Lab Report

Advanced Bio-Electronics

ELECTROENCEPHALOGRAPHY – EEG EXPRERIMENT

Group no. 6:

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Abstract:

EEG Is a method to measure and monitor the electrical activity of the brain. In this experiment a helmet with 14 electrodes connected to it, was used in order to reflect the electrical behavior in the brain of the human. The experiment was composed out of 2 different parts: the first one was to examine the EEG signal, from a relaxed person, attentive with open eyes and afterwards with closed eyes, in order to recognize and attenuate the noises out of the signal and to identify the different 4 sub waves (α, β, δ, θ) among the main signal in the time domain and also in the frequency domain.

The purpose of the first part was to recognize all the 4 sub waves of the EEG signal and to understand the influence of opening and closing of the eyes on the different brain waves.

In the second section of the first part, we were requested to identify the salt bridge artifact between neighboring electrodes, based upon the data which was provided. The purpose of this part was to locate whether there is a "short circuit" between different electrodes or not and when.

It is possible to decompose the EEG signal into 4 sub waves due to the fact that each one of them operates in a different range of frequencies [1]. Hence, we have the ability to know which range of frequencies belongs to which wave - In order to extract corresponding waves.

In the second part of the experiment, we were introduced to machine learning fundamental concepts and we used them in order to classify fear and relaxation emotions from an EEG signal and according to our results we achieved a high-performance classifier.

Introduction:

EEG is the monitoring of electrical activity of the brain. This is a noninvasive way to record and measure voltage fluctuations caused by ionic current.

The cells in the brain communicate with each other through electrical signals. This activity continues non-stop, even during sleep. the sensors (i.e. electrodes) in the EEG, are in the form of discs and are attached to the scalp. The EEG device translates the electrical signals of the brain into a diagram of wavy lines.

EEG is one of the main tests for diagnosing epilepsy, but may also help diagnose other brain problems such as stroke, sleep disorders, memory disorders, ADHD, suspected brain tumor, Injury following a head injury, disruption of brain function for various reasons (encephalopathy), Brain inflammation. [1]

The electrical activity brain produced by the test is characterized by wavy lines with a frequency that varies depending on the state of consciousness. For example, during sleep the waves are slower than in the waking state. In addition, there are patterns typical of waves that represent normal electrical activity. The amplitude of the voltage in the EEG signal is relatively low and measured in units of micro volt.

There are four simple periodic rhythms recorded in the EEG: alpha, beta, delta, and theta. These rhythms are identified by frequency (Hz or cycles/sec)

In addition, the signal's frequency range is usually 1-40 Hz and it can be analyzed by its 4 components, which are 4 sub-waves, α, β, θ and δ.

Alpha waves are the waves in the frequency range of 8-12 Hz. They are the electrical activity waves of the brain during pre-anesthesia relaxation, hence when the subject is quietly resting or while his eyes are closed. one of their hallmarks is the neat form of drawing, reminiscent of comb teeth. When a person closes his eyes and calms down, the electrical activity in his brain changes from a state of alertness (in which the electrical activity is of the fast beta waves), to a state of relaxation and slow activity of the brain waves. The wave usually appears at the posterior portion of the cerebral cortex of the scalp. Since they characterize a state of relaxation, alpha waves have gained much popularity.

Beta waves are waves in the frequency range 13-30 Hz. They usually appear on both sides of the brain symmetrically, especially in the front. These waves have a low amplitude. They are present when a person is alert/attentive and thinking actively and also related to learning and to the cognitive ability of the brain at a given moment. This is a state where the brain is at a high energy level and needs a lot of metabolic resources. Pathologically, this range appears when using benzodiazepines. This range often appears during registry interruptions. Among the 4 sub waves this kind is considered as the lowest in its amplitude

The Delta waves which include all the waves in the EEG below 3.5 Hz. These waves have the largest amplitude and are also the slowest waves. They usually appear in the posterior brain in children and in the anterior brain in adults. they appear in adults during deep sleep, and in infants. Sometimes they can be also seen in activities that require constant attention.

The Theta waves have frequencies between 3.5 and 7.5 Hz. These occur mainly during rest in children but can be seen as well in adults. They are related to sleep, meditation or when a person is trying to process logical information or to be creative. The theta waves are usually maximal in the frontal or fronto-central regions and can be seen while at focused concentration and drowsiness.

The salt bridge artifact in EEG is a phenomena which comes from sweating, over-wetting of electrodes, a change in the conductivity of the skin and more. In this phenomenon there is minimal electrical conduction between 2 electrodes.

In this artifact, electrical conduction is created between two adjacent electrodes, through the electrolytic solution. This happened when 2 adjacent electrodes have identical or at least almost

identical electrical potentials. We can model it to a resistor with a low resistance that behaves as 'short circuit'.

Moreover, there are the surroundings and physiological artifacts:

The surroundings artifacts have different reasons such as electromagnetic waves outside to our system or the subject's body electricity, in addition also the national electricity grid adds a noise to the measurements and the baseline drift which is cause due to poor contact of the electrodes or perspiration during the operation of the EEG.

The physiological artifacts can be described as muscles movements, breathing, talking or the heart pulse. These activities can distort the EEG signal as well.

Introduction relevant for the second part:

SVM is a machine learning algorithm based on statistical learning, the principle is to deal with complicated data classification by solving the optimization problem and finding the optimal classification hyperplane in the high-dimensional feature space. In a way which enables to distinctly classify the data points. In order to separate two classes of data points it is possible to choose many different hyperplanes. But the issue is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

Sensitivity is another tool in machine learning which enables to determine the proportion of actual positive cases, which got predicted correctly, Respectively Specificity enables to define the proportion of actual negative cases, which got predicted correctly, the shortcuts are:
TP: number of positive examples classified correctly
FN: number of positive examples classified incorrectly
FP: number of negative examples classified incorrectly
TN: number of negative examples classified correctly
Formulas which are essential for this experiment are:

$$(1)\ specificity = TNR\ (true\ negative\ rate) = \frac{TN}{N} = 1 - FPR$$

$$(2)\ sensitivity = TPR\ (true\ positive\ rate) = \frac{TP}{P}$$

At the end of the experiment the results were evaluated using the ROC curve, which describes the true positive rate (TPR) versus the false positive rate (FPR) at various threshold settings.

The ROC can be about 1 when we classify all the examples as positive, but this is also problematic since This means that the model is very robust. Hence it is preferable to be somewhere so the TP is very high and the FP is very low. This is a curve that is interesting to look at, in order to select the bias point which is desired to work in. the points have to be selected according to the specified requirements - for example if we do not want to miss real cases and we want to minimize the non-necessary 'alerts', then we will select the point in the roc according to this request.

