ANALYSIS OF IMPACT OF ALCOHOL ON BRAIN'S ACTIVITY

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Analysis of Impact of Alcohol on Brain's Activity

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ABSTRACT

Electroencephalography is an electrophysiological monitoring process to capture electrical activity on the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain underneath. It is typically non-invasive, with the electrodes placed along the scalp. Computer programs in different programming language such as MATLAB, Python are used to simulate and study brain signals. This thesis focuses on utilizing Python, an open-source programming language to understand the impact of alcohol on one's memory and attention and comparing them with non-alcoholic brain. To carry out this research, we are using open-source EEG data collected from alcoholic and non-alcoholic subjects subjected to visual stimuli. Experiments are carried out to observe spatial patterns related to both groups' brain activity and their association with different region of brain such as memory, attention, somatosensory, and emotional regulation regions. Besides the spatial pattern, we are also focusing to find source signals and their association with respect to attention region to understand the impact of alcohol on one's attention function. Finally, the optimal sources based on optimal alpha and gamma rhythms are estimated. For these optimal source channels, we estimated time-frequency based spectrogram to understand the association of other band powers for both groups. Beta power activities from these spectrograms are analyzed for both groups to understand attention-deficit caused by alcohol consumption. By analyzing the results from the experiments can help us understand the impact of alcohol on one's brain's activity.

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Chapter 1

Introduction

A. Motivation

The brain is the most complex organ in the human body. It produces our every thought, action, memory, feeling and experience of the world. The complexity of the connectivity between these cells is mind-boggling. Each neuron can contact thousands or even hundreds of thousands of others, via tiny structures called synapses. Our brains form a billion new connections for every second of our lives. The pattern and strength of the connections is constantly changing, and no two brains are alike. It is in these changing connections that memories are stored, habits learned, and personalities shaped, by reinforcing certain patterns of brain activity, and losing others. The neurons in our brains communicate in a variety of ways. Signals pass between them by the release and capture of neurotransmitter and neuromodulator chemicals. Within individual neurons, signals are formed by electrochemical pulses. Collectively, this electrical activity can be detected outside the scalp by an electroencephalogram (EEG). These signals have wave-like patterns, which scientists classify from alpha (common while we are relaxing or sleeping), through to gamma (active thought). When this activity goes out of the normal, it is called a seizure or brain disease. For centuries, scientists and philosophers have been fascinated by the brain, but until recently they viewed the brain as nearly difficult to understand due to its complex mechanism. Now, however, many researchers are continuing their research to relinquish brain's secrets.

Brain's mechanisms can be affected by several reasons. It could be due to diet, sleep patterns, alcohol consumption, stress, excitement, or any kind of emotions. In this research we are focusing on the impact of alcohol on human brain and are comparing their activity to a non-alcoholic brain to find the difference in terms of the higher activity regions and other brain functions such as attention. Cognitive effects of alcohol use may include memory loss, problems with learning, dementia, and severely hindered mental functioning in most severe cases. People may experience improved social interaction or general feelings of well-being with moderate alcohol consumption. But it is important to understand that alcohol use can pose a risk to someone's mental health, overall mood, and daily cognitive functioning due to its impact on brain chemicals. However, it is hard to say anything strictly due to complex activity of our brains which varies from one person to another. In this research we are analyzing alcoholic and non-alcoholic EEG data using Python programming language.

In this work, our initial investigation includes scalp level analysis and statistical analysis of the dataset. In initial investigation we analyzed both alcoholic and non-alcoholic dataset to find difference between them. Our primary goal was to analyze EEG Source activity for both groups and finding the optimal sources based on certain criteria. The main goal of this work can be divided in to four sub activities: (i) Preprocessing of EEG data (ii) Finding EEG sources with maximum activity region (iii) Computing optimal sources and their associated channels based on NSGA-II (iv) Evaluating optimal source power (alpha, beta, and gamma power) and scalogram. As part of preprocessing, we centered our data by applying band pass filter and scale them. We applied common spatial filter to find the sources of brain activity. Then we applied NSGA-II, a probabilistic approach to compute optimal sources and their respective optimal channels. Then,

we computed the optimal source powers (alpha, beta, and gamma band powers) and scalograms of them to understand activity on source level for both groups.

B. Problem Statement and Objective

The problem addressed in this thesis concerns with the impact of alcohol on human brain. To assess this, the brain signals of alcoholic and non-alcoholic persons are measured when they are subjected to visual stimuli. Both groups are subjected to three different visual stimuli. In one stimulus they were shown a single image and in other two they were shown two images in both matching and non-matching way. While subjected to stimuli, their EEG data were captured. We are utilizing this EEG data to assess memory, attention, and other brain's executive functions for both groups and assessing these functions' association with respect to both groups. By comparing the signals of both groups, we can understand the impact of alcohol on one's brains cognitive functions. Figure. 1.1 shows an overview of application setup to analyze the brain signals. Brain signals that arise due to different thoughts are captured in open BCI devices. Then the data can be transformed from the EEG devices to our computer to analyze them. The analysis can be done in different programming languages. Here we are using open-source python programming language to develop small modules to achieve our objective. Figure. 1.2 shows an overview of the steps to estimate sources of EEG signals of alcoholic and non-alcoholic subjects and computation of optimal sources based on optimal alpha and gamma powers.

The three main problems addressed in this thesis are as follows:

1. To find EEG sources for both groups' alcoholic and non-alcoholic subjects.

2. Analyze the association of these sources with different emotions such as attention, memory, and executive functions based on brain regions.
3. To find optimal EEG sources based on certain criteria such as optimal alpha and gamma rhythm using Non-domination Based Genetic Algorithm (NSGA-II) for multi- objective optimization.

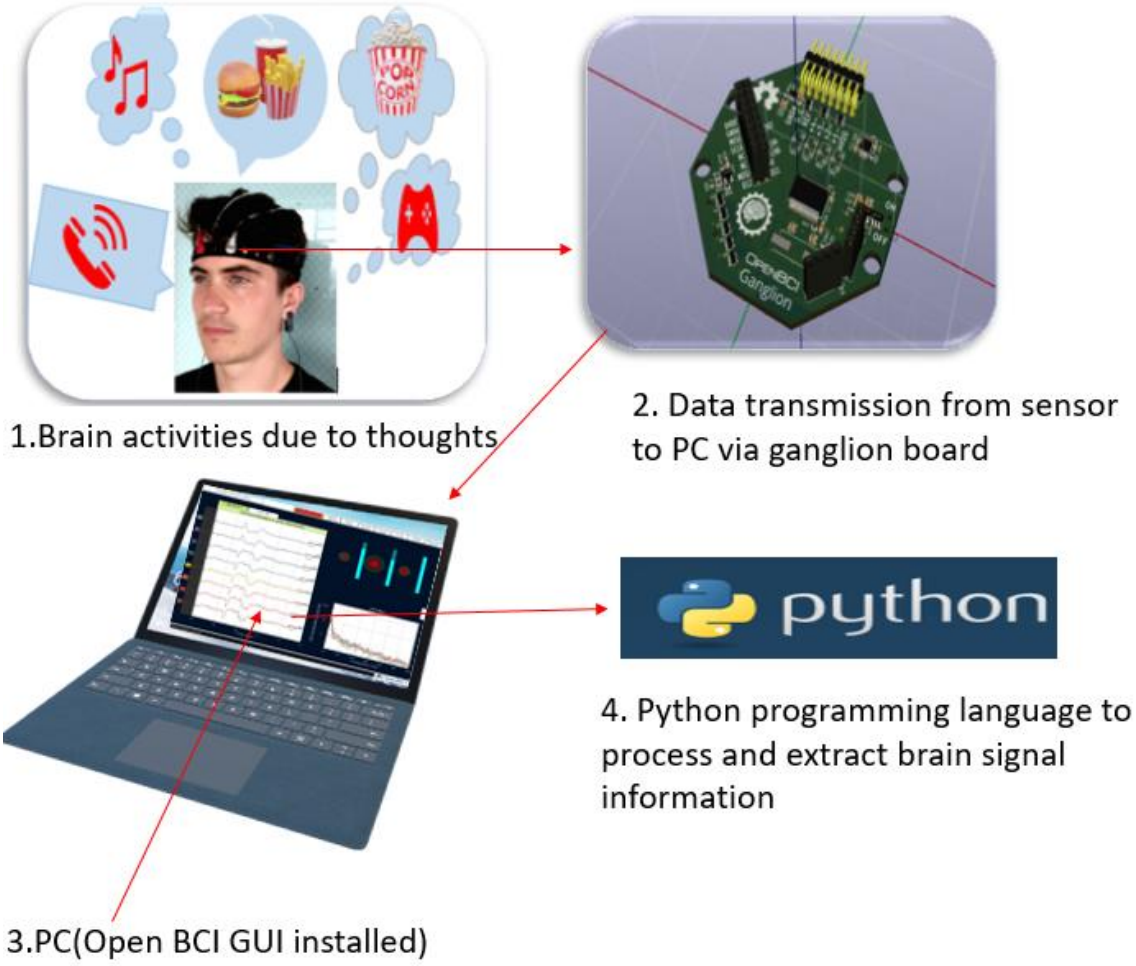

Figure 1.1 Overview of Application setup

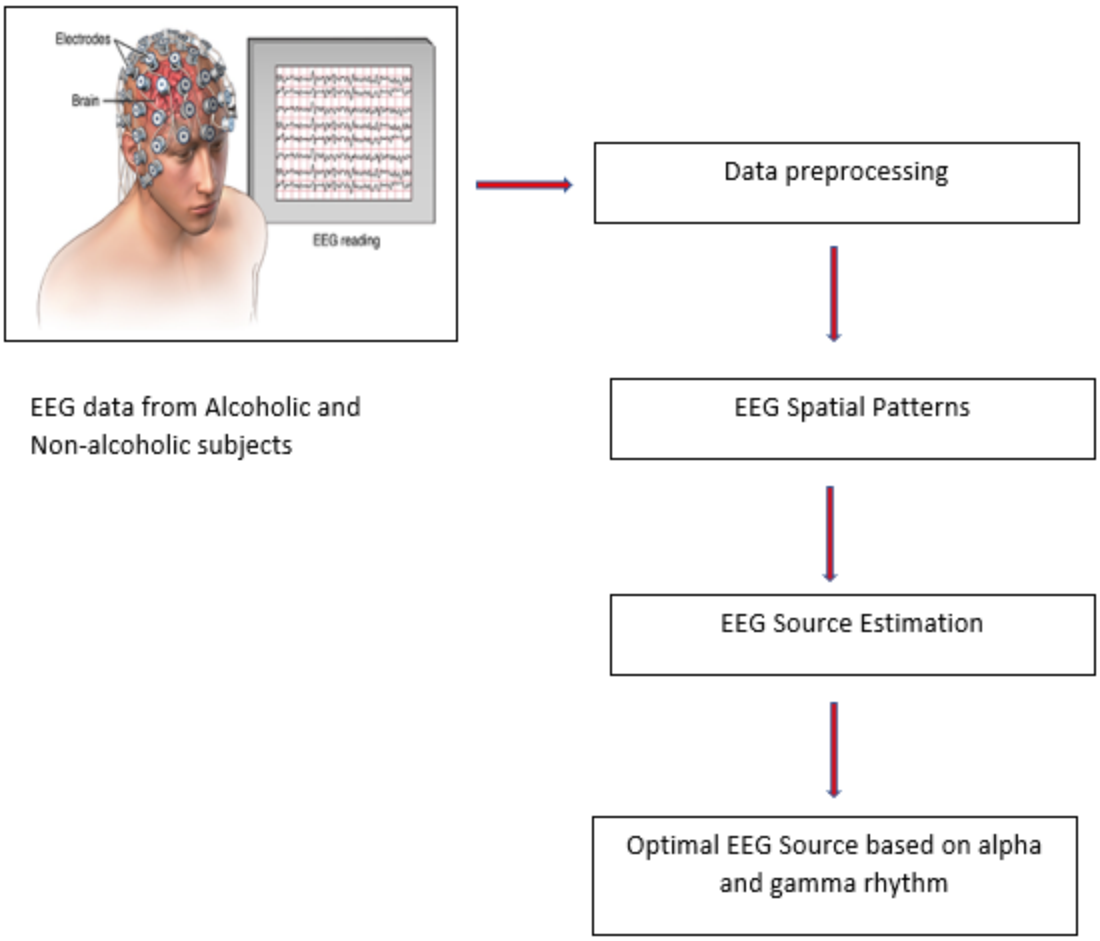

Figure 1.2 Overview of EEG Signal Processing

C. Thesis Organization

The remaining of thesis organization is as follows. Chapter 2 provides the background study of the topics covered in this thesis. Chapter 3 investigates the difference in scalp activity in both groups based on some visual and statistical analysis. Chapter 4 finds the source activity and spatial patterns associated with each group. Chapter 5 evaluates the optimal EEG sources based on optimal alpha and gamma rhythm using NSGA-II for both the groups. In this chapter we also

find the optimal channels based on these optimal powers and analyzed the association of beta power for both groups. Apart from this we computed scalogram of the optimal sources to do a time-frequency analysis of them. Chapter 6 summarizes conclusion and suggests possible future works.

Chapter 2

Literature Review

A. Introduction:

Analysis of electroencephalogram (EEG) signals is essential because it is an efficient method to diagnose neurological brain disorders. In this work, a single system is developed to diagnose neurological disorders related to alcoholism based on the association of activity of sources to different regions of brain. The association was found by estimating EEG source activity of alcoholic and non-alcoholic group and projecting them to different brain region based on the channel's coordinates. Later their association to different brain regions such as attention region, memory region, somatosensory region is compared between two groups. By doing above we found the maximum source activity regions for both groups. This chapter gives a brief background introduction to the field of studies that are applied in this thesis to understand the effect of alcohol on human brain. The discussion then moves forward to the scalp level analysis of alcoholic signals and comparing them with non-alcoholic signals. Later there is a brief analysis about source signals of alcoholic and nonalcoholic and the association of source activity with respect to different functional regions of brain. Then, the optimal source activities are found based on alpha and gamma rhythms. The EEG spectrogram feature is estimated from the optimal EEG sources. For this purpose, EEG time-frequency feature-extraction techniques are investigated to aid in the accurate diagnosis of neurological brain disorders associated with both groups.

B. Impact of Alcohol (Psychiatric Problems):

The use of alcohol is widespread among people of all ages and socioeconomic groups. Alcoholism and chronic use of alcohol are associated with numerous medical, and psychiatric problems. Alcohol has a profound effect on the complex structures of the brain. It blocks chemical signals between brain cells, leading to the common immediate symptoms of intoxication, including impulsive behavior, poor memory, lack of attention, and slowed reflexes. Excessive alcohol consumption causes brain damage, as evidenced by brain imaging, and related neurologic deficits, including impairments in working memory, cognitive processing of emotional signals, and executive functions [CAR 2007]. Another type of alcohol usage disorder is called fetal alcohol spectrum disorders. In this case alcohol usage in offspring is linked with paternal exposure to alcohol that can induce abnormal behavior in the offspring. In fetal alcohol spectrum disorders, it is found that alcohol usage can lead to sensorimotor integration deficits at P20, and decreased balance, coordination, and short-term motor learning at P30 [CON 2019]. This study was done on a group of mice where male mice were exposed to alcohol prior to conception. Following mating, researchers examined the effects of preconception paternal on offspring neocortical development at postnatal day (P) 0 and evaluated several aspects of behavior at both P20 and P30. One of the studies have explored that alcohol usage can impact the morphology of the brain which can in turn change different functions of brain [ROL 2020]. Another group of researchers studied the impact of alcohol on brain morphology in a large group of cognitively intact people. White and gray matter volumes were compared by magnetic resonance imaging (MRI). No differences in MRI white or gray matter volumes were found between alcohol users and non-users [PRE 2014]. Some other factors to be considered to analyze the impact of alcohol are the age of the person and amount of alcohol consumption. Few researchers mentioned that heavy drinking has been shown to affect the

neuropsychological performance (e.g., memory functions) of young people and may impair the growth and integrity of certain brain structures. Their research findings suggest that more enduring heavy-drinking patterns in adolescents and young adults are linked to smaller hippocampi and, because these brain structures are critical to learning and memory formation, may lead to more severe impairment of memory function [TAP 2004]. One of the effects of consuming alcohol is that the brain releases a signaling molecule (i.e., a neurotransmitter) called dopamine in a brain region known as the nucleus accumbens. Dopamine release activates the nucleus accumbens, which in turn stimulates the brain's reward system and triggers the desire for further positive stimulation, resulting in more alcohol use. Eventually, alcohol-related dopamine release may result in changes in brain development that lead to sensitization. This process also occurs in older people but may be accelerated when it occurs in conjunction with the normal developmental changes in adolescents [TAP 2004].

C. Working Memory and Attentiveness:

Some of the researchers investigate a study in which Magnetic Resonance Imaging (MRI) is combined with Electroencephalography (EEG) to examine working memory. The MRI provides a three-dimensional depiction of the structure of the brain and presents a natural spatial organization for the EEG sensors. Working memory is generally thought of as the neural assemblies governing short-term retention of information and the integration of this data into the executive decision-making process. They assessed working memory performance by measuring changes to the energy densities, phase relationships, and frequency shifts in the alpha band of frequencies (7-13 Hz) located in prefrontal cortex. They transformed the time series gathered from EEG sensors in specific locations into Fourier-based representations. They estimated spectral power at the alpha band of frequencies (7–13Hz) across the entire cortical surface and analyzed

the time-frequency representation of each sensor's data [SIL 2010]. Few of the researchers found association of higher alpha activity with attentiveness, and mindfulness in prefrontal cortex, fronto-central and centro-parietal regions [JAI 2019].

D. Techniques to Assess EEG Signal:

1. Fast Fourier Transform (FFT):

Some researchers used Fast Fourier Transform (FFT) and other parametric techniques to classify alcoholic and control subjects' activity [ACA 2005]. In this paper, a second order autoregressive (AR) model is proposed to discriminate alcoholics using gamma band Visual Evoked Potential (VEP) signals. A visual evoked potential is an evoked potential caused by a visual stimulus, such as an alternating checkerboard pattern on a computer screen. Most of the alcoholics had been drinking heavily for a minimum of 15 years. The diagnosis of alcohol abuse was made by the intake psychiatrist of the Addictive Disease Hospital in Brooklyn. The alcoholics were significantly older than the controls. After they evaluated AR coefficient, the PSD for each channel was derived and the peak value of the PSD values for all the 64 channels were concatenated into one feature vector that is utilized for classification.

2. Spectral Entropy:

According to some research Spectral entropy can be used as a measure to assess the impact of anesthetic drug that reflects the global changes in neuronal activity at the cortical level [HAN 2005] [OJA 2004]. Few researchers have stated that the problem of analyzing and identifying regions of high discrimination between alcoholics and controls in a multichannel electroencephalogram (EEG) signal is modeled as a feature subset selection technique that can

improve the recognition rate between both groups. Several studies have reported efficient detection of alcoholics by feature extraction and selection in gamma band visual event related potentials (ERP) of a multichannel EEG signal [SHR 2016].

3. Hilbert-Huang Transformation (HHT):

In one of the research papers, a Hilbert-Huang Transformation (HHT)-based time frequency scheme is applied to perform the analysis of clinical alcoholic and normal control FP1 electroencephalogram (EEG) signals. The differences in the responses of the EEG signals are measured as the intrinsic mode function (IMF), instantaneous frequency (IF), marginal frequency (MF), and the Hilbert spectrum to understand the difference between the simulation results of the clinical EEG signals of the alcoholic and control groups. When the clinical EEG signals of the alcoholic and control groups are compared, the EEGs of the control groups did not appear to indicate significantly larger voltage at FP1 EEG signals. The EEG signals of the alcoholic group in the experiment suggested that when they were exposed to the stimulus, brain cells were excited and emitted higher voltage. The researchers deduce that IMFs, IFs, Hilbert Marginal frequency, and Hilbert spectrum analysis of EEG signals of an alcoholic and a normal observers can be done to define an alcoholic illness [LIN 2009].

4. Band Power Analysis:

One of the researches suggested that decreased power in slow bands in alcoholic patients may be an indicator of brain atrophy or chronic brain damage, while increase in beta band is related to family history of alcoholism [COU 2006] . Few of the subjects found decrease in alpha band power. Some of the subjects did not show any abnormality. All patients with decreased delta band power had also decreased theta band power. Beta activity has been previously considered as

indicative of background excitation involving a frequency potentiation mechanism at the synaptic level of the recurrent loops [WHI 1997]. According to another large group of study, decreased frontal alpha has been related to alcohol use disorders [ENO 1999]. They initially utilized dataset of 120 subjects. The experiment was extended later to study a larger set of 149 unrelated individuals from a total sample of 247 subjects for whom psychiatric diagnoses and resting EEG phenotypes were available. They found low alpha power band may be a vulnerability factor for alcohol use disorders and anxiety disorders.

One study shows alcoholic subjects' EEG signal rhythms such as alpha, delta, theta, beta is less complex as compared with the normal subjects' EEG signal rhythms. According to this study, slow neuronal process of alcohol is related to depression. To evaluate the nature of neuronal process, they estimated entropy and negentropy. The entropy in EEG is called as the spectral entropy of the electroencephalogram (EEG) signals. It is a measure of the degree that the power spectrum is uniform. The negentropy can measure the non-Gaussian behavior of the signal. They also evaluated lower discriminative or p-value for each EEG rhythm, a statistical analysis to find discrimination between alcoholic and non-alcoholic groups. They found lesser variability for alcohol EEG rhythms due to less consciousness of alcoholic subjects in responding to different situations [TAR 2018].

Alcoholism is a socio-economical syndrome in which one may lose health and wealth. This paper reports an approach for quick detection of alcoholism using Electroencephalogram (EEG) sensors. The proposed method utilized absolute gamma band power used as a feature and ensemble subspace K-Nearest Neighbors (K-NN) used as a classifier to discriminate between alcoholics and normal subject [BAV 2019]. In this work they have utilized genetic algorithm. Fitness function for this optimization is evaluated using accuracy achieved from K-NN classifier. For this work, only

13 EEG channels is used to find the optimal EEG channels giving higher accuracy. The features estimated for this work are Delta, Theta, Alpha, Beta and Gamma power. For each power band they performed p-value estimation. They found that the gamma power band had discrimination capability [BAV 2019]

Another study was done to find genetic predisposition of subjects to alcohol and compared them with control subjects. A 0.5-g/kg dose of alcohol was administered to high risked (HR) biologic sons of alcoholics and control subjects aged 19 to 21 years. The HR subjects exhibited greater increases of slow alpha energy and greater decreases of fast alpha energy after alcohol administration than controls. This experimental EEG findings suggest that subjects at high risk for alcoholism are physiologically more sensitive to alcohol than control subjects [POL 1983].

One study emphasizes the utility of cognitive neuroscience methods based on EEG gamma band measures for the assessment of the functional outcomes of neurofeedback-based biobehavioral interventions for addicted individuals. This research showed increase in central sensorimotor rhythm (SMR) amplitude and frontal theta in addicted individuals [HOR 2010].

5. Time–Frequency Spectrogram Analysis:

Another group of researchers studied brain disorder called Autism. It is a type of neurodevelopment disorder in which individuals often have difficulties in expressing and controlling emotion. They utilized electroencephalography (EEG) to investigate the presence of autism. Their research aimed to develop an efficient autism diagnostic system that can automatically identify autism based on time–frequency spectrogram images from EEG signals. Firstly, the raw EEG data is pre-processed using several techniques, such as re-referencing, filtering, and normalization. After that, the pre-processed EEG signals are converted to two-

dimensional images using a short-time Fourier transform. These images are analyzed to carry out this research [TAW 2021]. Time–frequency spectrogram analysis is one of the important EEG signal analysis we have utilized in this work to understand the brain activity for both alcoholic and non-alcoholic group.

6. Common Spatial Pattern (CSP):

Some of the researchers have presented Common spatial pattern (CSP) method to analyze spatial patterns related to motor imagery. They classified the electroencephalogram (EEG) patterns of different imagination tasks, e.g., hand and foot movements. In this experiment two healthy subjects sat in a comfortable chair with arms resting. They were presented visual cues on computer screen. During this, subjects were performing three motor imagery tasks: movement of left hand, right hand, and right foot. The EEG data collected from this experiment is then preprocessed and their spatial patterns are analyzed to find maximum activity regions based on absolute activity [WAN 2005]. We have utilized common spatial pattern to find sources and their association with different regions.

Summary

Generally, EEG recordings generate huge volume data with dynamic behavior. In current practice, the massive EEG data are visually analyzed by specialist clinicians to identify brain disorder, which is time consuming, costly, subject to human error, and reduces decision-making reliability. Our goal in contrast, is to develop an application that can utilize python programming to understand the brain disorders associated with individuals consuming alcohol and comparing them with healthy controls. In this work we are analyzing scalp activity as an initial assessment and performing p-value statistical analysis to find out any differences between the two groups.

Later we focus on brain source activity of both groups followed by finding the optimal sources based on genetic algorithms. The genetic algorithm fitness function utilizes optimal alpha and gamma power bands. Upon finding the optimal sources we are estimating spectrogram to discriminate between these two groups. In this chapter, we have given a brief review about previous researchers work to understand the damage caused due to excess use of alcohol on human brain and applied in this thesis to carry out the research further.

Chapter 3

Data Analysis to Investigate Scalp Activity of Alcoholic vs Non-Alcoholic

This chapter explains the data collection process followed by the data preparation process that involves epoching, scaling, and averaging of the datasets to carry out the data analysis. Data analysis is done to investigate scalp activity of alcoholic vs non-alcoholic subjects. To show the experimental results, we have plotted them in different visual formats such as heatmaps, stack bar plots, and 2d-head plots. We also did P-value statistical tests to find the epochs that indicates significant difference between the two groups.

A. Overview of Data Collection

For this work we have utilized the dataset [BEG 1999] which contains measurements from 64 electrodes placed on subject's scalps which were sampled at 256 Hz (3.9-msec epoch) for 1 second. There were two groups of subjects: alcoholic and control. 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 Vander wart picture set [SNO 1980]. 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. There were 122 subjects and each subject completed 120 trials where different stimuli were shown. There are three versions of the EEG data set as small

dataset, large dataset, and full dataset. For this work we are using the large dataset. The large data set contains data for 10 alcoholic and 10 control subjects, with 10 runs per subject per paradigm.

B. Epoching

EEG epoching is a procedure in which specific time-windows are extracted from the continuous EEG signal. Multiple trials are recorded as part of data collection to adhere with EEG data collection practice. Each trial has event-locked (post stimulus) data as well as artifacts (pre stimulus). Below is the explanation of removal of pre-stimulus data to prepare the final dataset.

Given that, the original EEG samples collected per trial are 416 and post stimulus samples per trial are 368.

Hence, pre stimulus samples are 416-368 = 48.

48 pre-stimulus samples removed from the original data to prepare final dataset.

Given that, in final dataset 256 samples (out of 368 post stimulus samples) are kept with epoch time between two samples as 0.0039 second.

Duration of final dataset given is 1 second ($0.0039 \times 256 = 0.9984 \approx 1$)

The samples removed from post-stimulus samples (368 samples):

$= 1.43 (368 \times 0.0039) – 1$

$= 0.43$ seconds

$\approx$ 112 samples excluded of post-stimulus samples containing artifacts to get final data which are sampled at 256Hz for 1 second

C. Averaging data

In our dataset, total number of subjects in each group (alcoholic/control) is 10. each subject has 10 runs per paradigm. For each subject, 10 runs per paradigm are averaged to get average EEG waveform of the event-related potential, which reflects the average EEG activity triggered by a specific stimulus. Averaged data for 10 subjects belonging to each group (alcoholic/control) is shown in figure 3.1.

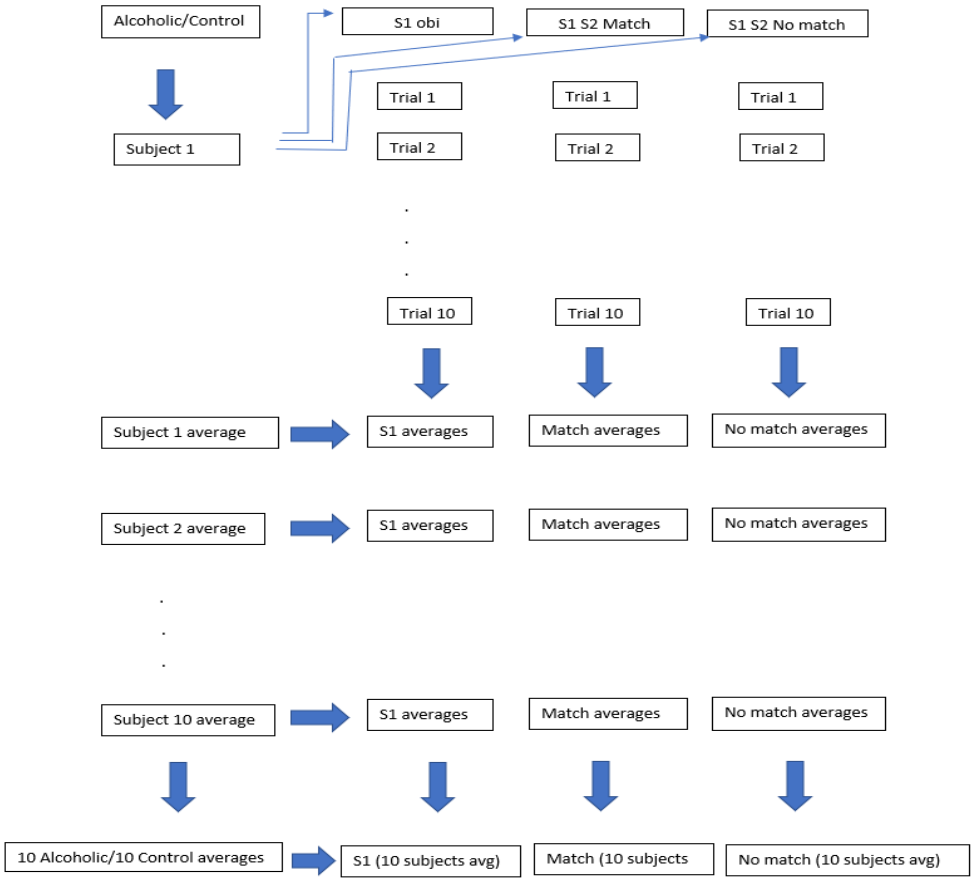

Figure 3.1 Averaged data for 10 subjects (alcoholic/control)

Before taking average of the trials, we scaled the data between -1 to 1 by implementing the algorithm described next. Scaling standardizes the data in a fixed range since the range of values of raw data varies widely. It basically helps to normalize the data within a particular range.

```
1.  function Scale (data, cols)
2.          for each col Є cols
3.                  voltages = data[col]
4.                  max_volt = max(voltages)
5.                  min_volt = min(voltages)
6.                  N = length (voltages)
7.                  For k Є 1 to N
8.                          If  voltagesk > 0
9.                              voltagesk = voltagesk /||max_volt||
10.                         voltagesk = voltagesk /||min_volt||
11.                         data = voltages
```

D. Initial Assessment on averaged data:

We find that the alcohol subjects have higher activities all over the brain regions and the activities are highly oscillatory for the entire period. An activity is a recorded waveform or the electrical activity of the brain from the scalp as shown in Figure 3.2 where the activities of different channels are plotted at different epochs. On the contrary, the control subjects have a pattern where it shows higher activities at the beginning and then, it gradually decreased towards the end of the trial. We also observed that when two images are shown in either matching or non-matching scenario, the alcoholic brain signals are spread on entire brain regions and were higher for the entire time of the experiment, whereas for control subjects the activities were higher at the beginning and slowly reduced towards the end of the experiment showing a stable pattern. Figure 3.2, 3.3 and 3.4 show activity results in three scenarios for one alcoholic subject and one control subject.

The scenarios in the experiment are:

- Scenario 1: one image is shown
- Scenario 2: two matching images are shown
- Scenario 3: two non-matching images are shown

The images are taken from 1980 Snodgrass and Vander wart picture set [SNO 1980].

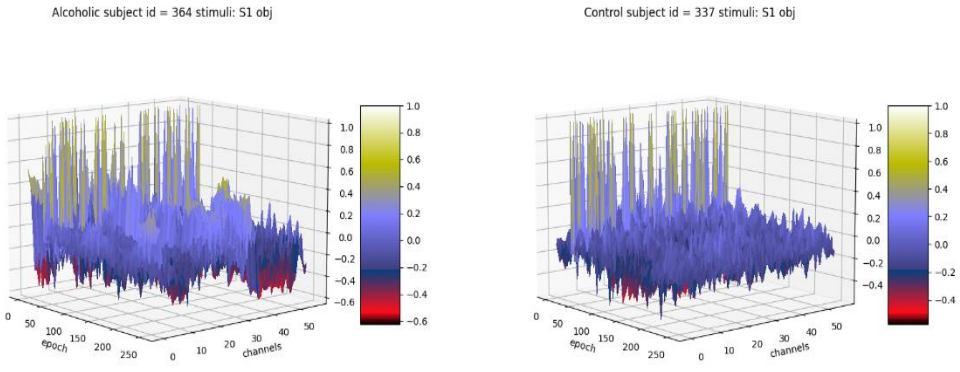

Figure 3.2 Activity of one alcoholic and one control subject shown for stimuli S1(One picture is shown)

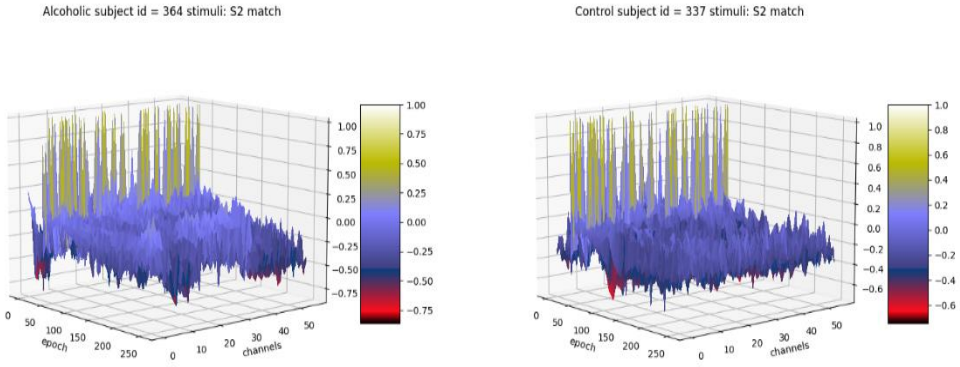

Figure 3.3 Activity of one alcoholic and one control subject shown for matching stimuli (Two matching pictures are shown)

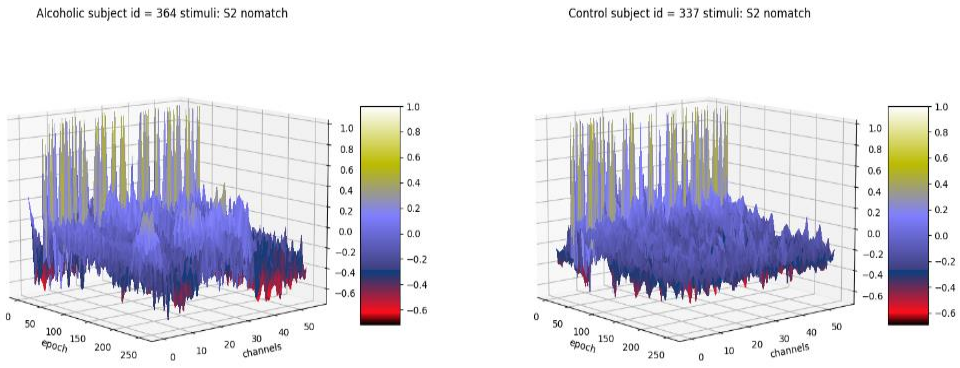

Figure 3.4 Activity of one alcoholic and one control subject shown for nonmatching stimuli (Two nonmatching pictures are shown)

Figure 3.2, 3.3, 3.4 shows electrical activity in response to three different visual stimuli for one alcohol subject and one control subject. In these three figures we find the electrical activities for alcoholic subject with subject id 364 are initially higher followed by either increased or decreased pattern or vice versa for all three paradigms whereas the control subject with subject id 337 shows higher electrical activities in the beginning followed by a decreased pattern for all three scenarios. Similarly, we got the averaged results for ten alcoholic and ten control subjects to do a group level analysis. To get an overall idea about each group, the average activity of ten subjects from each of their respective group is taken and the results are plotted as shown in Figures 3.5, 3.6, and 3.7.

