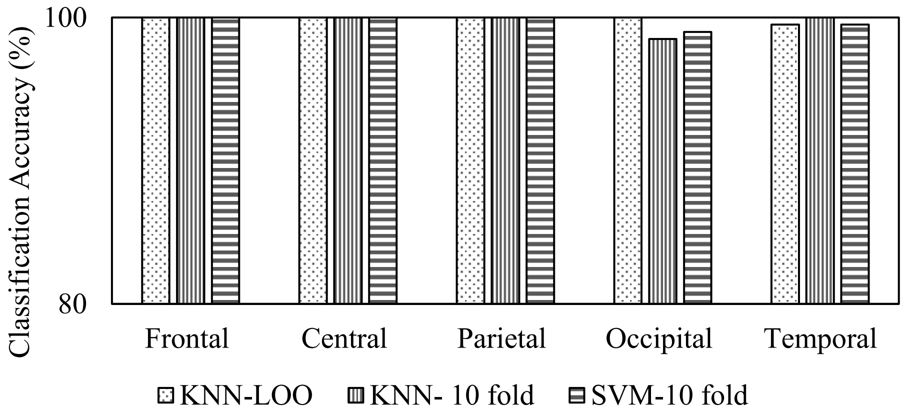


Figure 5.7: Effect of lobe-based channel reduction scheme on classification accuracy - nomatch

Although 100% accuracy was obtained in all stimulus condition while using all channels, that is not the cases for channels selected from a specific lobe of the brain. To investigate the reason for this, we observed the spatially filtered signal for both group of people in visual cue cases where accuracy deviated from the maximum level. For single stimuli, spatially filtered signal of 2 parietal channels, for match and nomatch, 2 occipital channels from each were observed with histogram of variances of all channels of each paradigm. The filtered waveforms and variance histogram are presented in Fig. 5.8, 5.9, and 5.10 correspondingly.

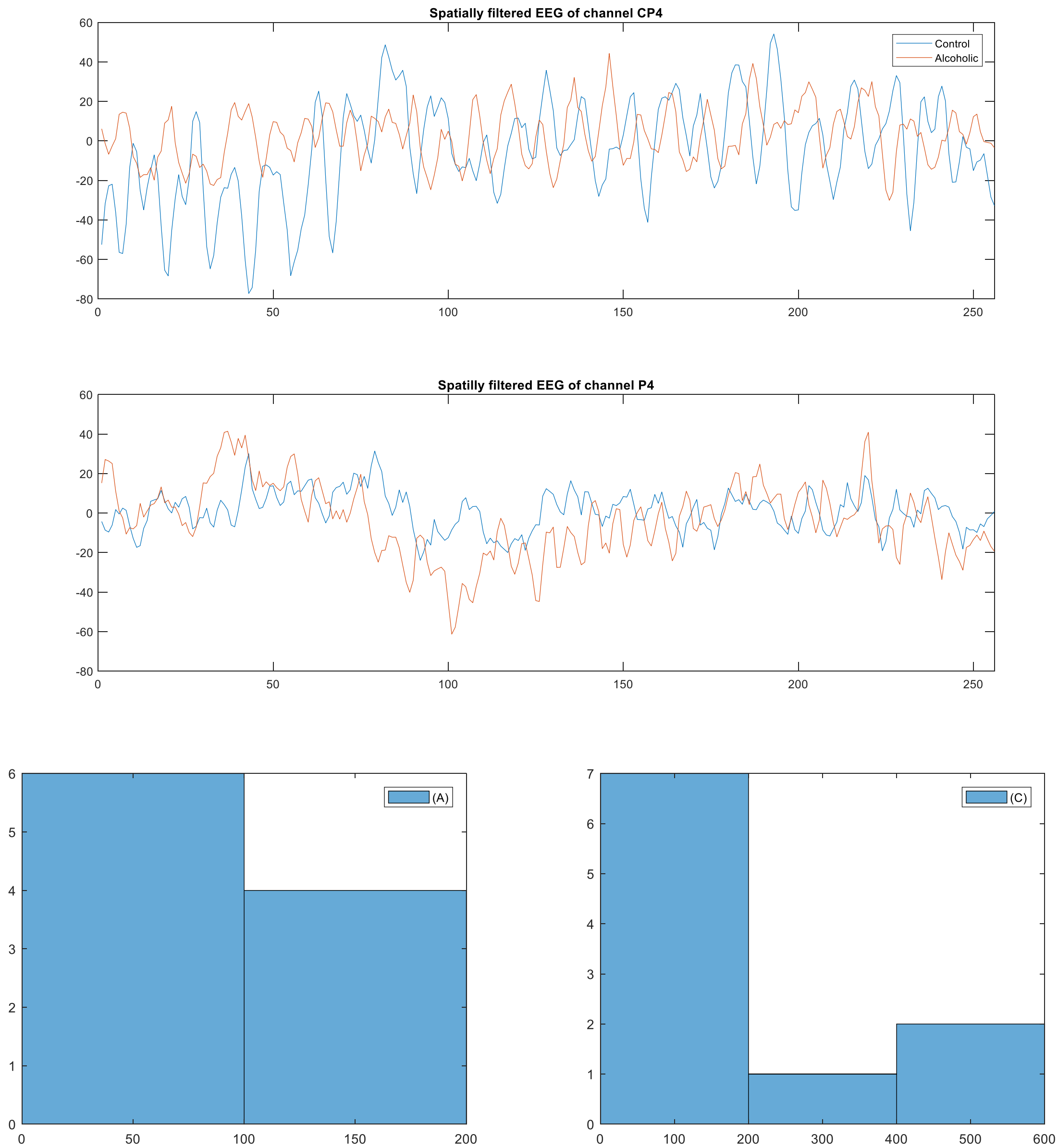


Figure 5.8: Spatially filtered EEG and histogram of sample variance of Parietal channel-Single

In the figures, (A) notation is used for alcoholic and (C) notation is used to indicate a control person. From Fig. 5.8, 5.9, and 5.10 it is easily understood that CSP cannot increase the difference in variance for all the channels. Thus, when channel dimension reduces, the signals from the channels that were not of high variance between the two groups, cause the accuracy to be lower. In case of single stimuli, all the variance of spatially filtered 10 parietal channels' samples of Alcoholic lie in the range of 0-200, whereas, the same case occurs in case of 7 parietal channels of control. In this way, accuracy deviated from the maximum level. Similar case occurs in occipital channels of these two class of people in match and nomatch condition. In case of occipital channel O2 and PO8, the spatial filtered signals of control and alcoholic do not have much variance under match paradigm. In the histogram of variance of some trials of EEG of occipital channels show that the sample variance of all 8 channels lie in the same level 0-2000 for both alcoholic and control. Under nomatch paradigm, as shown in Fig. 5.10 in some trials, variance of 5 channels' sample fall in 0-1000 for control whereas, for alcoholic 6 channels' sample variance lie in the same region as well.