Moreover, there is the overfitting term, which describes a situation when the machine has too much data, way more than it needs, results in a poor ability to predict because there are too many parameters than justified. A cross-validation is used in order to check the model's ability to predict new data that was not used in estimating it, it can help for example in overfitting by giving perception

of how the model should behave. With it we are able to get a better estimation of a model prediction performance.

The last term which we will discuss here in the context of machine learning is a hyperparameter, which stands for a parameter whose value is used to control the learning process. Unlike hyperparameters, the other parameters are determined by the training.

Methods & Results for part 1 (questions answers):

Question 1:

Firstly, following the recommendations of the protocol [2], in order to achieve the best results, we ignored the F7 & T7 electrodes, because they were either too noisy or not working according to the EEG software.

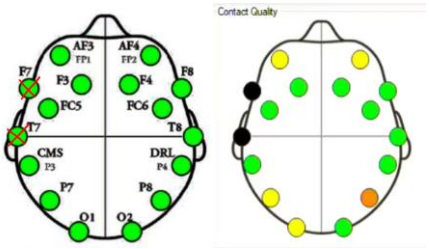

Figure 1- the electrodes map. the right figure demonstrated the electrodes we chose to "ignore", the figure on the right describes the quality of every electrode during the EEG recording for part 1, according to the EEG software, captured from the experiment video [2].

a. According to the video, the sample rate is $f_s = 128\ Hz$ which translates to:

$$T_S = \frac{1}{f_s} = 7.81\ msec.$$

b. Tmax, represents the total time length of the recorded signals and was calculated using this formula:

$$T_{MAX} = (num\ of\ samples - 1) * T_s = 8999 * 7.18m = \ 70.3sec.$$

c. The figure below depicts the effect of the noise filtering on a particular electrode.
The rest of the noise filtering results are attached in Appendix 1.

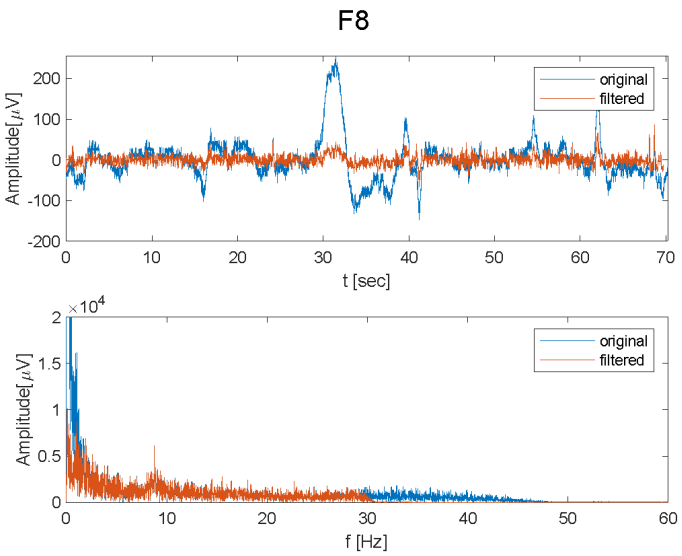

Figure 2- F8 electrode before and after noise filtering.

d. The signals were filtered with the aid of a FIR band pass filter (using "fir1" in Matlab). We selected the FIR filter over the IIR filter mainly because the FIR filter has a constant phase delay, while the IIR does not.

This delay will cause a delay of the signal in time, and in the case of the FIR filter we can overcome this phenomenon by calculating the delay of the filter, and adjust the time vector of the filtered signal accordingly.

We filtered the signal by passing it through a 1-30HZ band pass filter.

We chose this region because we know that this is the range of the common brain waves (delta to beta).

By doing so, we filtered out noises above and below this range, for example [2]:

- Powerline noise: 50 or 60 Hz (depends on the location)
- Muscle movements: ~100 Hz
- Heart pulse: ~60 Hz (depends on the person)
- Sweating, which can cause to a drift in electrode impedance: 0.01 Hz

By comparing the filtered signal to the original signal, in the frequency domain, we can see that the original signal had significant spectrum content in frequencies outside the relevant brain wave range (1-30Hz), after the filtering, we can clearly see that the signal is “cleaner” by observing the difference in the time domain: the original signal had a larger amplitude range and a “wilder” behavior, but the filtered signal amplitude range is much smaller and is almost symmetric around the 0 amplitude.

This is why we conclude there is an improvement after the filtering.

e. by examining the spectrum of the original signal and the filtered signal, we can see that the original signal had significant energy in the frequencies in the range 0-1Hz.

we assume the origin of this noise is the drift in electrode impedance or sweating, which is expected to be around 0.01Hz.

After the filtering the spectrum in this range of frequencies is significantly reduced, meaning the significant energy in this frequency range is lost.

Question 2:

a. We filter the signals according to the following table:

wave	Frequency range [Hz]
$\delta - wave$	1-3.5
$\theta - wave$	4-7
$\alpha - wave$	8-13
$\beta - wave$	14-30

Table 1 – the frequency range of each sub wave

b. In the following table we describe the electrodes which gave the best results:

wave	Chosen electrode
$\delta - wave$	O2
$\theta - wave$	F3
$\alpha - wave$	O2
$\beta - wave$	O2

Table 2 – the electrodes chosen for every sub wave

c. We chose an electrode for every wave based on the maximum energy level.

for each wave, after filtering the signal to the specified frequency range of the desired wave, we calculated the fft of the signal. (by signal we mean the signal of each electrode)

Then, we selected the electrode that corresponds to the highest energy (has the highest fft value).

In order to ensure we select an electrode as free of noise as possible, we ignore the non-green electrodes in the prosses of this selection (figure 1).

In appendix 2, we attached a visualization of the alpha-waves extracted from each electrode as an example of the individual wave extracting results.

Question 3:

a. The following figures represent the selected waves during each segment when in the time domain and in the frequency domain.