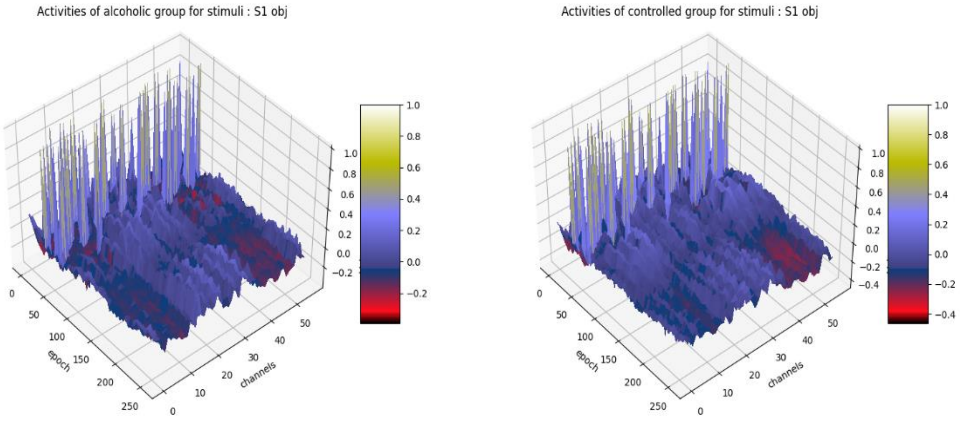

Figure 3.5 Activity of 10 alcoholic and 10 control subjects shown for stimuli S1(One picture is shown)

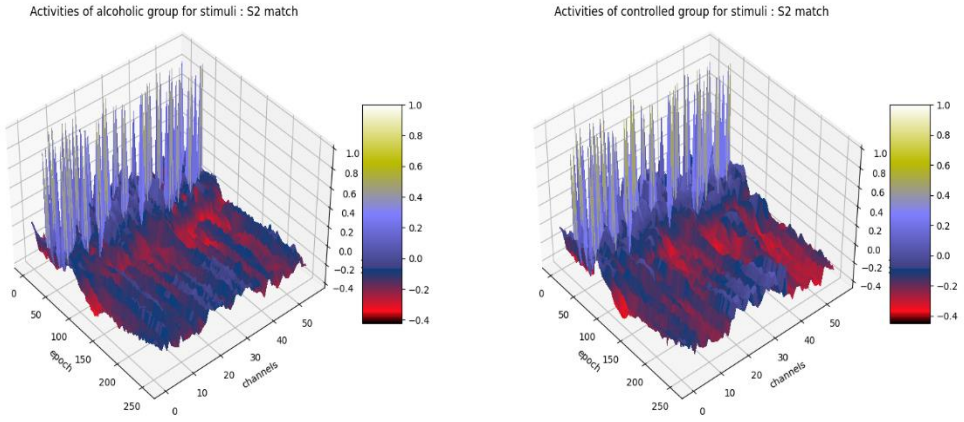

Figure 3.6 Activity of 10 alcoholic and 10 control subjects shown for matching stimuli (Two matching pictures are shown)

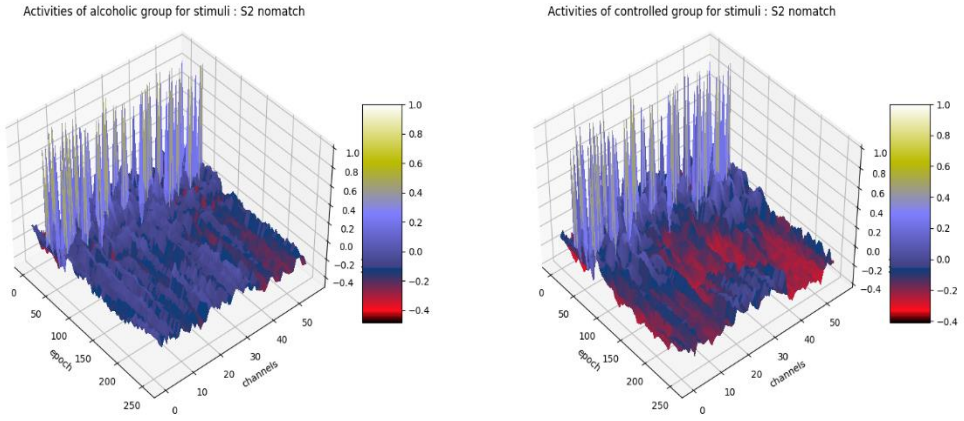

Figure 3.7 Activity of 10 alcoholic and 10 control subjects shown for nonmatching stimuli (Two nonmatching pictures are shown)

From the above Figures 3,5, 3.6, 3.7 we observed that the alcoholic group's electrical activity is spread for the entire period in all three scenarios. Control group shows a particular pattern in all three scenarios. At the beginning of stimuli, we see higher activity that is decreased

gradually towards the end of the stimulus. The alcoholic group does not show any pattern in a single scenario as well as in the other two scenarios.

To find more insight information on these subjects, we plotted heatmaps of averaged data for 10 subjects from each group (for all three scenarios). A heatmap is a graphical representation of data that uses a system of color-coding to represent different values. The primary purpose of heatmaps is to better visualize the events within a dataset. As shown in Figure 3.8 we find stronger positive voltage in alcoholics in comparison with control subject across all three stimuli. We also analyzed individual subjects heatmaps to get an idea at individual level. Two of the individual results are shown in Figure 3.9 and Figure 3.10. By analyzing individual heatmaps we find that alcoholic subjects have higher voltage than control ones. There are few exceptions where few control subjects have higher amplitude than the control. By looking at individual heatmaps we find alcoholic subjects have higher amplitude mostly at the beginning and end of the stimuli whereas control subjects have higher amplitude in between them if we divide entire period of stimuli in to three sections as beginning, middle and end periods. Overall Alcoholic subjects' higher amplitude than control group. These higher values can be due to higher neural excitation in alcoholic group in response to visual stimuli.

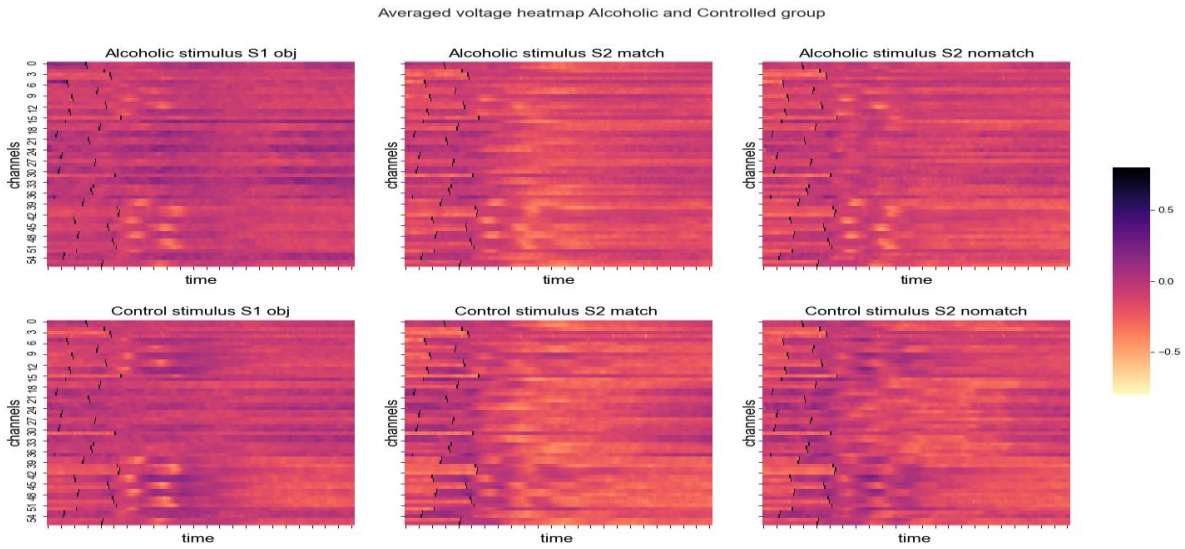

Figure 3.8 Activity comparison between alcoholic and control group using heatmap

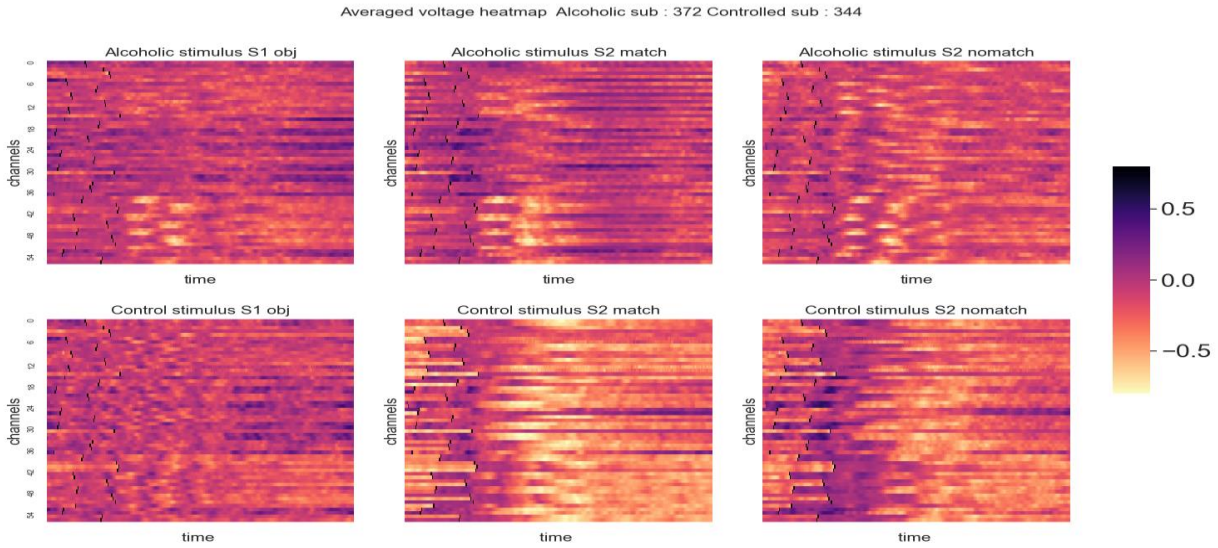

Figure 3.9 Activity comparison between alcoholic and control group using heatmap (one subject from each group)

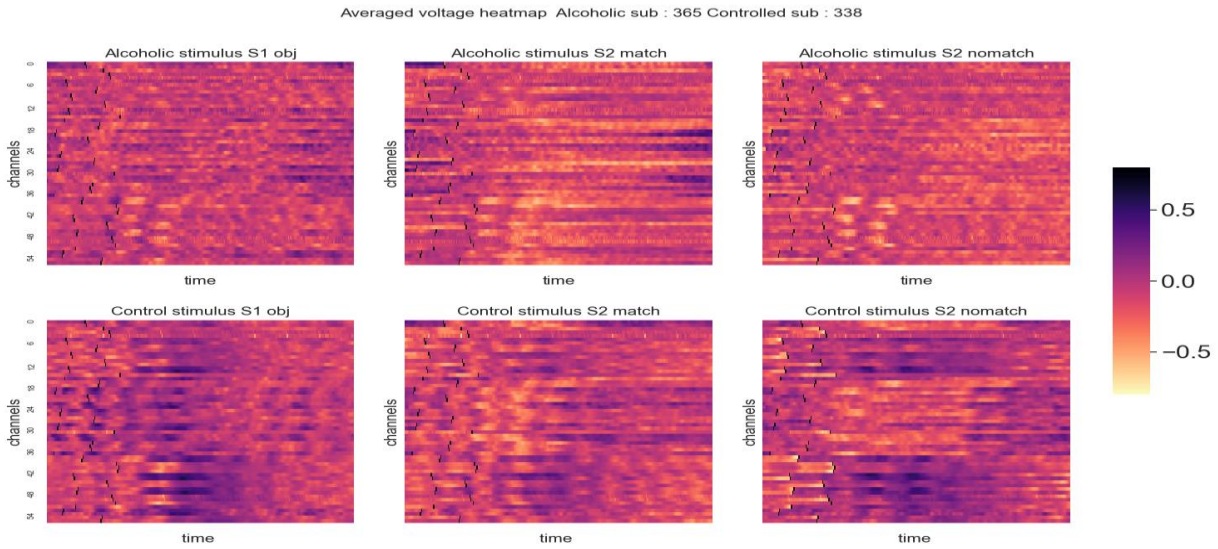

Figure 3.10 Activity comparison between alcoholic and control group using heatmap (one subject from each group)

To compare the EEG activity across the channels between alcoholic and normal individuals we plotted stacked bar plots. For this, average activity for 10 subjects belonging to each group and their respective standard deviations are shown in a single stack bar plot which gives better insight about the activity for both groups. The plots are shown in the Figures 3.11 to 3.16 for single stimuli S1, Figures 3.17 to 3.22 for matching S1 S2 stimuli, and Figures 3.23 to 3.28 for nonmatching S1 S2 stimuli. For instance, in Figure 3.11, blue stacks represent alcoholic group score, and orange stack represents score for control group. The score per stimulus for each channel is the averaged voltage estimated for 10 subjects for each group. Considering a specific channel AFZ to explain further, the value shown at the center of the bars represents average score of their respective group and the value at outside the stack bar represents summed average score of both the groups with respect to the channel. Similarly rest of the stacked bar plots are plotted.

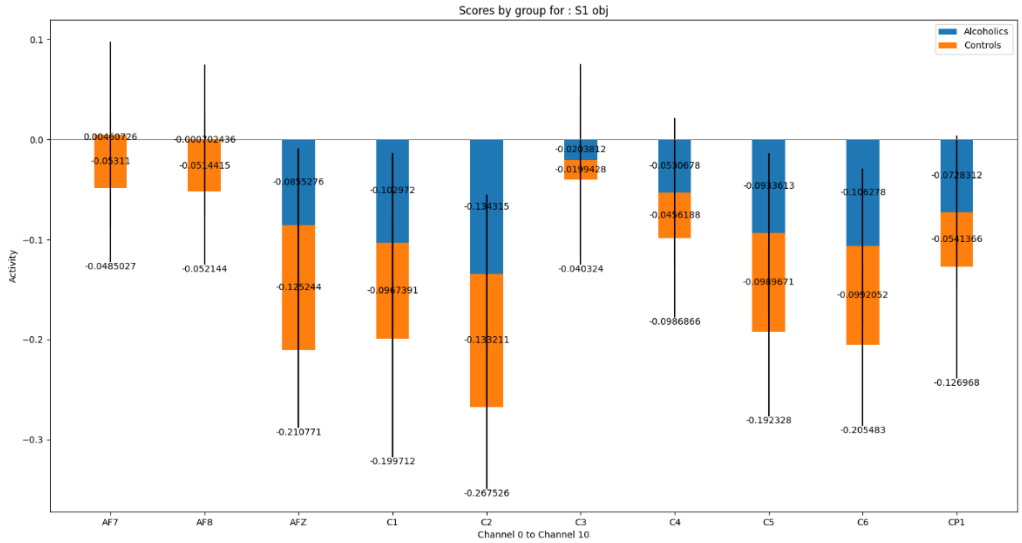

Figure 3.11 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels AF7, AF8, AFZ, C1 -> C6, CP1)

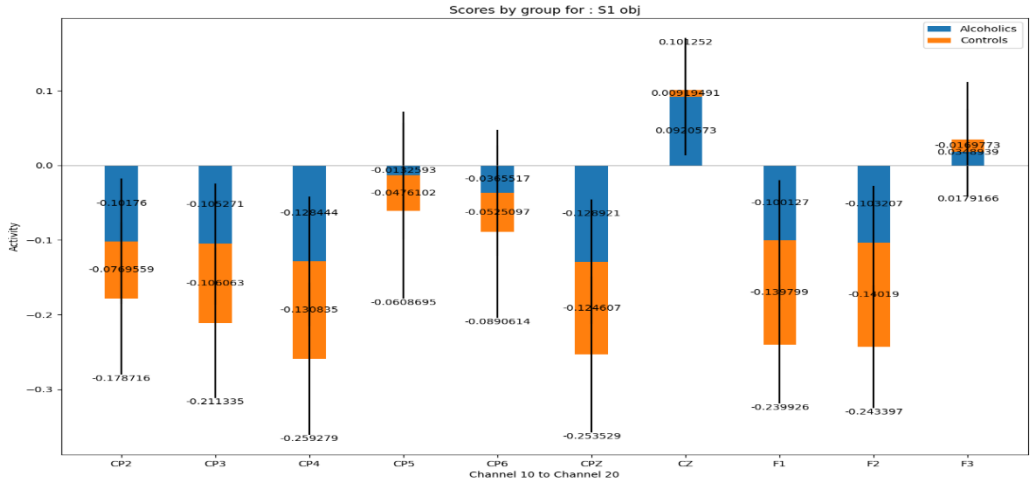

Figure 3.12 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels CP2 ->CP6, CPZ, CZ, F1 -> F3)

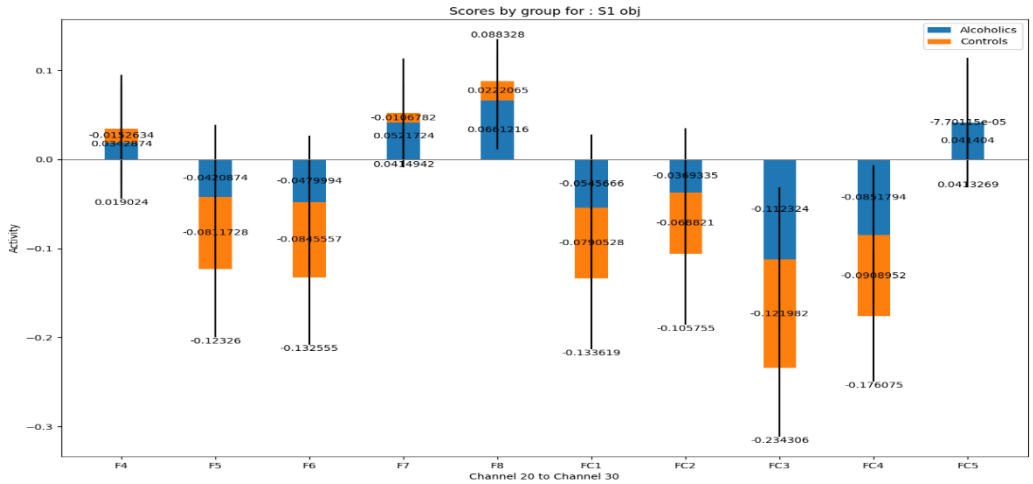

Figure 3.13 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels F4 ->F8, FC1 -> FC5)

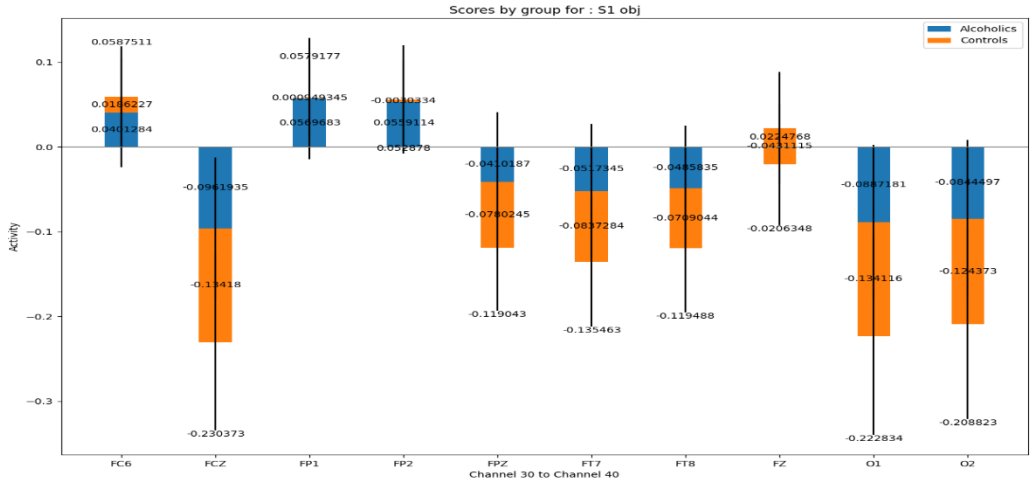

Figure 3.14 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels FC6, FCZ, FP1, FP2, FPZ, FT7, FT8, FZ, O1, O2)

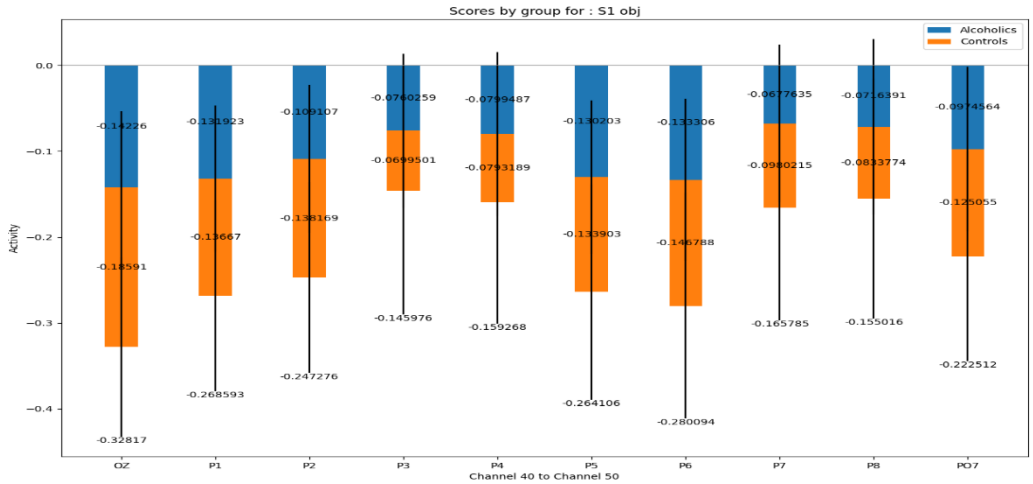

Figure 3.15 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels OZ, P1 ->P8, PO7)

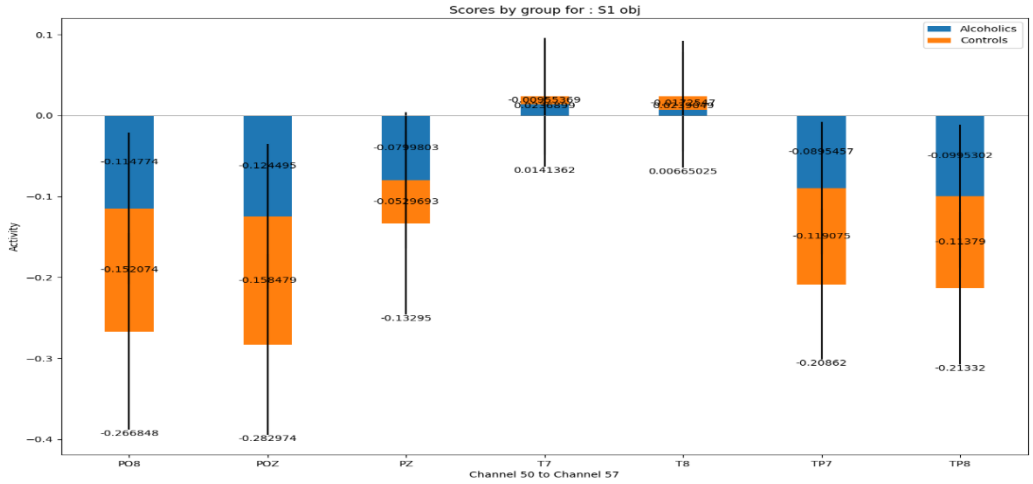

Figure 3.16 Activity comparison between alcoholic and control group using stack bar (S1 stimuli, Channels PO8, POZ, PZ, T7, T8, TP7, TP8)

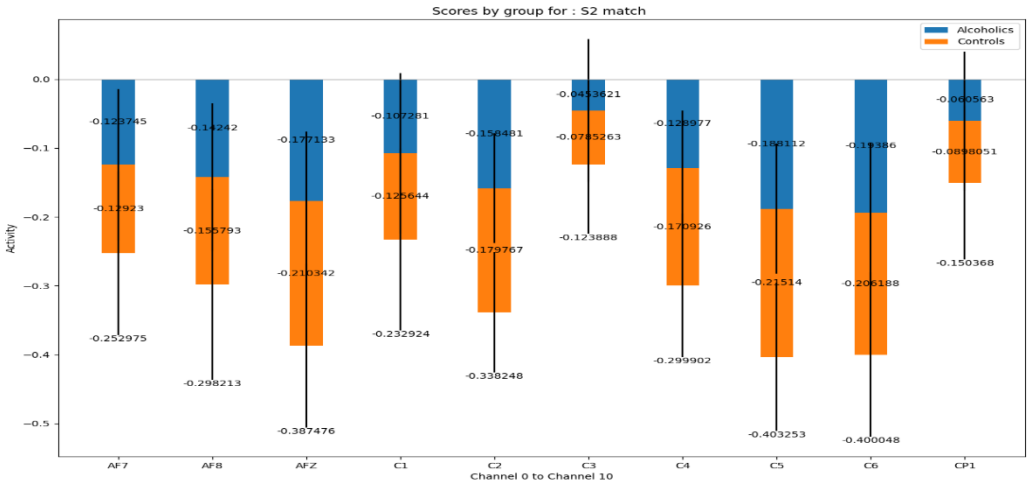

Figure 3.17 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels AF7, AF8, AFZ, C1 -> C6, CP1)

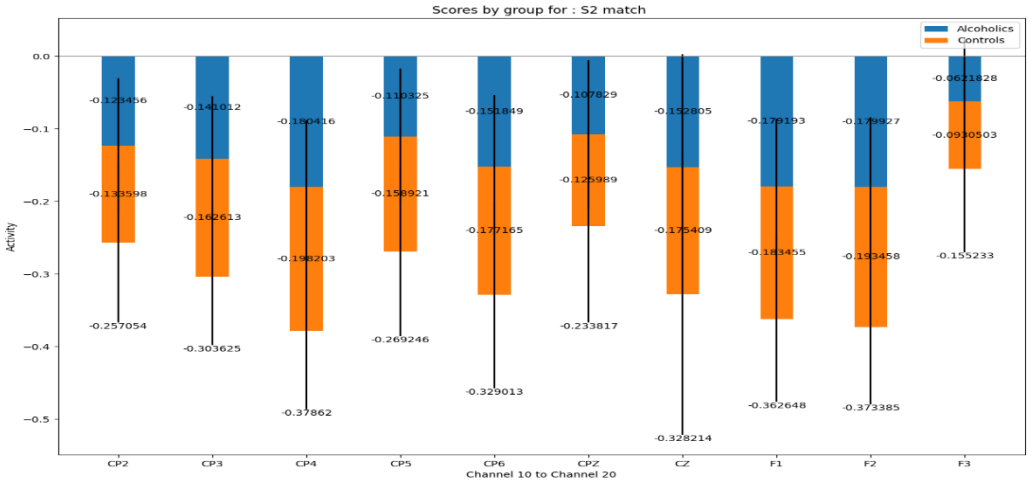

Figure 3.18 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels CP2 ->CP6, CPZ, CZ, F1 -> F3)

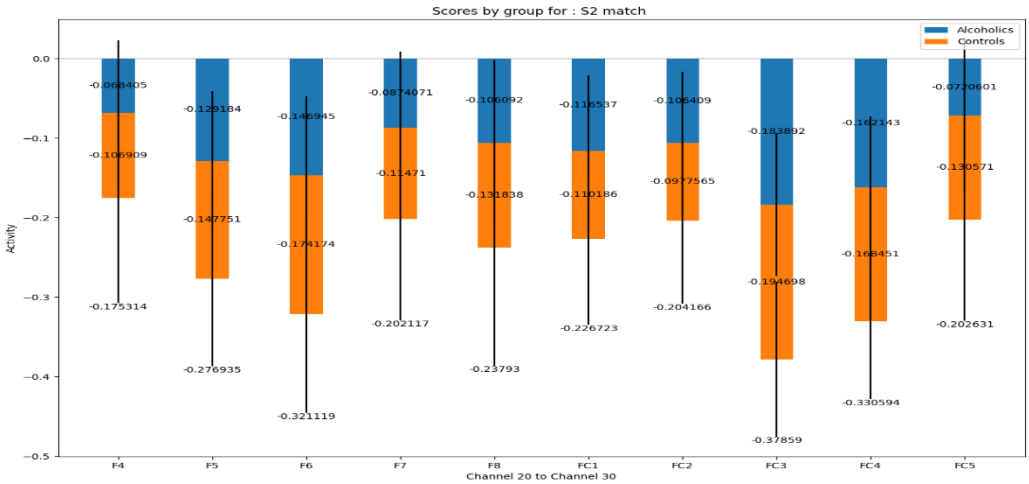

Figure 3.19 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels F4 ->F8, FC1 -> FC5)

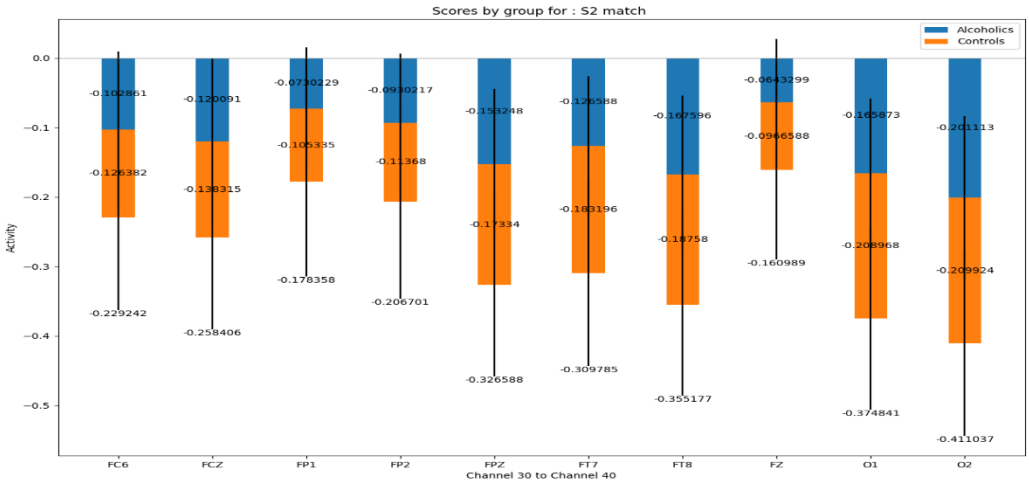

Figure 3.20 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels FC6, FCZ, FP1, FP2, FPZ, FT7, FT8, FZ, O1, O2)

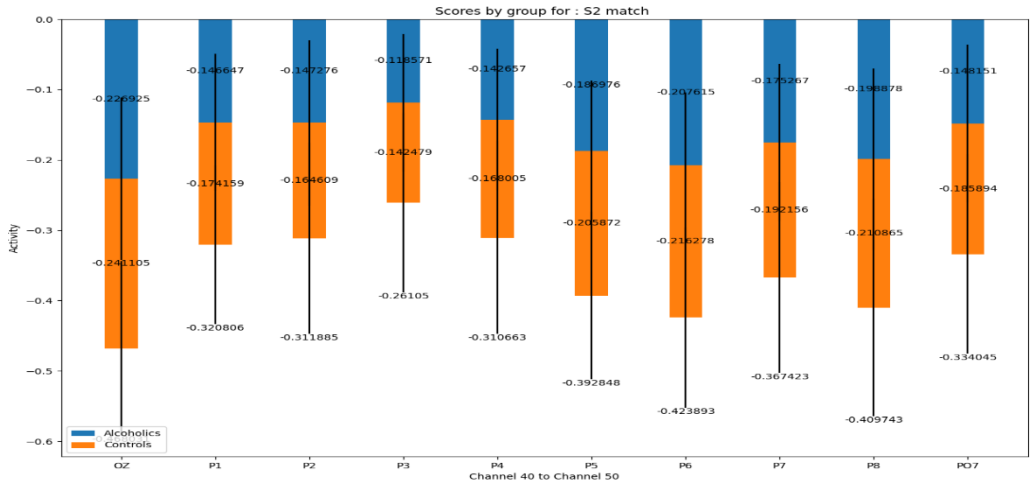

Figure 3.21 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels OZ, P1 -> P8, PO7)

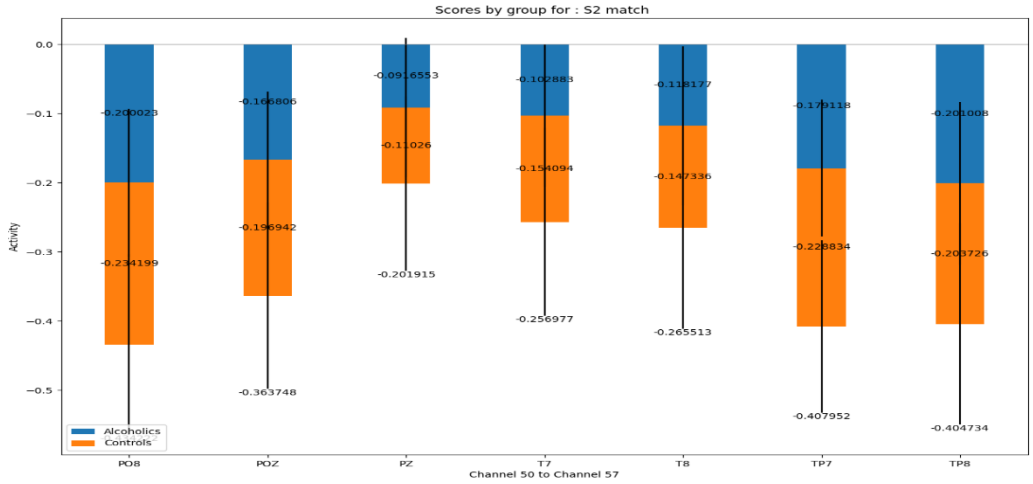

Figure 3.22 Activity comparison between alcoholic and control group using stack bar (S1 S2 match stimuli, Channels PO8, POZ, PZ, T7, T8, TP7, TP8)

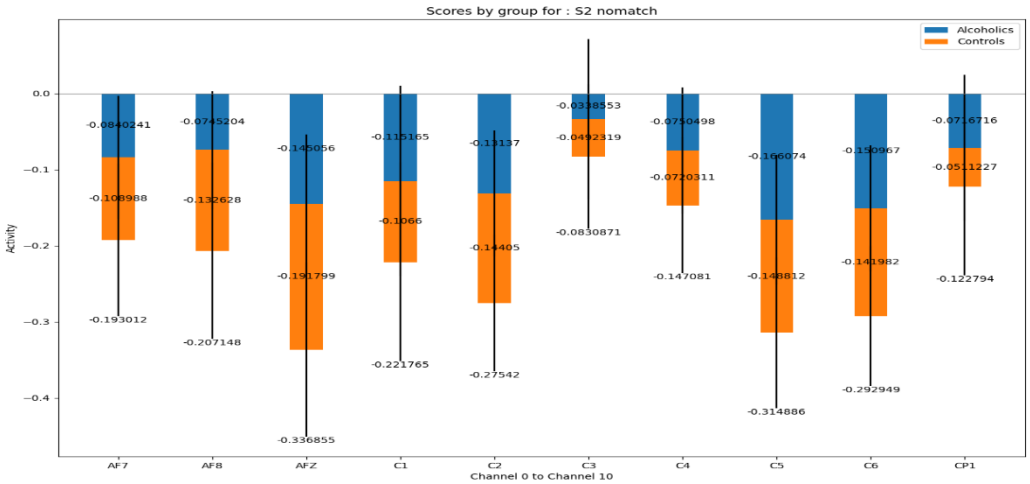

Figure 3.23 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels AF7, AF8, AFZ, C1 -> C6, CP1)

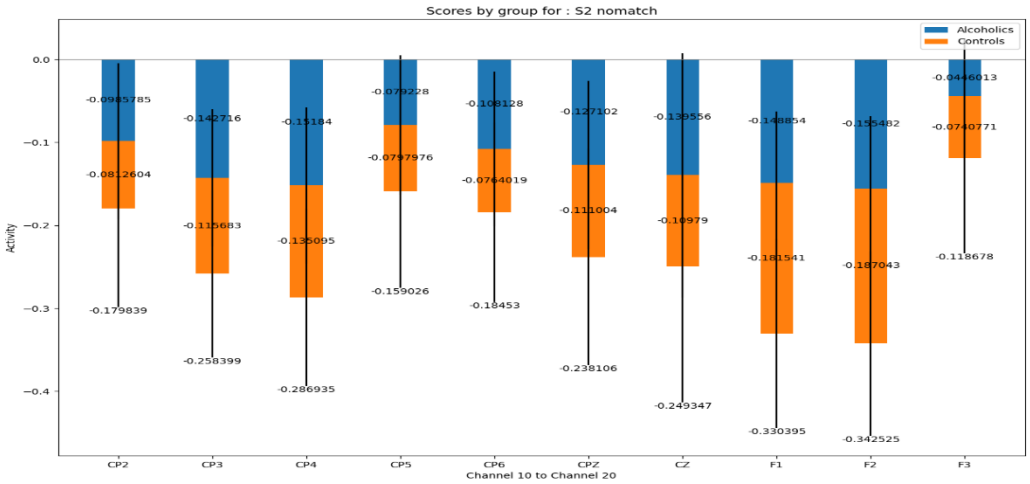

Figure 3.24 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels CP2 ->CP6, CPZ, CZ, F1 -> F3)

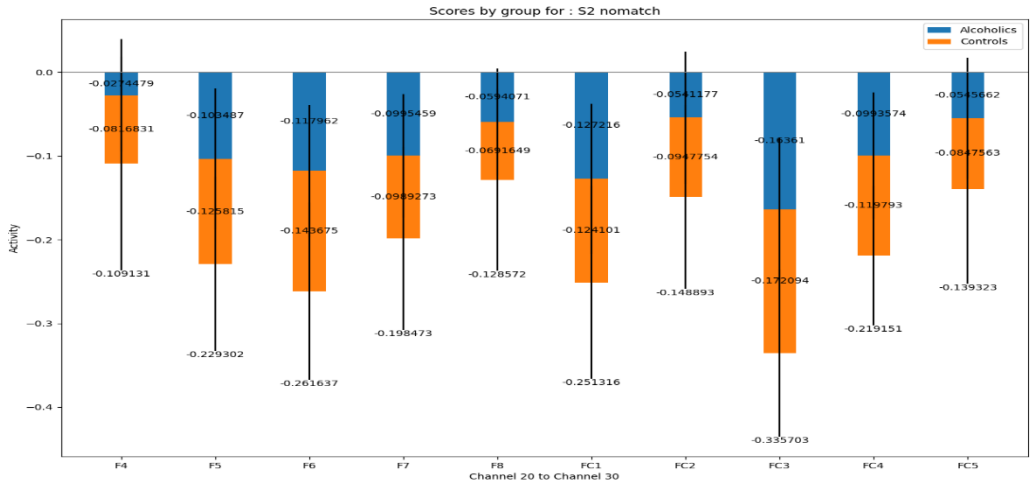

Figure 3.25 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels F4 ->F8, FC1 -> FC5)