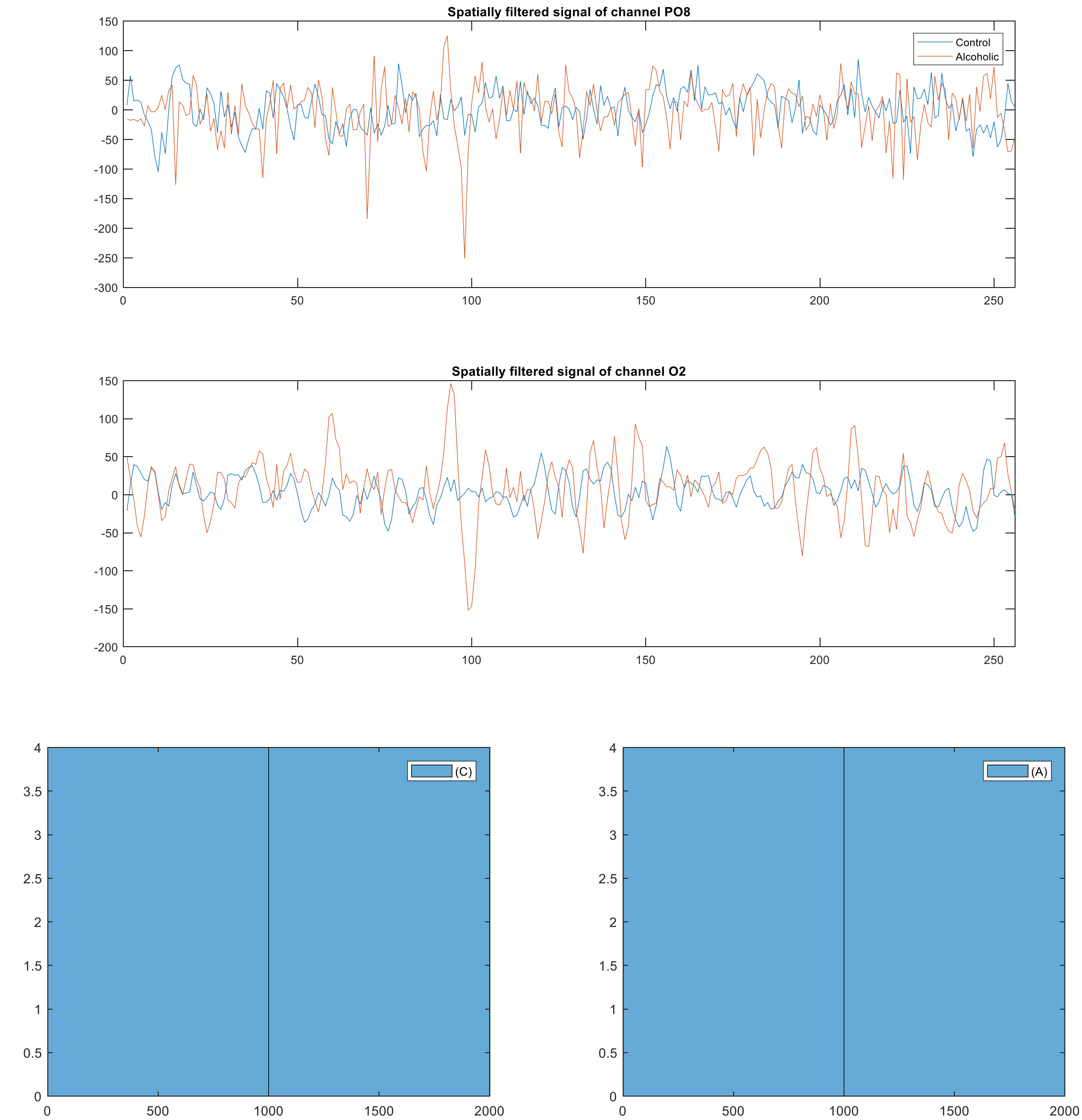


Figure 5.9: Spatially filtered EEG and histogram of sample variance of Occipital channel - Match

