Final Report EEG

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Abstract—This report deals with the EEG method. The electroencephalogram (EEG) is a record of the oscillations of brain electric potentials recorded from electrodes attached to the human scalp. EEG is an electrophysiological monitoring method used to record the electrical activity in the brain.
In this article, we will discuss the EEG method and analyze signals generated by the EEG . First, we use a filter to analyze the signal and break it down into small components. We analyzed the EEG data given to us and extracted and presented the different waves we had studied in the theoretical background. Second, we will discuss the Salt Bridge Artifact. We will use a known algorithm in order to detect the artifact from the given data. Finally we will take an EEG dataset from a specific source, process and analyze it and use some features to train and cross-validate a simple classifier.

1. INTRODUCTION

EEG- An electroencephalogram (EEG) is a non-invasive and relatively inexpensive method for assessing neurophysiological function and used to evaluate the electrical activity in the brain. Brain cells communicate with each other through electrical impulses. An EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the scalp with wires. The electrodes analyze the electrical impulses in the brain and send signals to a computer that records the results. An EEG is used to detect problems in the electrical activity of the brain that may be associated with certain brain disorders. The measurements given by an EEG are used to confirm or rule out various conditions, including head injury, stroke, memory problems and more. **[1] [2]**

Types of waves in the brain:

The EEG can be decomposed to few brainwaves. We focused on four specific recorded waves:**[2]**

- ***δ***- delta
- ***θ***- theta
- ***α***- alpha
- ***β***- beta

***δ* brainwave, 0.5 - 4 [Hz]:** This brainwave is characterized in state of deep sleep or slumber and with biggest amplitude and lowest frequency.

***θ* brainwave, 4 - 8 [Hz]**

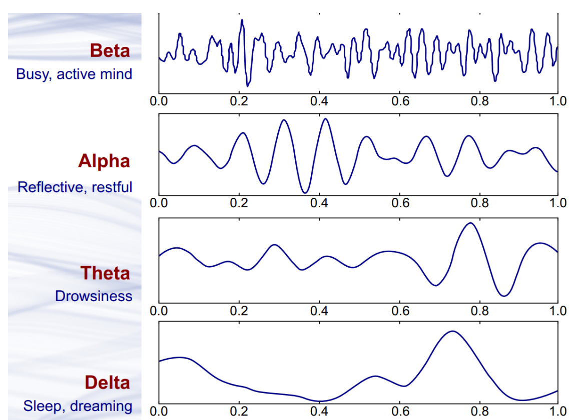
This brainwave is characterized by a state of Deep relaxation, inward focus, higher amplitude, and lower frequency (comparing to ***α*** and ***β*** waves).

***α* brainwave, 8 - 12 [Hz]**

This brainwave is characterized by a state of being Very relaxed, passive attention and with higher amplitude, and a lower frequency (comparing to ***β*** wave).

***β* brainwave, 12 - 35 [Hz]**

This brainwave is characterized by a state of Anxiety dominant, active and external attention. and with low amplitude and a high frequency.



2.

Figure 1- Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves.[2]

Noises and artifacts:

Ambient noises are external electromagnetic waves that reach the sensor of the EEG device. This noises originated from

Electrical activity in the surrounding of the EEG device. These noises disrupt to get a proper reception of brain waves. Common ambient noises are network noises. In Israel, network noise usually appears at a frequency of 50 Hz.**[3]**

In addition to the Ambient noises, the EEG is also disrupted by Physiological noises. These noises result from normal physiological activity of the body systems regardless of The brain. physiological noises can originate from the eyes (eog), heart (ECG) or muscles (EMG), and may create much higher electrical potentials than the post-synaptic potential measured as the EEG signal. Therefore, these artifacts may disrupt the EEG signal and prevent it from being properly received.**[3]**

Another interference in measuring the EEG signal is a **salt bridge artifact.** This is a disturbance which is caused by the electrical conduction of electrolytes Between two adjacent electrodes. Salt bridge artifacts can occur by over-application of electrode gel or sweat particularly at vertically-aligned sites (e.g. inferior sites on posterior and lateral surfaces of the scalp). **[4]**

Support Vector Machine (SVM)

The SVM is a machine learning algorithm. The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space (when N is the number of features) that distinctly classifies the data points.**[5]**

Independent component analysis (ICA)

ICA is a technique applied to the analysis of EEG signals. ICA may be used to segregate obvious artifactual EEG components from sources, The main task of ICA for a random vector includes searching for a linear transformation which minimizes the statistical dependence between the components involved in the signal. ICA can segregate artifacts embedded in the data and make it possible to get less contaminated EEG signal.**[6]**

Using ICA allows us to get a clear **IC MAP** (independent component map) which is a visual product obtained by analyzing the various signals in the various channels obtained from the electrodes scattered on the scalp. In fact, it creates a heatmap that makes it possible to visually identify which areas of the brain were active. **[7][8]**

receiver operating characteristic (ROC)

ROC curve is an evaluation metric for binary classification problems. It is a probability curve that plots the TPR (sensitivity) against FPR (1-specificity) at various threshold values and essentially separates the signal from the noise**.[9]**

The **Area Under the Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve. The range of AUC is [0,1]. The higher the AUC (closet to the value 1) , the better the performance of the model at distinguishing between the classes.**[10]**

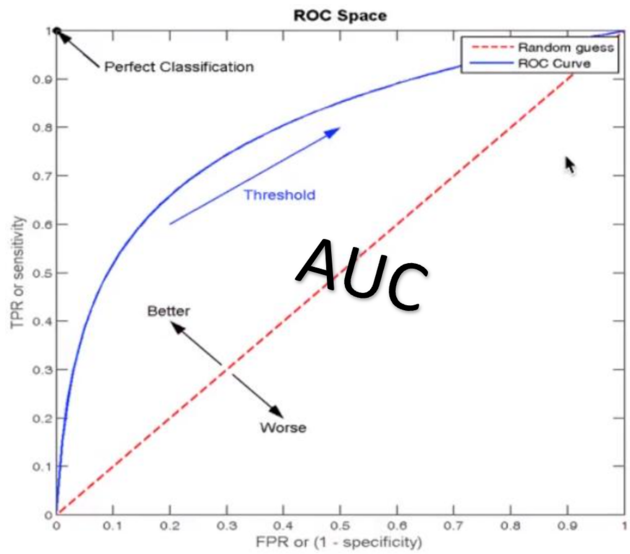


Figure 2- ROC curve and AUC.