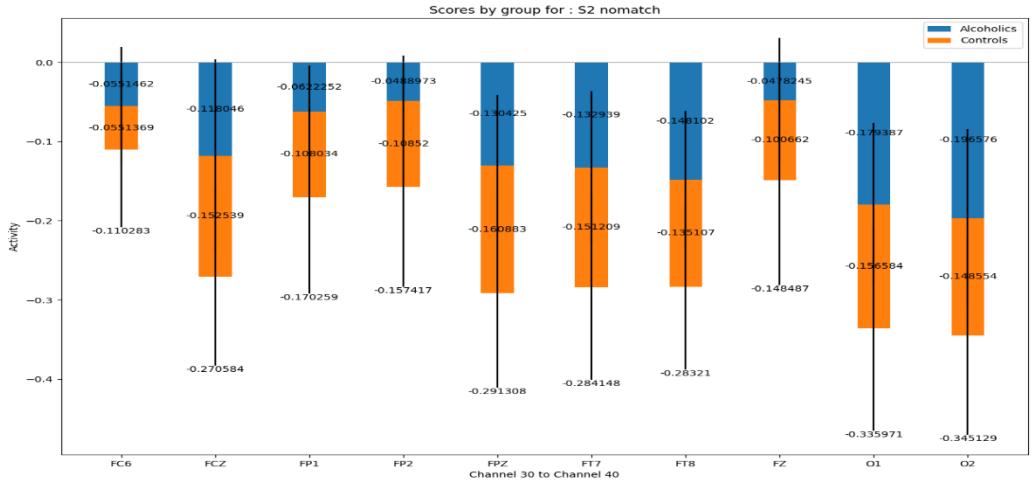

Figure 3.26 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels FC6, FCZ, FP1, FP2, FPZ, FT7, FT8, FZ, O1, O2)

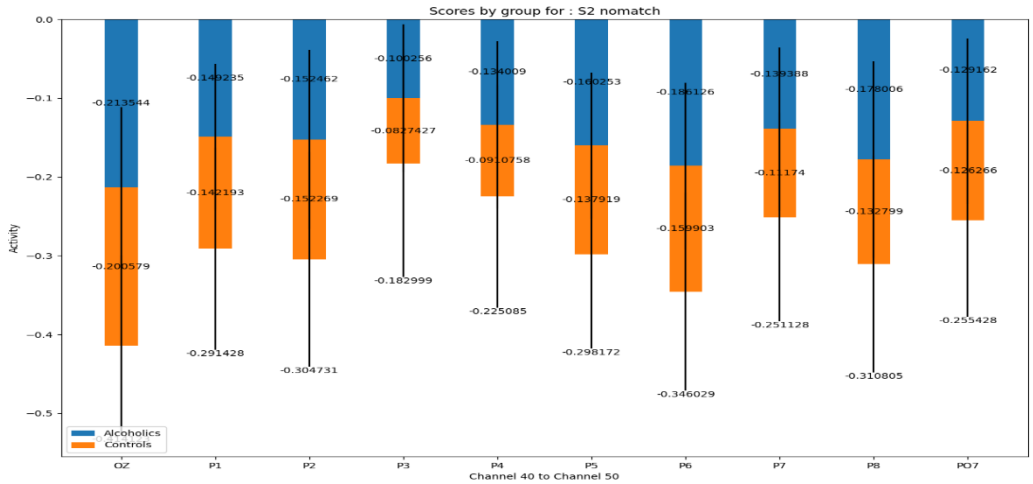

Figure 3.27 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels OZ, P1 -> P8, PO7)

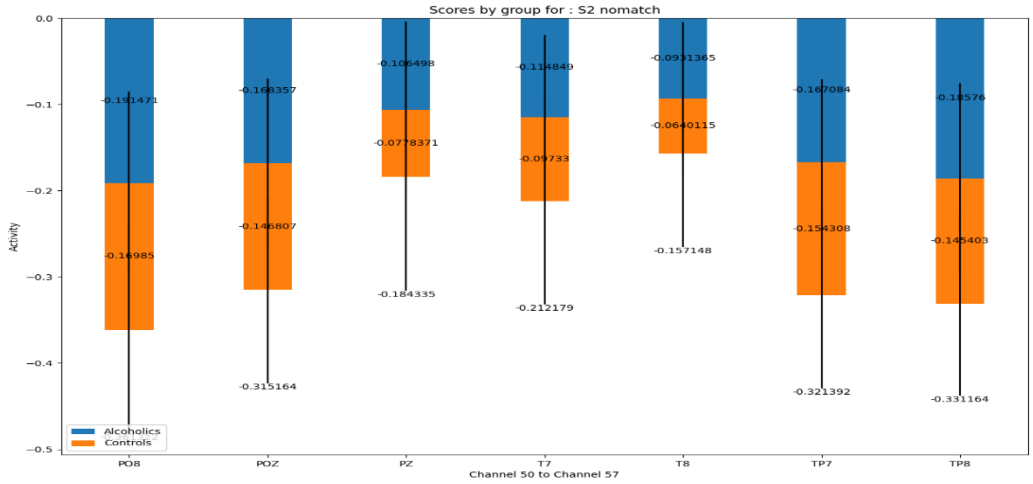

Figure 3.28 Activity comparison between alcoholic and control group using stack bar (S1 S2 no-match stimuli, Channels PO8, POZ, PZ, T7, T8, TP7, TP8)

Stimulus	Alcoholic (Higher activity regions)	Non-alcoholic (Higher activity regions)
S1 obj (Figures 3.11 to 3.16)	Frontal, occipital, temporal, left central, central parietal	Middle frontal, right central, parietal
Matching images (figures 3.17 to 3.22)	All regions except frontal central	Left frontal-central, right frontal-central
Non-matching images (figures 3.23 to 3.28)	Frontal-parietal	Central, parietal, frontal-central, central-parietal, parietal-occipital, and occipital

Table 3.1: Higher active regions for Alcoholic vs Non-alcoholic group.

The findings from the above stacked bar plots for both groups are summarized in Table 3.1 based on their higher activity region per stimulus. For stimuli 1 (S1) we find that frontal, occipital, temporal, left central and central parietal lobe are high activity regions for alcoholic group. For same stimulus, middle frontal, right central and parietal lobe are higher activity regions for the control group. For matching stimuli, we observe higher activities for all regions except at left frontal-central and right frontal-central regions for alcoholic group than control group. Overall, when two matching pictures were shown the alcoholic group has higher activities than control group all over the scalp. For non-matching stimuli, control group has more activity along frontal-central, central, central-parietal, parietal, parietal-occipital and occipital lobes whereas alcoholic group has higher activity on the frontal-parietal lobe.

To visualize the spread of signals in different brain regions, head plots are used for both groups as shown in Figure 3.29. For this we utilized averaged data for each group and projected them to their respective scalp positions based on their sensor coordinates. Data are interpolated and plotted over the head map for three different stimuli.

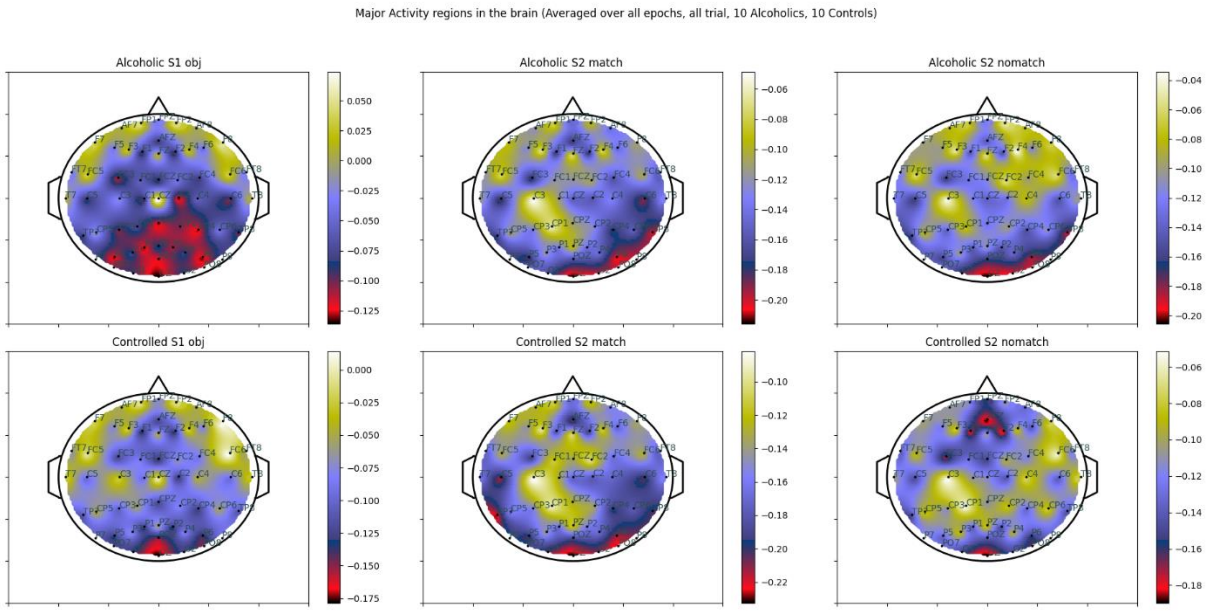

Figure 3.29 Scalp data projection based on sensor coordinates.

From the above scalp projection, the control group shows higher activity in frontal, parietal, occipital region than alcoholic group for S1 obj and matching images. For non-matching images, the alcoholic group shows more activity in frontal regions than non-alcoholic group whereas non-alcoholic subjects have more activity in central and parietal regions. For control subjects we see in general across the three stimuli that the brain activity is higher.

We also found difference between the two groups in terms of correlations as shown in Figure 3.30. A correlation is an indication that those two parts (channels) of the brain fire together. It is important to know whether this characteristic show any marked differences in alcoholic and control group. We evaluated correlation matrix for both groups per each scenario. We set correlation cut-off value of 0.6. The channel pair having correlation above the cut off are included for each group per stimulus and frequency of the appearance of the pairs above the required correlational value are estimated.

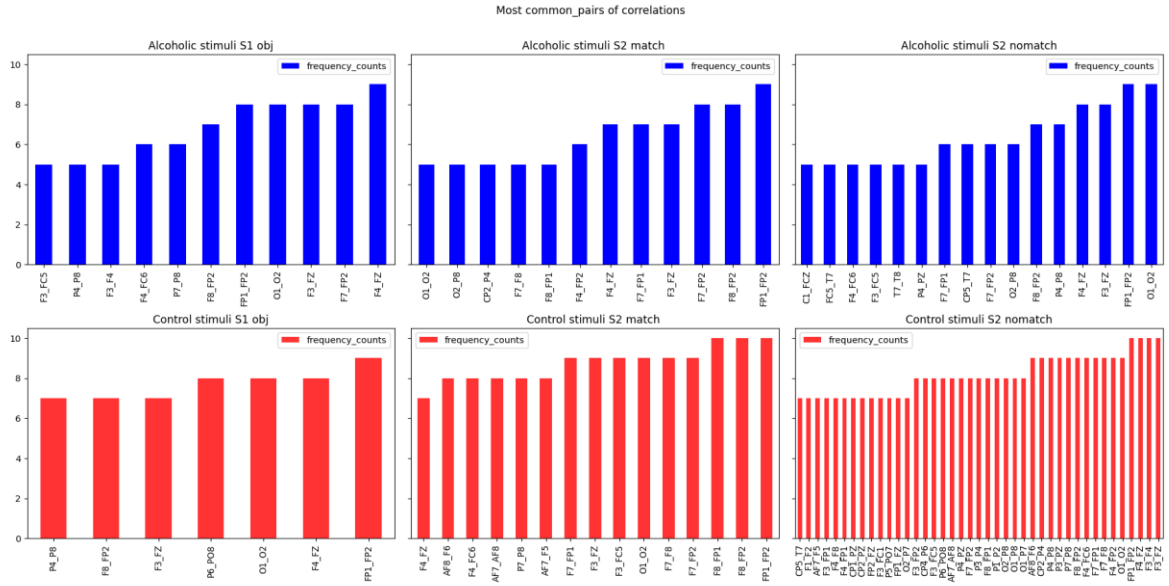

Figure 3.30 Correlations among channels.

From the Figure 3.30 bar chart, it is obvious that the pairs with most correlations are different for alcoholics and control. Now we will visualize these results. We evaluated the frequency of correlation of each channel with other channels above the threshold value 0.7. In the end, we passed this frequency score array containing number of correlations of each channel to the function for plotting head maps as shown in Figure 3.31.

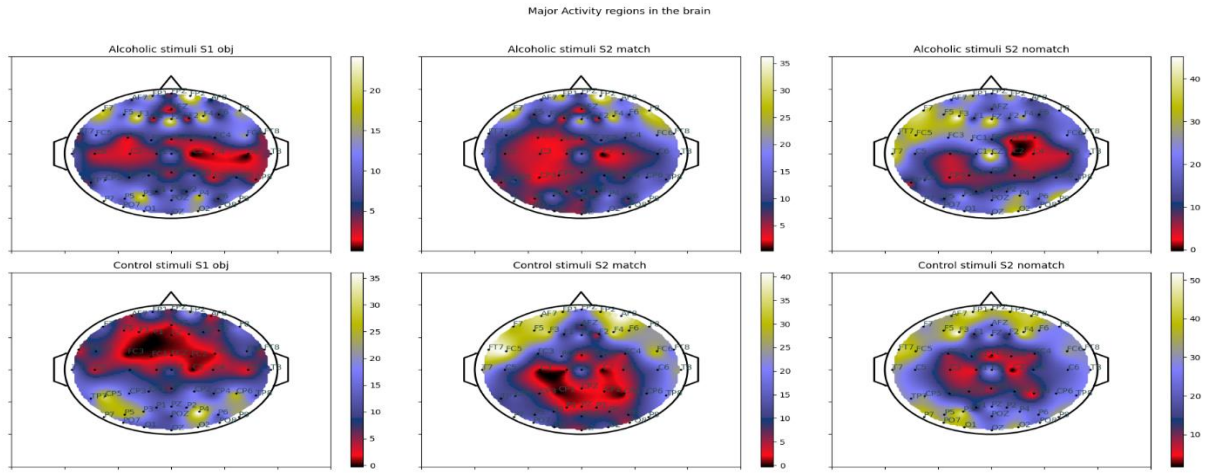

Figure 3.31 Maximum correlation projection.

The head maps in the above plot are not representing averages but the regions of brain with maximum correlations. Red being low and blue and yellow been high as per the scale shown. This can be interpreted as the major activity regions in the brain. Control group shows maximum correlation in occipital, and parietal region for single image visual stimulus. For matching and non-matching stimulus, control group has maximum correlation in the frontal region. For control subjects we see in general across the three stimuli that the brain activity is higher in terms of correlation scores.

So now we are going to analyze the voltage distribution over certain epochs and see if there are any differences between the two groups (10 subjects each from two groups). For this we will perform P-test which is a statistical method that test the validity of significance difference between two groups. There is significant difference between two groups if the value for P-test score is < 0.05. We tested for all channels and all epochs and recorded their p-test score and filtered the time points that gave the score < 0.05. We captured the score for all three stimuli. In Figure 3.32, we have shown the p-value for channel F2 and channel FC1 at epoch 108 and 105 respectively. We overplot the mean voltages for 10 subjects each from two groups across the above-mentioned epochs. This process is repeated in the experimental results shown in Figures 3.33 to 3.35. Figure 3.33 illustrates the voltage distribution over certain epochs for a single stimulus - 'S1 obj'. We overplot the mean voltages for 10 subjects each from two groups across 10 different epochs. The same applies for Figures 3.33 and 3.34. Figures 3.33, 3.34, and 3.35 illustrates mixed scores such as significant and nonsignificant differences for a single stimulus (S1 obj), two stimuli (matching), and two stimuli (non-matching) respectively. We plot the mean voltages for 10 subjects each from two groups across 10 different epochs.

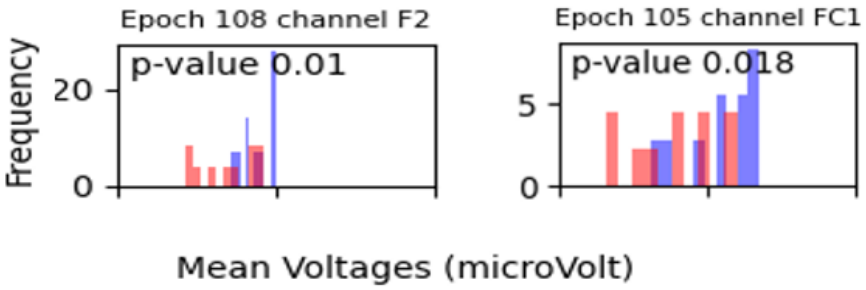

Figure 3.32 P-test scores for channel F2 epoch 108, channel FC1 epoch 105 (S1 obj)

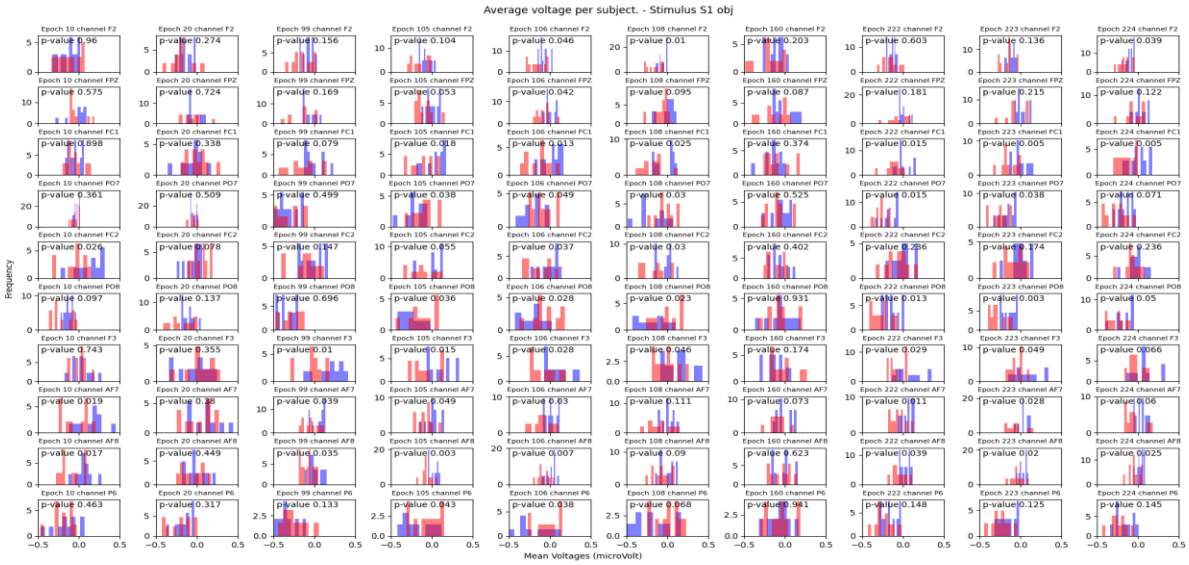

Figure 3.33 P-test scores for 10 different epochs, 10 different channels (S1 obj)

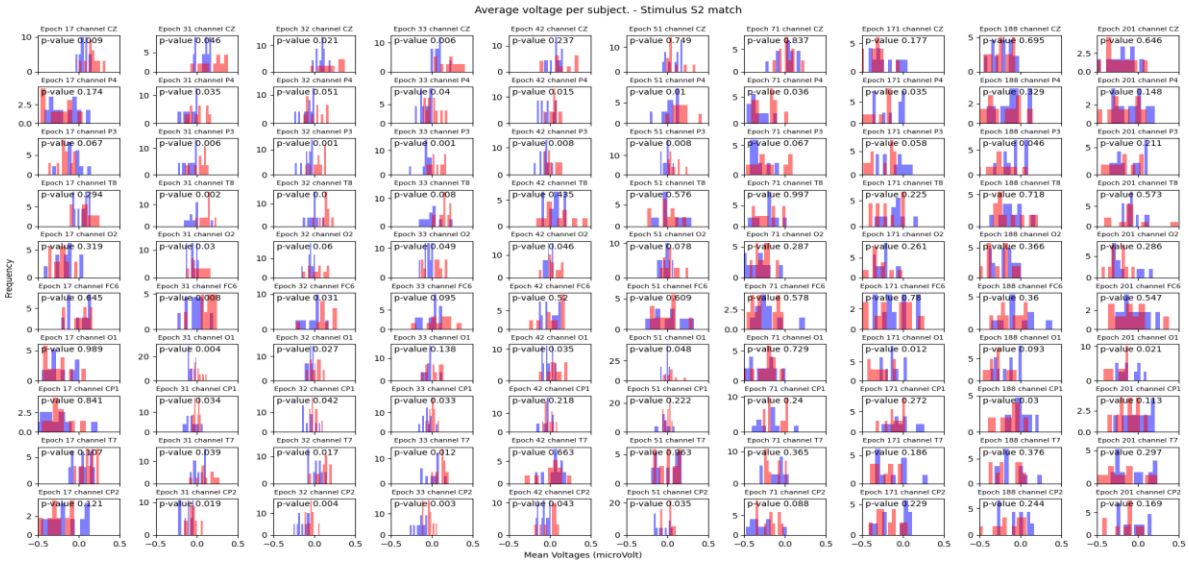

Figure 3.34 P-test scores for 10 different epochs, 10 different channels (S1 S2 matching)

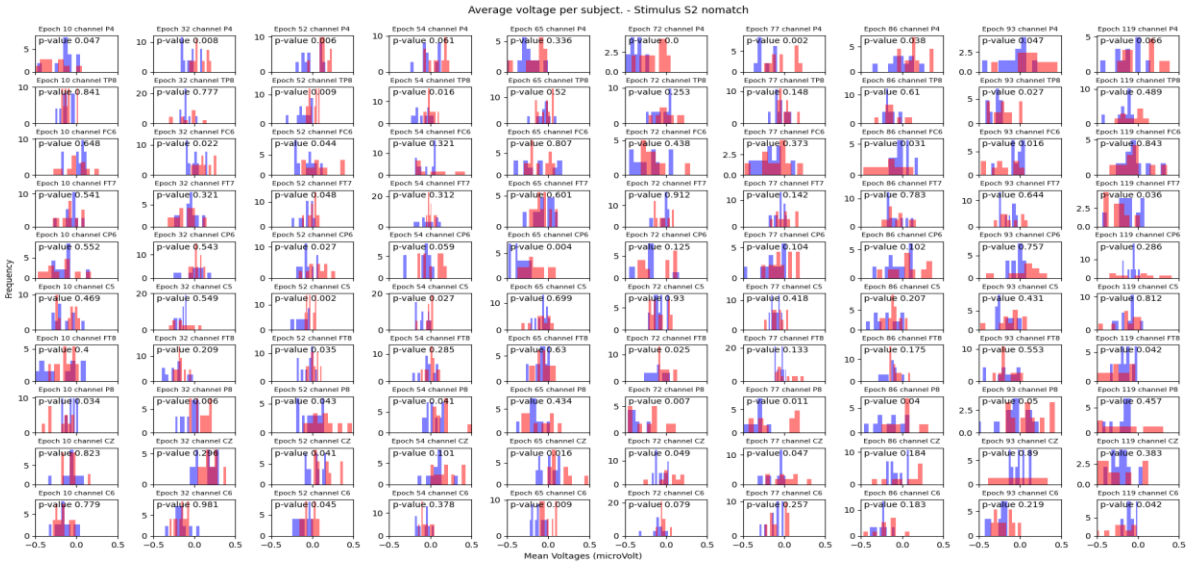

Figure 3.35 P-test scores for 10 different epochs, 10 different channels (S1 S2 non-matching)

From the above p-test scores we found that some time points show better differentiability signified by their low p-values. For instance, when subjects are shown one picture (S1 obj),

activities of two groups are significantly different for epoch 106 at channels F2, FPZ, FC1, PO7, FC2, PO8, F3, AF7, AF8 and P6. For matching stimulus, we observed difference at epochs 31, 32 and 33 at the channels CZ, P4, P3, T8, O2, FC6, O1, CP1, T7 and CP2. For non-matching stimulus, it illustrates different activity for alcoholics and controls at epoch 52 for the selected channels.

Apart from these visualizations, results of all the differentiable timepoints (Epochs) at different channels for all three stimuli for both the groups are calculated, which gives us insight about the difference in activities across different regions of the brain. Those are not included here because of the large number of records. However, from these results we can conclude that these timepoints could be a good indicator that the voltage distributions might be different for alcoholic and control subjects after each stimulus. After we get the timepoints where there is significant difference in activity between the two groups, we constructed mean voltage across the trials at these timepoints and grouped their respective channels to different regions. This is how we got regional differentiable activities for the two groups. For the experiment we considered 10 subjects for each group, and we only focused on three different regions as listed in Table 3.2.

Region	Channels
Frontal	['AF7', 'AF8', 'AFZ','FP1','FP2','FPZ']
Parietal	['P1','P2','P3','P4','P5', 'P6','P7', 'P8','PO7','PO8','POZ','PZ']
Occipital	['O1', 'O2', 'OZ']

Table 3.2: Channels and their respective regions.

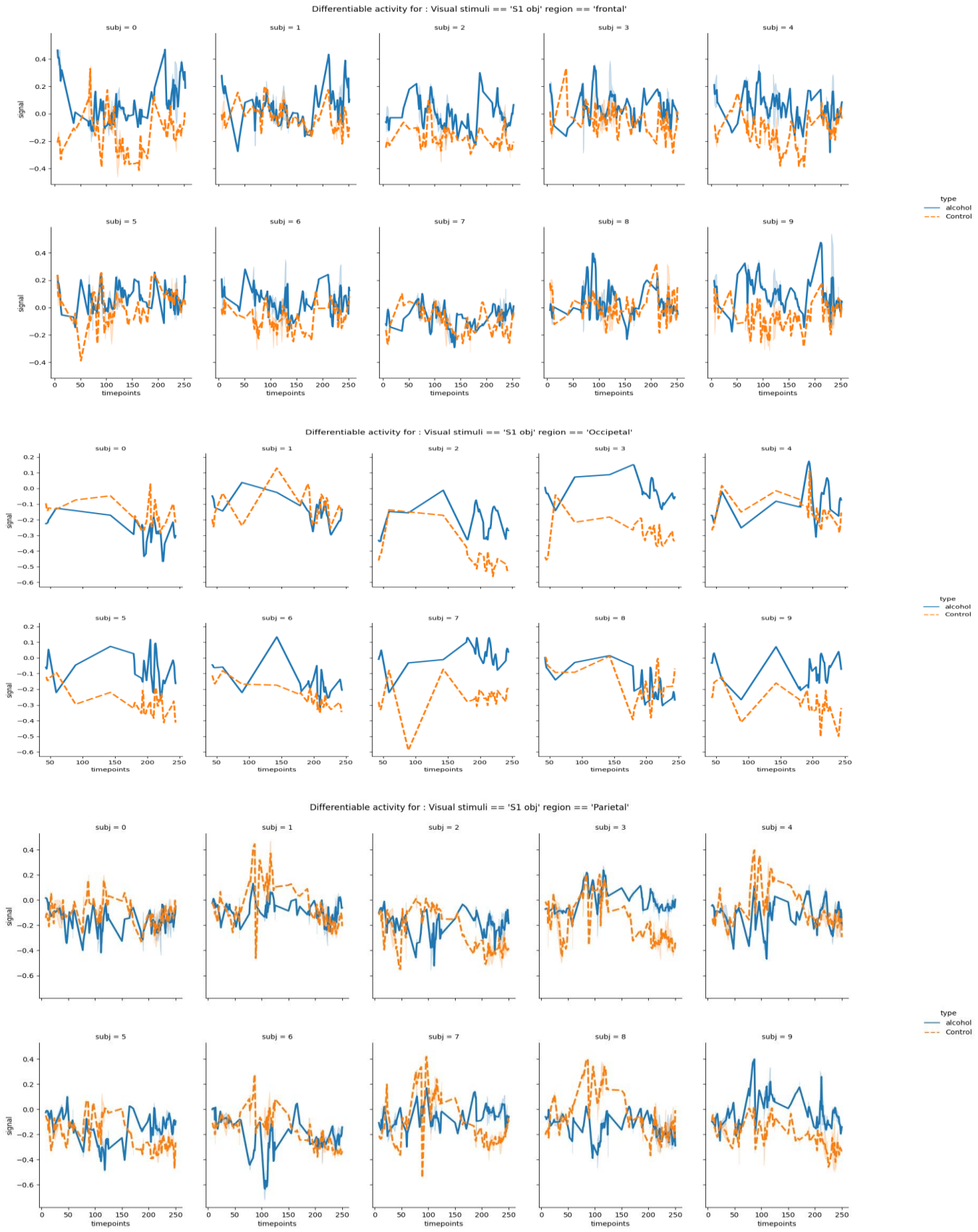

Figure 3.36 Differentiable activity for S1 obj stimulus across frontal, parietal, and occipital Region.

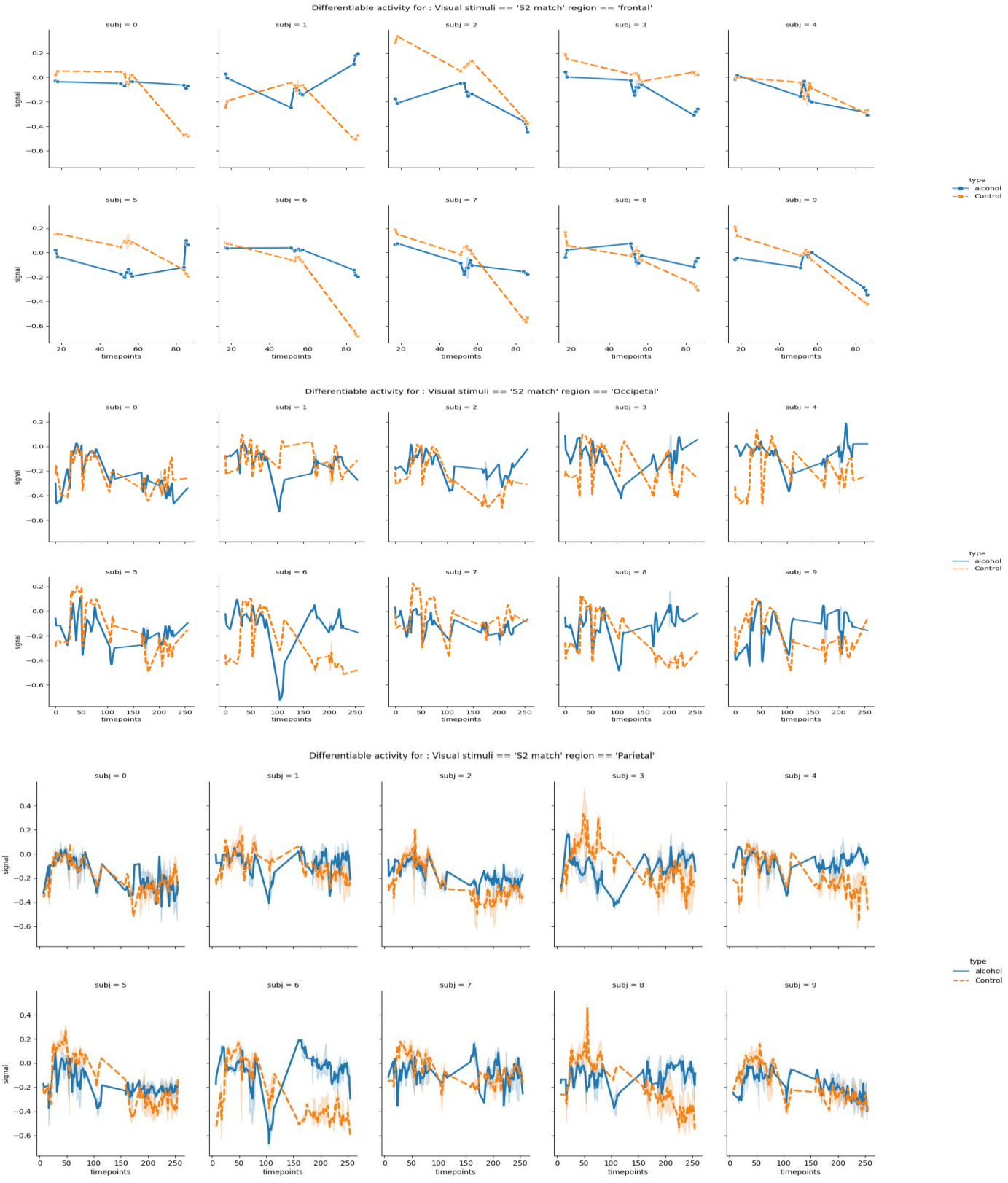

Figure 3.37 Differentiable activity for S1 S2 matching stimulus across frontal, parietal, and occipital Region.

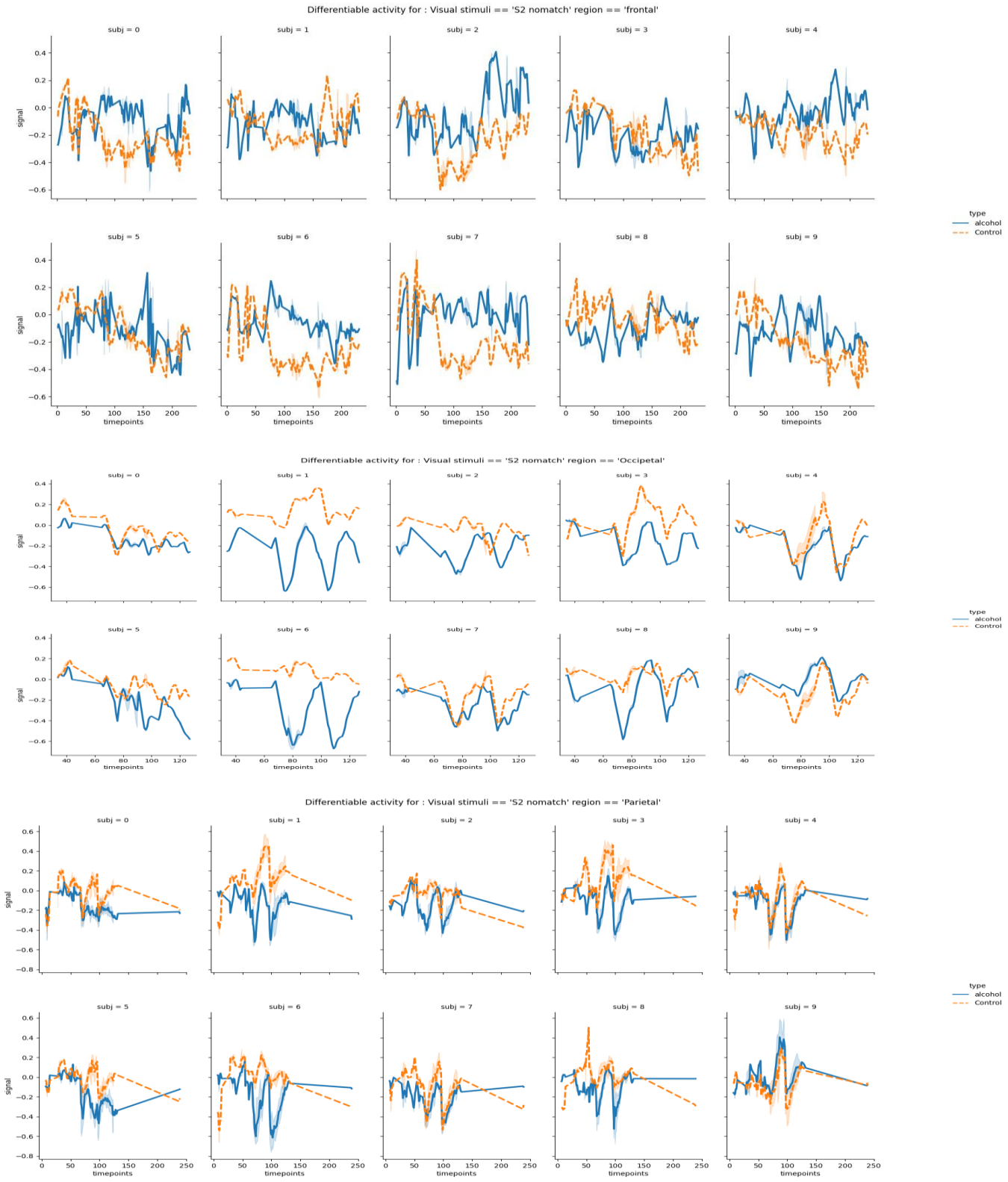

Figure 3.38 Differentiable activity for S1 S2 nonmatching stimulus across frontal, parietal, and occipital Region.

Figures 3.36, 3.37, and 3.38 show differentiable activity across different regions at different time points for three different stimuli. When both alcoholic and control subjects visualize single object, more activity are related to frontal and parietal region than occipital region. Alcoholic group has higher activity than control group in frontal region whereas the control group has higher activity pattern in the parietal region. If we analyze the second case where two matching objects are shown to both the groups, we see more activities are related to occipital and parietal region than the frontal region. Alcoholic group has higher oscillatory pattern than control group for this such that activities have sudden increasing trend towards the end of the stimuli in both occipital and parietal region whereas control group has more stable pattern showing higher activity at the beginning and gradually decreasing towards the end in both regions. For the third scenario, when two non-matching objects are shown, the control group has higher activity than the alcoholic group in both occipital and parietal region whereas alcoholic group has oscillatory and higher activities in the frontal region. For all three stimuli, the above plots illustrate an unstable, oscillatory pattern and sudden increasing trend in the alcoholic group.