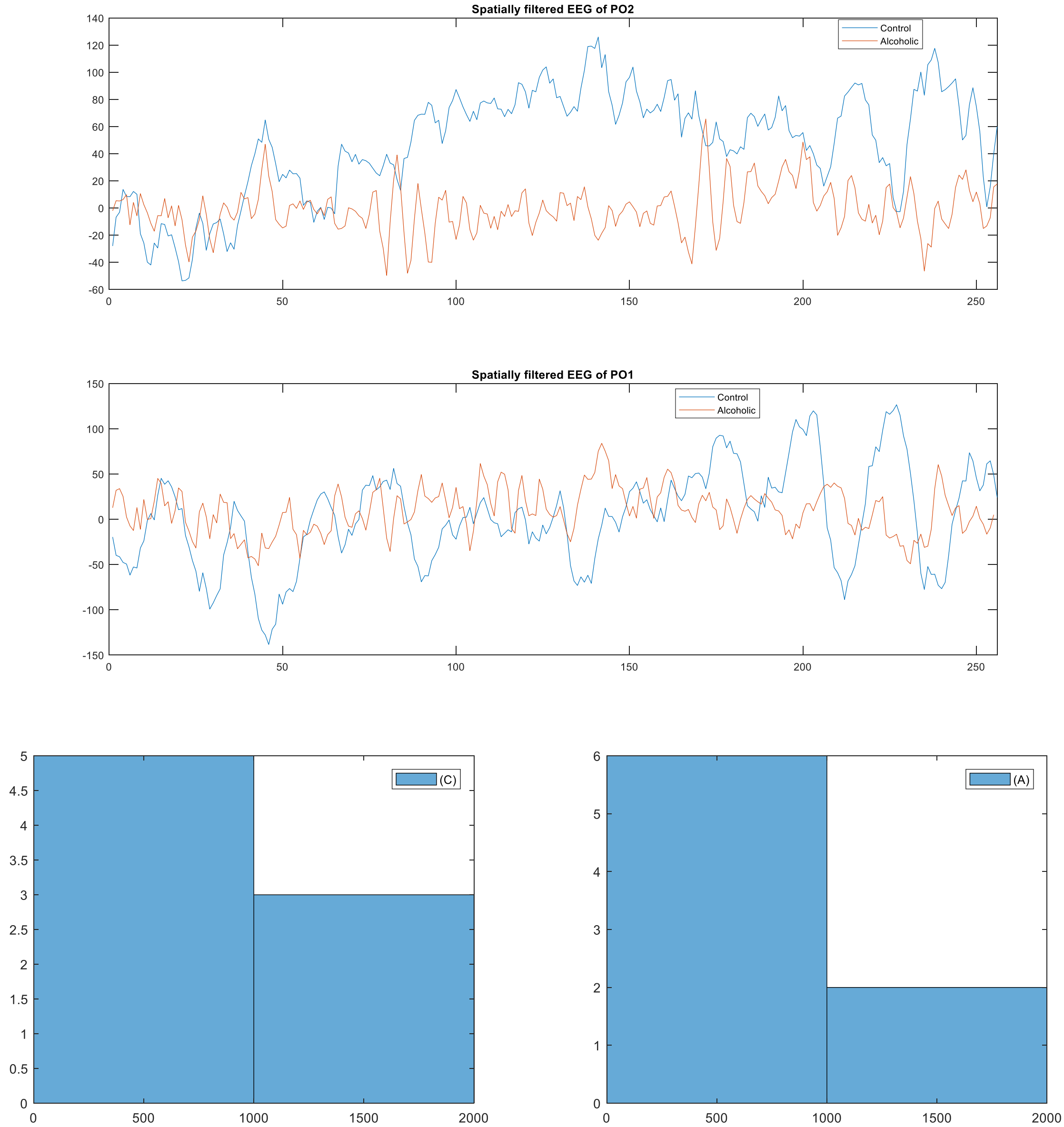


Figure 5.10: Spatially filtered EEG and histogram of sample variance of Parietal channel-Nomatch

(ii) Accuracy in cortical function-based scheme

By utilizing the correlation between the functional areas of cerebral cortex and Brodmann's areas, a total of 36 electrodes were identified. The effect of this channel reduction technique on classification accuracy is listed in table 5.4 and Fig. 5.11.

Table 5.4: Classification accuracies using 36 channels

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	100	100	100
	Match	100	100	100
	No-match	100	100	100

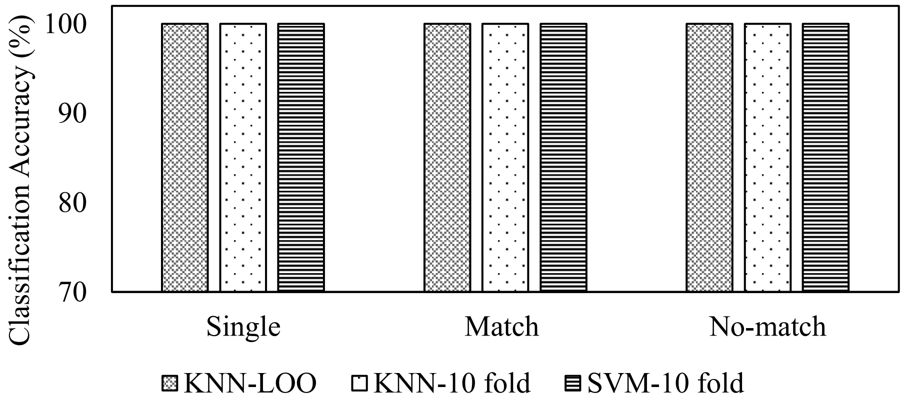


Figure 5.11: Effect of channel reduction based on cortical functions

100% accuracy is obtained in all types of stimuli using variance of spatially filtered EEG when only 36 channels based on cortical lobar functions are taken into account.

(iii) Accuracy in hemispheric lateralization-based scheme

According to this method of channel reduction, 29 different channels are selected. The effect of this channel reduction technique on classification accuracy is listed in table 5.5 and Fig. 5.12.

Because of the strong feature consistency of the 29 channels obtained by hemispheric lateralization-scheme, in this case also 100% accuracy is obtained under all three stimuli.

Table 5.5: Classification accuracies using 29 channels

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
Classification Accuracy (%)	Single	100	100	100
	Match	100	100	100
	No-match	100	100	100