2. METHODOLOGY

Experiment system

- EEG device +headset that contains 14 electrons.
- computer system with Emotiv software.
- saline

Experiment procedure

The electrodes in the EEG helmet were wetted with saline before being placed on the subject's head.
The TestBench Emotiv software was then used to verify that the software Properly connected to the helmet, and picked up the signal from the connected electrodes. The electrodes were presented on the screen in green (good connection) yellow (decent connection) orange(less than decent connection) and black (poor connection).

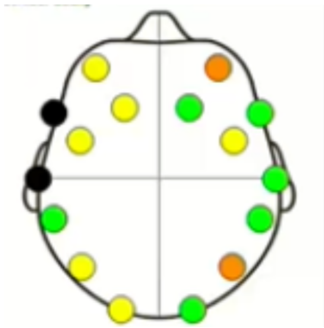


Figure 3- EEG electrodes locations and connections.

The recording of the EEG signal was performed in two stages, with each stage lasting 30 seconds, without stopping the recording between.

1. 30 seconds eyes open
2. 30 seconds eyes close

Data analysis

The signal in this experiment was sampled at a rate of fs=128[Hz].

We use equation (1) in order to calculate the time sample:

(1) $T_S = \frac{1}{fs}$

In order to calculate T_{max} we used the following equation:

(2) $T_{max} = (num\ of\ samples - 1) * T_S$

In order to filter the signal in a goal to get less contaminated signal and get rid of noises (e.g, powerline interference , breathing interference and other physiological artifacts), we used MATLAB “filtfilt” function and applied FIR filter (bpf) in a range of 0.5-30 Hz. Physiological noises like breathing and noise originating from the muscles are characterized with lower frequencies (0-0.5 Hz). However network noises characterized with high frequencies (about 50 Hz in israel) so the filter we chose will be able to deal with the noises we noted.

Waves Detections

The wave detection part was applied only on the first 15 seconds of the EEG recording. After filtering the noises we extracted the four types of waves (θ, δ, β, α) according to the frequencies corresponding to them using specific filters for each wave, relying on frequencies ranges we had presented in the introduction. The filtered signals will be used to determine which electrode we will use to examine each one of the waves. We determined which electrode corresponds best to each wave by examining two characteristics. We had tried to obtain which signal has higher power spectral density (PSD) using the MATLAB function “pwelch” and by examining the plot which of them is least disrupted by noise.

We used an “STD” built in function in MATLAB for each wave in the first two segments, in order to examine the amount of noise in each wave. In the first segment (first 30 seconds) the subject was with his eyes open and the second segment (the next 30 seconds) the subject was with close eyes. In our experiment, the larger the deviation, the greater the differences between the measured voltages (wave amplitude) and the mean of the signal. Noise added to the signal significantly increases the std.

Sub part 2 Detecting salt bridges

This part of the experiment uses pre-prepared files that contain recording data for 14 different electrodes, which Recorded at a sampling rate of 128 samples per second. The recording data is represented by 14 vectors, with 3000 values, with each vector representing a lead from EEG measurement. We analyzed leads from the given data in order to determine between which pair of electrodes we can detect the effect of salt bridge artifacts.

In order to do so we relied on a method from an article provided to us ([9] in references) **.**
A potential difference waveform is defined as the difference between the time-varying potentials P of channels i and j, computed as:

(3) $p_{i-j}(t) = p_i(t) - p_j(t)$

when $p_i(t)$- the potential measured in lead i,
$p_j(t)$- the potential measured in lead j and
$p_{i-j}(t)$- the difference between two leads in time t.

Two leads will be connected to each other by a salt bridge when the potential measured between them will be almost the same, so they can be identified as a pair which is characterized by a gradient with low amplitude.The overall amplitude of a difference waveform can be quantified by its variance over time T defined by the following equation:

(4) $ED_{i-j} = \frac{1}{T}\sum_{t=1}^{T} (p_{i-j}(t) - \overline{p_{i-j}(t)})^2$

when ED_{i-j}- the variance of the difference between each two electrodes

We set the threshold to $500\mu v^2$ so when the value of th ED_{i-j} Falls below this value we mark these to leads as potential connected by salt bridge.

The identification of the salt bridge artifact is made on the assumption that only adjacent electrodes can create a salt bridge between them. Therefore we determined that only adjacent electrodes from the pairs we had calculated using the calculation of the ED_{i-j} were marked as leads with salt bridge artifacts between them.

<u>part 2- EEG classification</u>

In this section we were provided the “Imagined Emotion Dataset”. This dataset contains measurements of the electric potential in two independent components (IC1,IC2) throughout the time of the emotion task. In this task 10 subjects were asked to think different thoughts in order to evoke different emotions. When they felt that they were experiencing the emotions, they were asked to press a button. We chose the emotions “anger” and “happy” because we wanted to examine two emotions that are opposites from one another. Using MATLAB we analyzed the changes in the electric potential in the two emotions in a time window of 10 seconds starting right after the subject pressed the button.

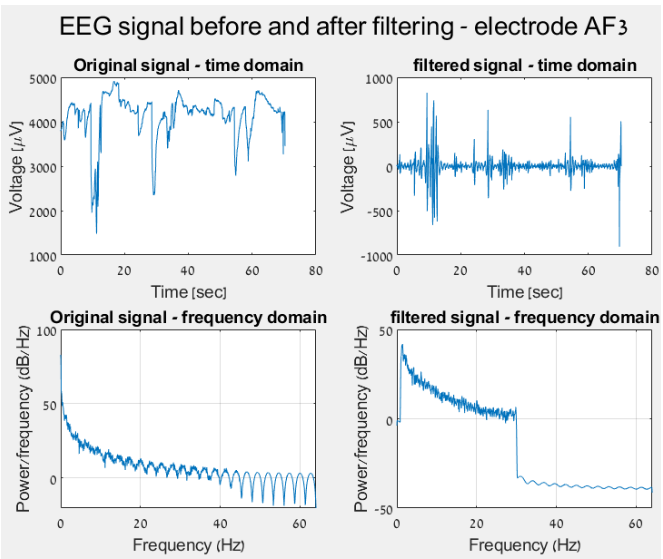
We used the same method from part 1 in order to filter the signals and to distinguish between the brain waves ($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$). Then we calculated the STD for every type of wave for all 10 subjects, again, by using MATLAB’S built in function “std()”.