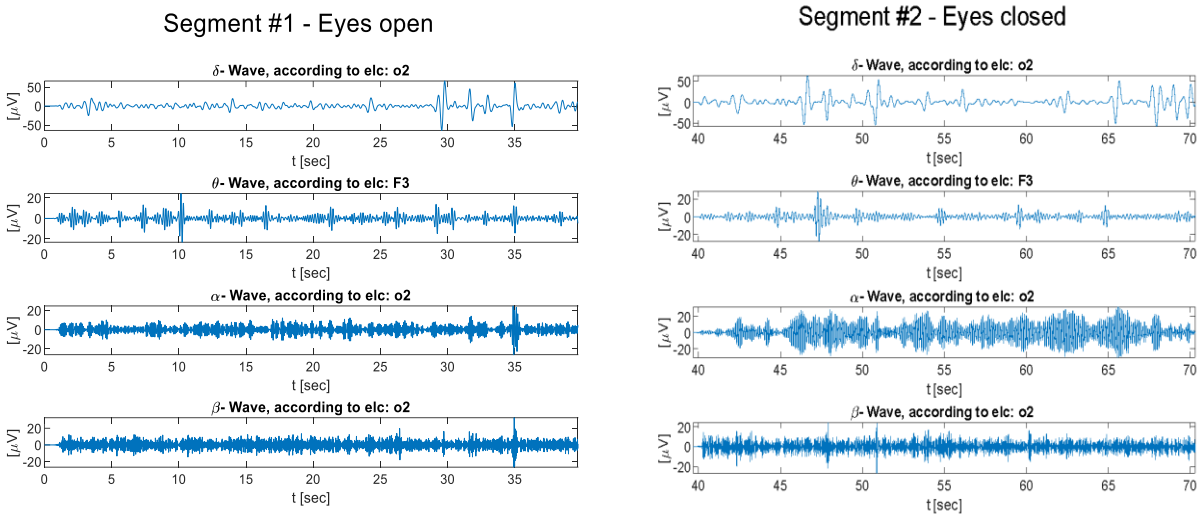

Figure 3- the 4 chosen brain waves, in time domain, when the subject's eyes are opened and closed.

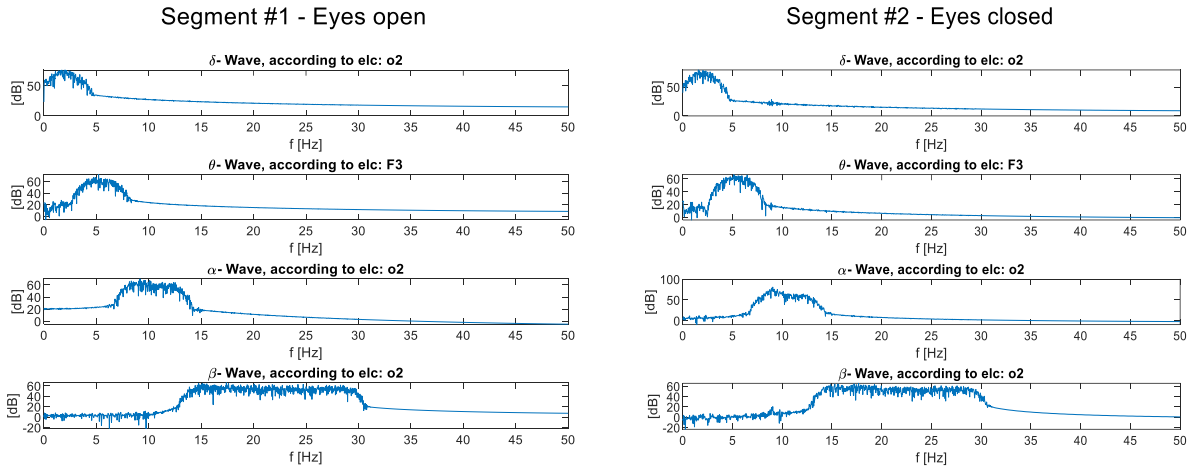

Figure 4- the 4 chosen brain waves, in the frequency domain, when the subject's eyes are opened and closed.

b. measurements of std for each wave:

	Segment 1 – Open eyes $\sigma[\mu V^2]$	Segment 2 – Closed eyes $\sigma[\mu V^2]$
$\delta - wave$	9.53	13.3
$\theta - wave$	3.48	3.53
$\alpha - wave$	4.08	10.6
$\beta - wave$	4.33	4.92

Table 3 –the standard deviation of every wave, when eyes are opened compared to when they are closed.

c. The signals “we have in our hands” are concentrated around zero volts, meaning the mean value of each signal is zero volts.

So, in our case, the standard deviation represents the mean value of the squared signal.

This value is directly corelated with the average amplitude of the signal in absolute value.

higher σ indicated a higher energy signal.

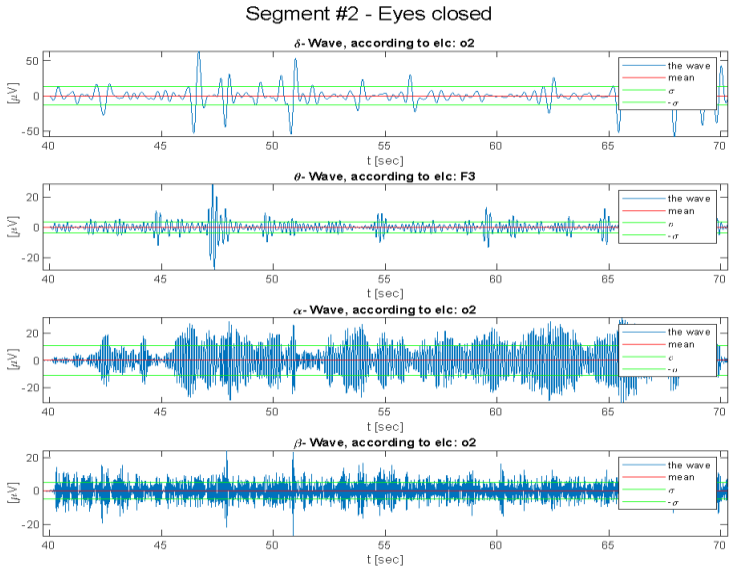

Figure 5 – visualization of the relation between the amplitude of the signal to the std.

d. as we can see from table 3, the $\delta - wave$ had the highest σ value in both cases, this is expected because the $\delta - wave$ is known to have the highest amplitudes [1].

In the first segment, when the eyes where open, the σ value for the α, β, θ waves are similar.

In the second segment, when the eyes where closed, there is a significant change in σ_α , this meets our expectations because α waves are expected to increase when the eyes are closed [3].

There is also an increase in the σ value for the other 3 waves.

The beta waves indicate a state of focusing and thinking actively, the results suggest that the subject was more focused when his eyes were closed.

	Relative change in σ from segment 1 to segment 2
$\delta - wave$	+39.6 %
$\theta - wave$	+1.5%
$\alpha - wave$	+161%
$\beta - wave$	+14%

Table 4 – the change between the 2 segments in term of the σ

e & f.