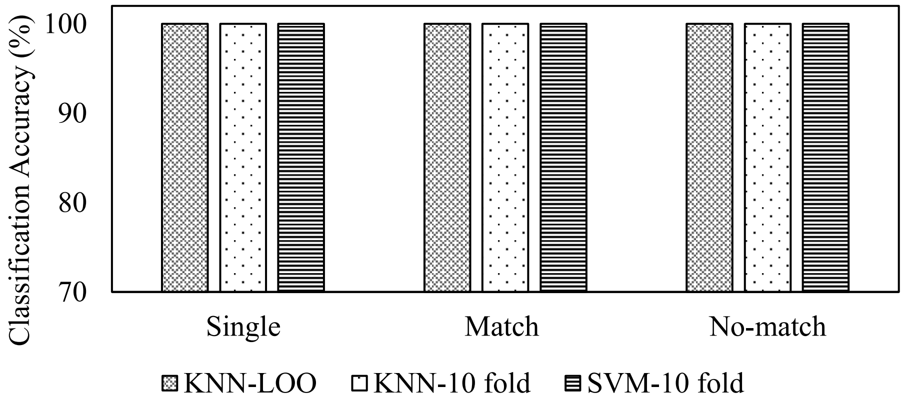


Figure 5.12: Effect of channel reduction based on cortical function

(iv) Accuracy in Brodmann's localization theory-based scheme

According to this method, at first, a total of 16 channels were identified that are highly expected to contribute while a subject is exposed to visual cue, then required to recognize it, perceive it, and recall to match with a second piece of cue. Later, based on the reflection coefficient feature, 2 more channels were reduced and 14 channels were suggested to be able to clearly distinguish the two groups. Now, the accuracies for both 16 channel and 14 channel-domain are reflected in table 5.6 and Fig. 5.13 & 5.14.

Table 5.6: Classification accuracies using 16- channel & 14-channel

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
16-channel	Single	100	100	99.5
	Match	99.5	99.5	100
	No-match	100	99.5	100
14-channel	Single	100	99.5	100
	Match	100	100	100
	No-match	99.5	99.5	99.5

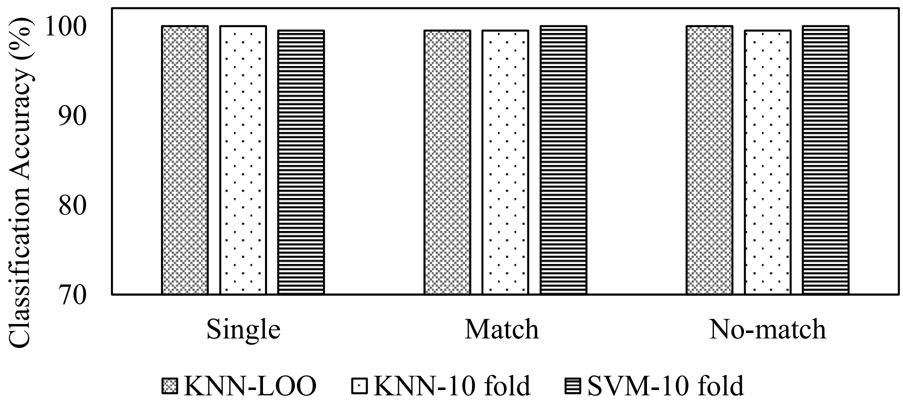


Figure 5.13: Effect of channel reduction based on Brodmann's localization theory-based scheme on classification accuracy (16-chanel)

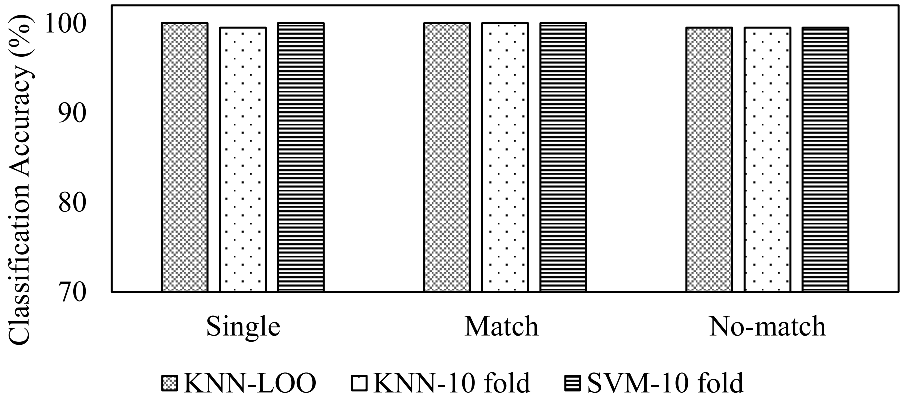


Figure 5.14: Effect of channel reduction based on Brodmann areas on classification accuracy (14-channel)

The 14-channel domain works very good for both single and match. However, this is not the case for nomatch.

(v) Accuracy in weighted scoring scheme

Table 5.7: Classification accuracies using 16- channel & 11-channel (Weighted scoring)

		Classifier		
	Stimulus Condition	KNN-LOO	KNN-10 fold	SVM-10 fold
16-channel WS	Single	99.5	99.5	100
	Match	99.5	99.5	100
	No-match	100	100	100
11-channel WS	Single	100	100	100
	Match	100	100	100
	No-match	100	100	100

In weighted scoring (WS) method, initially 16-channels were sorted out based on their ranking in terms of weighted score and relevance of activity. Later, upon the consideration of discriminating behavior carried out by reflection coefficients, 5 channels were excluded from the list and finally, 11 were found to be the most relevant ones. The accuracies of these 2 sets of channels are listed in table 5.7 and Fig. 5.15 & 5.16 respectively.

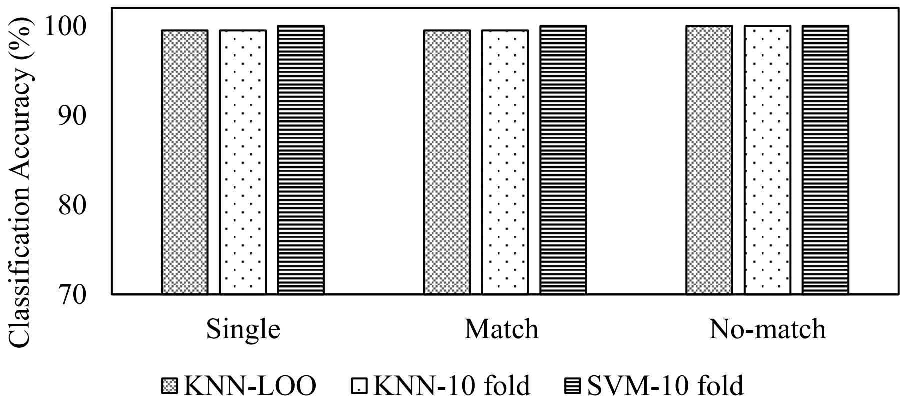


Figure 5.15: Effect of channel reduction in weighted scoring method (16-channel WS)