Summary

A detailed experimental data analysis on the dataset is done in this chapter. To understand the results better, we did plot the results to get insights on the brain's activity of the subjects under study. From the surface plots, it is evident that Alcoholic group's electrical activity is spread for the entire period in all three scenarios. Control group shows a particular increasing pattern in the beginning followed by decreasing pattern towards the end for all three scenarios. From the heatmaps we found overall Alcoholic subjects have higher amplitude than the control group.

As explained in Table 3.1 we found highly active regions for both alcoholic and non-alcoholic groups as shown in the stack bar plots for all three scenarios. From the above scalp projection, the control group showed higher activity in frontal, parietal, and occipital regions than alcoholic group for S1 obj and matching images. For non-matching images, the alcoholic group showed more activity in frontal regions than non-alcoholic group whereas non-alcoholic subjects had more activity in central and parietal regions. By performing P-test, we found the epochs for which there were significant differences in activity between the two groups. We also plotted differentiable activity across different regions at different time points for three different stimuli. For all three stimuli, the plots illustrate an unstable, oscillatory pattern and sudden increasing trend in the alcoholic group whereas the control group showed a stable pattern.

Chapter 4

Source Activity of Alcoholic vs Control Subjects

This chapter finds source activity for both alcoholic and control subjects. To find the source activity, we have utilized CSP (common spatial pattern algorithm). Prior to that, we have pre-processed the dataset by centering the data and scaling it within a specific range. Once we pre-process the data, we applied CSP to it to find spatial patterns and plotted them in a 2d brain plot. We also highlighted the 1^{st} , 2^{nd}, 3^{rd} and 4^{th} most active source regions based on the channel coordinates. Then we have plotted the source activity in a 3d brain plot and compared them with the brain's functional region map. By this, we compare the source activity to different functional regions to find the association of activity specific to a region. We also masked the regions with maximum source activities. The regions associated with maximum source activities for both groups are compared.

A. Data Preprocessing:

As part of data preprocessing, we bandpass filtered our dataset. Each trial is convoluted with Butterworth band pass filter of 10-20Hz of order 3. By filtering we want to zero mean our data which is called centering around mean. Data filtration is followed by scaling data between the range [-1,1].

B. Common Spatial Pattern:

To analyze EEG signals at source level we use the common spatial pattern approach to find the source activities for alcoholic and non-alcoholics subjects. The method of common spatial patterns (CSP) designs the filters in a such a way that the variances in the filtered time series data are optimal for discriminations among two groups. These filters are multiplied to scalp recordings to get sources activity. We are given input data $\{X_c^i\}i =_1^k$denoting EEG data from trial i for class c $\in$ {1,2} (e.g., alcoholic vs non-alcoholic). Each X_c^i is an N × T matrix, where N is the number of EEG channels and T the number of samples in time per channel.

C. Common Spatial Patterns (CSP) Algorithm:

The CSP algorithm finds spatial patterns to evaluate the brain source activity.

Input: EEG datasets for alcoholic and control group

Experiment paradigms: Three sets of visual stimuli: S1(One picture), S1 S2(matching pictures), S1 S2(nonmatching pictures)

Subjects: 10 subjects in each group.

Trials: 10 trials per paradigm. 30 trials (3 paradigm x 10) for one subject.

Details of the algorithm as follows:

Step 1: We calculate R_a and R_c

$$R_a = \frac{X_a\, X_a^T}{trace(X_a\, X_a^T)}$$

$$R_c = \frac{X_c\, X_c^T}{trace(X_c\, X_c^T)}$$

where

R_a = Alcoholic group covariance for all trials

R_c = Control group covariance for all trials

Xa and Xc = input data matrixes with dimension N × T

N = the number of channels

T = the number of time points.

Step 2:

The averaged covariance is evaluated by averaging over all trials as shown below:

$$R = \overline{R_a} + \overline{R_c}$$

R can be factorized as shown below:

$$R = E\, U$$

where

E = eigenvalues

U = eigenvector.

Then we sort them as it is required for CSP to have higher variance at the top and lower variance at the bottom.

$$E = E_{sorted}$$

$$U = U_{sorted}$$

$$P = \Sigma^{-1/2} U^T$$

P = whitening transformation matrix

Σ = diagonal matrix of E.

Now we transformed the mean covariance matrix as shown in below equations:

$$S_a = P \overline{R_a} P^T$$

$$S_c = P \overline{R_c} P^T$$

where

S_a = Mean covariance matrix with largest eigenvalues

S_c = Mean covariance matrix with smallest eigen values Now the transformed mean covariance matrix can be factorized as below to get eigen vectors and eigen values such that Sa will have largest eigenvalues and Sb will have smallest eigen values. To do this we first factorize the transformed matrix to eigenvalues and eigen vectors and sort the eigenvalues and eigenvectors in descending order which is explained below:

$$(S_a S_c) = E_1 U_1$$

where

E_1 = eigenvalues

U_1 = eigenvector.

$$E_1 = E_{1_{sorted}}$$

$$U_1 = U_{1_{sorted}}$$

As part of the final step the projection matrix (the spatial filter) may now be obtained by multiplying the whitened matrix P obtained earlier with U1 as shown below:

$W = U_1 P$ where

W = spatial filter matrix.

It is also called as unmixing matrix which is used to compute source components.

The goal of CSP is to find M spatial filters, given by an N × M matrix W (each column is a spatial filter), that linearly transform the input signals according as shown below:

$$S = W^T X$$

Where

S = Source matrix

D. Results:

1. Data Centering:

As part of data centering, we applied a temporal filter as Butterworth band pass filter of 10-20Hz of order 3 to all input trials before applying CSP. We plotted some of the results showing original data and centered data in Figure 4.1. Figure 4.1 shows results related to channels AF7, AF8, C1, C2 for one subject each from both alcoholic (subject id 364) and control (subject id 337) groups.

2. Scaling Data:

Our data is scaled between the range -1 to 1.

3. Spatial Patterns:

As shown in the CSP Algorithm, we are estimating the mean covariance across all trials, where the shape of each trial is N x T (channel x timepoints). Hence, the resulting spatial pattern matrix will take the shape of a square matrix size N x N (channel x channel). In our case it will be matrix of dimension 57 x 57. Each column of this matrix is a spatial filter of a source distribution

vector. Out of 56 source distribution filters (for one alcoholic and one control subject) we have shown 10 filters showing maximum activity region (optimal). By optimal means, we took maximum absolute value of every filter and showed them as a higher activity region.

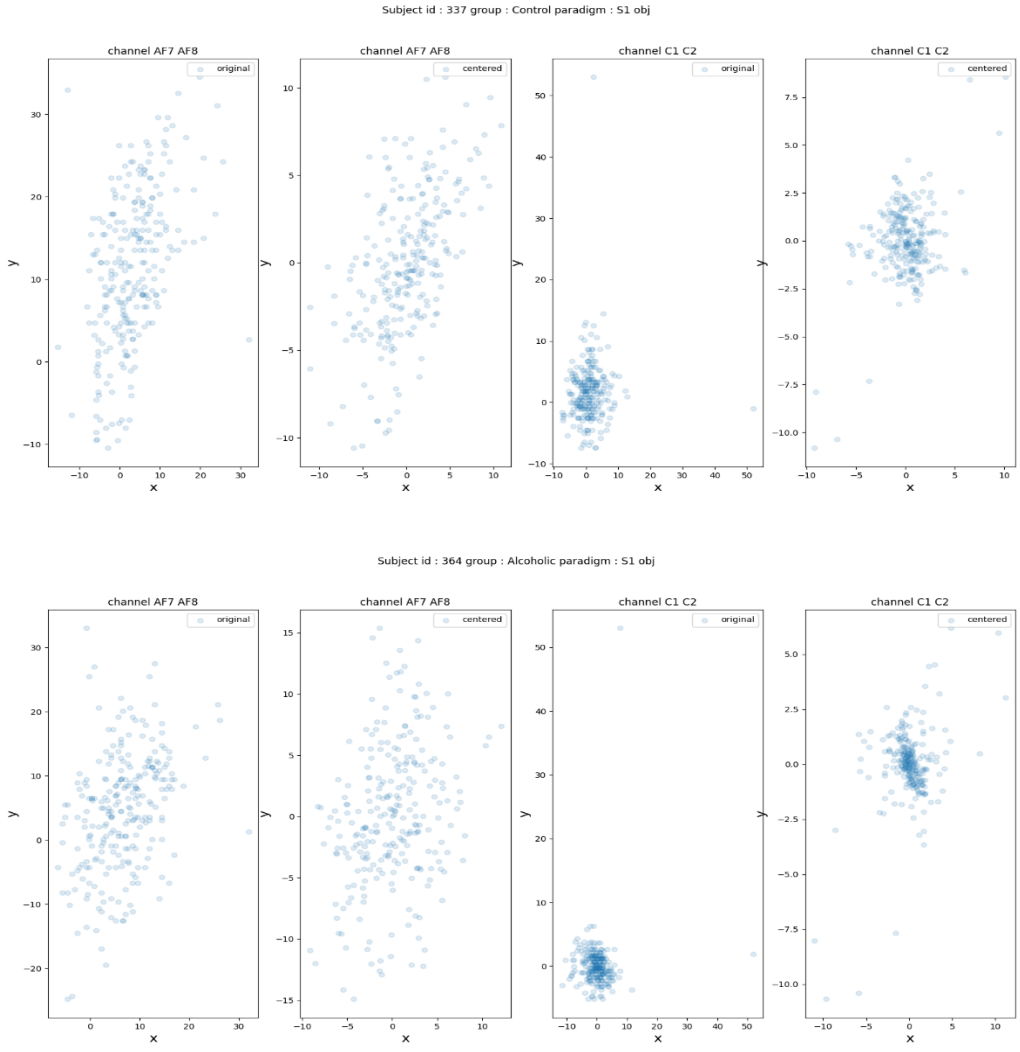

Figure 4.1 Centering of data

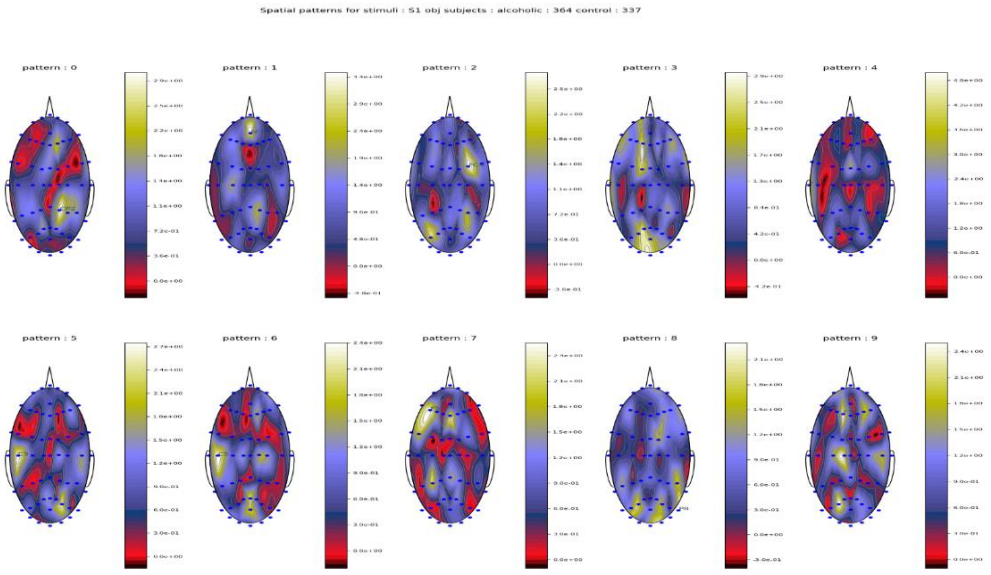

Figure 4.2 Visualization of ten spatial patterns for subject 364(Alcoholic) and subject 337(Control) for Stimulus: S1 obj

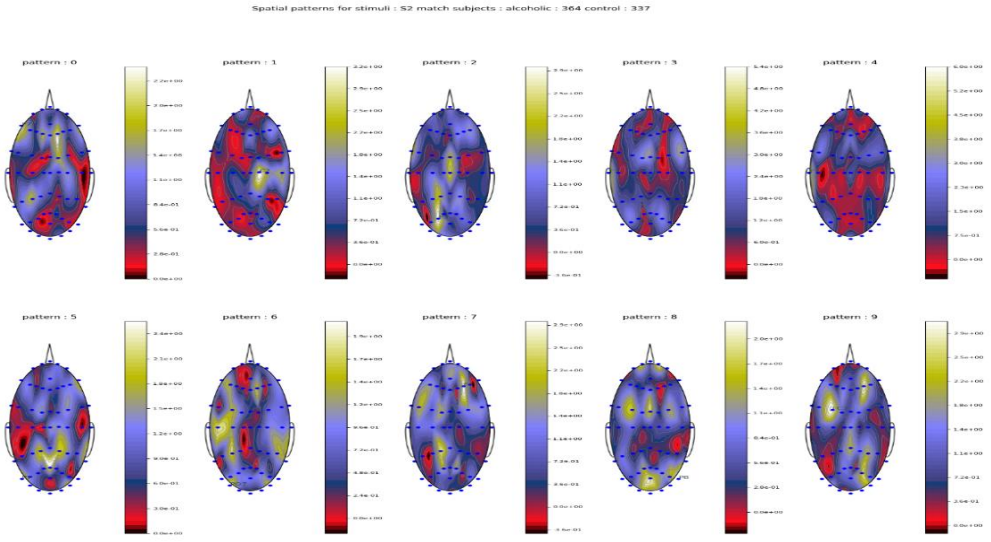

Figure 4.3 Visualization of ten spatial patterns for subject 364(Alcoholic) and subject 337(Control) for Stimulus: S2 match

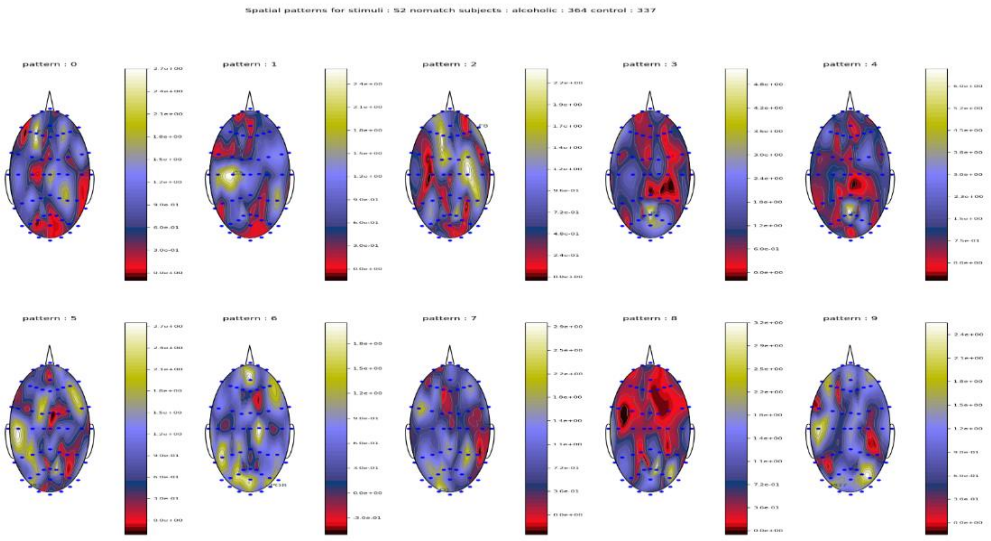

Figure 4.4 Visualization of ten spatial patterns for subject 364(Alcoholic) and subject 337(Control) for Stimulus: S2 no match

In Figure 4.2 we can see the subject specific maximum activity regions in 10 different patterns for Stimulus S1 obj. In Figure 4.3 we can see the subject specific maximum activity regions in 10 different patterns for Stimulus S2 match. In Figure 4.4 we can see the subject specific maximum activity regions in 10 different patterns for Stimulus S2 no match. Then in Figures 4.5 to 4.7 we have shown consolidated 10 patterns for all ten subjects for three stimuli where the patterns of 10 different subjects belonging to each group are summed and their optimal activity regions are plotted.

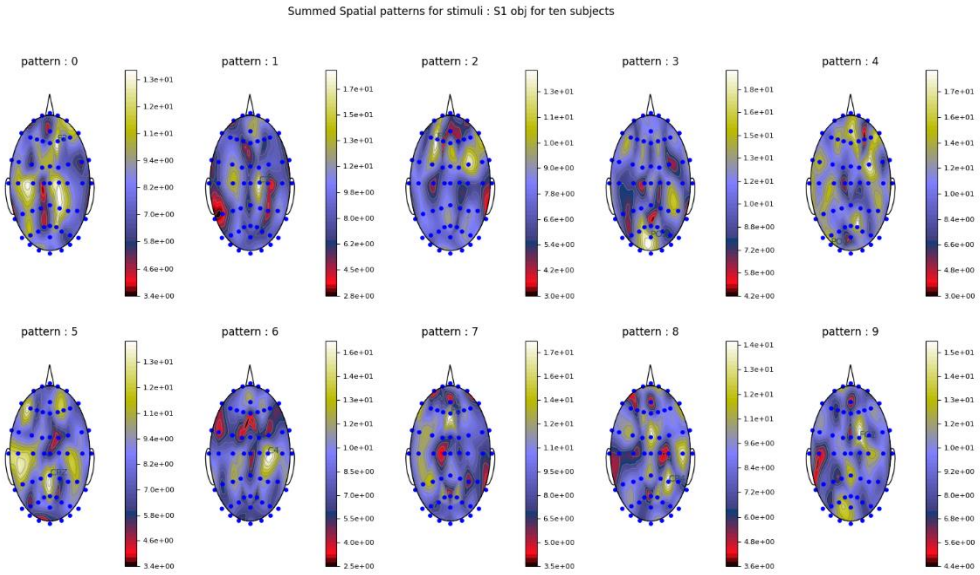

Figure 4.5 Visualization of ten spatial patterns for ten subjects (Alcoholic) and ten subjects (Control) for Stimulus: S1 obj

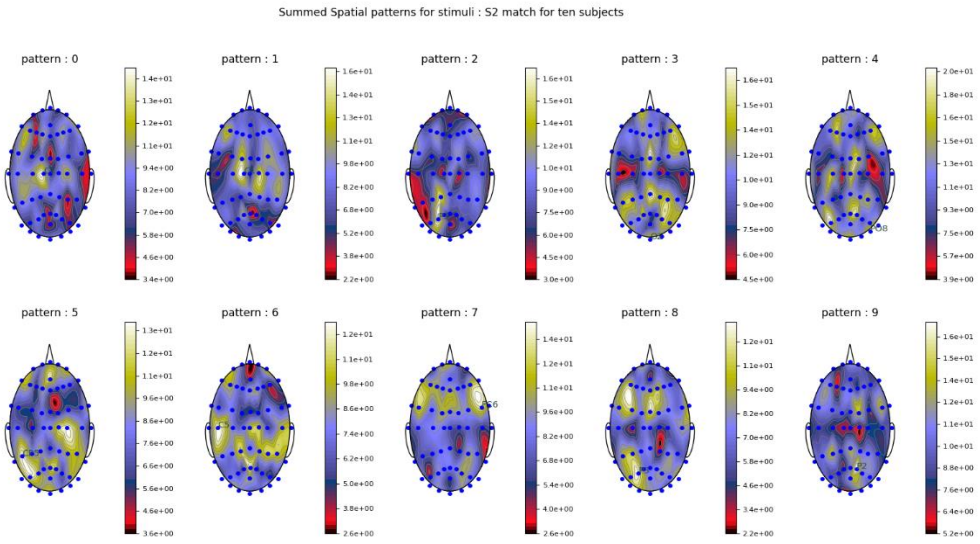

Figure 4.6 Visualization of ten spatial patterns for ten subjects (Alcoholic) and ten subjects (Control) for Stimulus: S2 match

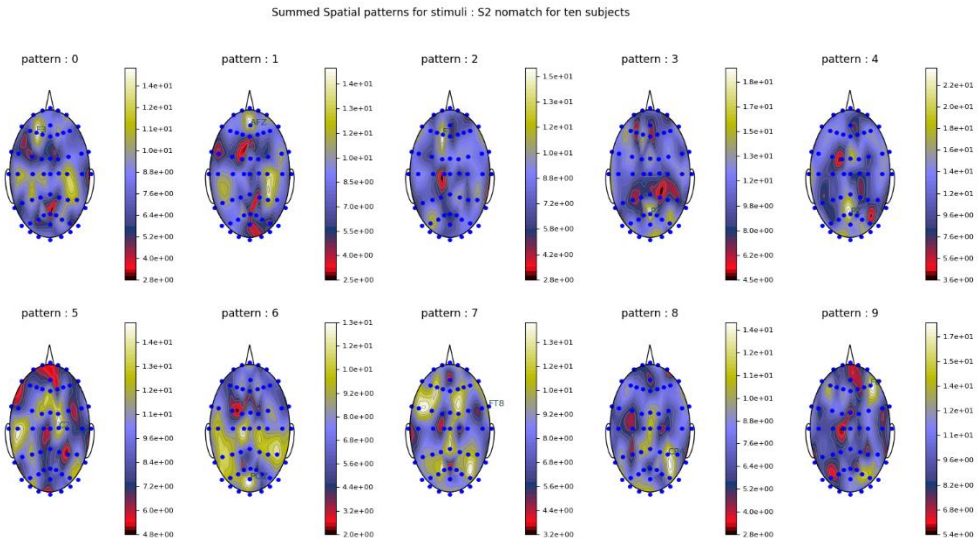

Figure 4.7 Visualization of summed spatial patterns for ten subjects (Alcoholic) and ten subjects (Control) for Stimulus: S2 no match

To find out the maximum activity regions of alcoholic and control groups, we took the inverse filter which is W^{-1} (See CSP algorithm above). The first and last column of it are the most important spatial patterns that explain the largest variance across one task (performed by alcoholic) and smallest variance across another (performed by control). Hence, we assume that the first and last spatial patterns are related to specific sources of two group. The two channels related to maximal coefficients of these two spatial patterns may be the channels that are correlated with the task specific sources. Figures 4.8 to 4.11 plot the results related to high activity regions for each group. Four different consolidated results are shown based on from the topmost till the fourth most activity regions for each group.

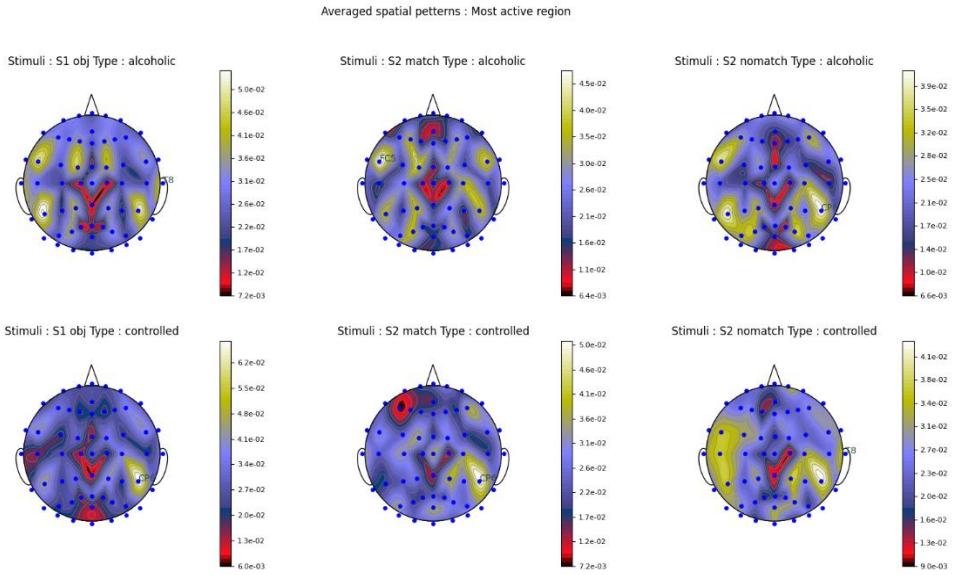

Figure 4.8 Visualization of averaged spatial patterns with most active region for ten subjects (Alcoholic) and ten subjects (Control) for three stimuli

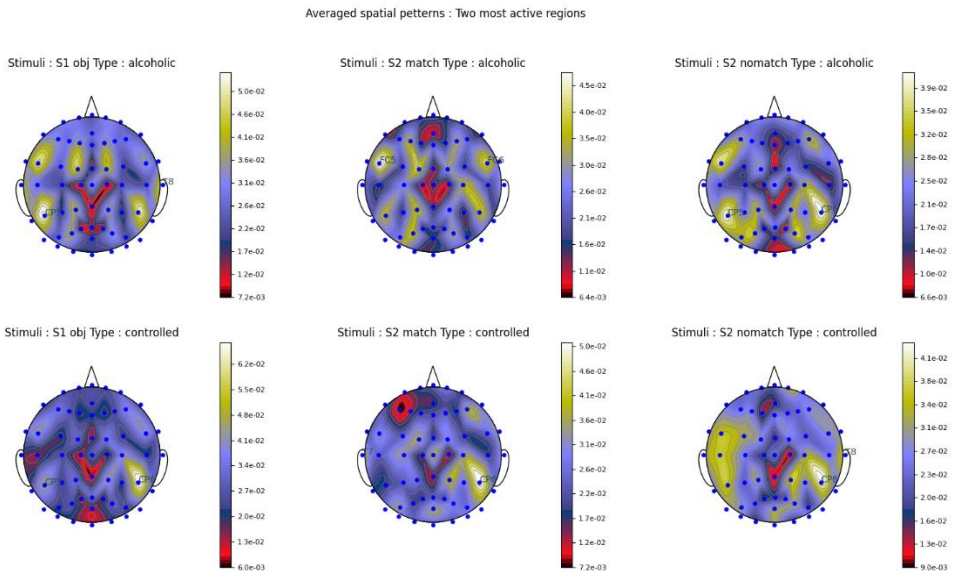

Figure 4.9 Visualization of averaged spatial patterns with two most active regions for ten subjects (Alcoholic) and ten subjects (Control) for three stimuli

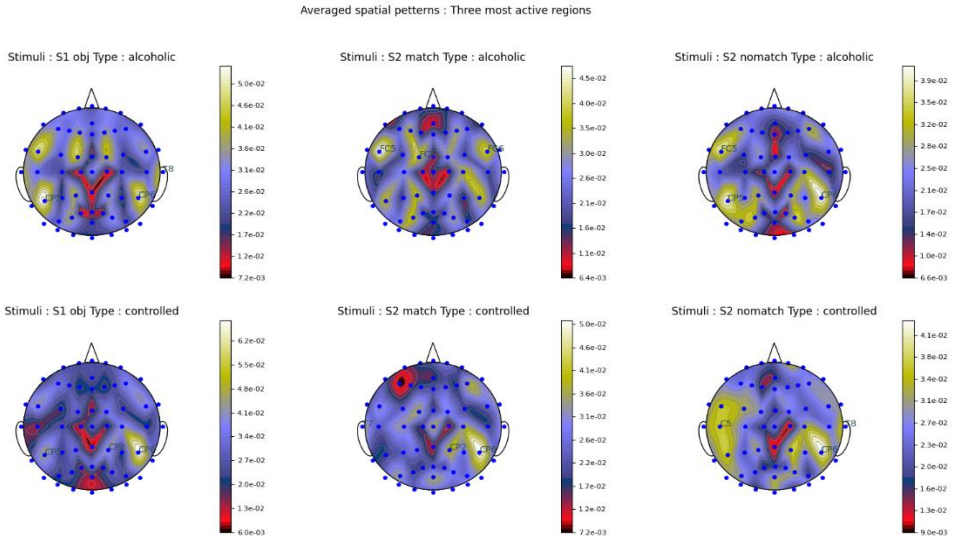

Figure 4.10 Visualization of averaged spatial patterns with three most active regions for ten subjects (Alcoholic) and ten subjects (Control) for three stimuli

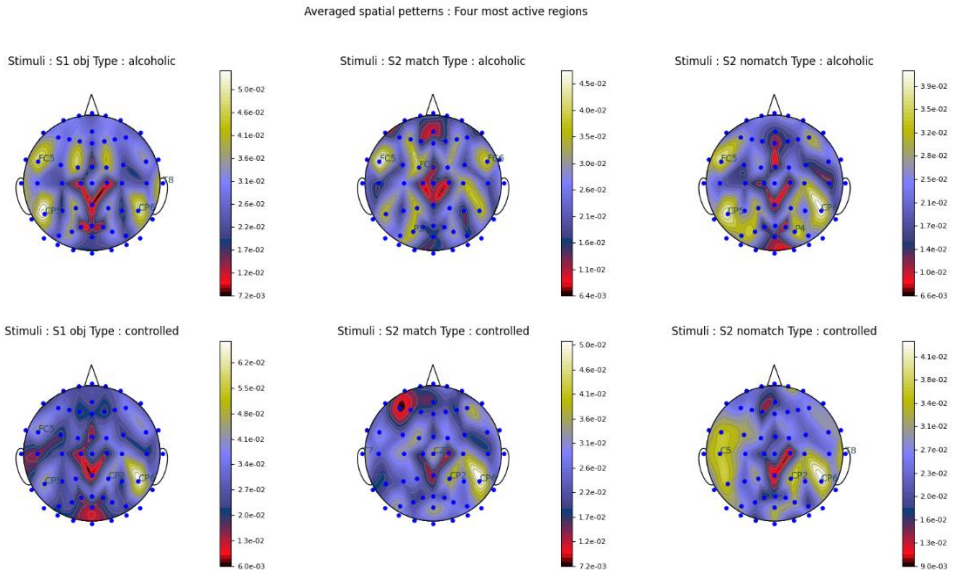

Figure 4.11 Visualization of averaged spatial patterns with four most active regions for ten subjects (Alcoholic) and ten subjects (Control) for three stimuli

From the above spatial patterns, we find the four most active regions for alcoholic (first spatial filter) and control (last spatial filter), which are shown in Table 4.1.

Stimulus	Alcoholic	Non-alcoholic
S1 obj	T8-CP5-CP6-FC5	CP6-CP5-CP2-FC5
Matching	FC5-FC6-FC1-P3	CP6-T7-CP2-CZ
Non-matching	CP6-CP5-FC5-P4	T8-CP6-C5-CP2

Table 4.1: Most active regions.

Table 4.1 indicates the active regions associated with Alcoholic and Non-alcoholic groups in decreasing order for visual stimulus. From the above results we found that alcoholic subject's right temporal region is engaged with higher activity whereas for control subjects central-parietal region is the most active region when they are shown a single image. For matching images, alcoholic subjects have frontal-central as the most active region whereas for control subjects central-parietal region is the most active region. For non-matching images, alcoholic subjects have central parietal as most active region whereas for control subjects right temporal region is the most active region.

Next, we will visualize spatial patterns and source activity by projecting them on a 3D brain. By this, we can understand the association of activity to different regions of the brain better. The spatial filters on a 3D brain for both groups are shown in Figure 4.12.

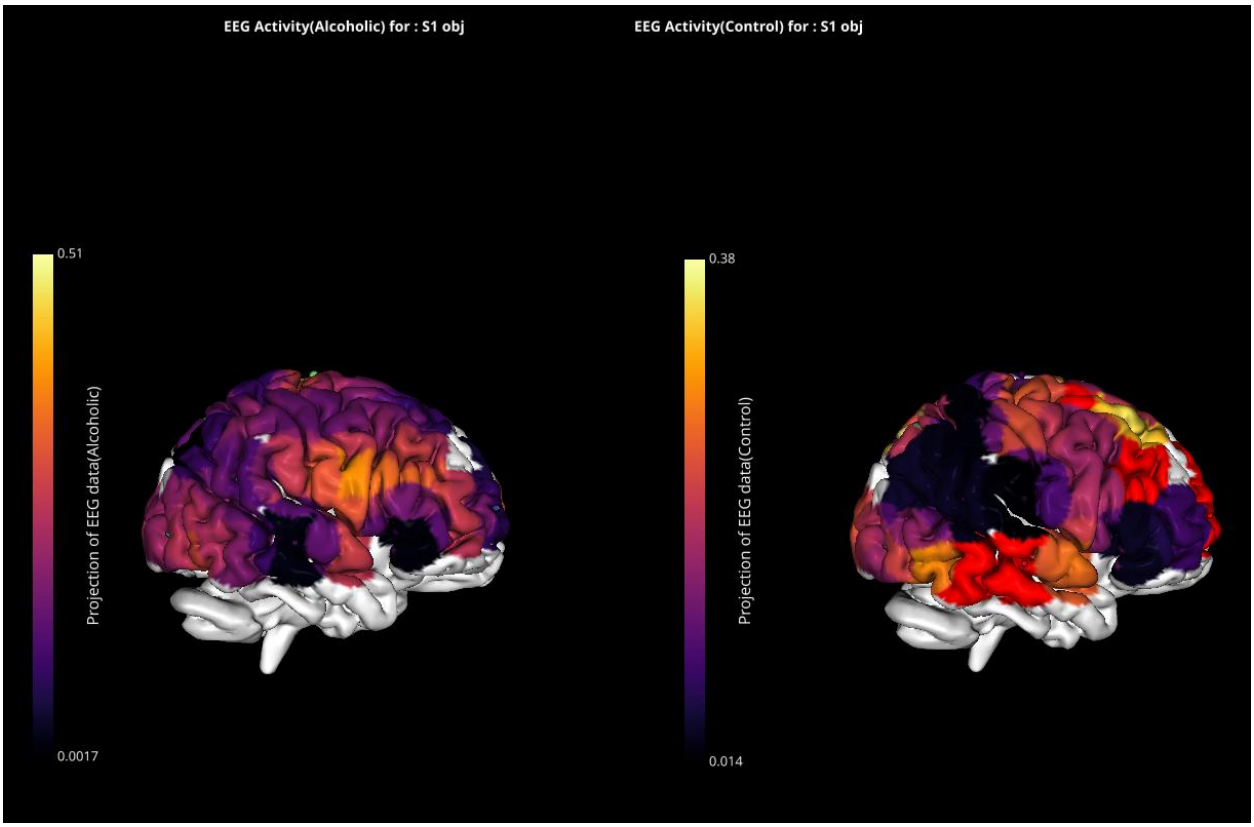

Figure 4.12 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Right Brain view

Figure 4.12 shows brain activity for two groups subjected to the S1 obj paradigm. This plot is to visualize right brain. Maximum activity regions are masked in red color. Masking is done based on the top 2 regions with maximum absolute spatial filter coefficients. In this plot different activities are represented by different colors. The scale for colors other than red color can be referred from the color bar. For Figure 4.12 visualization, the alcoholic group has no masked activity in right. For the control group, the maximum activities for the right side of the brain seem to be executive functions/ cognition region and the visual-temporal or memory region. The temporal lobe is at the lower front of the brain. This lobe has strong links with visual memory, and emotion.

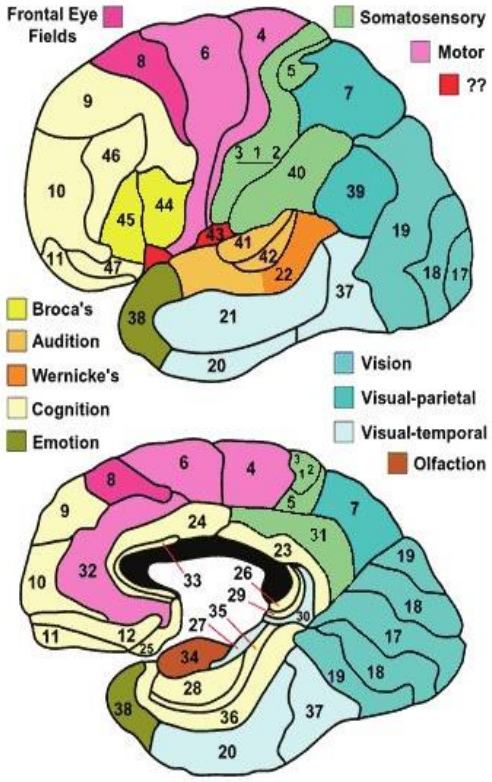

Figure 4.13 Brain region map

Figure 4.13 indicates the brain's regional map. We will utilize this map as reference to find the brain activity's associated region projected on 3D brain. Figure 4.13 uses different color to indicate different regions of brain.