	Segment 1 – Open eyes Frequency range [Hz]	Segment 2 – Closed eyes Frequency range [Hz]	Average Frequency range [Hz]	Theoretical Frequency range [Hz]
$\delta - wave$	0-4.6	0-4.5	0-4.55	1-3.5
$\theta - wave$	2.9-7.7	3-7.8	2.9 -7.75	4-7
$\alpha - wave$	7-13.6	7-13.7	7-13.65	8-13
$\beta - wave$	13.2- 30	13.4-30	13-30	14-30

Table 5 – the frequencies in which the sub waves appeared

We selected the frequency ranges under the assumption that a 40dB threshold is sufficient.

Appendix 3 included a visualization of the measurements and the threshold choice.

We can see that the frequency ranges in both segments agree with each other, and agrees with the theoretical values, therefore averaging the frequency ranges has no significance.

There are small deviations from the theoretical values (no more than 1Hz), and we assume this difference might be a result of the selected threshold value we discussed earlier. It seems we could slightly increase the threshold.

Part 1b - The salt bridge artifact

In this section we are asked to detect the neighboring electrodes suffering from salt bridge artifact,

In order to find these electrodes, we calculated the potential differences between every couple of neighboring electrodes at any given moment. We defined a threshold of $100\mu V$, such that if the potential difference at a specific moment, is smaller or equal to the threshold voltage then the salt bridge artifact is present between the electrodes at this specific time.

Then, we defined the similarity between every pair of electrodes in the following way:

$$(3)\ similarity_i = \frac{\sum_{k=0}^{N} T_{i,k}}{N}$$

where N equals the number of time samples in the EEG signals and

$$T_{i,k} = \begin{cases} 1, if\ the\ potential\ diffrence\ between\ electrode\ i\ and\ electrode\ (i+1) \\ \quad at\ a\ moment\ k\ is\ smaler\ or\ equals\ 100\mu V, and\ 0\ otherewise. \\ 0, \qquad otherwise \end{cases}$$

Following this definition, a pair of electrodes are suspect of salt bridge artifact, if their similarity value is smaller than the average similarity of all the electrode pairs.

Using this method, we obtained the following salt bridge couples of electrodes which were suspected to suffer from the artifact:

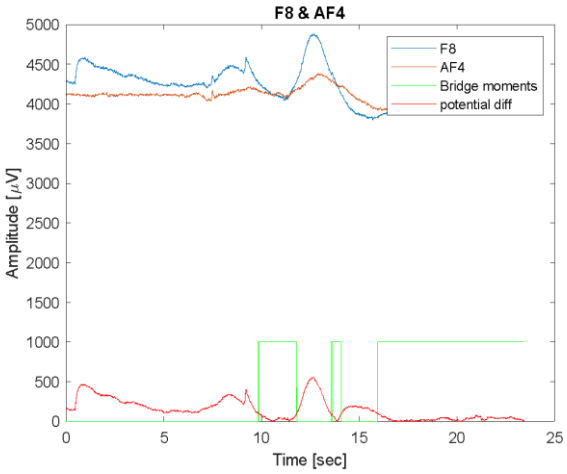

Figure 6- visualization of salt bridge artifact between neighboring electrodes

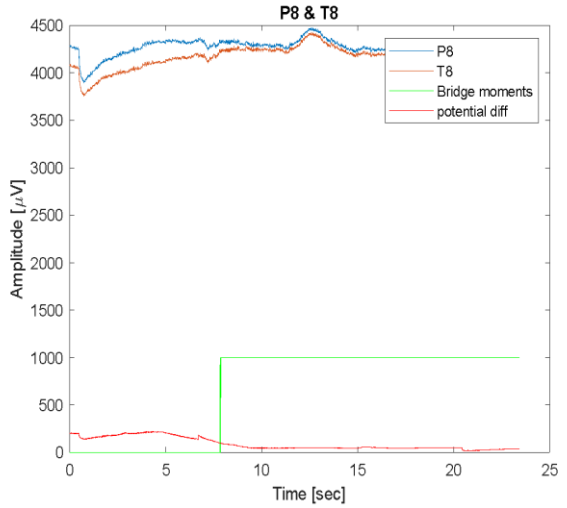

Figure 7- visualization of salt bridge artifact between neighboring electrodes

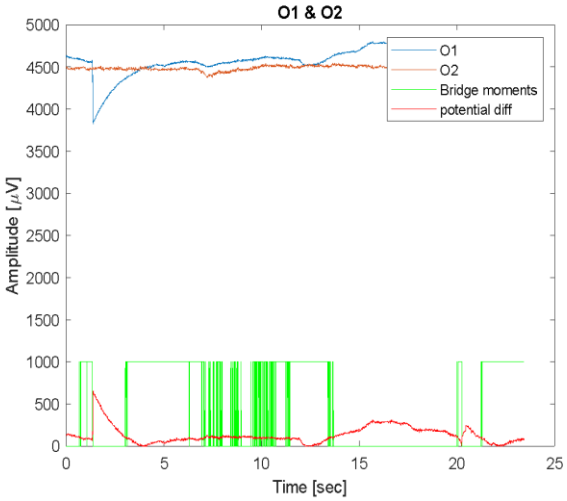

Figure 8- visualization of salt bridge artifact between neighboring electrodes

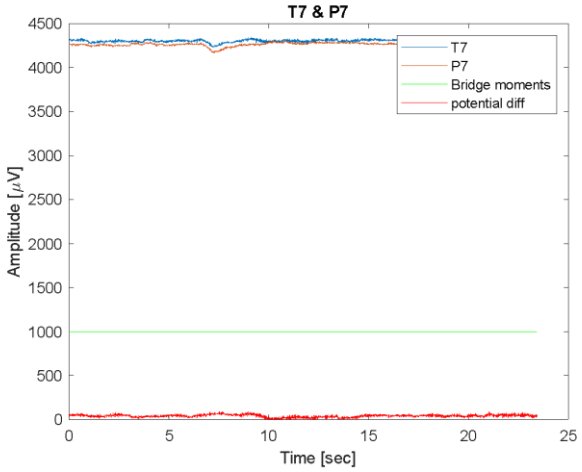

Figure 9- visualization of salt bridge artifact between neighboring electrodes

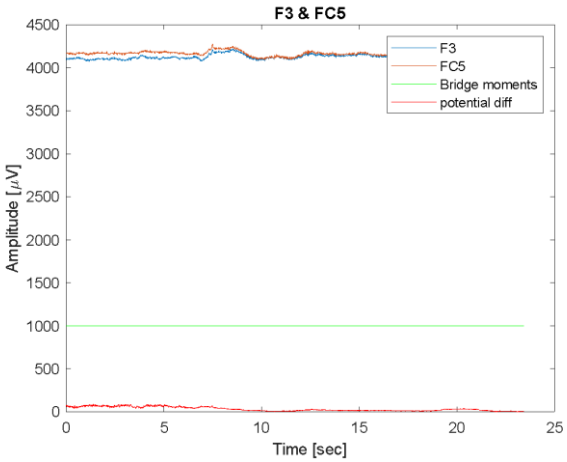

Figure 10- visualization of salt bridge artifact between neighboring electrodes

Part 2:

Methods

In this part of the experiment, we used the public EEG Dataset- Emotion Study dataset, provided by the "OpenNEURO" website.