We exported the table of STD to WEKA software as a csv file. Then, we followed the instructions of WEKA software in order to implement the SVM method to classify the EEG signal using the IC’S given to us. We set the cross-validation folds to 20. The IC’S were provided to us by the lab instructor using the EEGLAB software. We extracted from WEKA the ROC curve of both emotions we chose.

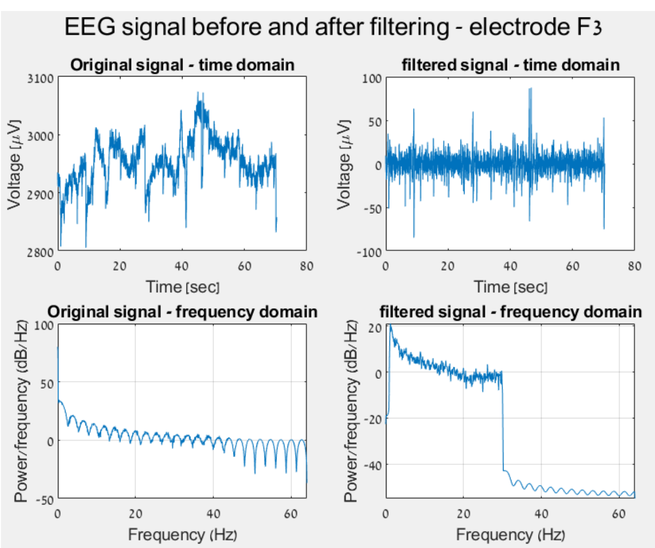
3. RESULTS

Analyzing EEG signal in time and frequency domains

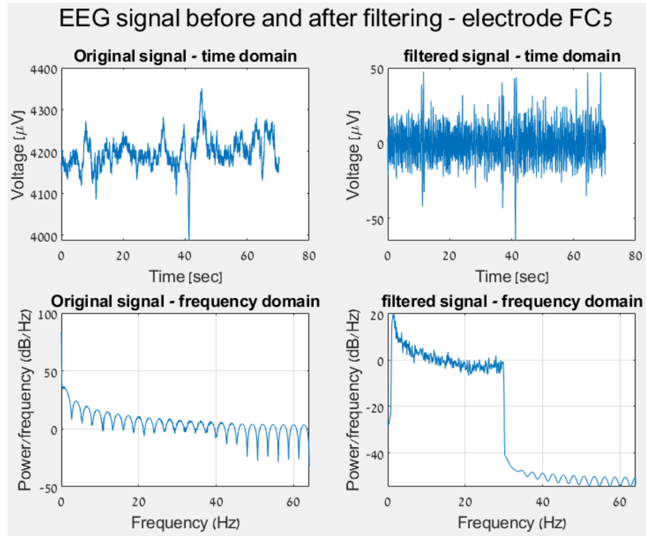
In the graphs below we can see the EEG signals of the electrodes we have chosen, before and after filtering, in time domain and in frequency domain:



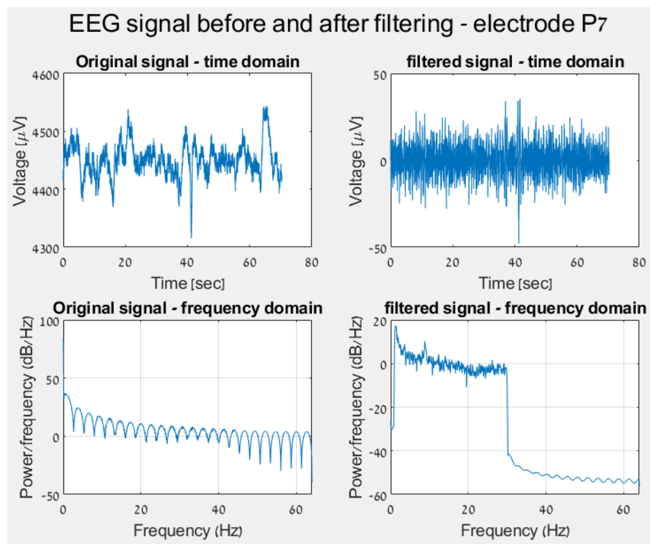
figure(4) - EEG signal before and after filtering - AF3



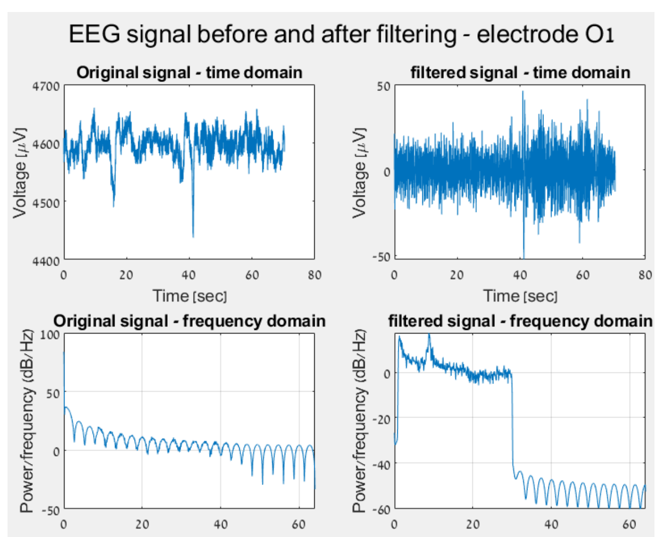
figure(5) - EEG signal before and after filtering - F3