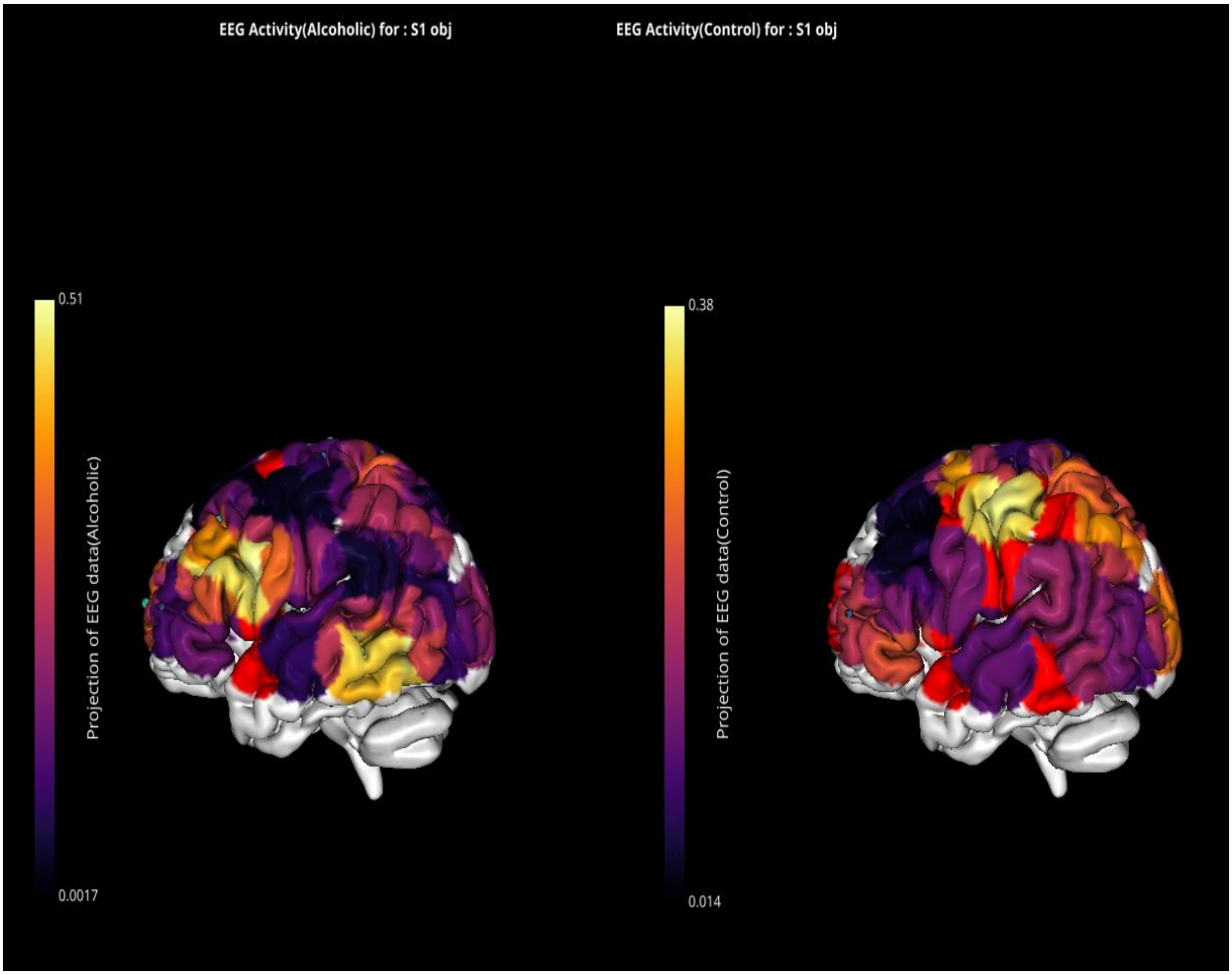

Figure 4.14 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Left Brain view

Figure 4.14 shows visualization of left brain for two groups subjected to paradigm S1 obj. Left brain has different regions involved with maximum activities. For alcoholic group, the maximum activity involved regions are emotional regulation region. Control group has higher activity at visual temporal, somatosensory, and vision region. The somatosensory cortex is a part of your brain that receives and processes sensory information from the entire body.

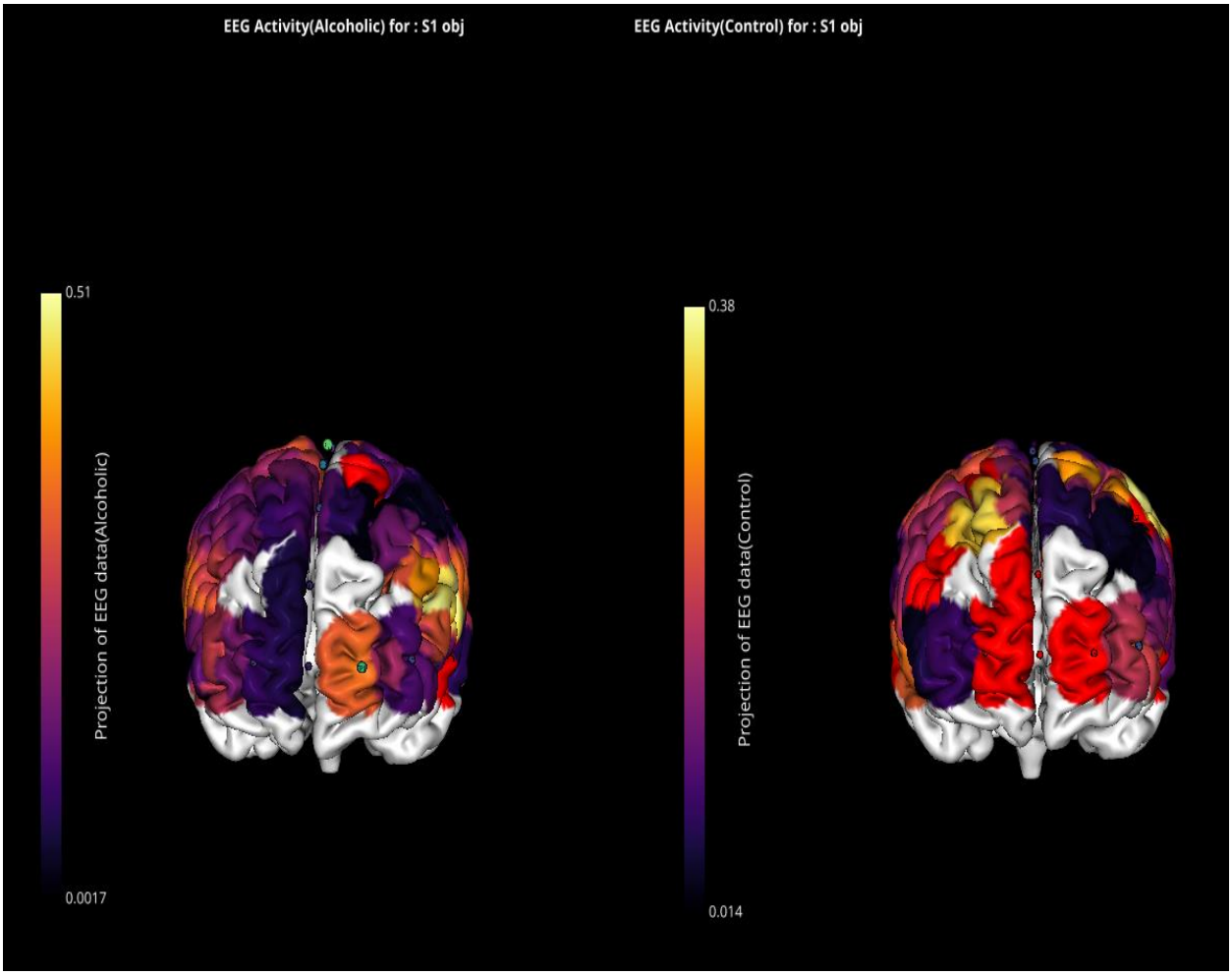

Figure 4.15 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Frontal Brain view

Figure 4.15 shows frontal region visualization of two groups for first paradigm. We see masked activity in frontal region in control group.

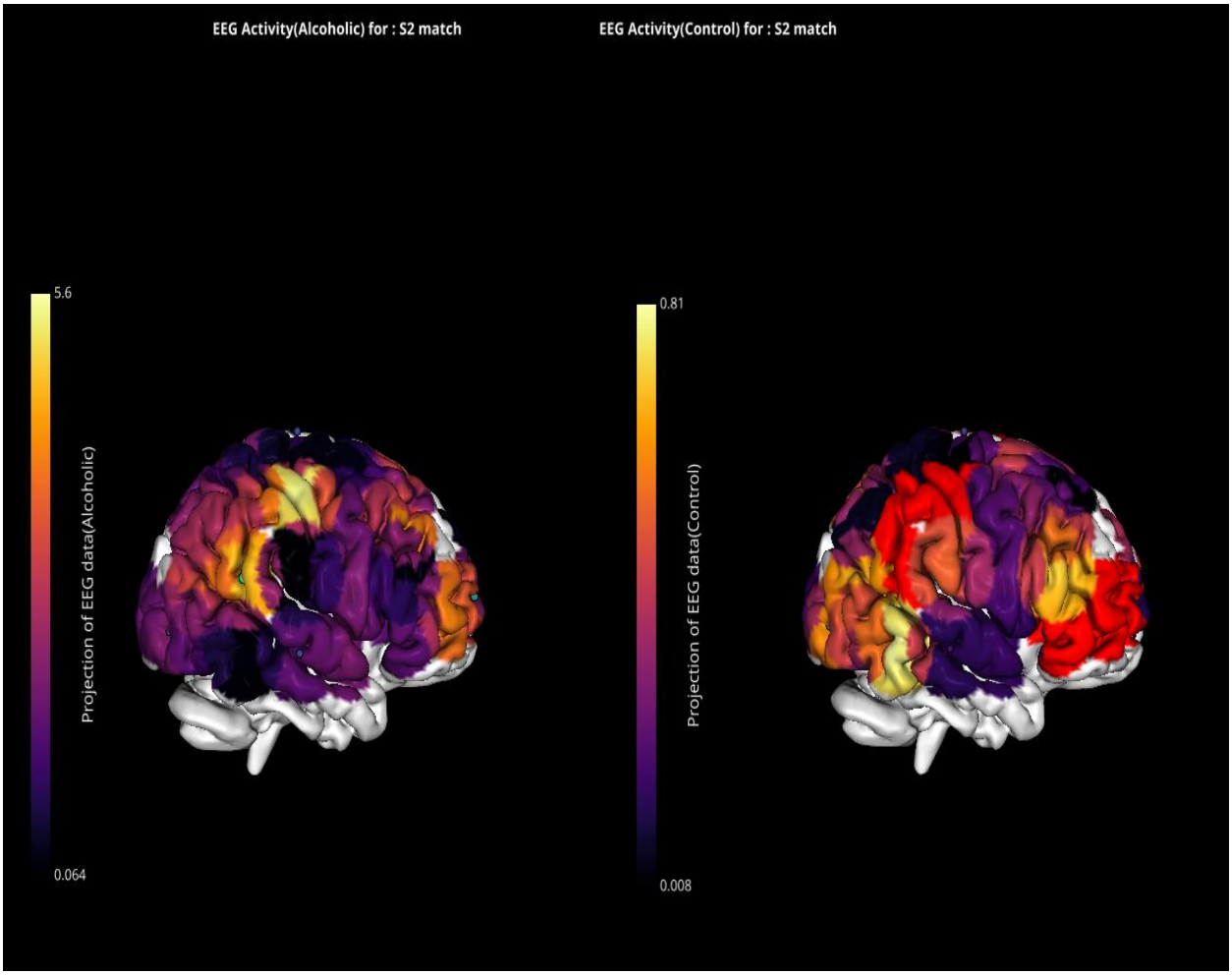

Figure 4.16 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Right Brain view

Figure 4.16 indicates activity for two groups when they are shown matching pictures. These plots are for right brain visualization. There is no masked maximum activity in the right brain of alcoholic groups. For the control group we see that the red regions are the executive functions/cognition region, the somatosensory functions regions, and the vision region.

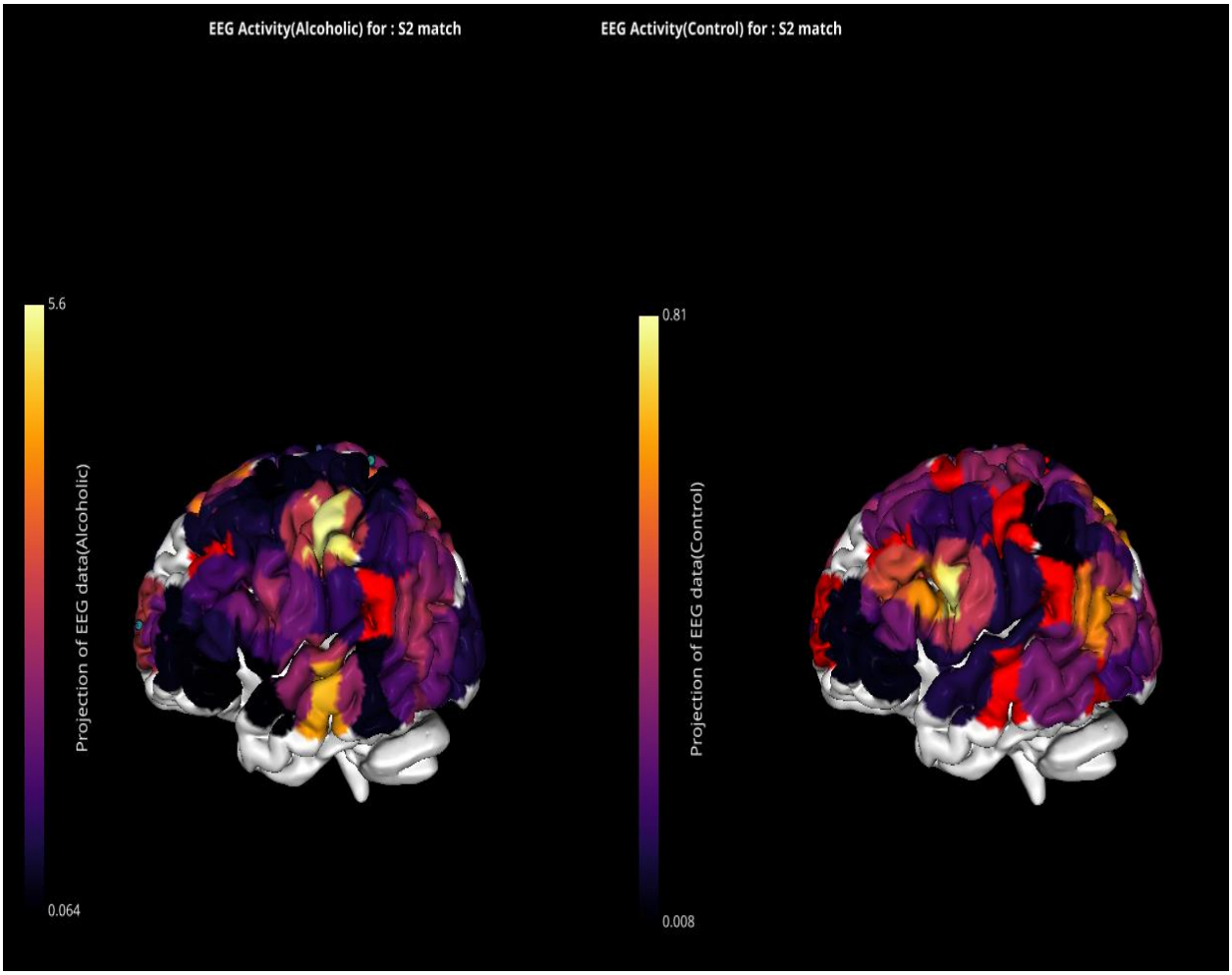

Figure 4.17 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Left Brain view

For the S2 match paradigm, we have shown maximum active regions in the left brain associated with both groups in Figure 4.17. For alcoholic group, the associated regions are vision region and few parts of the cognition region. The control group has activity associated with the visual temporal/memory region, the cognition region, the motor activity region, and the somatosensory region.

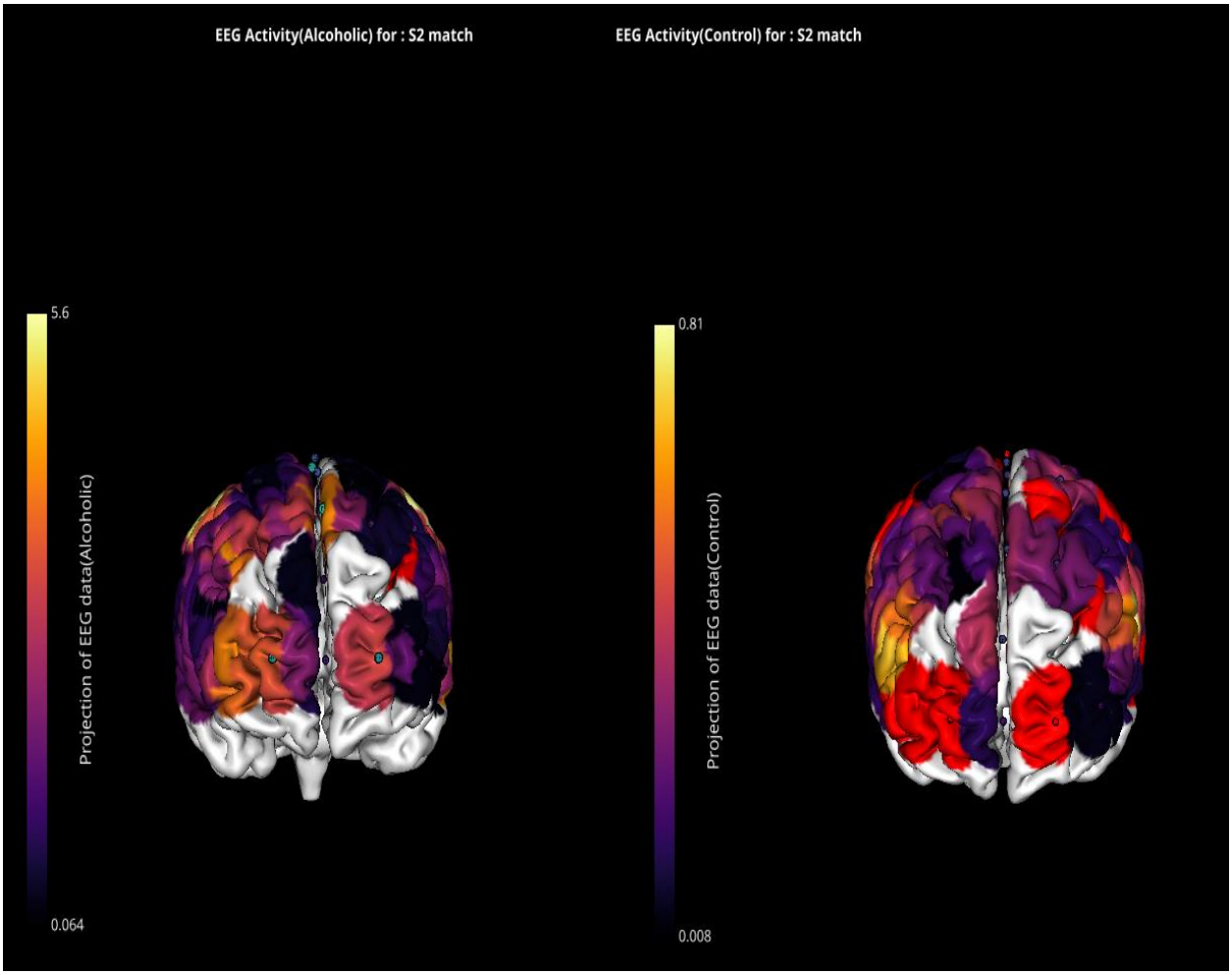

Figure 4.18 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Frontal Brain view

Figure 4.18 shows frontal region visualization of two groups for matching paradigm. We see masked activity in the frontal region in the control group.

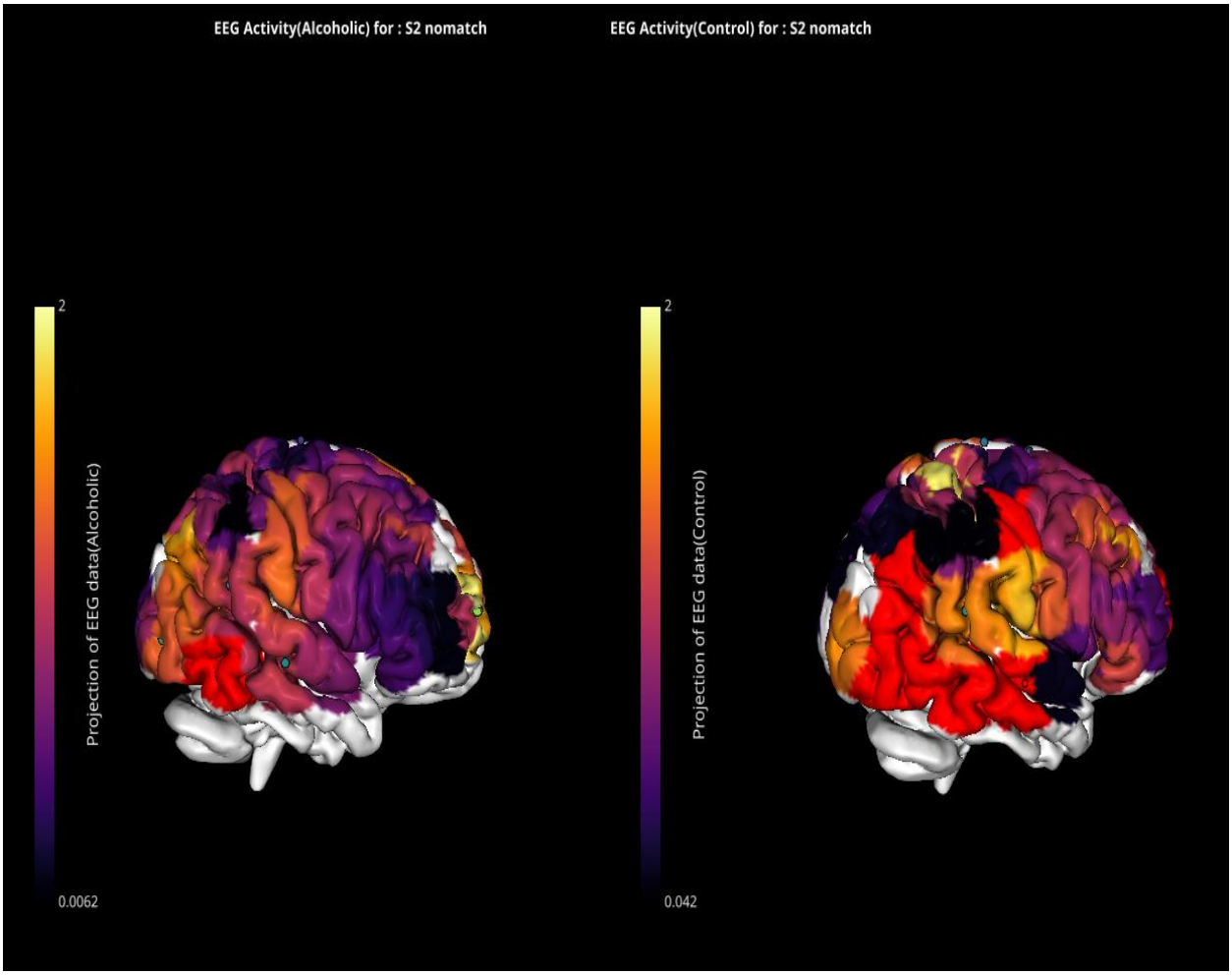

Figure 4.19 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match: Right Brain view

Figure 4.19 shows plot for the two groups subjected to visualize two nonmatching pictures. For the alcoholic group, the higher activity region is the visual-parietal region whereas for the control group the regions in the right brain with higher activities are the emotion region, the frontal eye field region, the visual-temporal, and part of the visual-parietal regions.

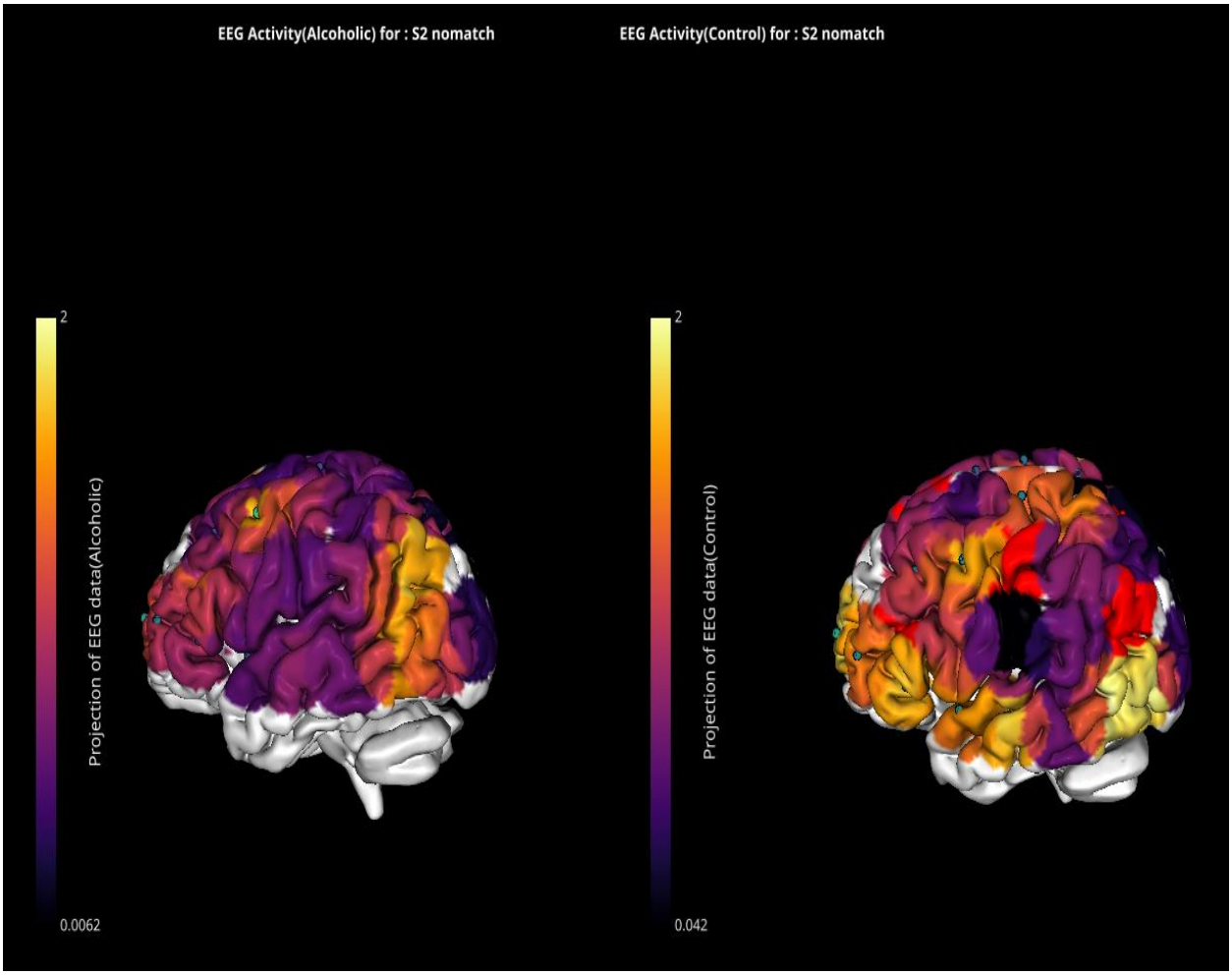

Figure 4.20 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match: Left Brain view

Figure 4.20 indicates left brain's activity for the nonmatching visual stimuli. There are no high activity regions for the alcoholic group in left brain whereas somatosensory, visual-parietal, and cognition regions are higher activity regions for the control group.

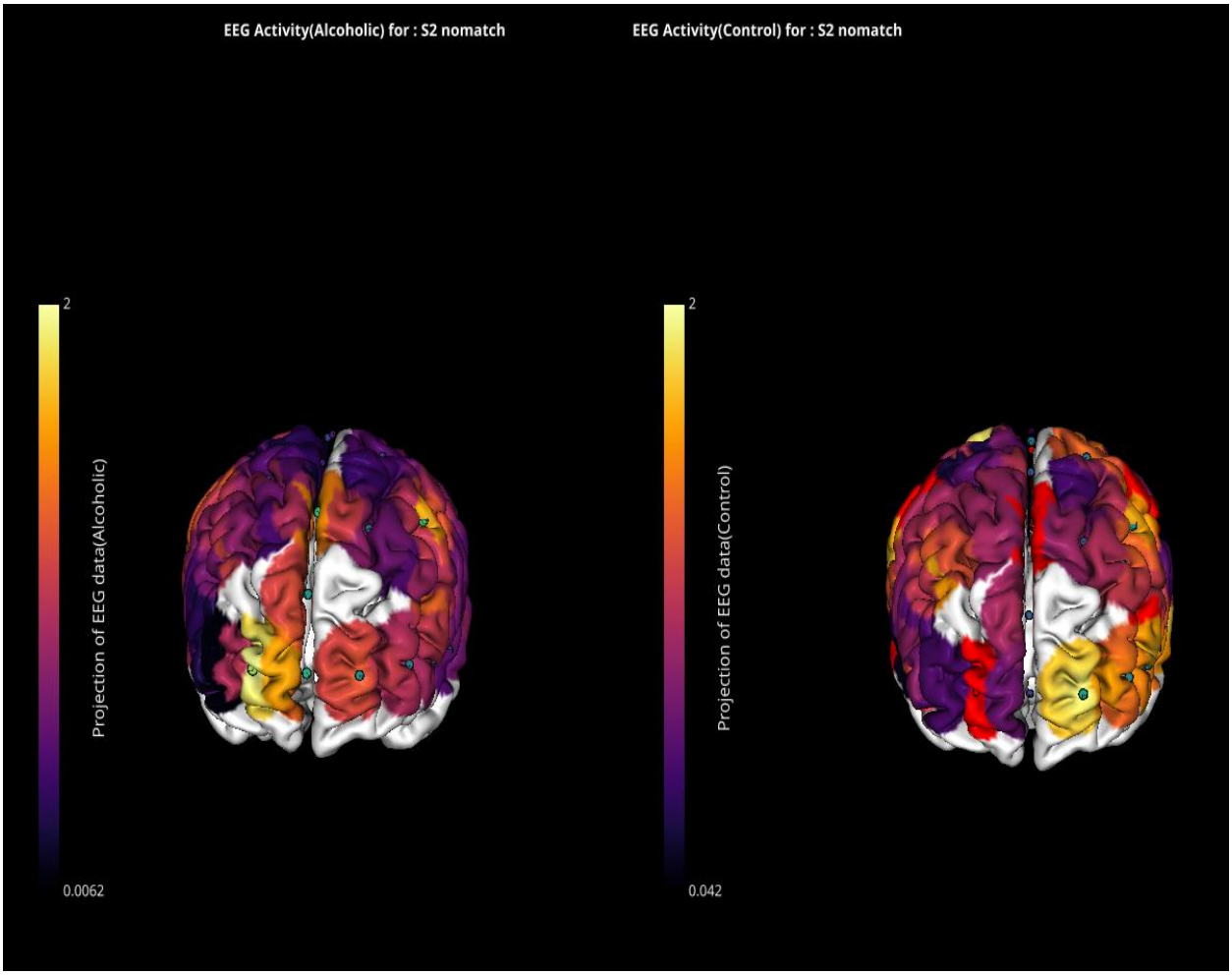

Figure 4.21 Visualization of averaged spatial patterns with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Frontal Brain view

Figure 4.21 shows frontal region visualization of two groups for non-matching paradigm. We see masked activity in the frontal region in the control group.

Next, we analyze the sources for both the groups for all three paradigms. Regions with maximum source activities are masked. The regions associated with maximum source activities for both groups are also compared.

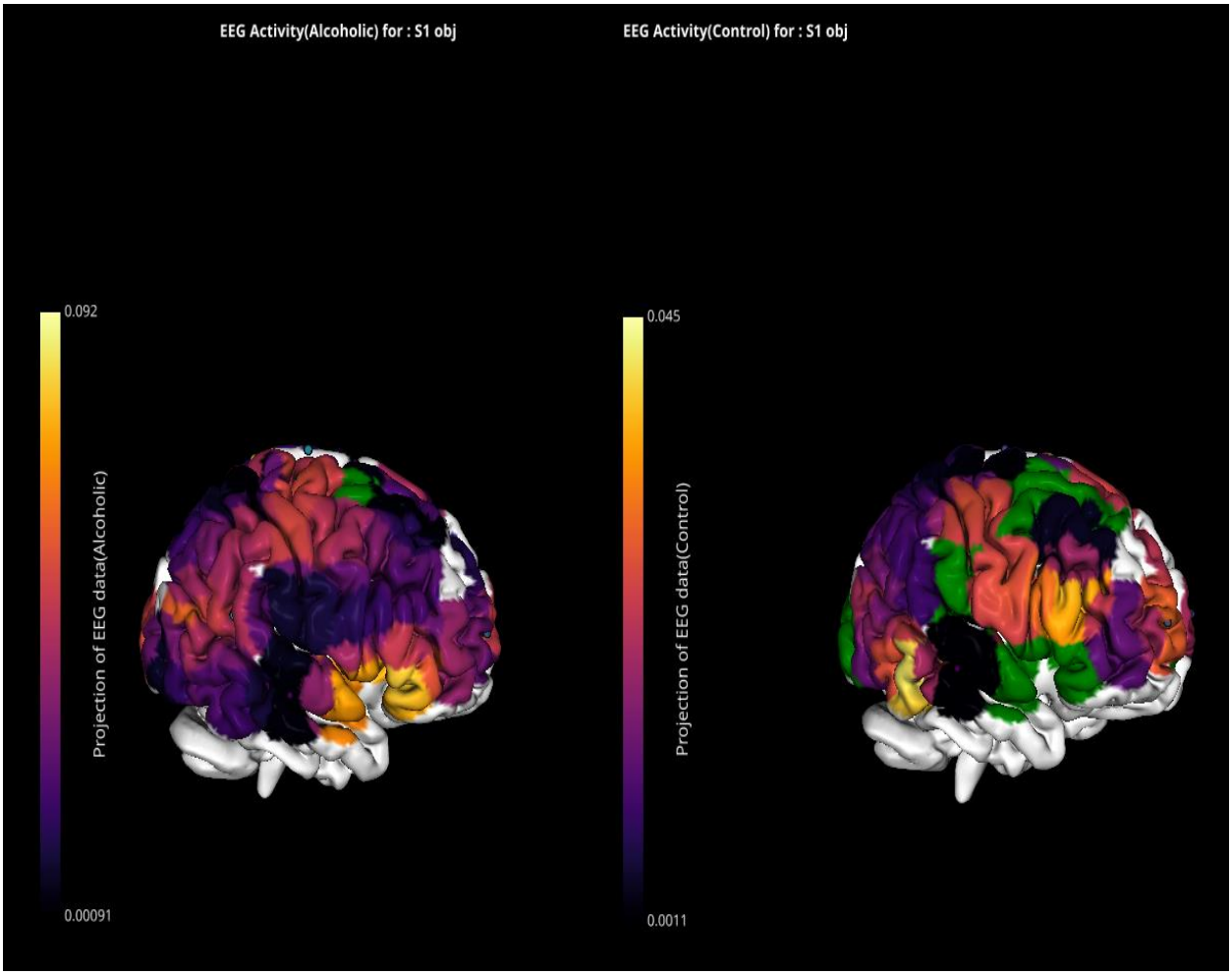

Figure 4.22 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Right Brain view

From Figure 4.22, we observe that the control group has masked activities in the right brain. The alcoholic group has very minimal activity in the right brain. There is a slight masked activity for alcoholic group in motor region in right brain whereas for the control group somatosensory, visual-parietal, memory, and few of the motor regions are highly active regions.

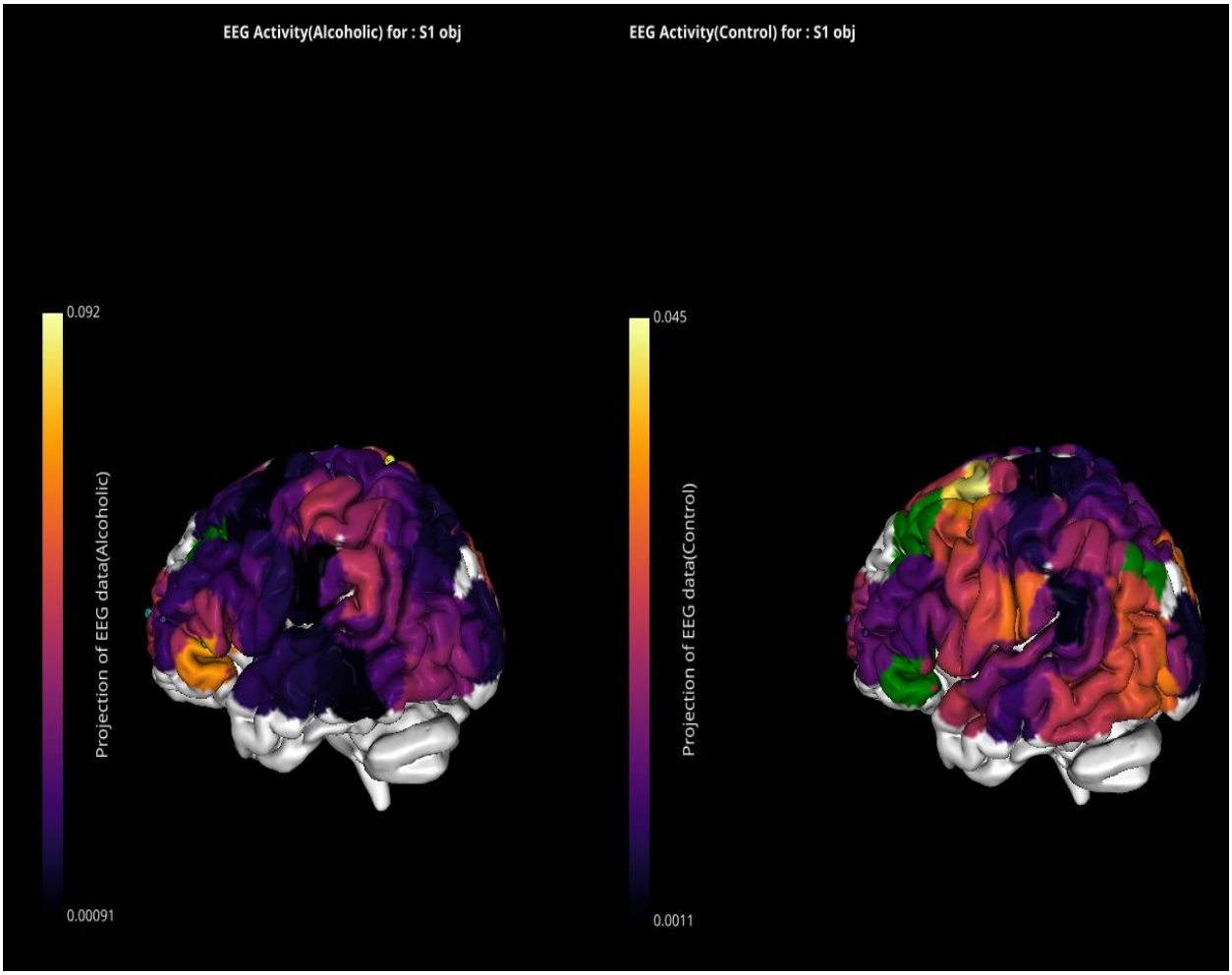

Figure 4.23 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Left Brain view

From Figure 4.23, we observe that control group has masked activities in left brain. Alcoholic group has very minimal activity in the left brain. There is a slight masked activity for alcoholic group in motor region in the left brain whereas for the control group emotional regulation, attention, and visual-parietal regions are highly active regions.