We processed the data of 10 subjects from dataset using the EEGLAB Matlab program, to extract 2 independent components for every subject.

The selection of the components was based on our purpose to classify between the emotion of fear and relaxation.

According to the literature, the emotion of relaxation comes from the frontal lobe of the brain.
In terms of EEG electrodes location, the frontal lobe signals are expected to appear in the area above the eyes [4].

The emotion of fear comes from the amygdala and signals from the amygdala are expected to be detected by electrodes in the area above the left ear [5].

Following these facts, we selected one independent component from the area above the ear, in order to ensure we will be able to keep the signals that are relevant for the emotion of fear, as can be in seen in figure 11.

And similarly, we selected the second independent component corresponding to the brain waves from the area above the eyes as depicted in figure 12.

In order to ensure that the signal is originated from the brain and not from the eyes we used the IC label tool available in the EEG Matlab program. We knew figure 12 is originated for the brain because the label states that this component is above 98% brain functionality. The components were slightly different for every subject but our selection of components was easy to spot.

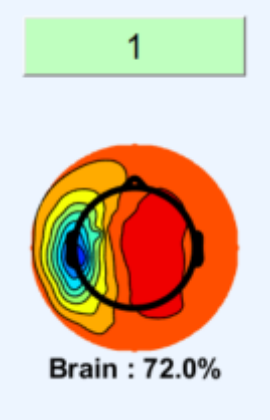

Figure 11- first Independent component

Figure 12- second independent component

After extracting the components for every subject, we loaded the component signal into Matlab (2 signal for every subject for a total of 20 signals).

Using the .tsv events files, we saved the time frames of the relaxation and fear emotion for each one of the 10 participants.

Then we calculated the standard deviation of every brain wave (alpha, beta, theta, delta) in the time frame of each emotion, meaning for every subject we calculated the 4 standard deviations for every emotion out of every component (a total of 16 standard deviation for every participant, 8 corresponding to fear and 8 corresponding to relaxation).

In order to construct the classification model, we built a training set. The training set contains 20 samples, 10 labeled to class fear and 10 labeled to class relaxation. Every sample contains a feature vector of length 8, which includes the 8 suitable stds described in the last paragraph.

Afterwards, the rest of the classification process was done using the aid of 'Weka' program.

We imported our training set into 'Weka', normalized it and standardized using the available filter, and chose the 'LibSVM' function as our classifier, specifying the cross-validation folds to 20.

Selecting the hyper parameters according to the following table:

gamma	cost	Kernel Type	Probability Estimates
0.01	3.0	polynomial	True

Table 6 - the selected hyperparameters for the classification using WEKA.

The values for gamma and cost were selected after multiple trials with different values, until obtaining the sufficient classification (sufficient in our terms is when the ROC area is larger than 0.8).

Results

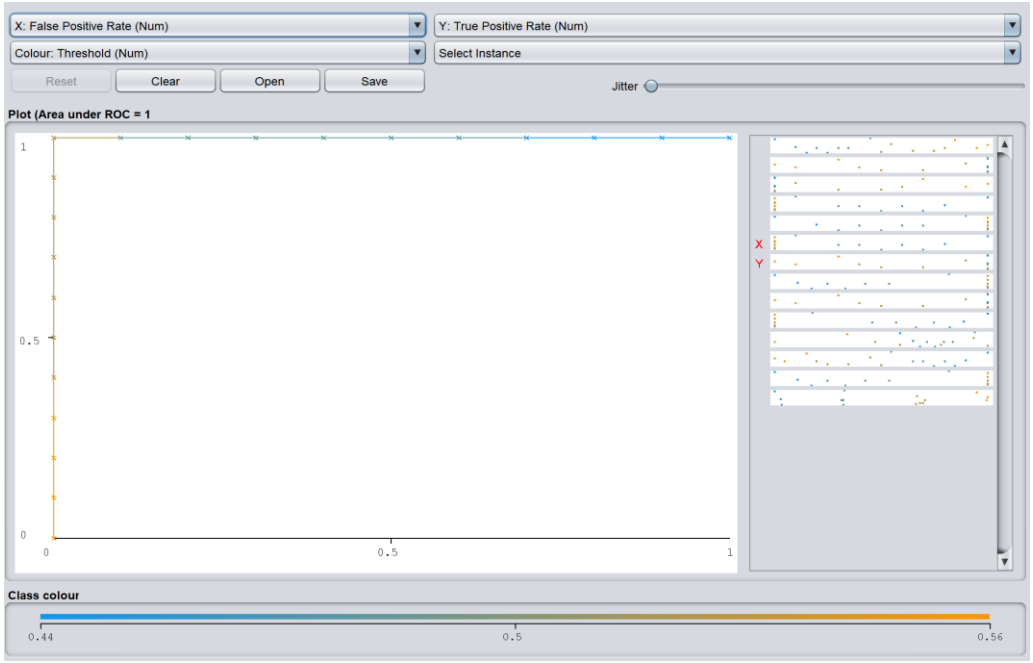

Figure 13 - the ROC curve of the classifier obtained by 'Weka'

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          20               100      %
Incorrectly Classified Instances         0                 0      %
Kappa statistic                          1
Mean absolute error                      0.4679
Root mean squared error                  0.4682
Relative absolute error                 89.324  %
Root relative squared error             89.3774 %
Total Number of Instances               20

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     Relaxation
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     Fear
Weighted Avg.    1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000