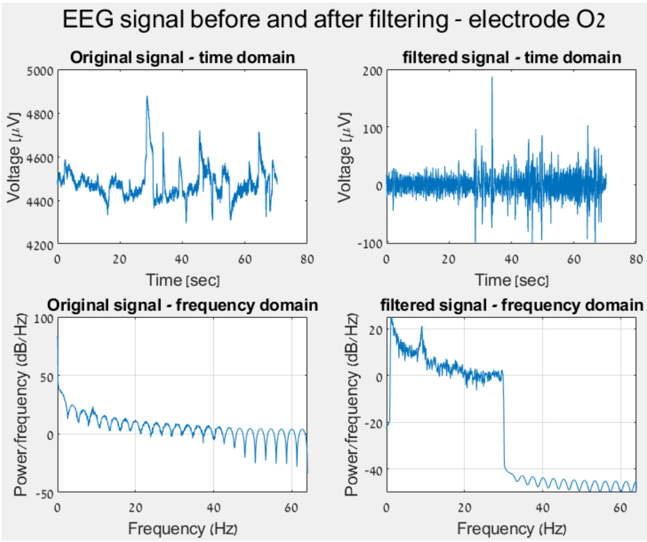
figure(6) - EEG signal before and after filtering - FC5



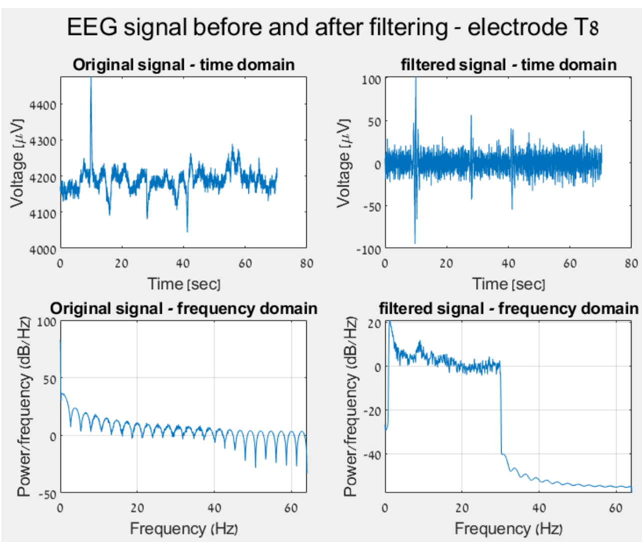
figure(7) - EEG signal before and after filtering - P7



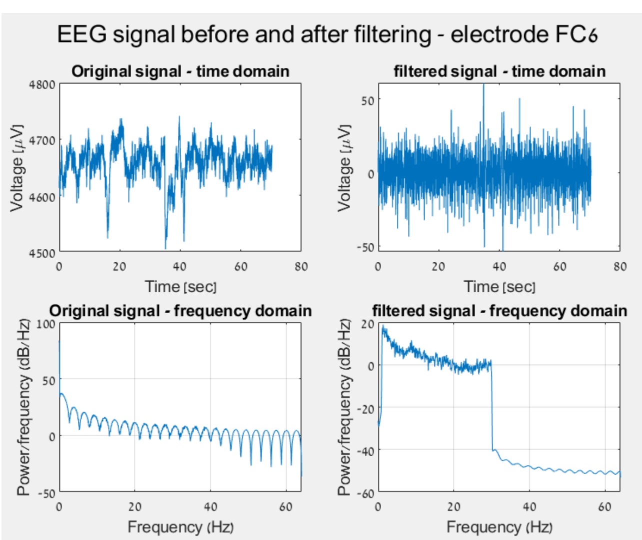
figure(8) - EEG signal before and after filtering - O1



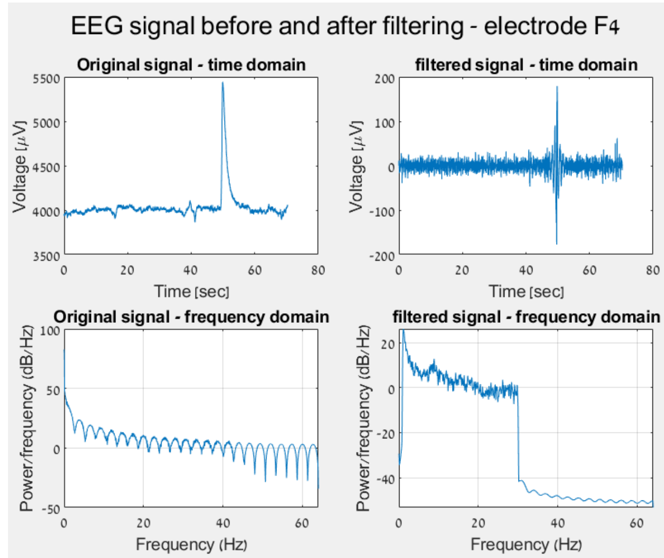
figure(9) - EEG signal before and after filtering - O2



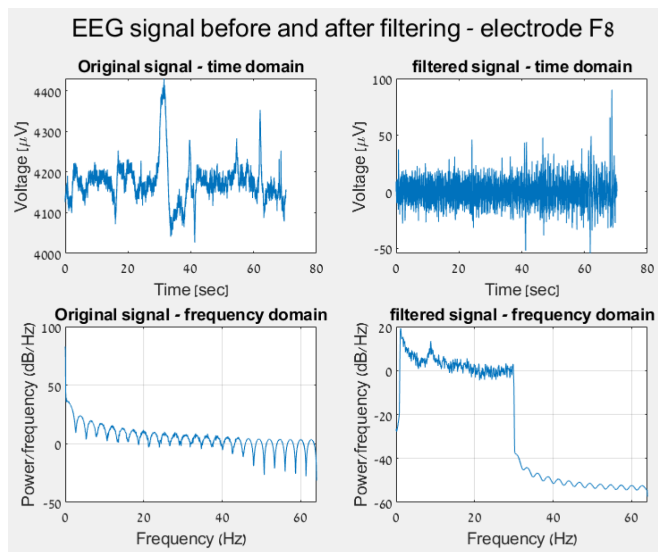
figure(10) - EEG signal before and after filtering - T8