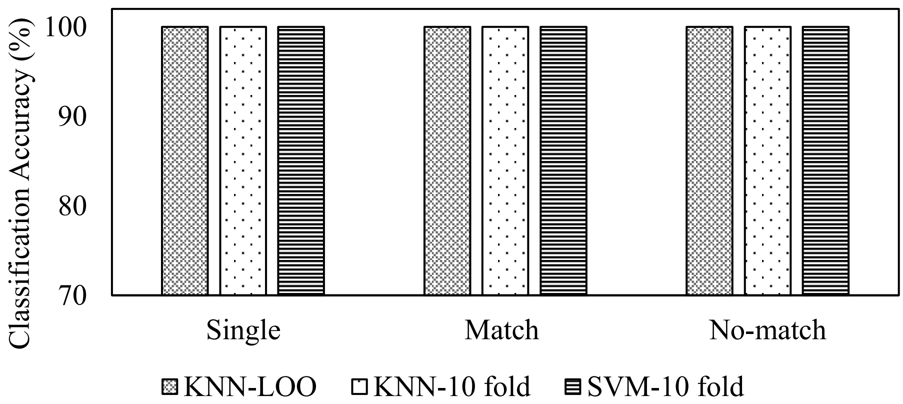


Figure 5.16: Effect of channel reduction in weighted scoring method (11-channel WS)

Fig. 5.17 reflects the scatter plot for variance of two sample trials of control and alcoholic persons while using the 11-channel domain. The variances of the two groups are wide apart, thus, can be easily distinguishable.

Although, the 11 channels from the 16 channels were brought down depending on reflection coefficient feature, these channels are working good in spatial domain also. These 11 channels can classify alcoholic from non-alcoholic group very precisely and at a very short time. Feature dimension is also very small, only 200×11.

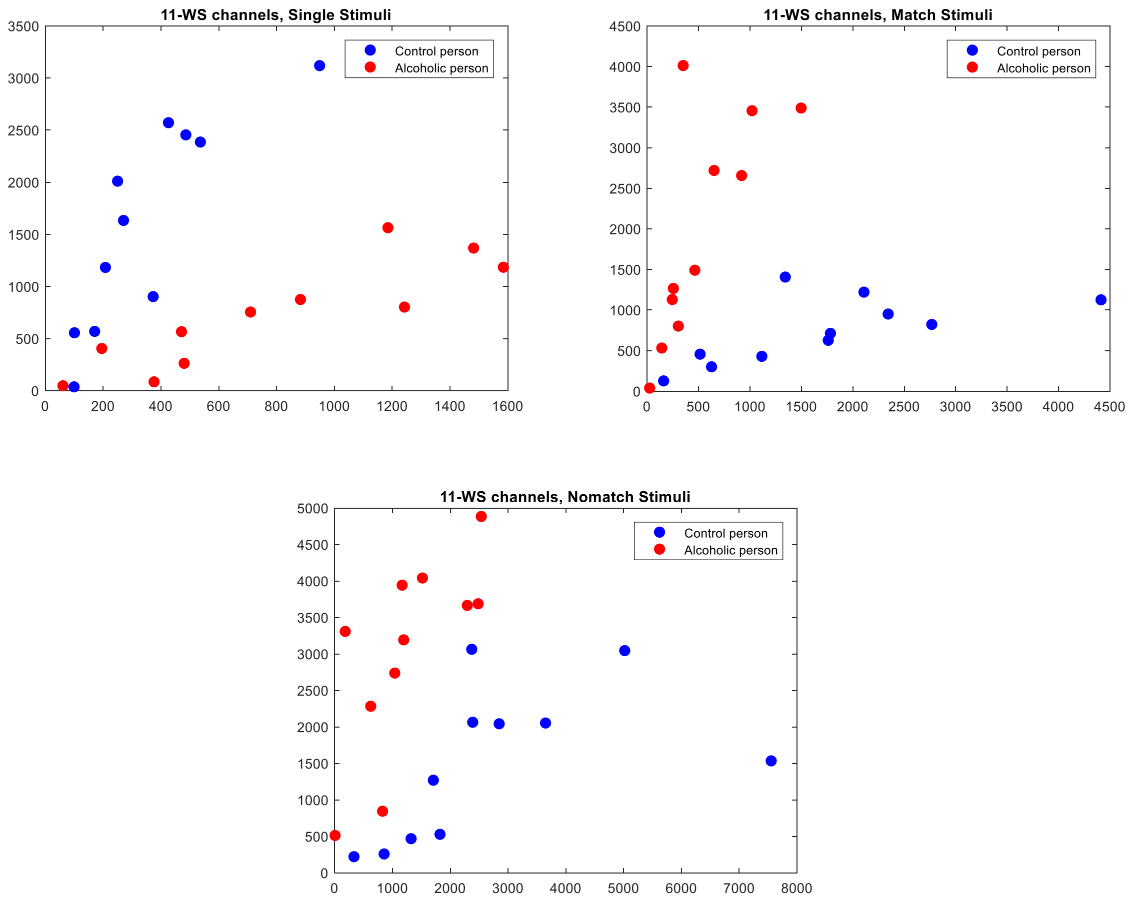


Figure 5.17: Variance of two sample trials of alcoholic and control persons under 11-WS channels

When CSP-variance is used as feature, the feature vectors of the two classes are situated with a huge gap and that is why it becomes easier for SVM to find the support vectors from the hyperplane to maximize the margin between the two classes. This justifies the high accuracy rate of SVM in this feature domain.

5.3.3 Statistical significance

An ANOVA test was run on the variances of the spatial filtered EEG data of the proposed 11 channels and the rest of the channels for both alcoholic and control persons. It was found that the F-value exceeds the critical F-value and thus we reject the null hypothesis that the mean variances of the two locations are the same. The p-value is $2.46677e^{-5}$ and 0.001928854 for alcoholic and healthy persons respectively which means that the difference in the feature of the proposed 11 channels and the other 50 channels is statistically significant for 95% confidence interval. The results are summarized in table 5.8 and 5.9 for alcoholic and healthy persons correspondingly.