=== Confusion Matrix ===

  a  b   <-- classified as
 10  0 |  a = Relaxation
  0 10 |  b = Fear
```

figure 14- the classification results given by 'Weka'

Using formula (1) the specificity of our classifier equals 1 (because FPR=0 as can be seen is figure 14)

Similarly, using formula (2) the sensitivity equals 1 (because TPR=1 as can be seen is figure 14)

Discussion and Conclusions

The results of part 1 agree with the theory, for example, table 4 confirm that the appearance of the alpha waves increased significantly when the eyes were closed and table 3, confirms that the delta waves have the highest amplitude out of all the 4 brain waves.

We conclude that our salt bridge detection algorithm works well.
We came to this conclusion because we have managed to detect electrodes pairs which are clearly bridged- for example figures 9 and 10 who are bridged during the whole-time interval, and also detected electrodes that are borderline bridged for example figure 8 and 6 who are bridging on and off. We can confirm that the bridging indeed occurred not only based on the threshold we set in our algorithm but also from the similarity between the 2 waves form.

For part 2, we believe the classifier worked well, based on the fact that we achieved the highest possible value for sensitivity and specificity which led to optimal ROC curve. The results we obtained were even better than what we have expected to achieve.

firstly, we would like to discuss the atmosphere\the environment in which the experiment was conducted. we can conclude that the work environment is important and in order to get neat and clear results we should have as less electronic distortions as possible, this is especially important because in our experiment the signals measured by the EEG are very small (measured in microvolts) which means the signals are sensitive to environment noise.
The ideas we have regarding ways to improve the recording of the signal are first, we would suggest to take the measurement from a subject which has thinner hair or at least a small amount of hair on his head, to improve the quality of signal reception in the electrodes to the scalp. It is also recommended to place the electrodes at stable points.