figure(11) - EEG signal before and after filtering - FC6



figure(12) - EEG signal before and after filtering - F4

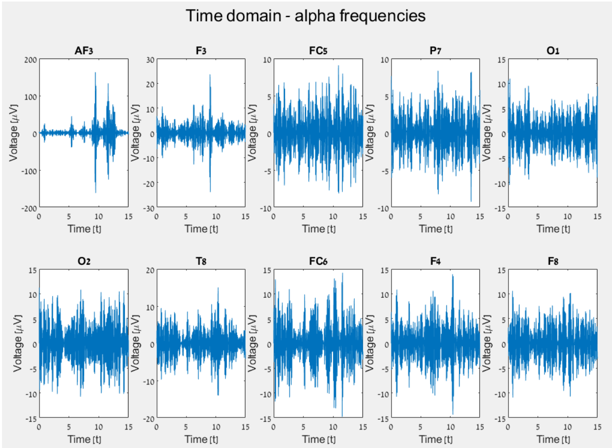


figure(13) - EEG signal before and after filtering - F8

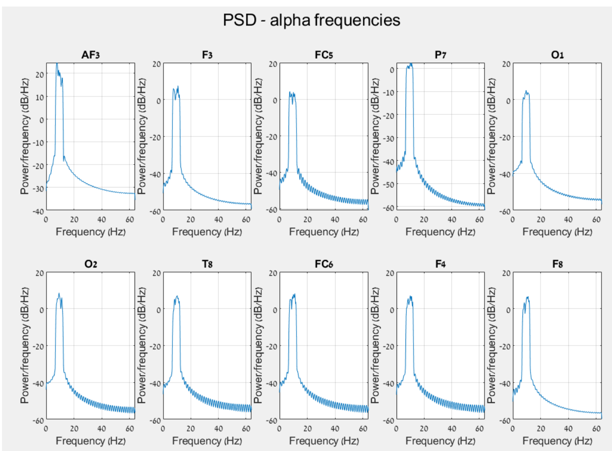
Choosing optimal electrodes

In order to determine which electrodes produce the best signal for each of the brain waves, we filtered all of the signals to contain only the frequencies of each of the brain waves, and for each wave we examined the different electrodes in time and frequency domains. The plots we created in order to choose the best signal for each wave are shown below:

Alpha waves

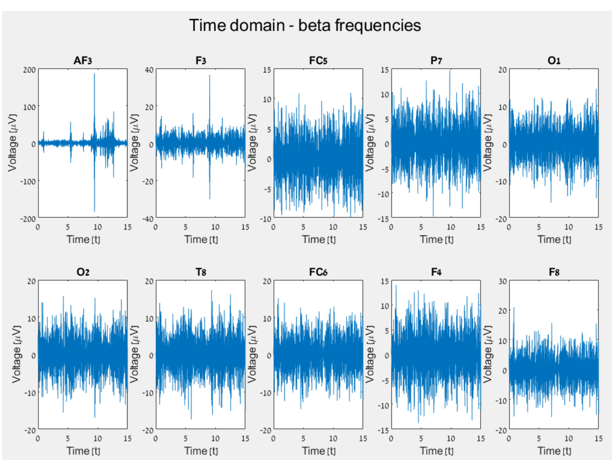


figure(14) - first 15 seconds of each electrode - alpha frequencies

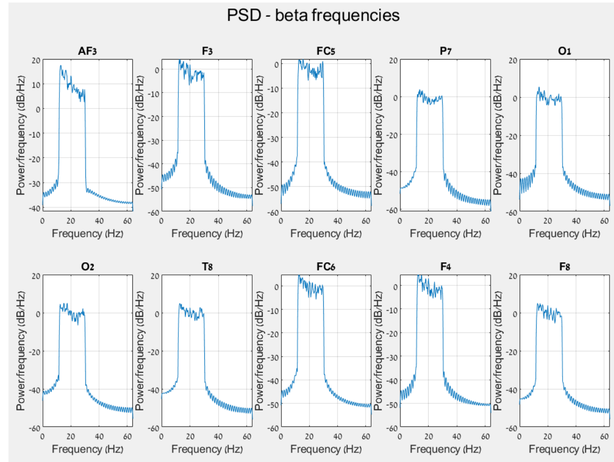


figure(15) - PSD of each electrode - alpha frequencies

Beta waves

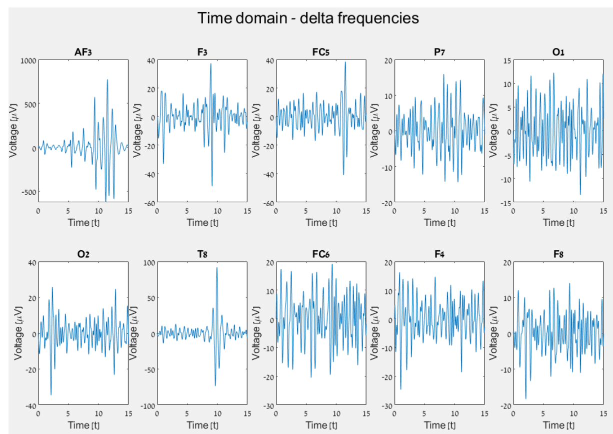


figure(16) - first 15 seconds of each electrode - beta frequencies

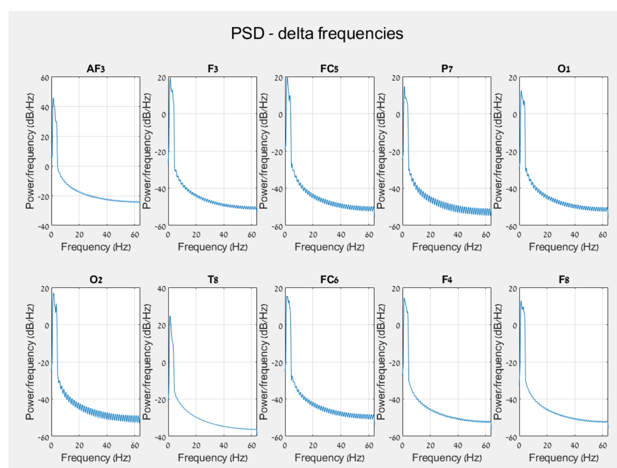


figure(17) - PSD of each electrode - beta frequencies

Delta waves

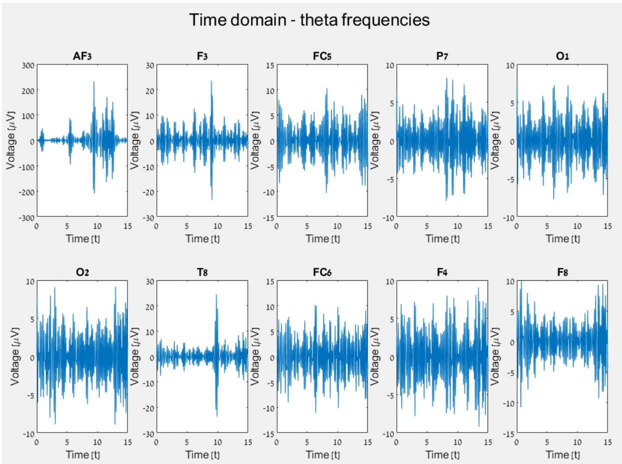


figure(18) - first 15 seconds of each electrode - delta frequencies

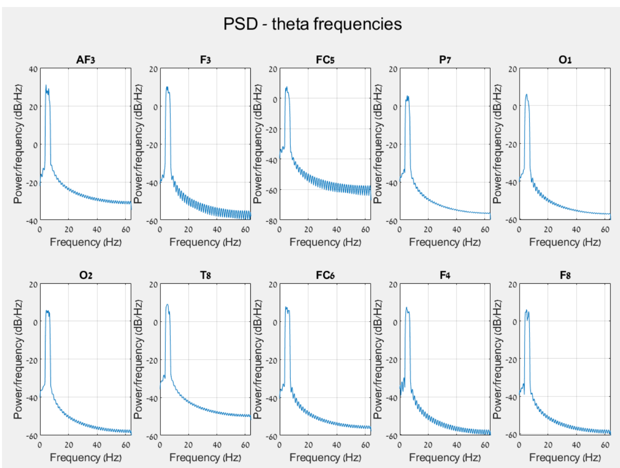


figure(19) - PSD of each electrode - delta frequencies

Theta waves



figure(20) - first 15 seconds of each electrode - theta frequencies



figure(21) - PSD of each electrode - theta frequencies

After examining the shown figures, we chose which electrodes are best for analyzing each brain wave by comparing the PSD of each electrode and the noise to signal ratio of each electrode, after filtering the signals with the brain wave filters.

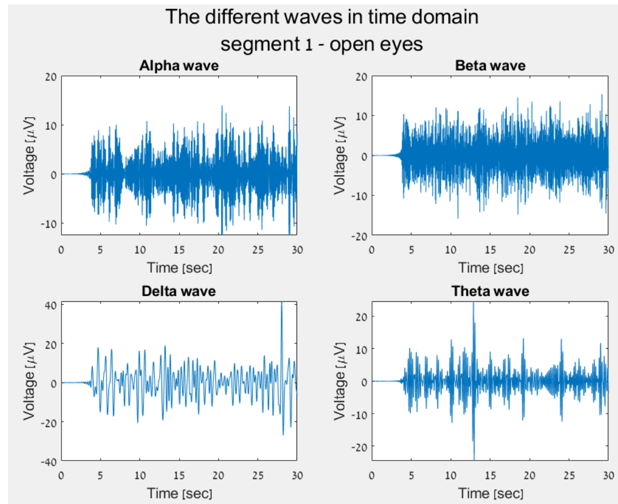
The electrodes we chose for each brain wave are shown in the table below:

Wave	α	β	δ	θ
Electrode	O2	O1	FC6	F3

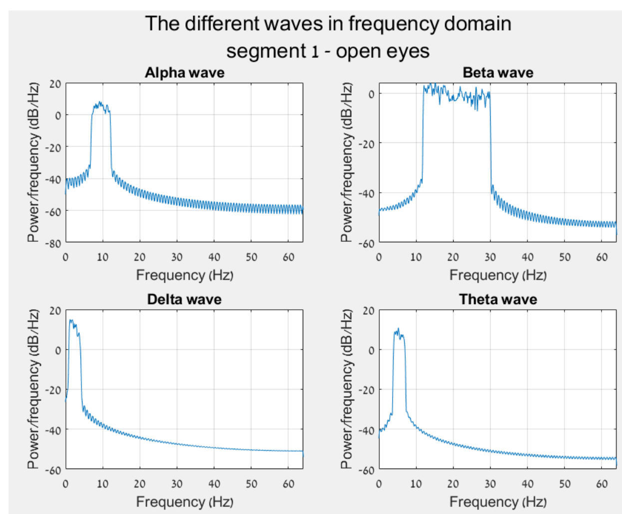
table(1) - selected electrode for each brain wave

Analyzing the different brain waves

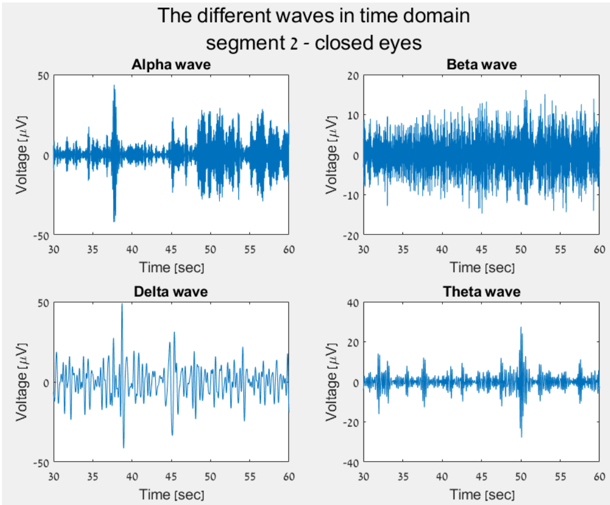
The graphs below demonstrate the different waves from the electrodes we chose, in the two segments recorded, in time domain and in frequency domain:



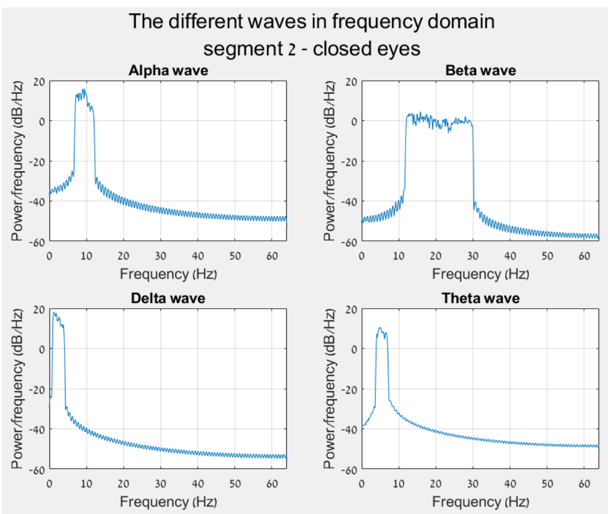
figure(22) - the different waves in time domain - open eyes



figure(23) - the different waves in frequency domain - open eyes



figure(24) - the different waves in time domain - closed eyes



figure(25) - the different waves in frequency domain - closed eyes

The following table shows the STD of each wave at each segment:

	open eyes $\sigma[\mu V^2]$	closed eyes $\sigma[\mu V^2]$
α	3.89	9.04
β	4.16	4.37
δ	7.34	9.73
θ	3.83	4.07

table(2) - STD of the different waves

The table above exhibits that the STD of the different waves change in the different segments, we will of course elaborate in the discussion part of the report.

The table below shows the frequencies of each wave in the different segments, as shown in the graphs of the waves in the frequency domain.

	open eyes frequencies [Hz]	closed eyes frequencies [Hz]
α	7.12-12.00	6.87-12.00
β	12-29.88	11.88-29.88
δ	0.87-4.00	0.75-4.12
θ	3.87-7.12	3.87-7.12

table(3) - frequencies of the different waves

Detecting salt bridges

By using the algorithm described in methods, we computed the variance over time of the subtraction vector between each two electrodes. The table below shows the suspected salt bridges, with variance lower than 500 [μV^2]:

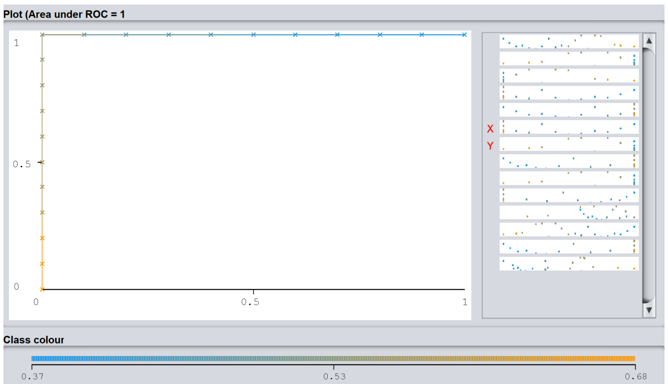
Salt bridges	Variance [μV^2]
T7 - P7	246.76
T7 - F4	424.43
P7 - O2	231.92
P7 - F4	246.22
O2 - F4	414.18

table(4) - suspected salt bridges

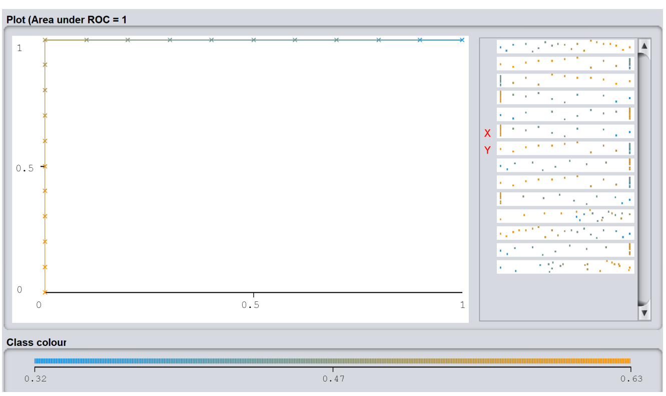
By examining the location of the electrodes on the head, we can conclude some of the suspected salt bridges are not relevant because they are too far apart, so the only two suspected salt bridges left are T7 - P7 and P7 - O2.

Part 2 - EEG classification

We used the IC's given to us by the lab instructor in order to train a SVM model that classifies an EEG signal segment to 'anger' or 'happy' classes. The ROC's of the model performance are shown in the figures below:



figure(26) - ROC of the model performance - anger



figure(27) - ROC of the model performance - happy

4. DISCUSSION

Part 1 - Analyzing EEG signal in time and frequency domains

In figures 4-13 we can see the original EEG signals in each one of the electrodes along with the filtered signals in time and in frequency domains. We can see from the frequency domain graphs, that by filtering the signals we were able to get rid of the unwanted frequencies, which do not contain information relevant for the EEG processing we intend to carry out. In addition to this we see from the time domain graphs that filtering the signals enabled us to get rid of the base-line wander of the original signal, and reduce significantly the noise of the signal, thus improving the signal to noise ratio. By filtering the signals we were able to clean the signal sengifinetly, but the filtered signals still contain a considerable amount of noise, we will mention three possible ways to improve the signals:

- In order to reduce the noise caused by ECG, we can record the subjects ECG while performing the EEG test, and after normalizing the signals - subtract the ECG from the EEG signal, thus eliminating the ECG noises.

- The subject in our experiment had thick curly hair, that may cause a lot of noise while recording the EEG signal. By choosing a subject with less hair, or using electrodes that somehow attach better to the scalp, we are probably able to improve our signals.

- We were not present in the room while the experiment was taking place, but we assume that the room possibly might have been hot and humid, therefore by making sure that the air conditioner is on, we can reduce the sweating of the subject, thus preventing salt bridges from occurring and improving the signals.

By looking at the graphs of the frequency domain of the filtered signals, we can see that a significant energy loss occurs at about frequency 30 Hz. This energy loss occurs due to the filtering we performed on the original EEG signals.