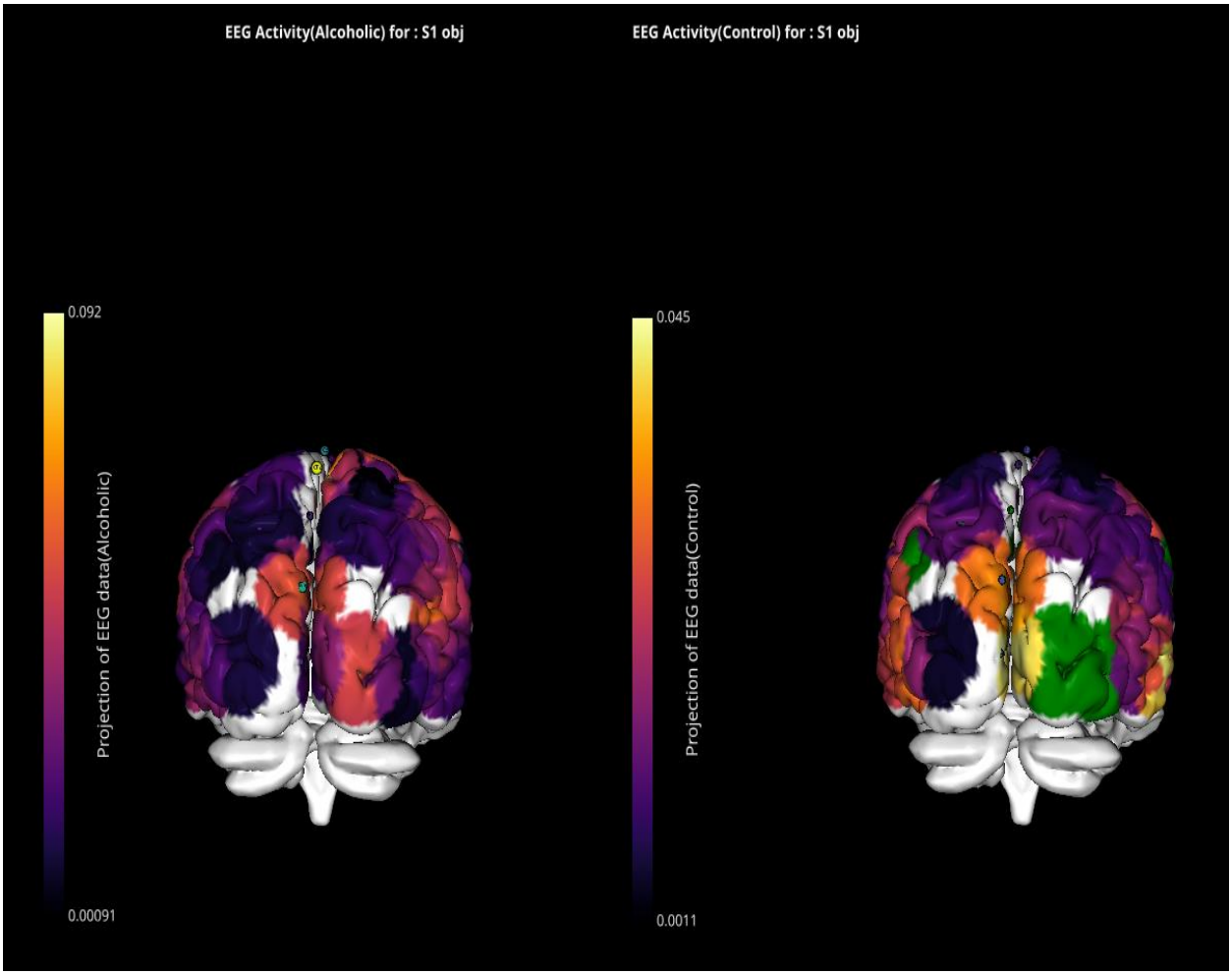

Figure 4.24 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj: Occipital Brain view

From Figure 4.24, we observe that control group has masked activities at the visual region whereas the alcoholic group has no masked activity in the occipital lobe.

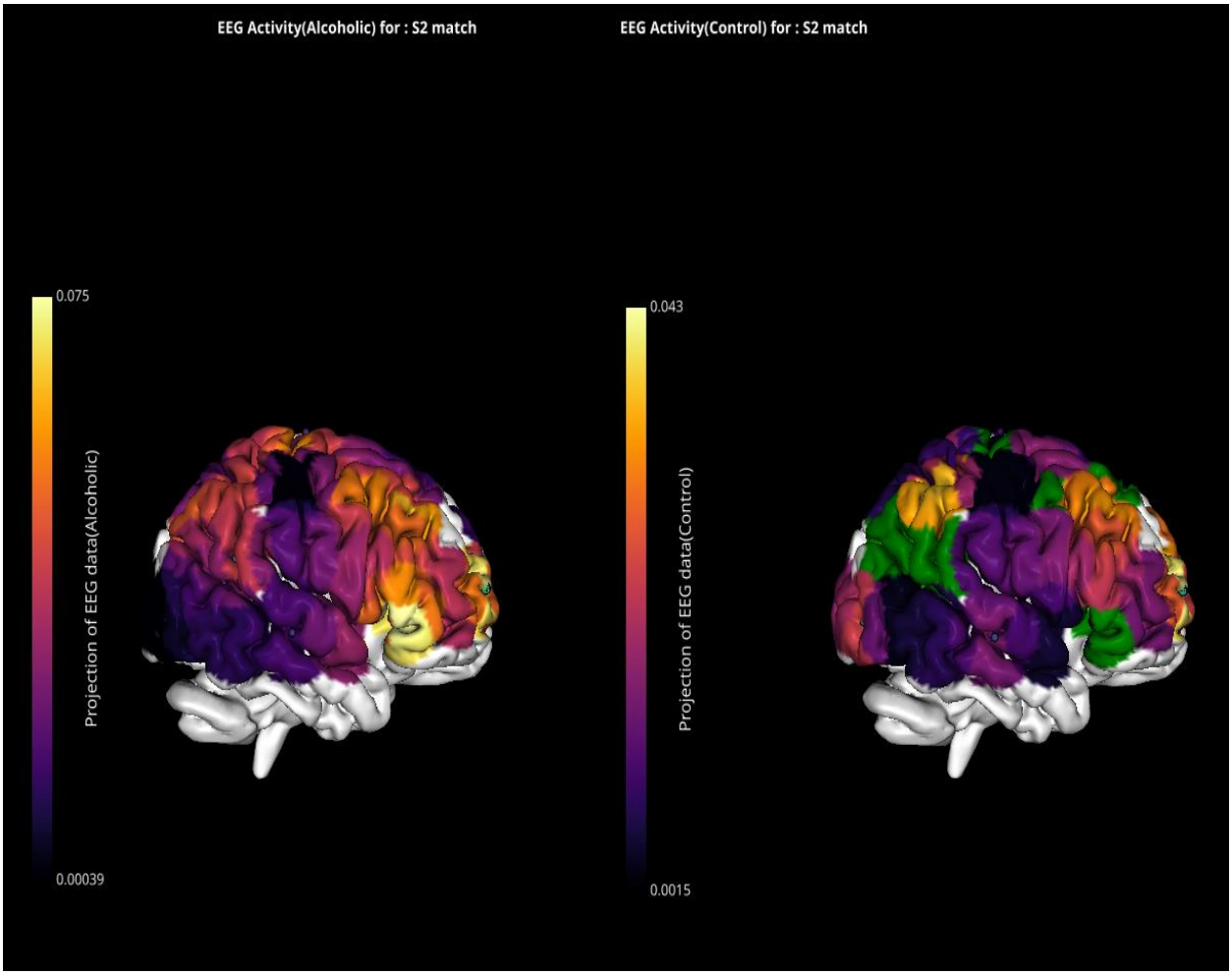

Figure 4.25 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Right Brain view

From Figure 4.25, we observe that control group has masked activities in the right brain. Alcoholic group has no masked activity in the right brain. For the control group, emotional regulation, attention, and few of the motor regions are highly active regions.

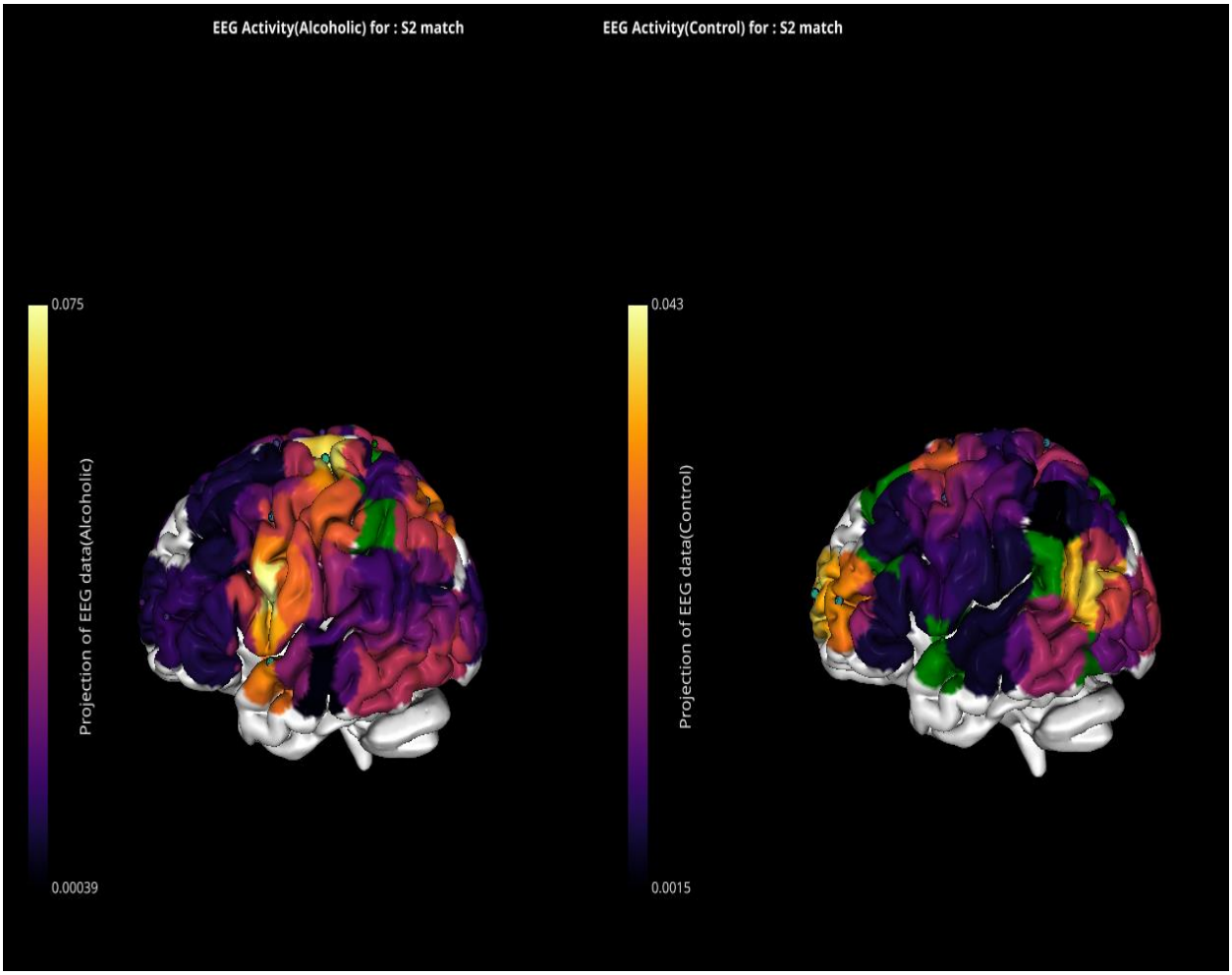

Figure 4.26 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Left Brain view

From Figure 4.26, we observe masked activities in left brain for both groups. Alcoholic group has masked activities in few of the attention regions in the left brain. For control group, somatosensory, emotional regulation, memory, and few of the motor regions are highly active regions.

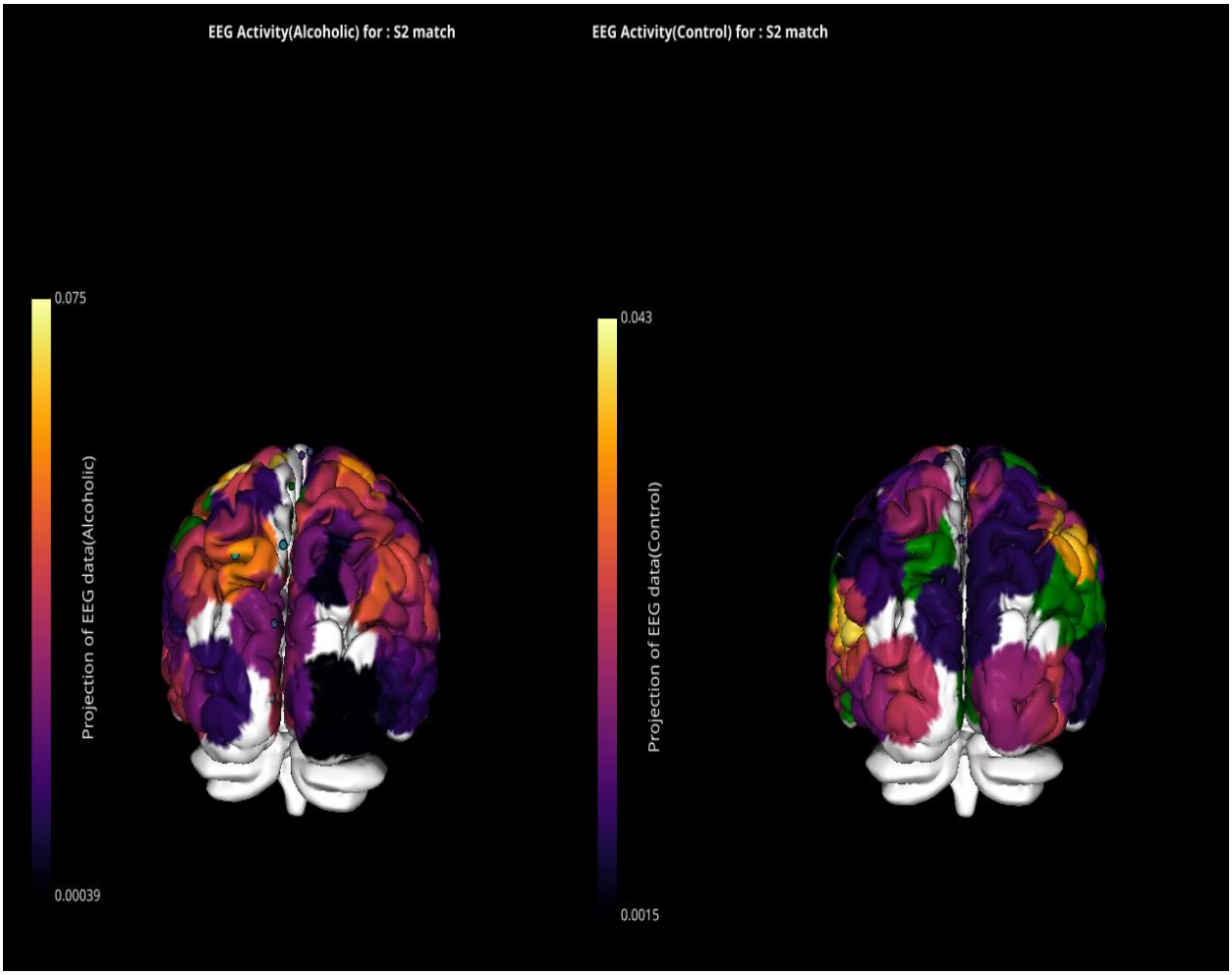

Figure 4.27 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match: Occipital Brain view

From Figure 4.27, we observe that there are few masked activities in the occipital region in the control group whereas the alcoholic group has no masked activity in the occipital lobe.

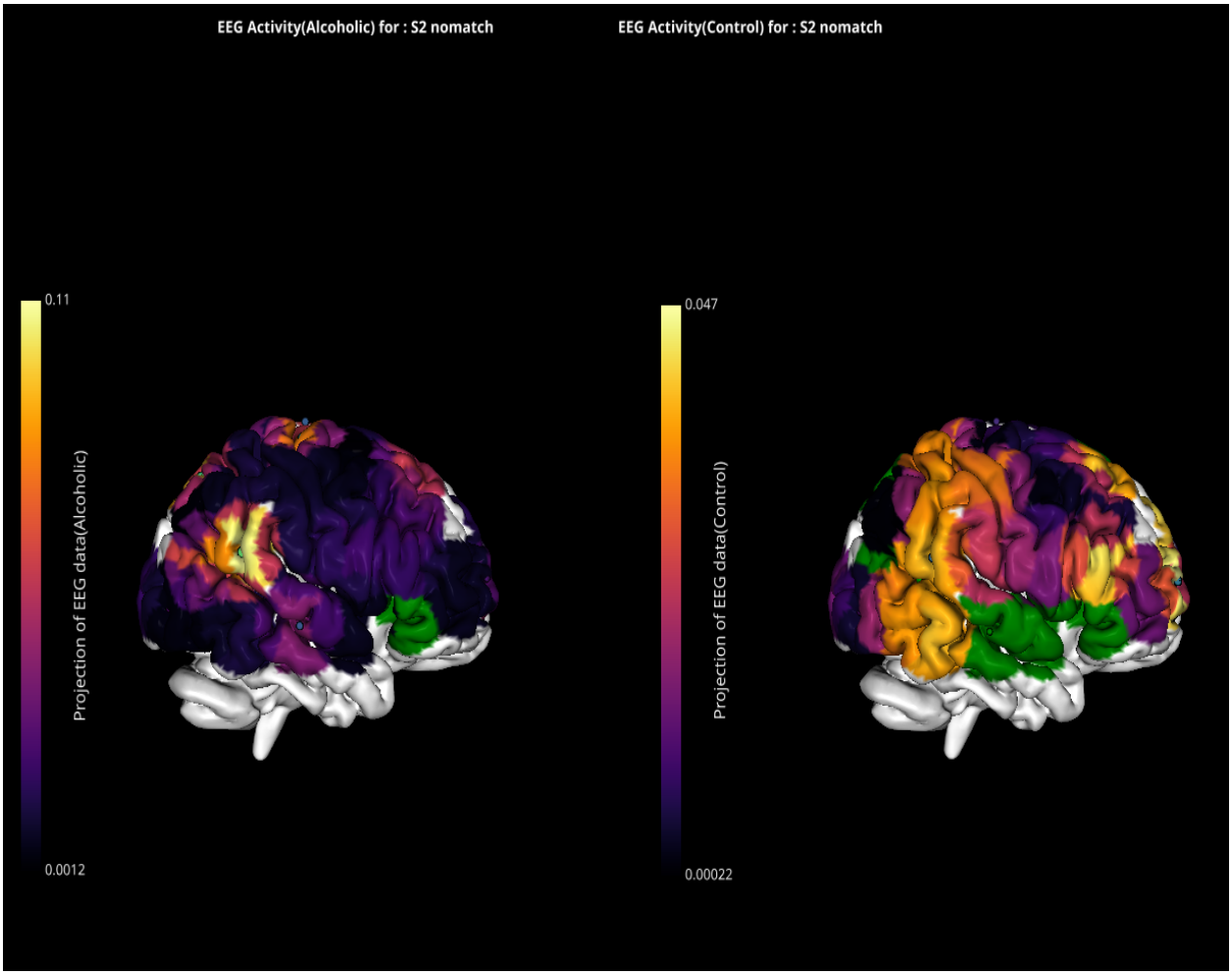

Figure 4.28 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match: Right Brain view

Figure 4.28 indicates the visuals for the right brain for nonmatching visual stimuli. Alcoholic group has masked activity in the emotional regulation region. Control group has activity in the emotional regulation, memory regions and few activities are seen in the vision region.

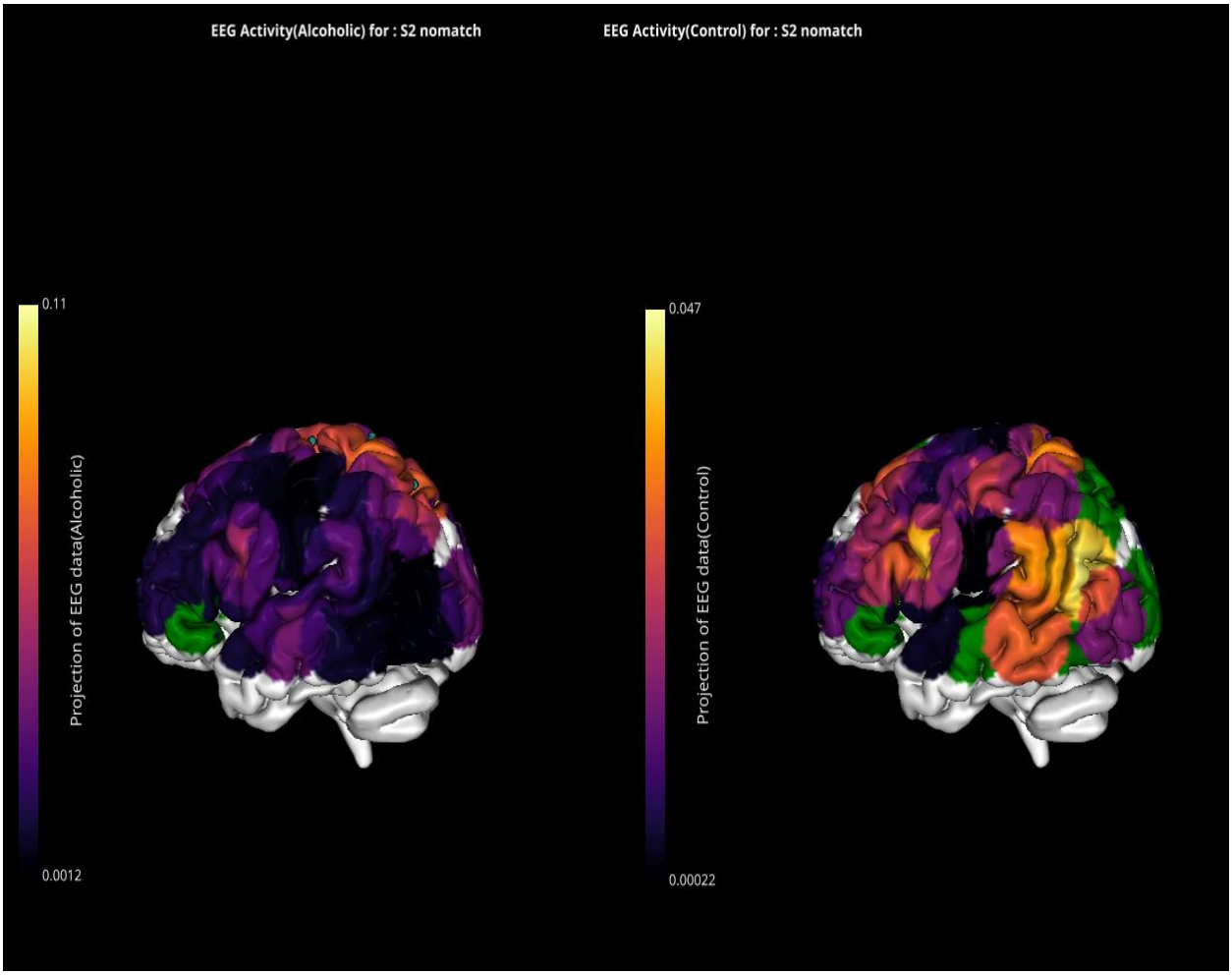

Figure 4.29 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match: Left Brain view

Figure 4.29 shows the visuals for the left brain for nonmatching visual stimuli. Alcoholic group has masked activity in the emotional regulation region. Control group has activity in the emotional regulation, attention and memory regions and few activities is seen are vision region.

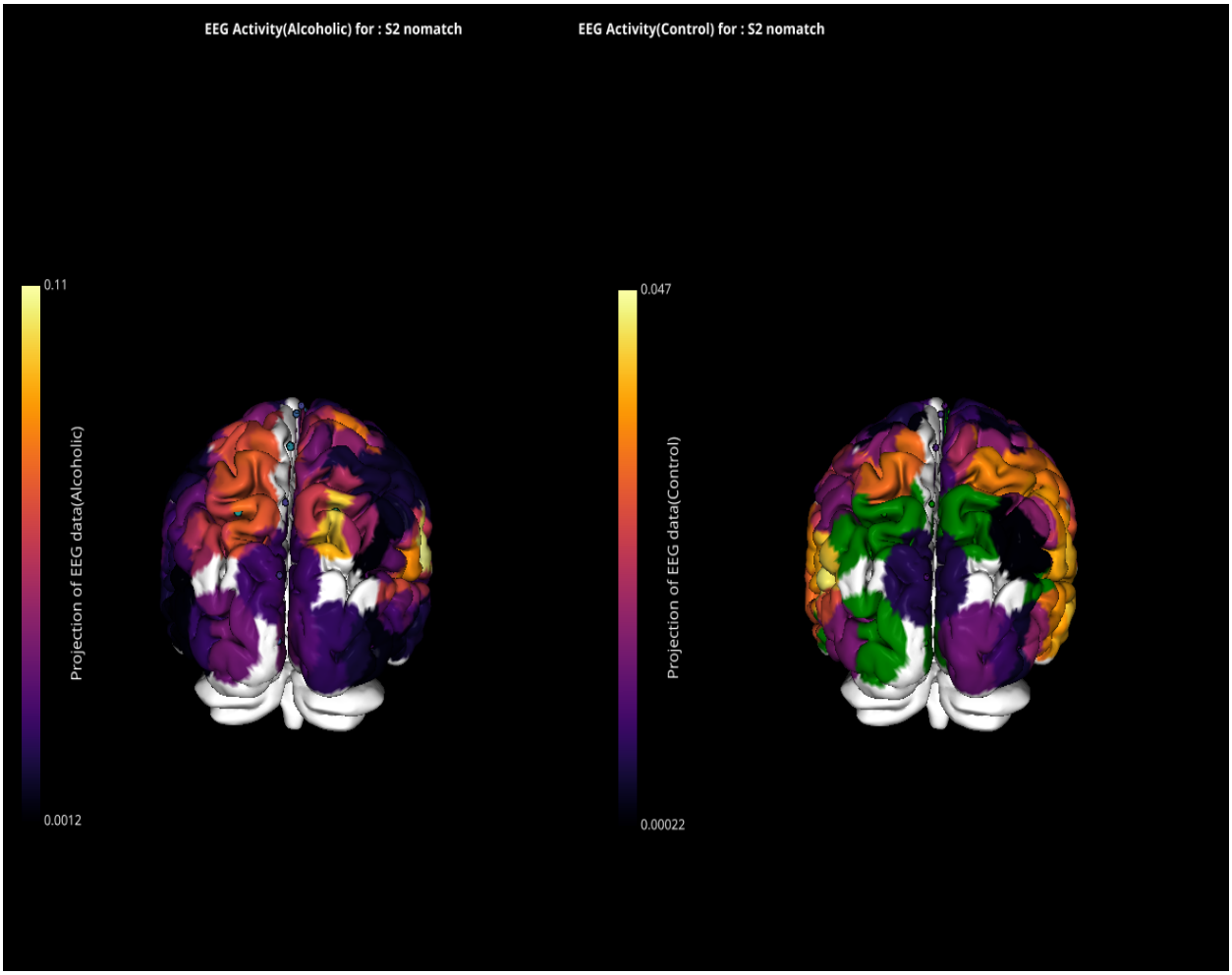

Figure 4.30 Visualization of averaged Source activity with masked region for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match: Occipital Brain view

Figure 4.30 shows the visuals for occipital lobe for nonmatching visual stimuli. Alcoholic group has zero masked activity in this region. Control group has activity in attention and vision regions of the occipital lobe.

Next, we focused on attention related activity between two groups based on projection of the source activity into the attention region and comparing the source activity values for both groups.

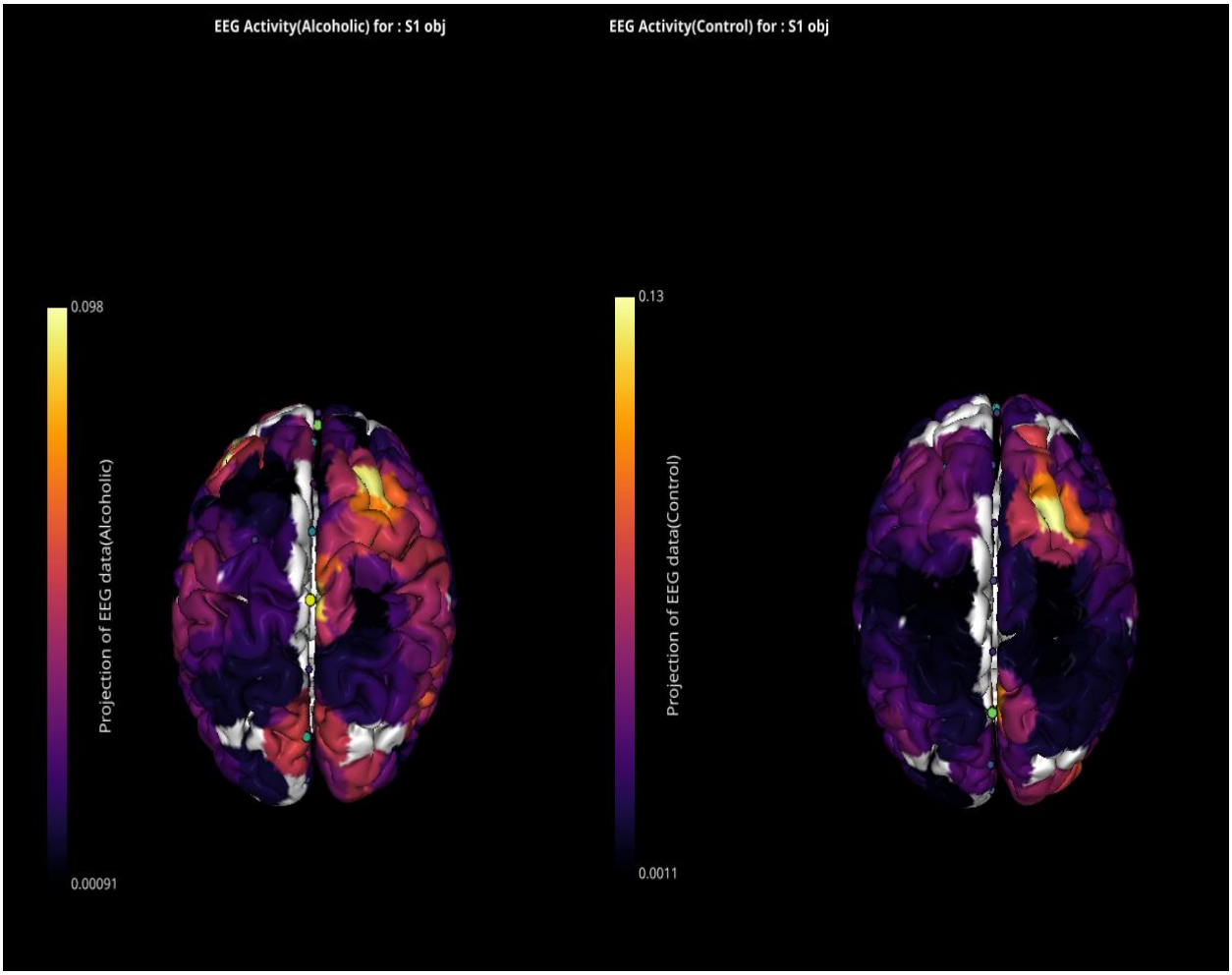

Figure 4.31 Visualization of association of averaged Source activity to attention regions for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S1 obj

From Figure 4.31, we observe that the control group has higher activity in the attention region in comparison to alcoholic group when single image is shown.

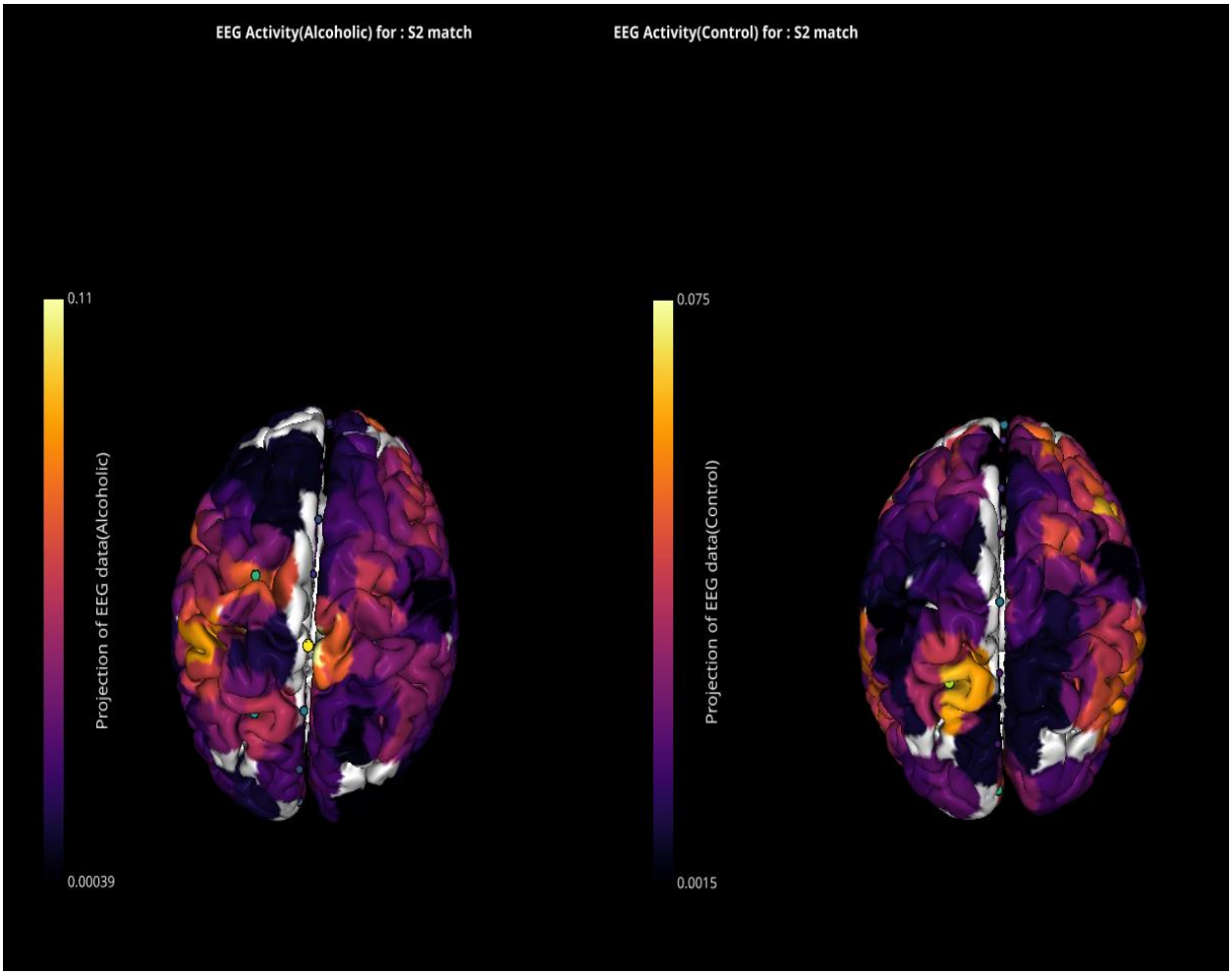

Figure 4.32 Visualization of association of averaged Source activity to attention regions for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 match

From Figure 4.32, we observe that for matching pictures as well, the control group has higher activity in attention region in comparison to the alcoholic group.