Second, to take test several times until the desired signal is received and to strive for as little presence as possible of groups in the laboratory so that undesired noises will not disturb us from getting reliable results. Third, that the subject will be focused solely on the test itself without thinking of anything else as much as it is possible.
During this experiment we were given data of 2 different segments to understand how motor actions affect the reading of the EEG. Another way to get better results is by attaching the electrodes to the scalp with glue - in EEG tests, it is common that the electrodes are attached to the skin with a special adhesive, which improves the quality of the signal and prevents noises made by displacements and insufficient linkage. Other recommendation we found important before conducting the experiment is to wash the hair before, in order to avoid a situation in which a subject is very sweaty so there is a bigger chance for the salt bridge artifact to create and disrupt our results.

It is possible to name different reasons to errors and non-ideality in our results such as: the quality of the equipment- using more advanced equipment would have given us better results. As can be seen in the beginning of this report - not all the electrodes in the helmet we used worked properly, maybe if we could have them all working, then we had a bigger information to examine. Another reason is that the experiment may have been conducted in an environment which was not enough calm and optimal for performing the experiment, for example- there might have been distractions around the subject which had an effect on the quality of the signal received. The requirement to keep the subject's eyes open for 15 seconds is not easy to some people, so there is an option that the subject blinked during this period of time when he should have kept his eyes opened.

There are other implementations for the EEG in various of fields for example one of them is related to marketing and to the way people look at different products. By understanding the mental states which people hold while being in a store or surfing online, companies can use this data to enlarge their sales. Through the use of the EEG test, these companies are able to learn about processes in the brain that motivate consumers to purchase a product.