Table 5.8: Result summary of ANOVA test on the variances of the proposed 11-channel and the rest of the channels of alcoholic persons.

SUMMARY (Alcoholic)

Groups	Count	Sum	Average	Variance
11-channels	11	8108.13175	737.1028863	196525.6447
50-channels	50	548486.9086	10969.73817	54186441.56

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	944077929.2	1	944077929.2	20.96292164	2.46677E-05	4.003983
Within Groups	2657100893	59	45035608.36			
Total	3601178822	60				

Table 5.9: Result summary of ANOVA test on the variances of the proposed 11-channel and the rest of the channels of non-alcoholic persons.

SUMMARY (Control)

Groups	Count	Sum	Average	Variance
11-channels	11	7073.266187	643.0241988	217694.0783
50-channels	50	379322.5932	7586.451863	49618671.61

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	434691036.9	1	434691036.9	10.53908242	0.001928854	4.003982503
Within Groups	2433491850	59	41245624.57			
Total	2868182887	60				

5.3.4 Effect of reduction in number of trials

Since, 11-channels WS (weighted scoring) can yield 100% accuracy in all condition, let us examine whether it works in reduced number of trials as well. The trial number were reduced down to 2 and 5 and the effect of such reduction is observed on classification accuracy. The results are summarized in table 5.10 and Fig. 5.18, 5.19 and 5.20.

Under match stimuli, there is no impact of trial number reduction. However, it is affected in single and nomatch condition. Specially, in KNN-10-fold cross validation it reduces to as low as 92.5% only in single stimulation.

Table 5.10: Effect of trial number reduction on accuracy using 11 channel-WS -domain

		Classifier		
Stimulus Condition	Trial	KNN-LOO	KNN-10 fold	SVM-10 fold
Single	2	100	92.5	100
	5	100	100	100
	10	100	100	100
Match	2	100	100	100
	5	100	100	100
	10	100	100	100
Nomatch	2	100	97.5	97.5
	5	100	99	100
	10	100	100	100

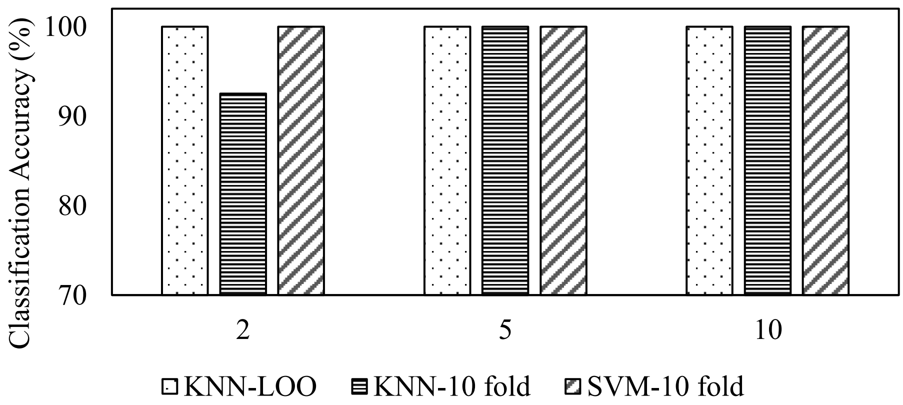


Figure 5.18: Effect of trial number reduction- single

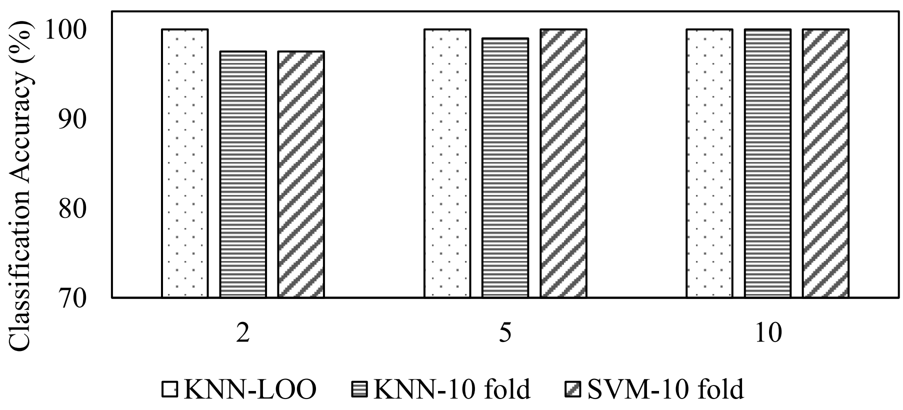


Figure 5.19: Effect of trial number reduction- match

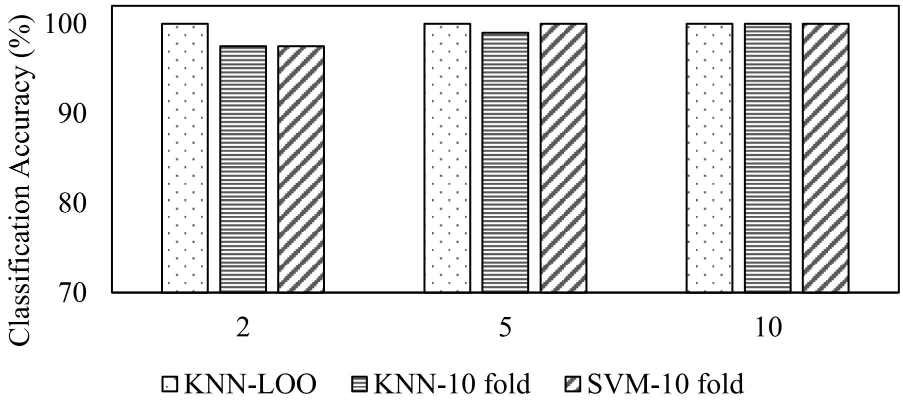


Figure 5.20: Effect of trial number reduction- nomatch

5.3.5 Computation time

Because of the ability of this work to reduce number of channel as well as feature dimension significantly, to discriminate alcoholic and control persons, the length of time required to execute the testing for classification, has come down to a great extent. The comparison of the time required in the two methods in case where all channels are used and the other where only 11 channels are used are presented in Table 5.11 and Fig. 5.21.