In order to select the optimal electrode for each brain wave, we filtered the first 15 seconds of the signals from each one of the electrodes with the different brain waves filters we created, and examined the results in time and frequency domain. When examining the graphs we received in this part, we decided to neglect electrodes which have very large peaks, considering them as noisy signals. After neglecting those electrodes we chose the best electrode for each wave by examining which electrode has the biggest PSD for each wave.

After choosing the optimal electrode for each wave, we used those electrodes in order to analyze the different waves while the subject was with open and then closed eyes. By looking at the graphs of the different brain waves in the two segments, and examining the STD of each one of the waves, we noticed that all four of the waves are more dominant when the eyes are closed and decrease when they are open, and that particularly the STD of the alpha and delta waves increased dramatically whereas the beta and theta wave only increased slightly when the subjects eyes were closed. Possible reasons that alpha and delta waves intensifies significantly are that as we saw in the introduction alpha waves tend to intensify in states of relaxation and delta waves tend to intensify in states of slumberness, because closing our eyes is associated with both of these states, it is reasonable that the alpha and delta waves will intensify significantly when the subject closes his eyes.

The importance of the STD of the different waves is that it allows us to examine the intensity of the signal - a signal that has high STD will have a high intensity, therefore STD is a simple tool to evaluate the intensity of the EEG signal, and therefore it is useful when examining and analyzing the behavior of the brain waves in different situations.

When we examined the frequencies of the different brain wave signals, we witnessed that each brain wave signal contains almost the exact frequencies we expected for each brain wave. This is reasonable because those signals were filtered using filters that reduce all frequencies that do not match the frequencies of the wanted brain wave. Because of this, we have decided that calculating the mean frequencies of each brain wave has no significant meaning when analyzing the EEG signal.

Detecting salt bridges

In this part we based on a known article in order to detect electrodes that might be connected with salt bridges. The threshold we had set was 500 [μV^2]. This value was set following educated guesses (not scientifically backed) after examining the data we received. We believe that if we had chosen higher threshold value we probably would get more suspected salt bridges. In order to minimize this phenomenon of the salt bridge we suggest that besides using AC to cool the room in order to prevent sweat, the wetting of the electrodes using the saline should be carried out under the supervision of an experienced person. This is due to the fact that over wetting the electrodes is a common factor for the creation of salt bridges.

Part 2 - EEG classification

According to the results of this part we got a perfect AUC, meaning that we got an accurate model for the specific dataset we dealt with. Although we received accurate results we are assuming that using different dataset might produce less accurate results. We believe that if we were analyzing much bigger data we could get a better general model, even if it means that the ROC curve we will produce will show less accurate results. In addition we believe Choosing one emotion for the experiment and specifying at different times the level of emotion that is needed could improve our model because this way it is less likely that other feelings will affect the examination of specific emotion.

General errors in the experiment

- During signal processing we filtered the signal to a frequency range between 1-30 Hz optimal filtering of electronic or electromagnetic noises was not necessarily accurate, Which may impair the quality of the signal. Accordingly, we claim that if we had a better and more accurate understanding of what are the specific ranges of the noise frequencies we could filter them much better, and this way to get more accurate results.

- During the experiment the movements of the subject can be clearly seen in the video. It is important to note that even though there were small shifts
  They impaired the quality of the recording, as mentioned, activating muscles in the head area, can be recorded as an indication as well In the EEG records.

- Different device errors using EEG and the other processing softwares.

- Inaccurate placement of the electrodes on the scalp.

- Blinking during the experiment may cause noises in signal analysis

Ideas for different experiments relating to EEG :

- It can be interesting to examine the different brain waves when the subject is concentrating in a hard task, requiring a high level of concentration, in comparison to the same subject in a state of relaxation, when also examining the influence of different interruptions to the subject while he is trying to concentrate on his task.

- Another interesting experiment is to examine how listening to different types of music influences the behavior of the different brain waves, and if those influences vary between different subjects and if there is correlation to their musical preferences.

5. References

[1] *Light, G. A., Williams, L. E., Minow, F., Sprock, J., Rissling, A., Sharp, R., … Braff, D. L. (2010). Electroencephalography (EEG) and Event-Related Potentials (ERPs) with Human Participants. Current Protocols in Neuroscience, 52(1), 6.25.1–6.25.24.*

[2] *Abhang, P. A., Gawali, B. W., & Mehrotra, S. C. (2016). Technological Basics of EEG Recording and Operation of Apparatus. Introduction to EEG- and Speech-Based Emotion Recognition, 19–50.*

[3] *Sazgar, M., & Young, M. G. (2019). EEG Artifacts. Absolute Epilepsy and EEG Rotation Review, 149–162. doi:10.1007/978-3-030-03511-2_8*

[4] *Tenke, C. E., & Kayser, J. (2001). A convenient method for detecting electrolyte bridges in multichannel electroencephalogram and event-related potential recordings. Clinical Neurophysiology, 112(3), 545–550.*

[5]*Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: applications, challenges and trends. Neurocomputing.*

[6] *Lisha Sun, Ying Liu, & Beadle, P. J. (n.d.). Independent component analysis of EEG signals. Proceedings of 2005 IEEE International Workshop on VLSI Design and Video Technology, 2005.*

[7] *Cheema, M. S., & Dutta, A. (2018). Automatic Independent Component Scalp Map Analysis of Electroencephalogram During Motor Preparation. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).*

[8] *Classification of Movement Intention Using Independent Components of Premovement EEG Hyeonseok Kim1 , Natsue Yoshimura2,3 and Yasuharu Koike2*

[9] *Enhancing EEG Signals Recognition Using ROC Curve. Takashi Kuremoto1, Yuki Baba2, Masanao Obayashi1, Shingo Mabu1, Kunikazu Kobayashi 3.Journal of Robotics Networking and Artificial Life 4(4):283.*

[10] *Alschuler, D. M., Tenke, C. E., Bruder, G. E., & Kayser, J. (2014). Identifying electrode bridging from electrical distance distributions: A survey of publicly-available EEG data using a new method. Clinical Neurophysiology, 125(3), 484–490.*