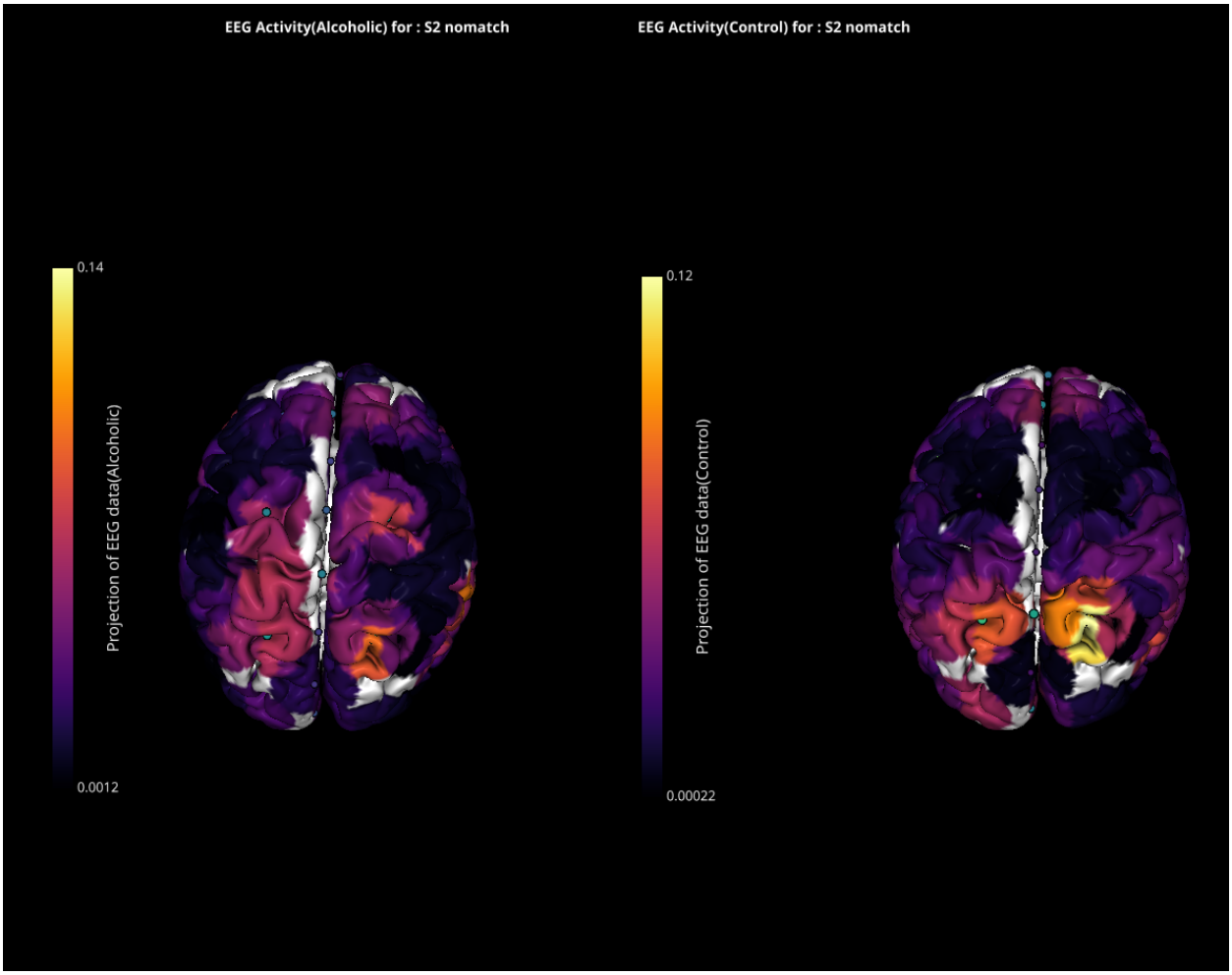

Figure 4.32 Visualization of association of averaged Source activity to attention regions for ten subjects (Alcoholic) and ten subjects (Control) for stimulus S2 no match

From Figure 4.32, we observe that for two nonmatching visual stimuli, the control group shows more activity in the attention region than alcoholic group.

Summary:

We estimated different spatial patterns for both groups alcoholic and non-alcoholic (control) per visual stimuli where we masked maximum activity regions to have a comparison between them. For the alcoholic group, there is no maximum activity found in the right brain for visualization of one picture and matching pictures. Negligible amount of activity is found for non-

matching images for the alcoholic group. Hence overall, the alcoholic group is found to be left-brained as majority of masked activity regions are found in the left brain. The regions in left brain where the alcoholic group has maximum activity are emotional regulation region, vision, visual-parietal, and few cognitions regions. Most active regions associated with control groups are executive function, memory, somatosensory, vision, frontal-eye, and visual parietal regions. There is no maximum frontal activity region found for the alcoholic group whereas we find the same for the control group.

We also evaluated source activity for each group per stimuli. For the alcoholic group, very few regions in the right and left brain such as emotional regulation region and motor region are involved in maximum source activities. For the control group, the major active regions are somatosensory, memory, visual, attention, and few emotional regulation regions. We also find maximum activity in the occipital regions for the control group whereas there is no such activity associated in occipital regions for the alcoholic group. The control group has higher source activities associated with the attention region than alcoholic group for all three stimuli.

Chapter 5

EEG Channel optimization Of Alcoholic vs Control Using NSGA-II

In this chapter, we have identified the optimized EEG channels for both alcoholic and control groups. For this, we utilized multi-objective non-dominated sorting genetic algorithm to find the optimal channels. We have used two objective functions in our program. The first function evaluates alpha power of EEG sources, while the second function evaluates gamma power. We have plotted both alpha and gamma band power for the optimal channels. The above program is executed on the source activity that we found in Chapter 4. Thus, we can say that the optimal channels are based on source activity. Besides this, we also did time frequency analysis of the optimal channels. Choosing the optimized EEG channel will help to do an effective and objective-oriented analysis on filtered data instead of working on the entire dataset.

To reduce the number of EEG channels, this work developed a method based on multi-objective Non-dominated Sorting Genetic Algorithm (NAGA-II) to extract optimal sources and their respective channels. This method maximizes alpha band power and gamma band power of sources to analyze EEG source signals and optimizes the source characteristics extracted based on Common Spatial Patterns (CSP).

Non-dominated sorting is mainly used to sort the solutions in population according to the Pareto dominance principle, which plays a very important role in the selection operation of many

multi-objective evolutionary algorithms. In this work, the pareto dominated solutions are evaluated based on their alpha power scores and gamma band power scores. The optimal fronts are the non-dominated solutions, and they consist of the solutions that maximizes both the alpha and gamma band power.

A. Non-Dominated Sorting Genetic Algorithm (NSGA-II)

NSGA-II stands for non-dominated sorting genetic algorithm [TAP 2002]. Using this algorithm, we can solve the MOO (Multi objective Optimization) problem. In this we divide the population into fronts. The solution in each front is nondominated with each other. Each solution in a front is dominated by solutions in the preceding front. A front is a set of nondominated solutions, being chosen as optimal.

The key process steps of NSGA-II are:

1. Start with a random population of solutions (P) in binary form (chromosomes).
2. Create a child population(Q) using crossover and mutation.
3. Combine parent(P) and child(Q) populations and score for all objective functions.
4. Repeat the above for maximum number of generations set.
5. Identify the first Pareto front (F1); that is all solutions where there are no other solutions that are at least equally good in all objectives and better in at least one objective.
6. If F1 is smaller than the required population size, then repeat Pareto selection (after removal of already selected solutions). This new set of solutions is F2.
7. Repeat Pareto selection until the required population size is reached.
8. Repeat from (2) for the required number of generations or until some other ‘stop’ criterion is reached.

9. Perform a final Pareto selection so that the final reported population are just those on the first Pareto front.

B. Objective Functions

We have two objective functions used in our program. The first function maximizes the alpha power of EEG sources. The second fitness function maximizes the gamma power of the same. The fitness function is evaluated for the required number of generations. Scores from both fitness functions are compared to find the non-dominated solutions. For non-dominated solutions crowding distance is evaluated to find the best front. This entire process is repeated for the required number of generations. In this case we have considered a given number of generations as the termination condition. The maximum number of generations in our case is set to 100 as the value of the fitness functions converges at this point.

C. Alpha and Gamma Power

One of the most widely used method to analyze EEG data is to decompose the signal into functionally distinct frequency bands, such as delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz). The most widely-used method to do that is the Welch's periodogram, which consists in averaging consecutive Fourier transform of small windows of the signal, with or without overlapping. Now, before computing the average alpha and gamma band powers, we defined the frequency bins that intersect the alpha and gamma frequency ranges. Then we estimated the power bands for the source signals and found the optimized channel that maximizes the source powers. We plotted the optimal band powers of the optimal sources. Besides this we also evaluated features such as short time Fourier transform and Continuous Wavelet Transform.

D. Optimal Combination of Channels

Table 4 shows optimal channels for both alcoholic and control groups that we calculated by applying NSGA-II with two objective functions.

Visual Stimuli	Alcoholic	Control
S1 obj	['C6', 'CP1', 'CP2', 'CP5', 'CP6', 'F2', 'F7', 'FC4', 'FC5', 'FPZ','FT7', 'OZ', 'P1', 'P3', 'P6', 'P7', 'P8', 'PO7', 'PO8', 'POZ', 'T7']	['C2', 'C4', 'C5', 'CP2', 'CP5', 'F1', 'F3', 'F4', 'FC3', 'FC5', 'FC6','FT7', 'O1', 'P3', 'P5', 'PO7', 'POZ', 'T7', 'TP7']
	['F7', 'FT8', 'TP7']	['C3', 'C4', 'C6', 'CP1', 'CP4', 'CP5', 'F4', 'F6', 'F7', 'FC2', 'FC6', 'FT8', 'P2', 'P5', 'P7', 'P8']
	['CP5', 'F2', 'FC2', 'FC5', 'FC6', 'FPZ', 'FT8', 'O2', 'OZ', 'P3', 'P4', 'P5', 'P6', 'P8', 'PO8', 'T7', 'TP7', 'TP8']	['C3', 'C4', 'C5', 'C6', 'CP1', 'CP3', 'CP5', 'CP6', 'CZ', 'F2', 'F3', 'F4', 'F6', 'F7', 'FC3', 'FP2', 'FPZ', 'OZ', 'P7', 'PO7', 'POZ', 'TP7']
	['CP1', 'CP2', 'CP5', 'CZ', 'FC3', 'FC4', 'FC6', 'FCZ', 'FT7', 'OZ', 'P1', 'P3', 'P7', 'PO7', 'PO8', 'PZ', 'T8']	['C3', 'C4', 'C5', 'C6', 'CP1', 'CP2', 'CP4', 'CP5', 'CP6', 'F4', 'F5', 'F6', 'F7', 'FP1', 'FPZ', 'FT7', 'O2', 'P2', 'P8', 'T7', 'TP8']
	['C6', 'CP5', 'F2', 'F5', 'F8', 'FC5', 'FC6', 'FCZ', 'FP2', 'FT8', 'O2', 'OZ', 'P1', 'P2', 'P3', 'P7', 'P8', 'PO7', 'POZ', 'T7', 'TP8']	['C2', 'C6', 'CP1', 'F2', 'F6', 'FC5', 'FPZ', 'FT7', 'FT8', 'O1', 'P1', 'P6', 'P7', 'T7', 'T8', 'TP7']
S2 match	['C2', 'CP1', 'CP2', 'CP3', 'CP4', 'CP6', 'F1', 'F2', 'F7', 'FC3', 'FCZ', 'FPZ', 'FT8', 'FZ', 'O1', 'OZ', 'P3', 'P4', 'P8', 'PO7', 'POZ', 'PZ', 'T8', 'TP7', 'TP8']	['C2', 'C4', 'C5', 'CP1', 'CP2', 'CP4', 'CP6', 'F1', 'F3', 'FZ', 'OZ', 'P6', 'TP8']
	['CP1', 'CP3', 'CPZ', 'CZ', 'F4', 'F7', 'FC1', 'FC3', 'FCZ', 'FP2', 'FPZ', 'OZ', 'P1', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8', 'PO7', 'PO8', 'POZ', 'PZ', 'T7', 'T8', 'TP7', 'TP8']	['C4', 'C5', 'CP2', 'CP3', 'CP4', 'CP6', 'CZ', 'F1', 'F2', 'F3', 'F4', 'F8', 'FC1', 'FC2', 'FC6', 'FCZ', 'FT7', 'FZ', 'P2', 'P3', 'P4', 'P6', 'PO7']
	['C5', 'CP4', 'CP6', 'CPZ', 'F2', 'F7', 'F8', 'FC3', 'FC6', 'FCZ', 'FPZ', 'O1', 'OZ', 'P1', 'P2', 'P4', 'P7', 'PO7', 'PO8', 'POZ', 'PZ', 'T7', 'TP7', 'TP8']	['C4', 'C5', 'C6', 'CP2', 'CP4', 'CP6', 'CZ', 'F1', 'F2', 'F3', 'F4', 'F6', 'F8', 'FC1', 'FC3', 'FC4', 'FCZ', 'FT7', 'FZ', 'P1', 'P3', 'P6', 'PO7']
	['C5', 'CP1', 'CP4', 'CPZ', 'F4', 'F5', 'FC3', 'FC6', 'FP1', 'P3', 'P7', 'PZ', 'T7', 'T8', 'TP8']	['C3', 'C4', 'CP2', 'CP3', 'CP4', 'CP6', 'CPZ', 'F1', 'F3', 'F4', 'F5',

		'F6', 'F7', 'FC4', 'FC6', 'FP1', 'FPZ', 'FZ', 'OZ', 'P6', 'P8', 'PO7']
	['C5', 'CP1', 'CP2', 'CP3', 'CP4', 'F7', 'F8', 'FC3', 'FPZ', 'O1', 'O2', 'OZ', 'P3', 'P4', 'PO7', 'PO8', 'PZ', 'T7', 'T8', 'TP8']	
S2 no match	['C4', 'C5', 'CZ', 'F2', 'FT8', 'O2', 'OZ', 'P2', 'P4', 'P5', 'P7', 'P8', 'PO7', 'PO8', 'T8', 'TP8']	['C2', 'C5', 'C6', 'CP3', 'CP5', 'CP6', 'CZ', 'F1', 'F3', 'F4', 'F8', 'FC1', 'FC2', 'FC6', 'FCZ', 'P1', 'P3', 'TP7']
	['CP3', 'CP5', 'CZ', 'F1', 'F2', 'FC2', 'FC6', 'O2', 'P5', 'P6', 'PO7', 'PO8', 'POZ', 'TP7', 'TP8']	['C4', 'CP1', 'CP2', 'CP3', 'FC1', 'FPZ', 'O1', 'P3']
	['CP2', 'CP4', 'CZ', 'F1', 'F2', 'F3', 'F6', 'F7', 'FC3', 'FC5', 'FT8', 'O1', 'OZ', 'P1', 'P4', 'P5', 'P8', 'PO8', 'POZ', 'PZ', 'T8', 'TP7', 'TP8']	['C3', 'CP1', 'CP3', 'CP5', 'CP6', 'F1', 'F3', 'F4', 'FC1', 'FC4', 'FPZ', 'O1', 'P4', 'P5']
	['C5', 'C6', 'CP5', 'F3', 'F7', 'FC3', 'FC4', 'FC5', 'FC6', 'FCZ', 'FT8', 'OZ', 'P3', 'P4', 'P7', 'P8', 'POZ', 'T7', 'TP7', 'TP8']	['C3', 'C4', 'CP1', 'CP2', 'CP3', 'CP6', 'F1', 'F6', 'F7', 'F8', 'FC1', 'FC3', 'FC6', 'FP2', 'FPZ', 'O2', 'PO8', 'POZ', 'PZ', 'TP7', 'TP8']
	['C4', 'C6', 'CP5', 'F2', 'F7', 'FC4', 'FC6', 'FP2', 'FT8', 'O1', 'O2', 'OZ', 'P4', 'P5', 'P8', 'PO7', 'PO8', 'POZ', 'T7', 'TP7', 'TP8']	['C3', 'C4', 'C6', 'CP1', 'CP2', 'CP3', 'CP5', 'F1', 'F3', 'FC1', 'FPZ','O1', 'P4', 'P5']
	['C4', 'C5', 'F2', 'FT8', 'O2', 'OZ', 'P1', 'P4', 'P7', 'P8', 'PO7', 'PO8', 'POZ', 'T7']	['C2', 'C5', 'CP6', 'F2', 'F3', 'FCZ', 'FT8', 'PO8', 'POZ', 'T7', 'TP7', 'TP8']

Table 5.1: Optimized channels that maximizes alpha and gamma power.

For the optimized channels found in Table 5.1, we evaluated the power spectral density by using the Welch's periodogram to understand the association of alpha and gamma bands power for both alcoholic and control group. Apart from the band power analysis, we performed time frequency analysis on the individual optimized channels to see the association of other bands. In this case, we have considered the hamming window with three different values for three different

plots. The hamming windows are used as one of several windowing functions available for smoothing values.

Since a time-frequency visualization shows all representable frequencies at each timestep, this view allows the time series' frequency evolution to be analyzed. Figures 5.1 to 5.12 show a sample of the time-frequency visualization for optimized channels that were researched.