Table 5.11: Time required in the two methods

Method	Channel	Testing time (ms)
CSP-Variance	11 Channel-WS	4.38
	All channel	6.68
Gamma-RC	11 Channel-WS	4.89
	All channel	8.08

CSP-variance (variance of spatial filtered EEG) yields the best classification result at the shortest time whereas, the time required in Gamma-RC (gamma band reflection coefficient) method is longer than CSP-variance method for both 61-channel and 11-channel sets. Thus, we propose that the 11 -channel set followed by CSP-variance feature and KNN-LOO classifier and validation technique can classify the two groups with no error in the shortest possible time.

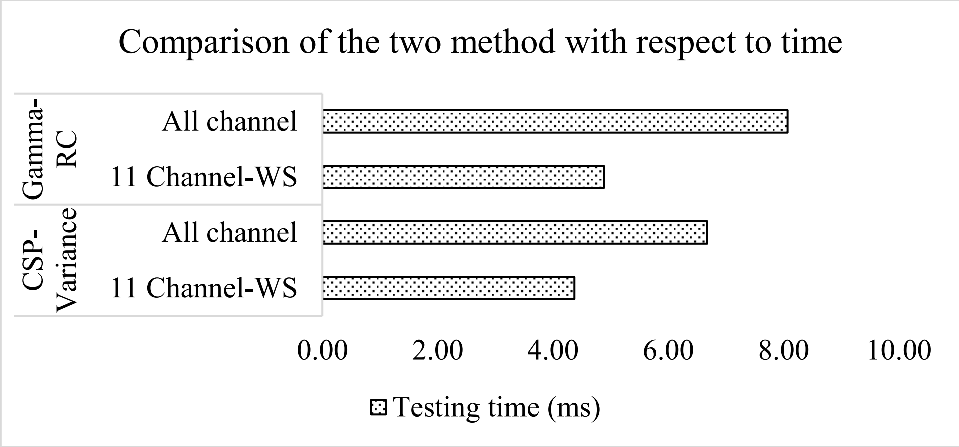


Figure 5.21: Comparison of required time among the methods and channel sets

5.4 Conclusion

The proposed method in this Chapter uses spatial filtering of the EEG signal before extracting the feature vector to discriminate the two groups. The unique property of spatial filtering to enhance the difference between the two signals from the two groups in terms of variance lead to the choice of variance of each spatially filtered channel's data as a feature to identify alcoholic from control group and high classification accuracy is obtained even after using the reduced set of channels under weighted scoring method. Thus, this method can classify the two classes using a very simple feature and the feature size is also very small. The effect of different classifiers with different validation techniques are again observed. Effect of channel reduction is also investigated. Furthermore, number of trials is also decreased to see the impact on accuracy. Finally, the computation time in both of the proposed feature extraction methods is compared using all channels and using the least possible number of channels. It is observed that the proposed CSP-variance feature can perform the desired classification task with 100% accuracy even when only two trials are used to train KNN classifier and testing is done in LOO technique. Moreover, if the computation time of the two proposed methods to perform a testing task is compared, it is observed that CSP-variance takes lower time than that taken by gamma-RC method. In fact, CSP-variance requires the lowest time when only 11-channels obtained under weighted scoring scheme are used.

Chapter 6

Conclusion

6.1 Concluding Remarks

In this thesis, five different neurophysiologically significant ways to reduce the number of channels used in the collection of EEG signals for a particular purpose are presented. Neurophysiologically significant ways are better compared to those obtained by complex algorithm because these methods are superior in preserving strong and consistent feature property and can perform very well during the classification task. Furthermore, very simple feature with small dimension and simple classifier are capable to perform the classification task very accurately in a very short time with less complexity. Next, reflection coefficient-based feature extraction technique is proposed where gamma band VEP is to be extracted first and then modeled using AR process. Classification performance is examined by varying AR model order, classifier and validation technique, and using reduced channel domain. Using the reflection coefficient feature some more channels are reduced and 11 channels are identified as the optimum number of channels which have neurophysiological significance, for the current classification task. Finally, another method of feature extraction and classification is proposed where the variance of each spatial filtered EEG channel is used as feature for classification. Since, 100% accuracy is obtained by using only 11 channels, sorted out in weighted scoring method, this method of channel selection is claimed to be the most efficient one in classifying the two groups of people in terms of number of channels, time length of computation and number of trials required while maintaining the same or better accuracy obtained by using all channels. Under match stimulus, better and consistent accuracy is obtained. Leave one out cross validation technique and K-nearest neighbor classifier are proposed to be the best combination for this task. Apart from the efficient channel selection, feature extraction and classification schemes proposed in this thesis, two more propositions are made. One is the brain functions that occur when a person is exposed to visual stimuli and another is that when EEG-based classification is to be performed, the entire process can be more efficient and effective if the subjects are engaged in some form of mental and cognitive task while observing visual stimuli rather than just visually stimulated. This is because, in almost all of the cases analyzed in the study, better results are achieved in match and no-match conditions than that obtained when the subjects were exposed to single visual cue.

6.2 Contribution of the Thesis

The major contributions of this work are summarized below:

One of the major contributions of this work is to deduce a neurophysiologically significant channel reduction technique useful for collection and analysis of the EEG signal for classification. Five different channel reduction and selection schemes are proposed namely: lobe-based scheme, cortical function-based scheme, hemispheric lateralization-based scheme, Brodmann's localization theory-based scheme and weighted scoring-based scheme. The lobe-based scheme uses 17 frontal, 14 central, 10 parietal, 8 occipital and 12 temporal channels. The cortical function-based scheme sorts out 36 channels whereas, hemispheric lateralization yields 29 channels. Later on, through Brodmann's localization theory-based scheme, 16 channels and by implementing weighted scoring method, another 16 set of channels are proposed. It is shown that weighted scoring method that considers not only the tasks related to the observation, perception, recognition and recall of visual stimuli but also takes into account the other ongoing background activities alongside the effect of nearby functional areas of a specific brain area, yields in the reduced channel set of 16 from 61, and the channels can result in classification accuracy of nearly 100% under all three stimuli paradigm. It is noteworthy that, classification accuracy using this reduced channel set is equal or even better than those using all the channels for all three stimuli conditions.

Next, reflection coefficient-based feature extraction scheme is proposed for analysis and classification purpose. Reflection coefficient of a 5th order AR model is used as feature and its performance analysis is done under different model order, different classifier and validation technique, and under the reduced set of channels. By analyzing the reflection coefficient property, channels can be reduced further by two in Brodmann's localization method and five in weighted scoring method resulting in the final channel number to be only 14 and 11 respectively. These channel sets, specially the one derived by weighted scoring method, provide better classification accuracy than using all the channels.

Variance of spatially filtered EEG is proposed as a simplistic feature to distinguish alcoholic from healthy individual. Use of spatial filtering in this database is not reported so far. This method is found to yield better accuracy than reflection coefficient-based feature extraction scheme. The most important point is that feature dimension is only 1×61 if all channels are used while the dimension is only 1×11 if the reduced channel set is used. Variance of spatially filtered EEG of alcoholic and control is such a strong discriminating information bearing feature, that 100% accuracy in achieved by using both all 61 channels and only 11 channels under all three visual cues. Thus, these 11 channels sorted out by weighted scoring method, electrical signal pattern and its feature properties, and neurophysiologic knowledge are the optimum channels. On the other hand, variance of spatially filtered EEG is explored as the simplest feature that yields the best classification accuracy. The optimum channels and the feature extraction scheme work well even when number of trials is reduced to as low as two. To ensure the maximum performance of the feature extraction and classification schemes, match stimulus condition and KNN-LOO classifier are proposed to be used.

Reflection-coefficient of gamma band VEP can perform the classification task in very short time. Variance of spatial filtered EEG takes the lowest time while ensuring 100% accuracy. Hence, the proposed channel reduction, feature extraction and classification schemes are efficient in the analysis of cognitive and mental task-based EEG because they utilize small feature dimension, simple technique and less time, and thus, reduce complexity of the entire process.

The proposed channel reduction, feature extraction and classification techniques can significantly help physicians in diagnosis and treatment of different brain-related disorders that cause mental and cognitive impairment e.g. delirium, dementia, autism, Alzheimer's disease, attention deficit hyperactivity disorder (ADHD), agnosia, etc. The selection of relevant activities and their weight open the door for extensive research since the relevance of the actions are highly dependent on the type of stimuli used for investigation and data collection. For example, in the case of Alzheimer's disease the memory related tasks have lot more significance than they have in any other disorders. In delirium, consciousness plays a noteworthy role for which selection of particular active locations of the brain can be very challenging. Furthermore, the type of evoked potential may not only be visual, rather it may be auditory, somatosensory and the like to observe the impact of disorder in different neurophysiological response. Thus, the research can be extended to many such fields. For analysis purpose alcoholic database is used in this research since alcoholics are proved to have mental and cognitive impairment even after a period of abstinence. However, the scope of the work is not confined to solely alcoholic study.

Any other brain-related disorders can be detected by using the EEG obtained from the proposed reduced set of channels if the disorders lead to mental and cognitive impairment of the subject. One instance may be the error or defect detection process of products in the factory like hardware manufacturing factory. After microchips are prepared, they pass on a conveyor belt and if any defect is there in any chip, it is displayed in a screen and an alarm is rung. The respective personnel in charge of the rectification of the defect, gets the idea about the location of the defect from the screen and takes necessary steps. Mental and cognitive soundness is essential in such cases. For the recruitment purpose of such jobs, fitness of the candidates can be examined by the proposed schemes. Moreover, the proposed methods can be used to identify the weak locations of the brain for implantation.

6.3 Scope for Future Work

In this thesis, some channel reduction and selection techniques, different from the conventional approaches are proposed. Of which, weighted scoring method is found to be the most effective one. Moreover, two efficient feature extraction and classification schemes for classifying alcoholics from healthy individuals are developed. However, there are some scope for future research. The similar channel reduction and selection technique can be applied to other applications of EEG-based systems, such as Brain Computer Interface, classification of motor imagery task, fatigue and non-fatigue condition, drowsiness etc. On the other hand, just changing the weights of the brain functions related to activities, that differ from the proposed activities in this study, another reduced set of channels having biological correspondence to those activities can be derived. For motor imagery or BCI, another different set of activities and actions will be more relevant to the tasks performed by the individuals that may or may not include the 34 different actions proposed by this work for mental and cognitive tasks. For instance, sense of fingers, sense of body, move hands, move mouth and tongue, muscle imagery, coordinate hands, start moves, imagined moves and many such activities will be more relevant and get higher weights as compared to object naming, same or different, error detection, stereopsis, perceptual priming, monitor color and shape, picture memory as proposed in visual cue based perception and cognitive tasks in the current study. Nevertheless, if visual cue is utilized for initiations of motor imagery-based hand or leg movement, then activities like eye movement, saccades, action planning, visual attention, visual memory, visual discrimination, visual categorization, eye guidance will play role as they are playing in the current work.

Moreover, the channel reduction, feature extraction and classification technique can be integrated to a Graphical User Interface (GUI) to implement a clinical decision support system (DSS) that will instantaneously differentiate alcoholic and uninfluenced people and help in the diagnosis of changes in functional behavior of alcoholic persons. In addition, such a system can help rehabilitation centers in getting to know about the subjects. Furthermore, a Computer-Aided Diagnosis (CAD) system can be implemented to recognize normal and alcoholic EEG pattern and generate automated diagnostic suggestions to any alcohol-related disorders.

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