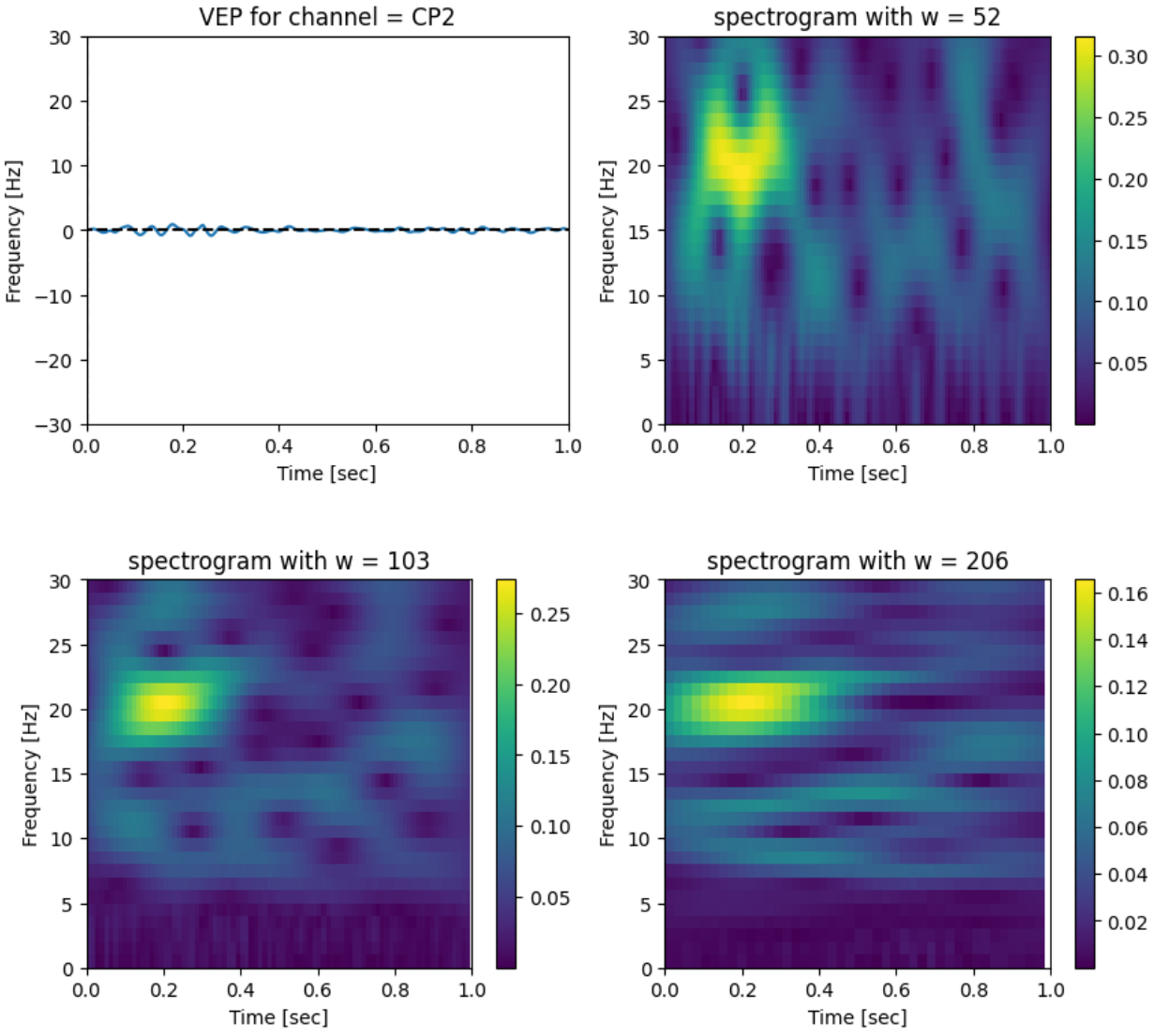

Figure 5.1 Time frequency analysis of Optimized channel CP2 (Alcoholic) S1 obj

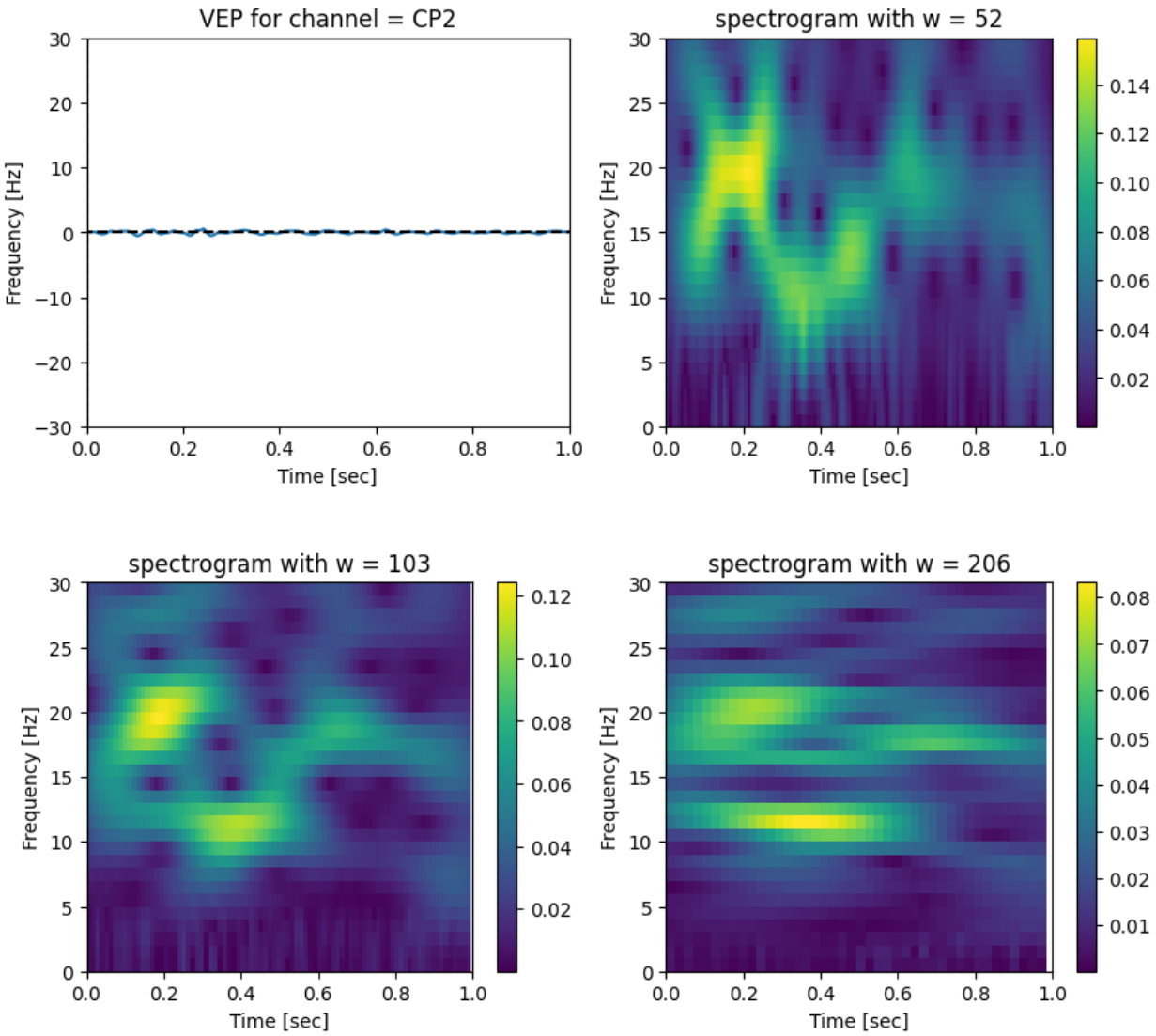

Figure 5.2 Time frequency analysis of Optimized channel CP2 (Control) S1 obj

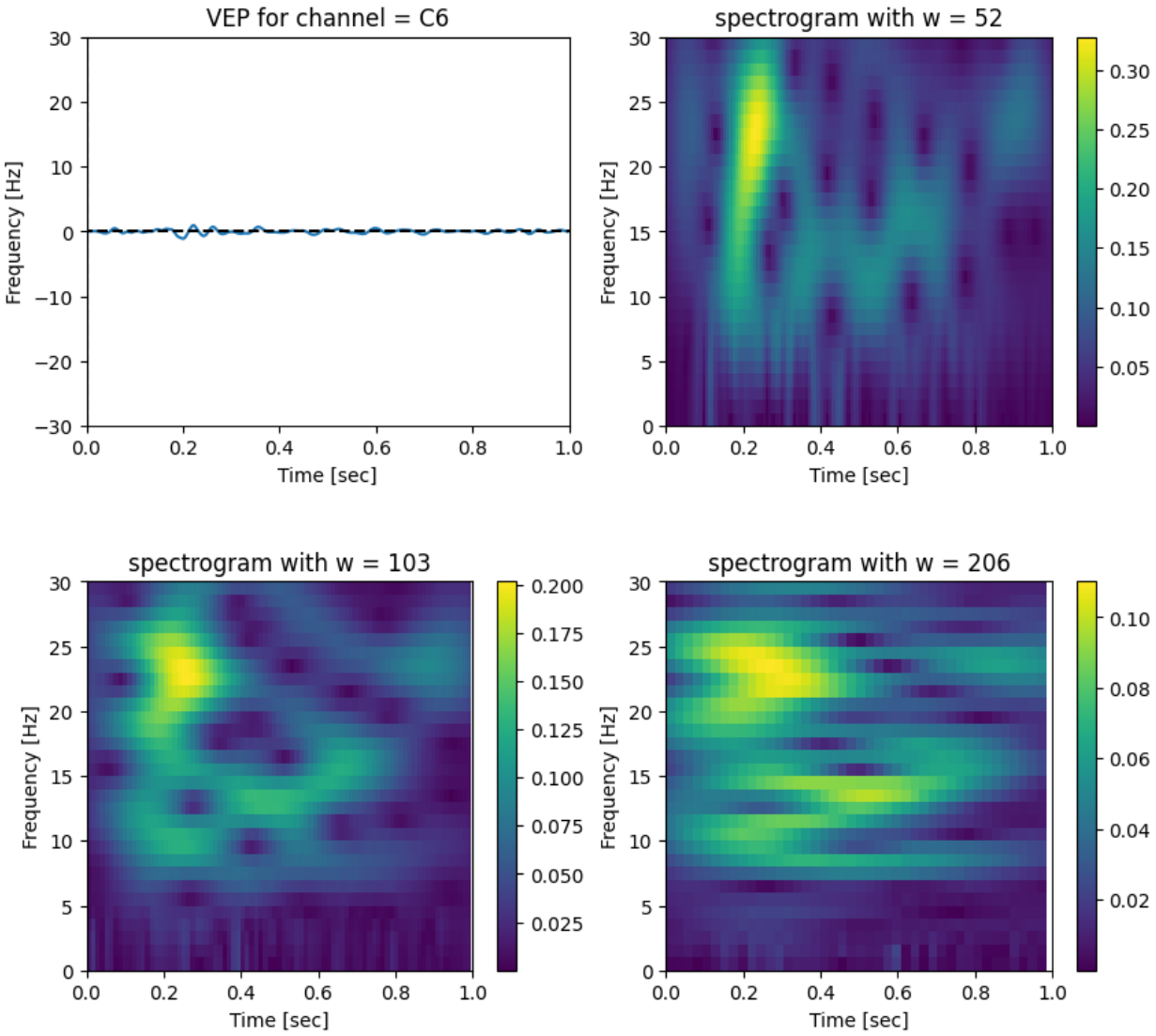

Figure 5.3 Time frequency analysis of Optimized channel C6 (Alcohol) S1 obj

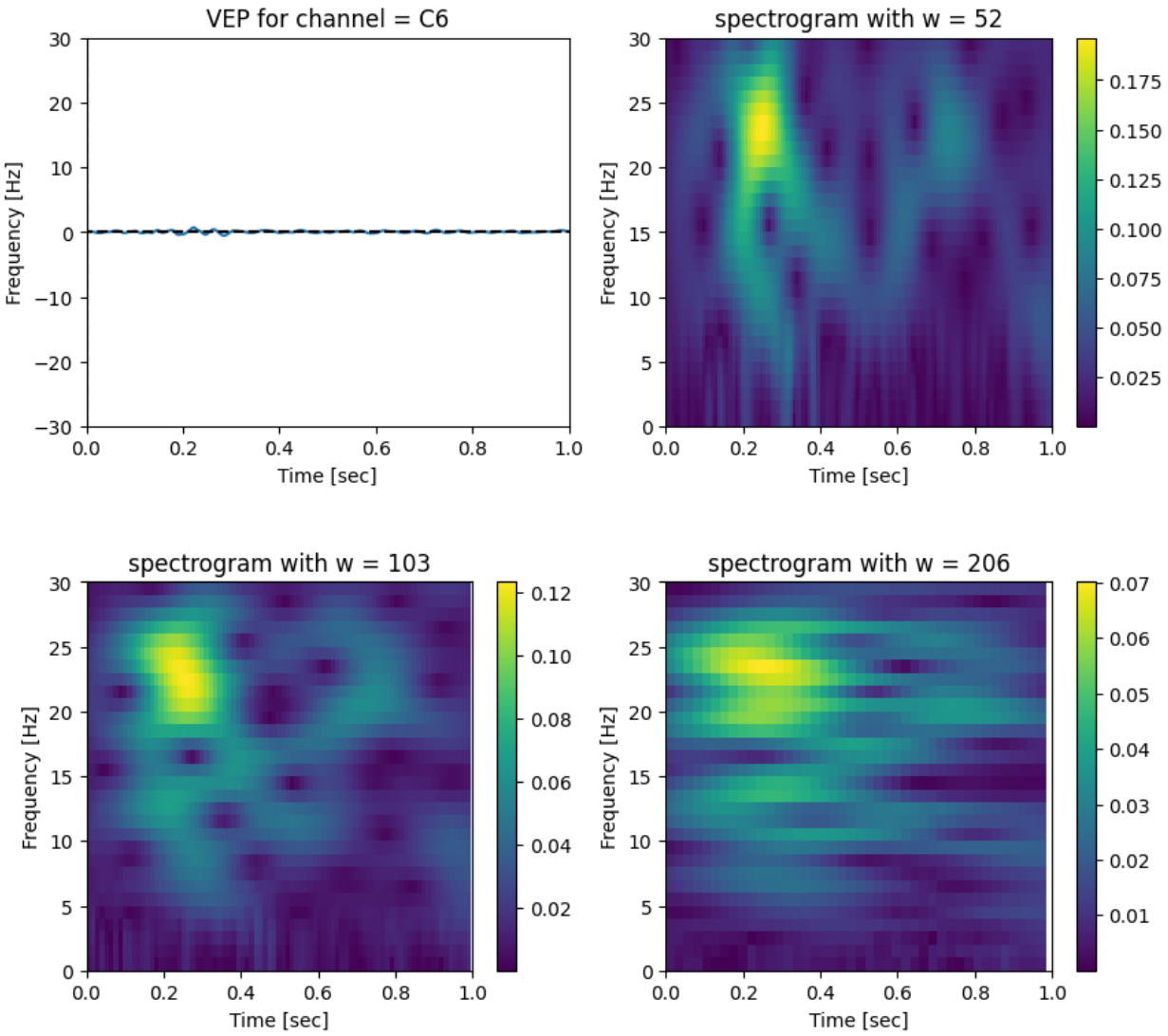

Figure 5.4 Time frequency analysis of Optimized channel C6 (Control) S1 obj

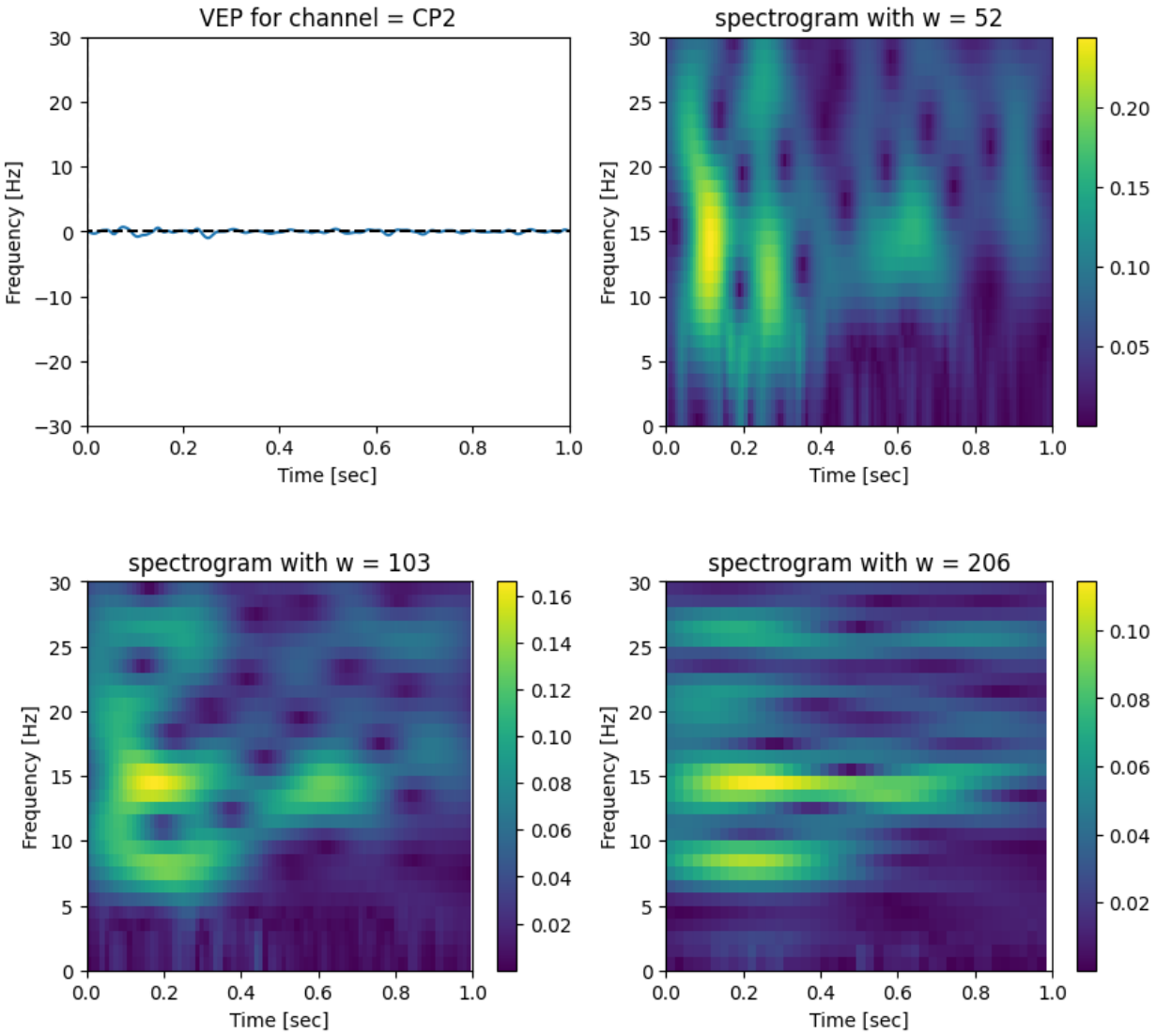

Figure 5.5 Time frequency analysis of Optimized channel CP2 (Alcoholic) S2 match

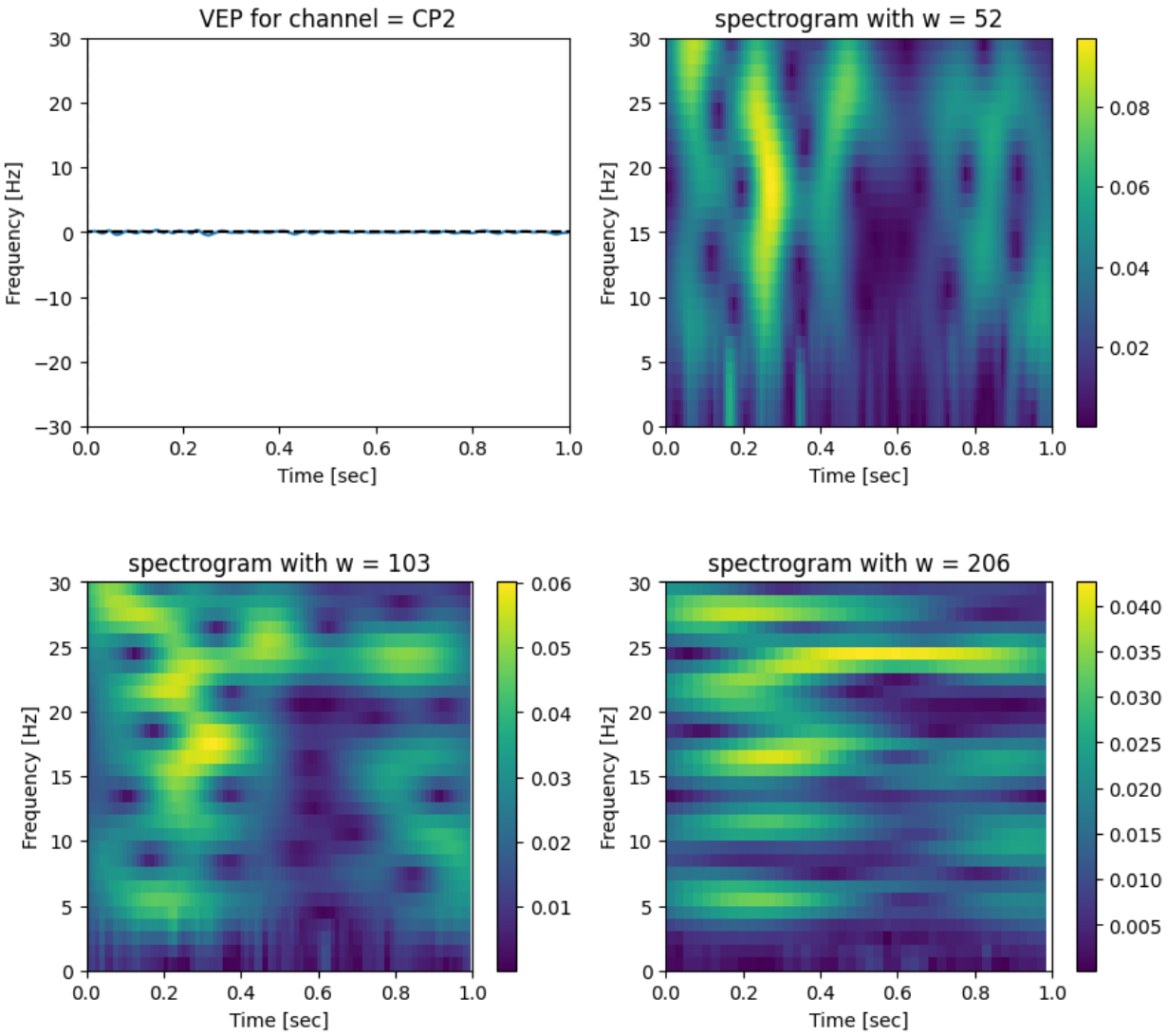

Figure 5.6 Time frequency analysis of Optimized channel CP2 (Control) S2 match

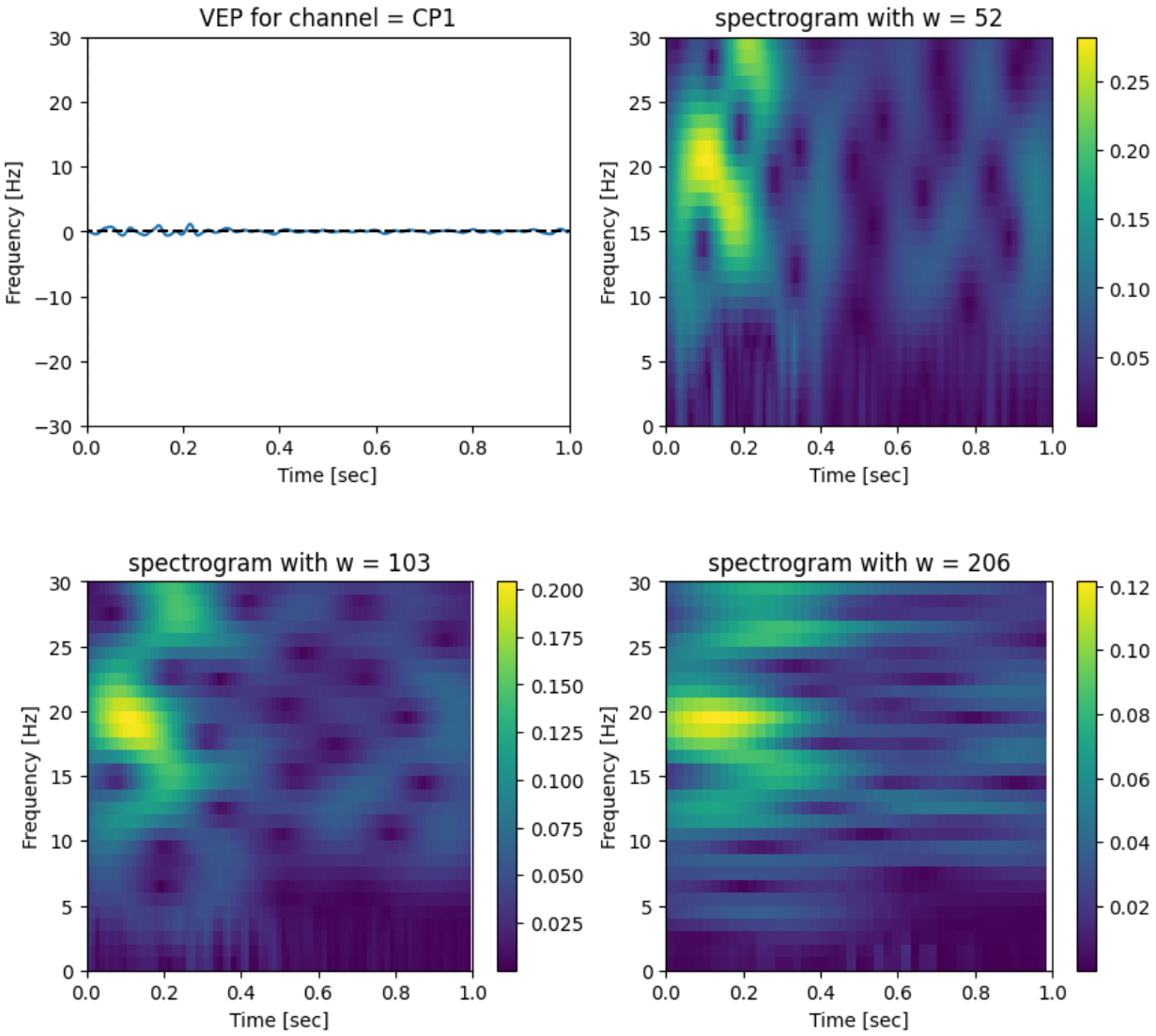

Figure 5.7 Time frequency analysis of Optimized channel CP1 (Alcoholic) S2 match

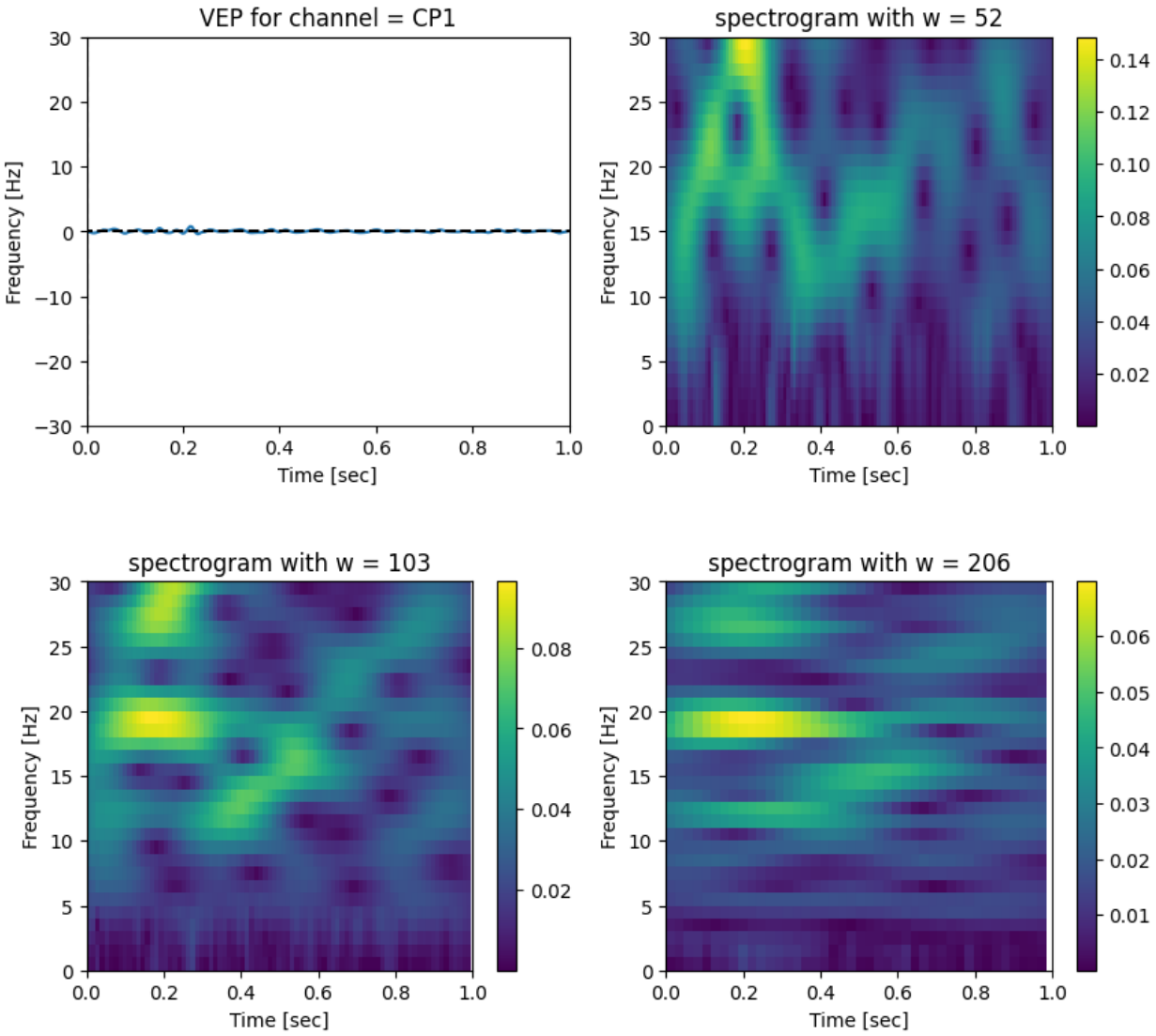

Figure 5.8 Time frequency analysis of Optimized channel CP1 (Control) S2 match

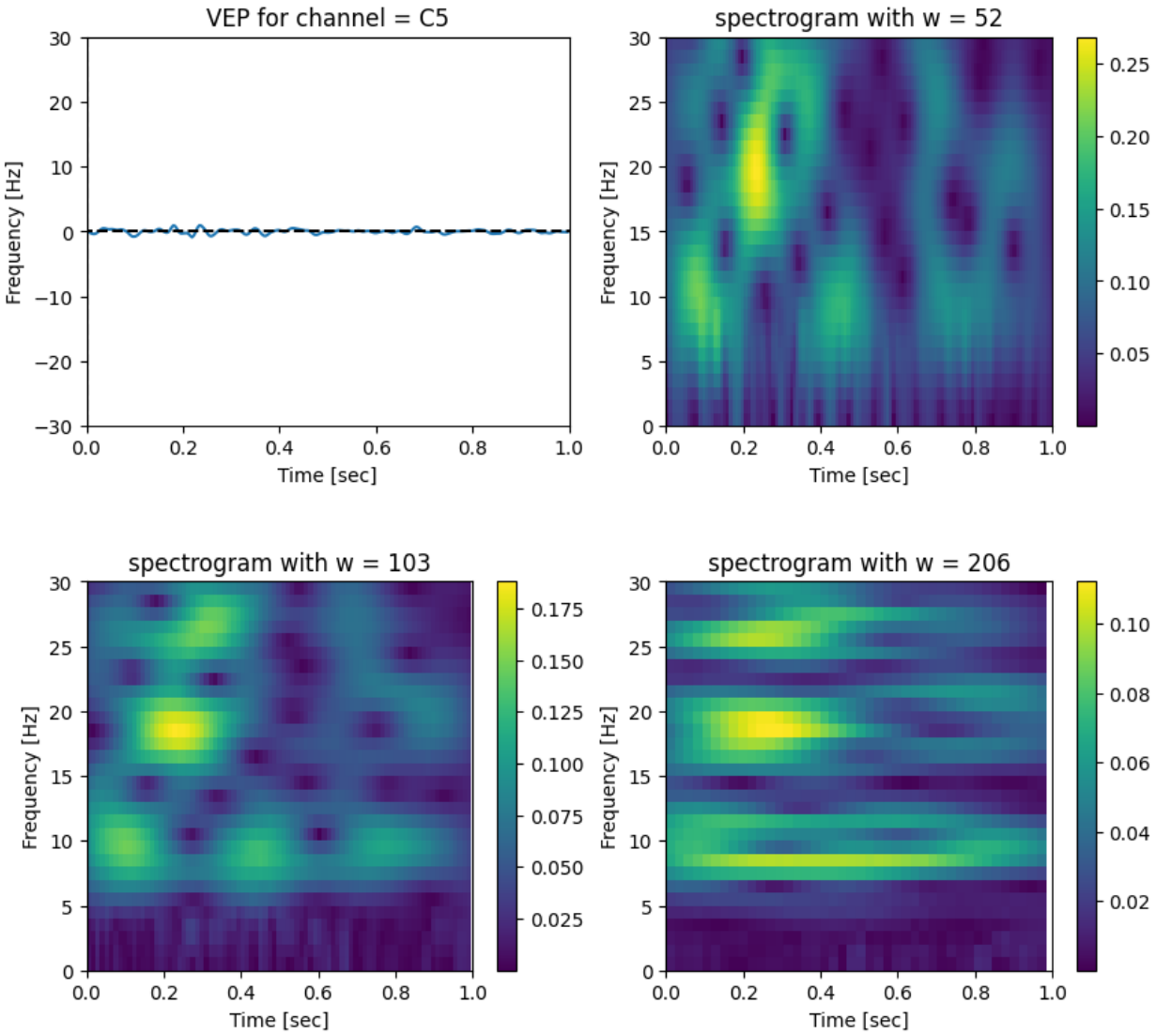

Figure 5.9 Time frequency analysis of Optimized channel C5 (Alcoholic) S2 no match

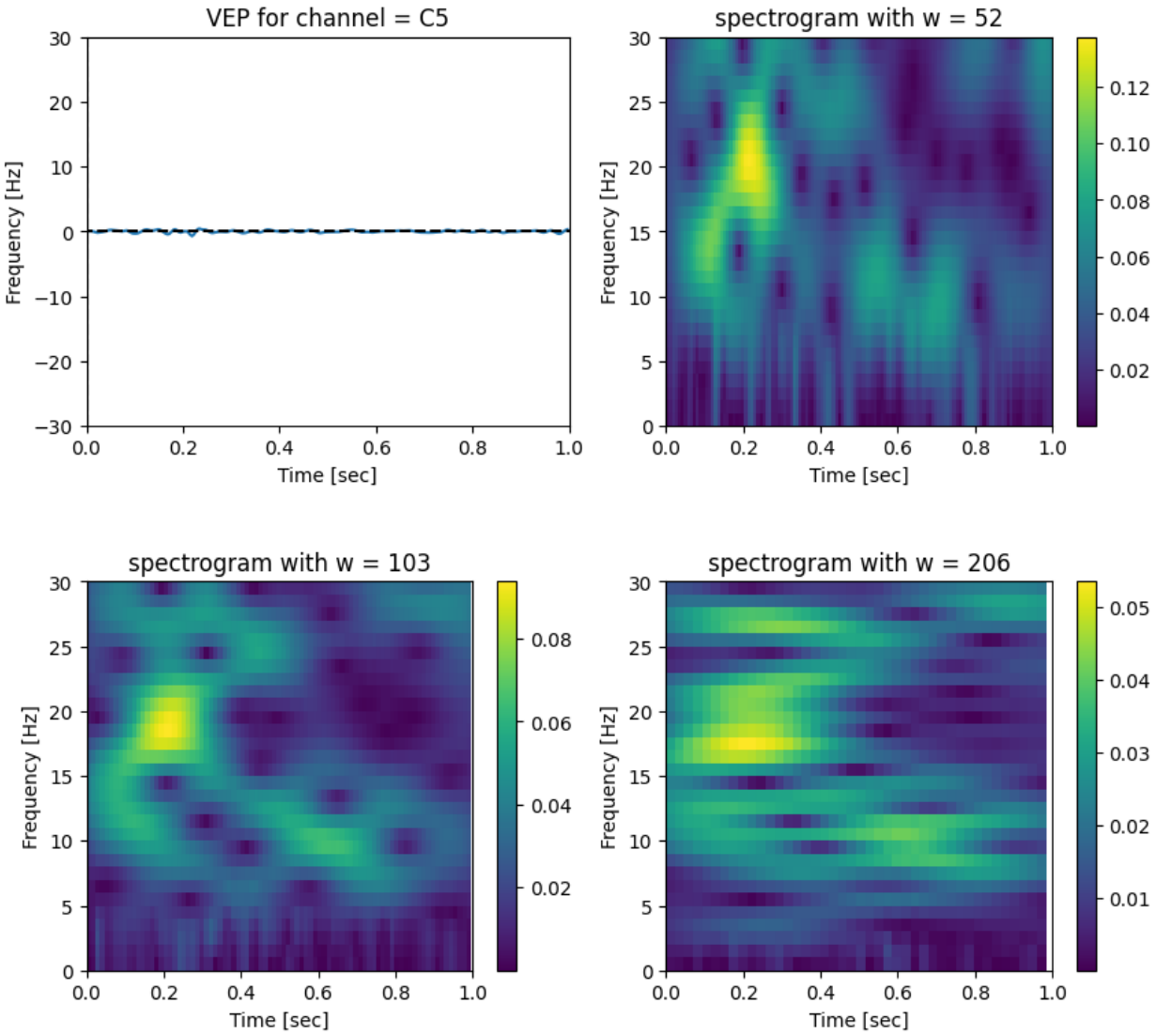

Figure 5.10 Time frequency analysis of Optimized channel C5 (Control) S2 no match

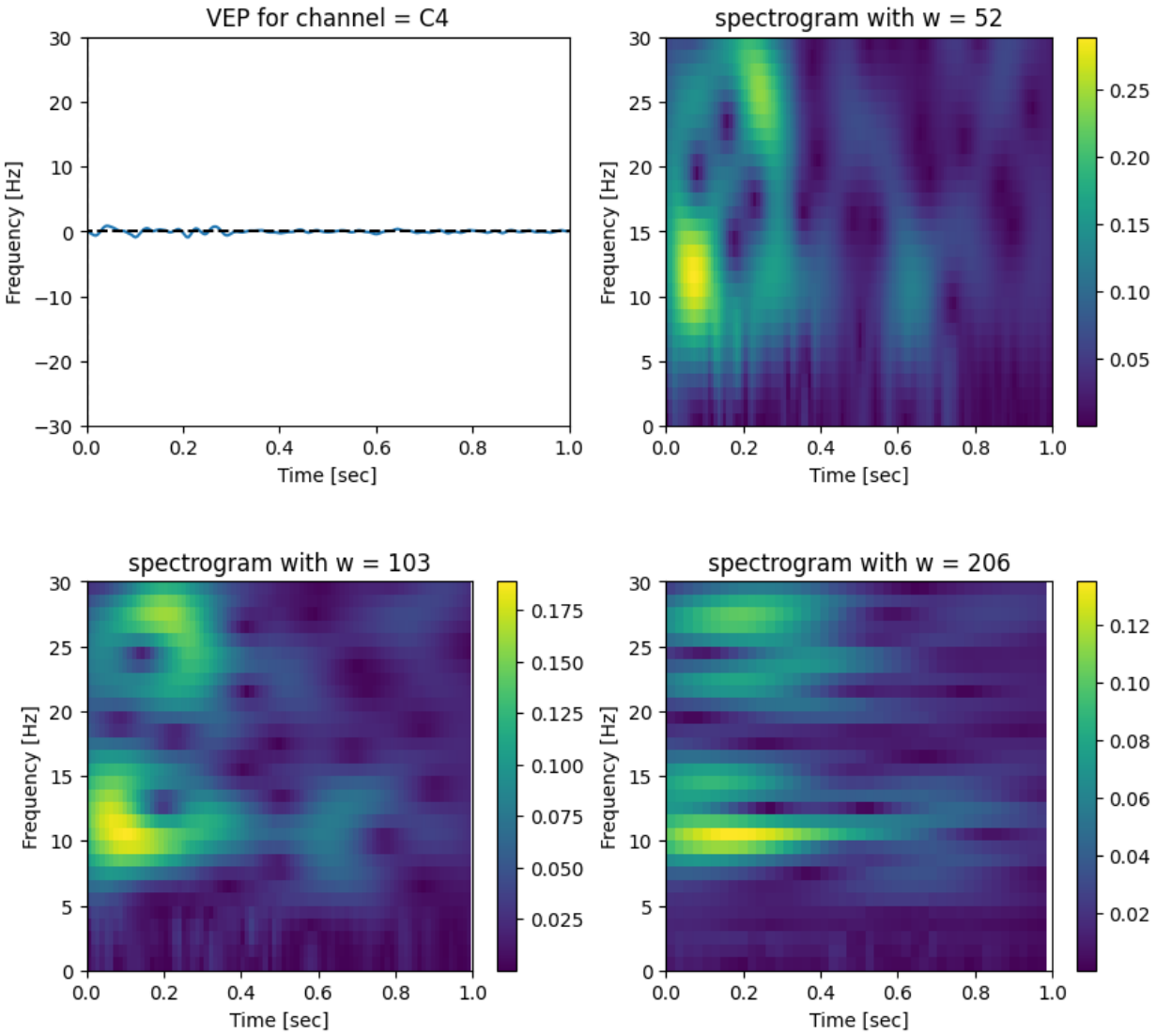

Figure 5.11 Time frequency analysis of Optimized channel C4 (Alcoholic) S2 no match

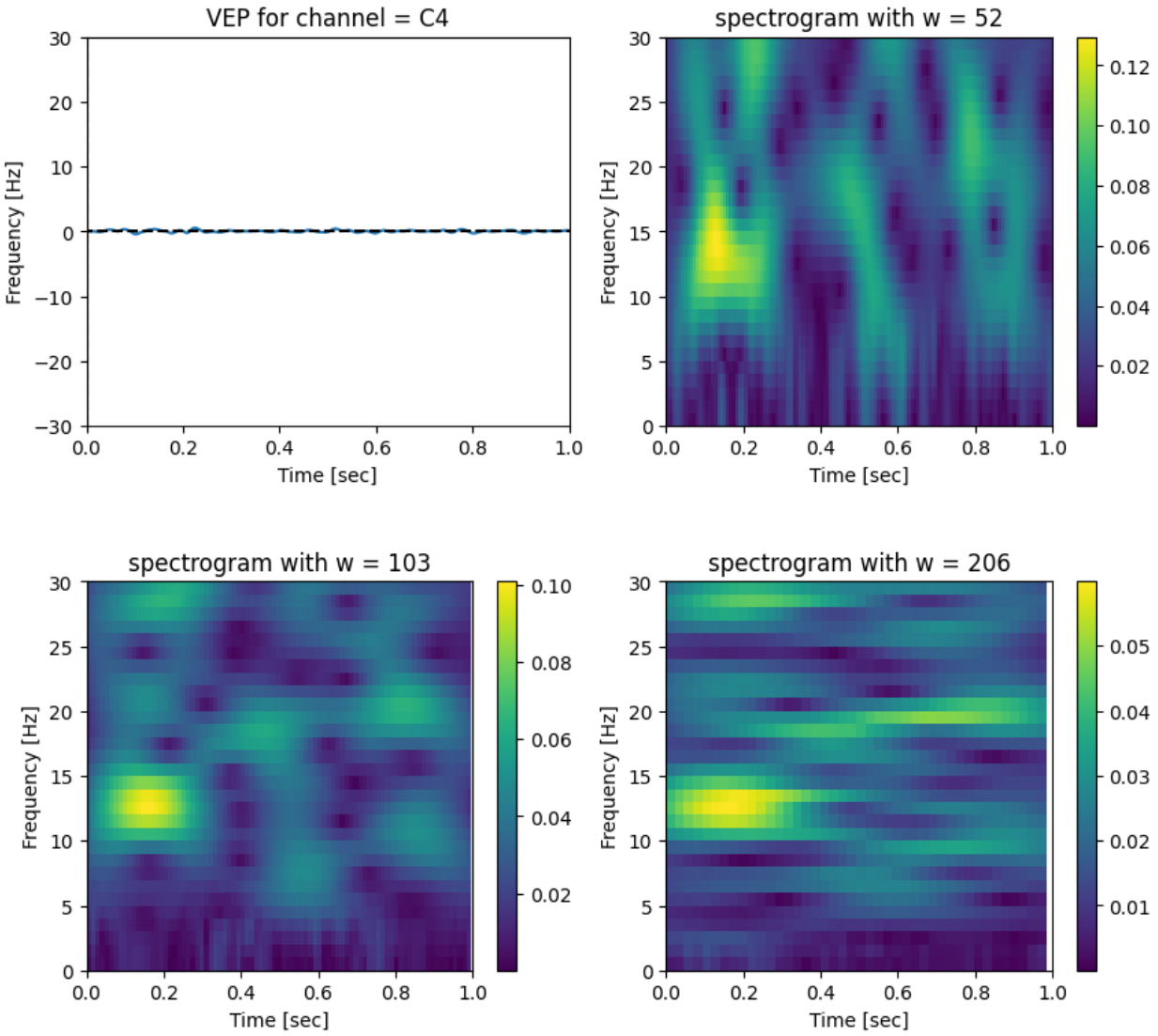

Figure 5.12 Time frequency analysis of Optimized channel C4 (Control) S2 no match

From the Figures 5.1 to 5.12, we see a particular pattern for alcoholic group around the time frame 0.1 to 0.3. It is evident that alcoholic group shows spike at 200 milliseconds. It indicates neural excitation in the alcoholic group. For the control group the pattern looks steadier than the alcoholic group. If we do a more detail analysis by considering few of the optimized channels, for example channel CP2, C6 as shown in Figures 5.1, 5.2, 5.3, and 5.4, we find higher beta activity for the alcoholic group at these channels for S1 obj stimulus. We find lower beta activity in the control group for S1 obj stimulus. The above analysis indicates that the alcoholic group's activity

is related to attention deficit that is associated with higher beta activity. Similarly, we have given few channels examples for other two paradigms. For example, channels CP2 and C6 for matching images shown in Figures 5.5 to 5.8 and channels C5 and C4 for nonmatching images shown in Figures 5.9 to 5.12. For both stimuli, we find similar results related to higher beta activity in the alcoholic group than the control group.

We also find the alpha activity in both groups. By comparing alpha activity for both groups for the same channels, we see that the alcoholic group has higher alpha activity than the control group. One example of it is shown for channel C4 for stimulus S2 no match. Their band plots are shown in Figures 5.13, and 5.14.

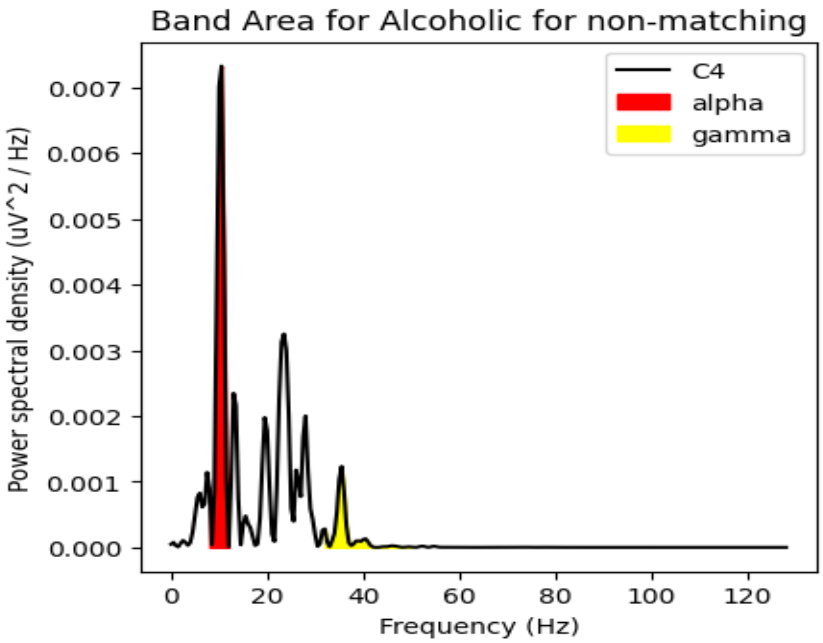

Figure 5.13 Band plot for channel C4 (Alcohol) S2 no match

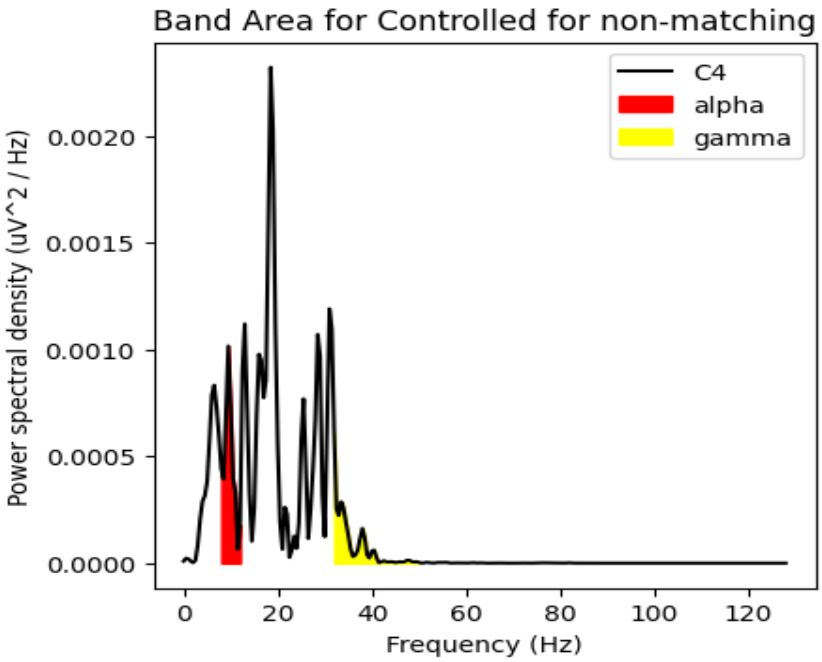

Figure 5.14 Band plot for channel C4 (Control) S2 no match

From Figures 5.13 and 5.14, we deduce that the alcoholic brain produces higher alpha waves (8 - 12Hz), which indicates relaxed state of mind and not processing much information. Another example we have given for alpha activity of channel F1 for both group in Figures 5.15 and 5.16., where we observed higher alpha waves produced by alcoholic group than the control group.

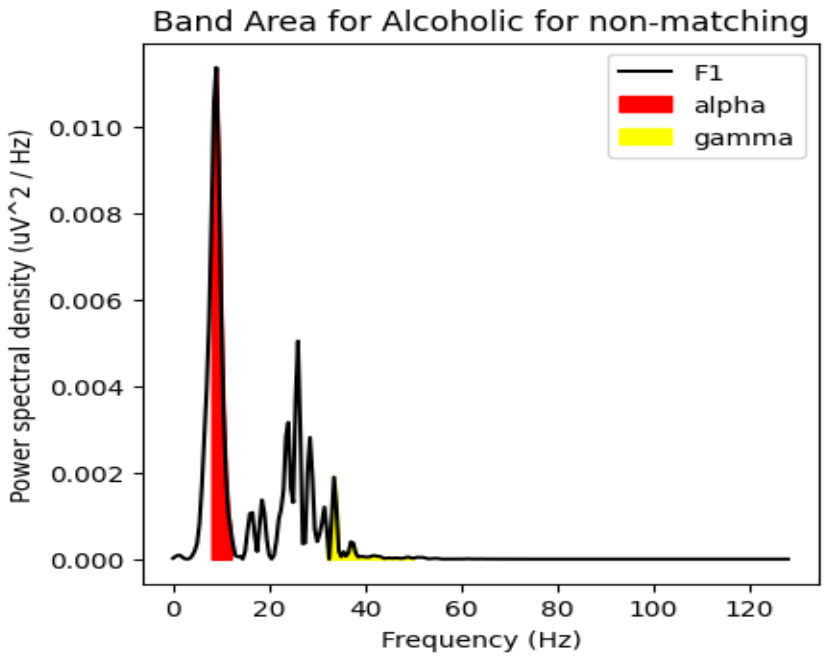

Figure 5.15 Band plot for channel F1 (Alcohol) S2 no match

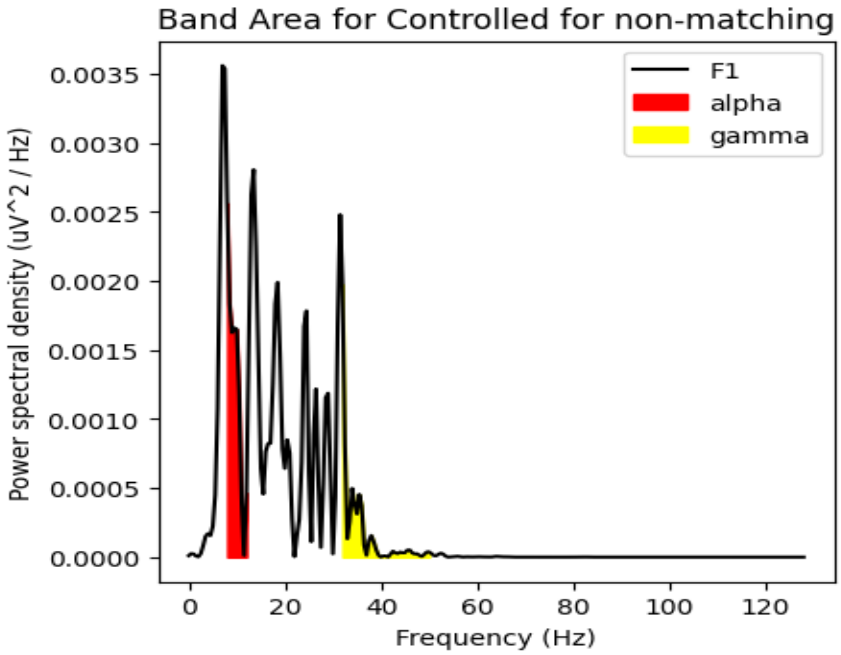

Figure 5.16 Band plot for channel F1 (Control) S2 no match

Summary:

We evaluated power spectral density using Welch's periodogram to find optimal channels associated with alpha and gamma band power for both the groups. These optimal set of channels can be utilized for further analysis related to these bands' power. By this, it reduces the large number of channels given in raw data to specific number of channels to carry out research specific to the optimal channels. We found that the alcoholic brain produces higher alpha waves (8 - 12Hz) which indicates relaxed state of mind and not processing much information. From time-frequency analysis, we see a particular patterns for alcoholic group around the time frame 0.1 to 0.3 showing spike at 200 milliseconds. It indicates neural excitation in the alcoholic group. For control group the pattern looks steadier than the alcoholic group. We find higher beta activity for alcoholic group at channels CP2 and C6 for S1 obj stimulus. We find lower beta activity in control group for S1 obj stimulus at these channels. The above analysis indicates alcoholic group's activity is related to attention deficit that is associated with higher beta activity. Some of the exceptions are observed at frontal-temporal regions (FT8) where control group has higher beta activity than the alcoholic group. We also observed some similarities in optimal source amplitude in both groups in the frontal-parietal (FP6) and occipital channels (O2).

Chapter 6

Conclusion and Future Works

A. Conclusion

As part of this research, we find more positive scalp activity in the alcoholic group than control ones. Few of the alcoholics showed exception as alcohol consumption does not impact everyone in a similar way as found in previous studies. In the control group, the maximum activity with respect to spatial patterns is observed in the right brain whereas the same is found in the left brain for the alcoholic group. The control group has higher source activities associated with attention region than alcoholic group for all three stimuli. We also evaluated source activity for each group per stimuli. For the alcoholic group, very few regions in right and left brain such as emotional regulation region and motor region are involved in maximum source activities. For control group, the major active regions are somatosensory, memory, visual, attention, and few emotional regulation regions. We also find maximum activity in the occipital regions for control group whereas there is no such activity associated in occipital regions for the alcoholic group. Apart from the above we utilized NSGA-II to find optimal channels producing maximum alpha and gamma power. Channel optimization is one of the contributions of this work. We also compared their respective band powers such as alpha, gamma, and beta band powers. We observed higher beta and alpha activity in alcoholic group than control group in central and central parietal sources which shows that alcohol can affect one's attention and memory capability.

By doing this research, it helped us to find differences in EEG activity of both alcoholic and control group to understand the impact of alcohol on brain. From the experimental evidence discussed, alcohol impacts memory and attention of a person. For the alcoholic group, we observed that activity is spread all over the scalp whereas the control group showed fixed EEG patterns. With this information, cognitive deficits caused by alcohol can be addressed in advance and provide management and treatment solutions to deal with these issues.

B. Future Works

As part of future works, features can be extracted from the optimal channels. Optimal channel specific feature analysis and classification using machine learning can be performed. Frequency domain features can be useful to get insight about the association of frequency with respect to both groups. Either nonparametric Fourier transforms, or parametric methods can be used for this purpose.

In this work, we have done P-value test statistical analysis. Hence, other statistical analysis method can be utilized to do analysis such as t-test and complex ANOVAs (Analysis of Variance) because these methods can provide statistically significant results if any group differs significantly from the overall group mean.

In this work we have done statistical analysis on raw data. However, it can be done based on optimal source activity to find any crucial information specific to the source activity. This will bring advantages for a deeper statistical analysis related to data from the EEG sources.

Another future work suggestion could be new dataset preparation and analysis of the new data. Latest visual paradigms can be utilized to collect data from alcoholic and control groups and

perform analysis on it. For an instance, visual odd ball task can be utilized to find reduced P300 responses to show deficit in cognitive functions.

Before analysing the group specific raw data, subject specific data should be analysed. There might be subjects that are outliers. In data analysis, data having exceptions can be removed from both alcoholic and control groups. By this a better comparison and analysis can be done between two groups.

A final suggestion for future work could be to perform analysis on optimal channels. Optimal channels can also be found with other objective functions based on the goal of the project such as maximizing or minimizing variance or maximizing classification accuracy. For instance, by maximizing classification accuracy, the optimized channels can be the ones that positively contribute towards the classification accuracy.

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