Another field which can take advantage of the EEG is for a medical assessment of the subject. To assess the effect of a clinical and psychiatric treatments for different problems as was mentioned in the introduction- for example to the ADHD, epilepsy, PTSD, coma and more. There are studies which investigate concentration, learning abilities and memory abilities and take advantage of the EEG test in order to collect the information and characterize the brain processes.
One more EEG related experiments could be for detecting how alertness is changing along the day in a subject as a function of time. In order to explore the changes, the researcher can check several EEG recordings of a subject in different times of the day. We would expect that the EEG waves would behave differently since people are tend to be more alert in different hours of the day.

References:

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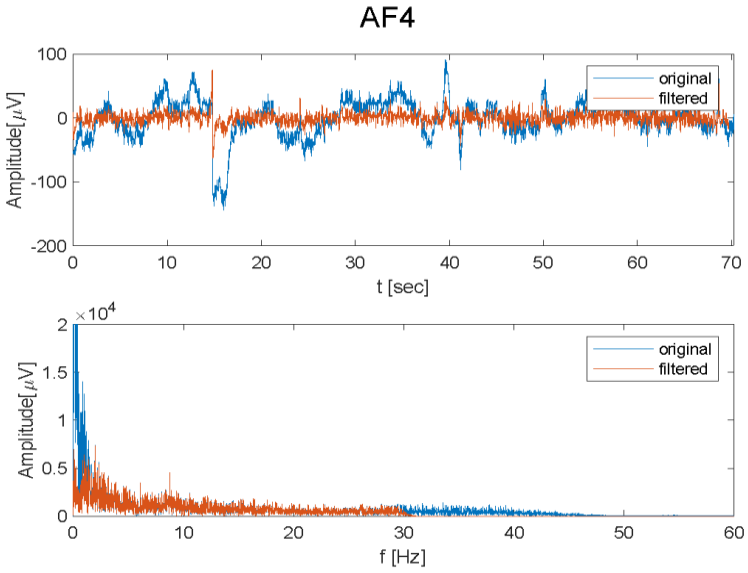
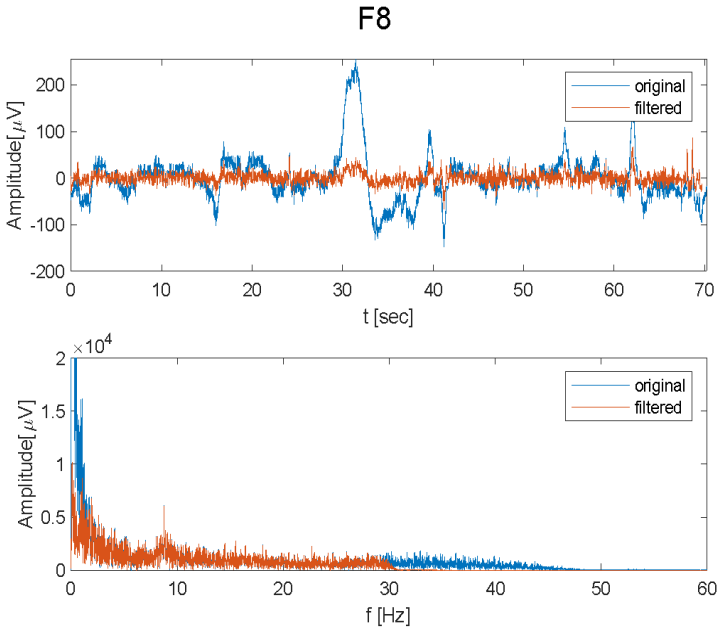
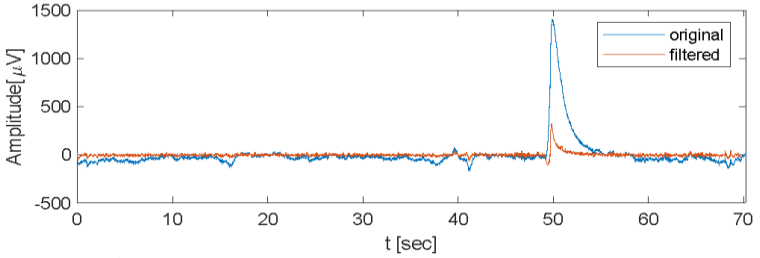
Appendix

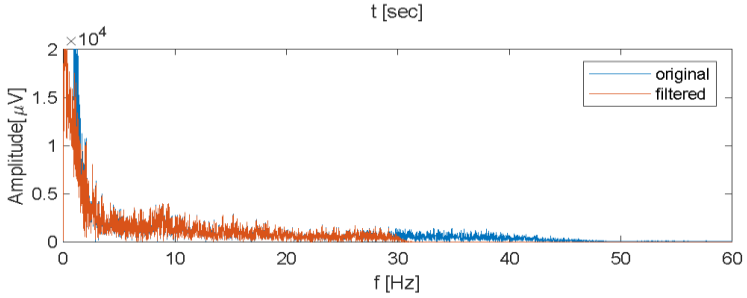
Appendix 1: Noise Filtering results



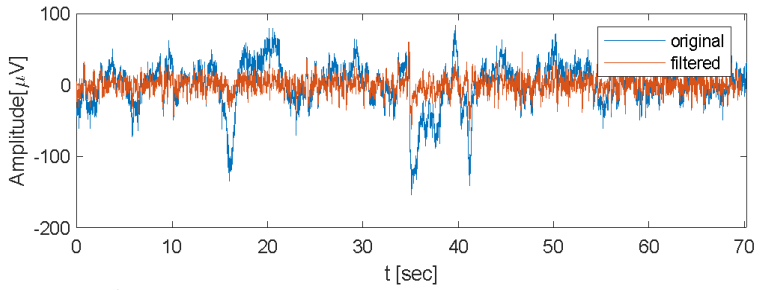


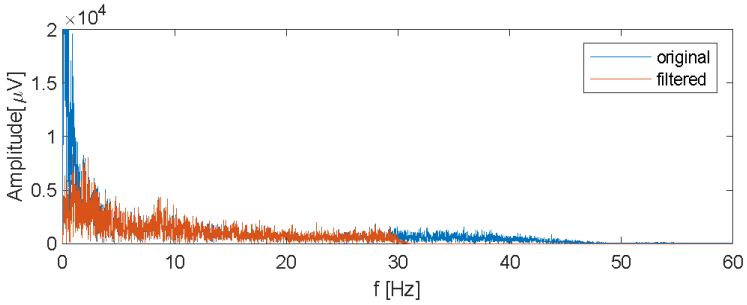
F4


original
filtered
Amplitude[μV]
t [sec]

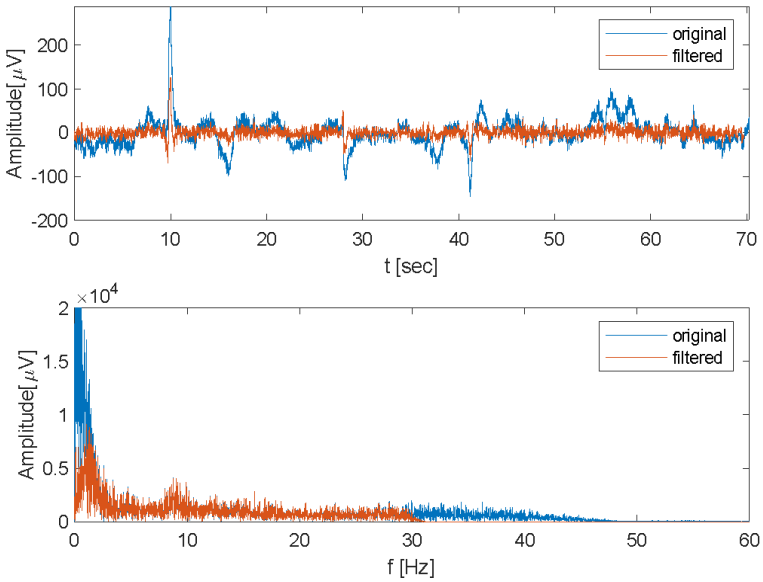

$\times 10^4$
original
filtered
Amplitude[μV]
f [Hz]

FC6

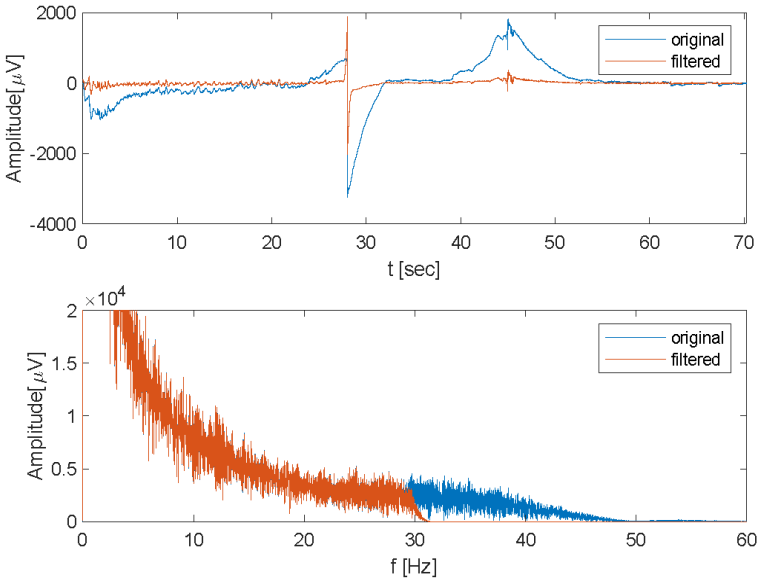

original
filtered
Amplitude[μV]
t [sec]


$\times 10^4$
original
filtered
Amplitude[μV]
f [Hz]

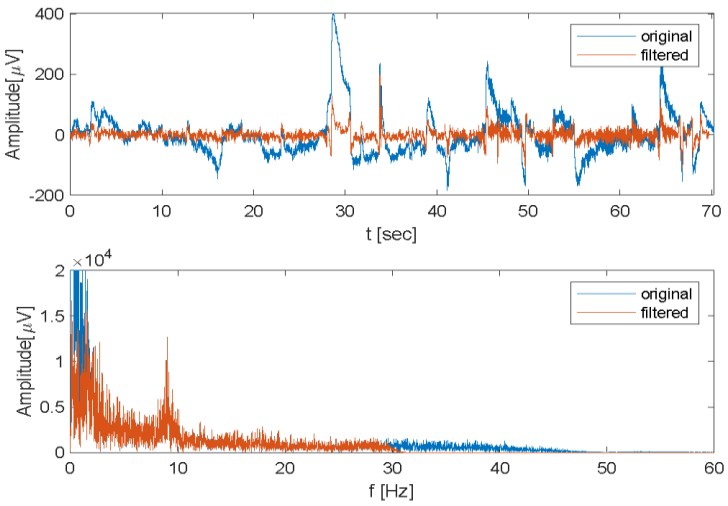
T8


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

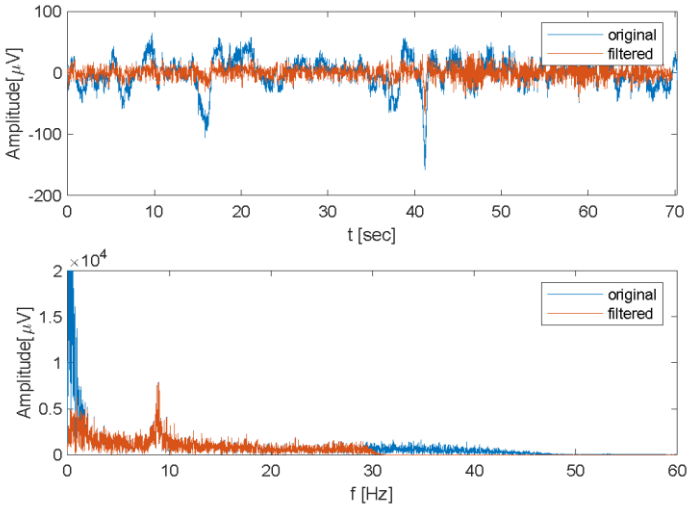
P8


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

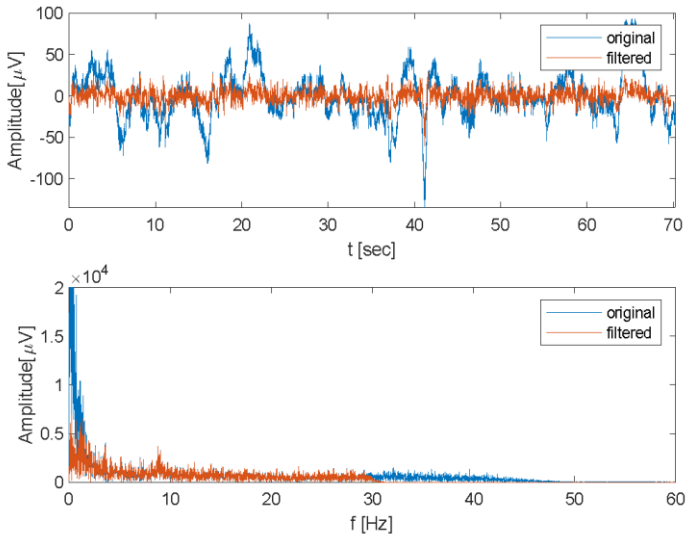
o2


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

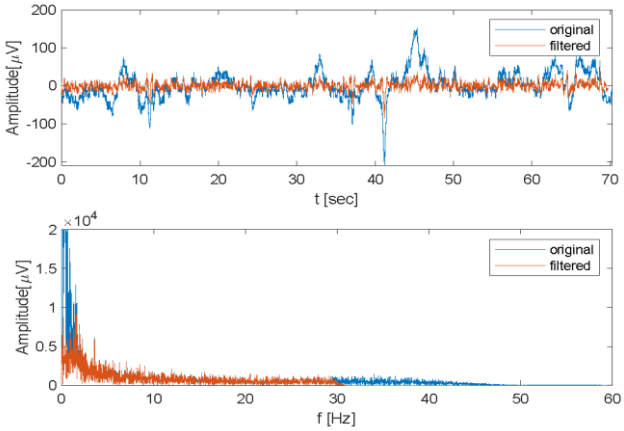
o1


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

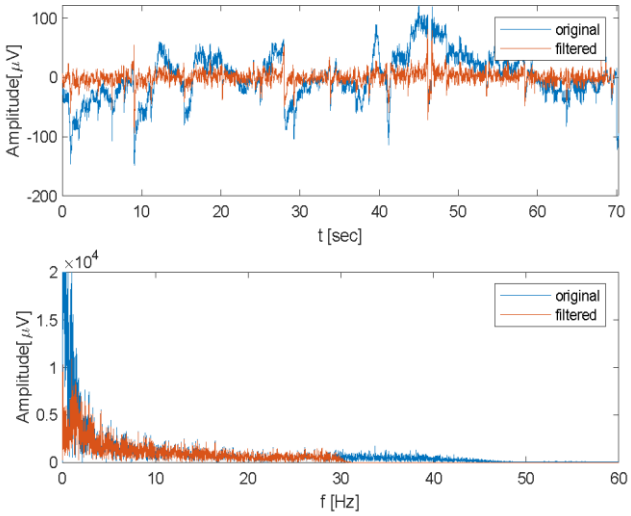
P7


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

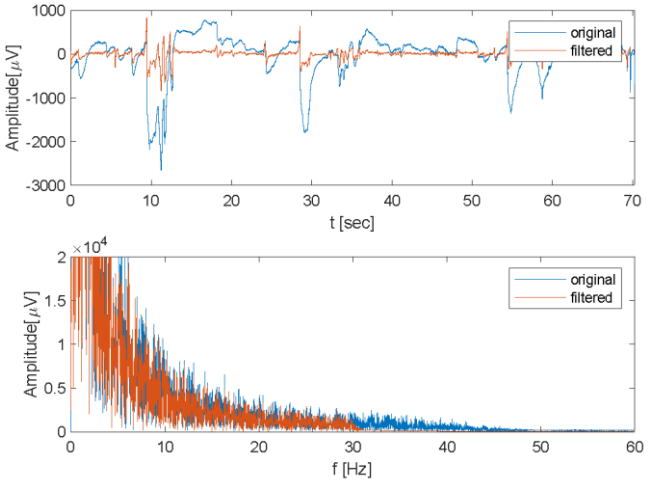
FC5


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

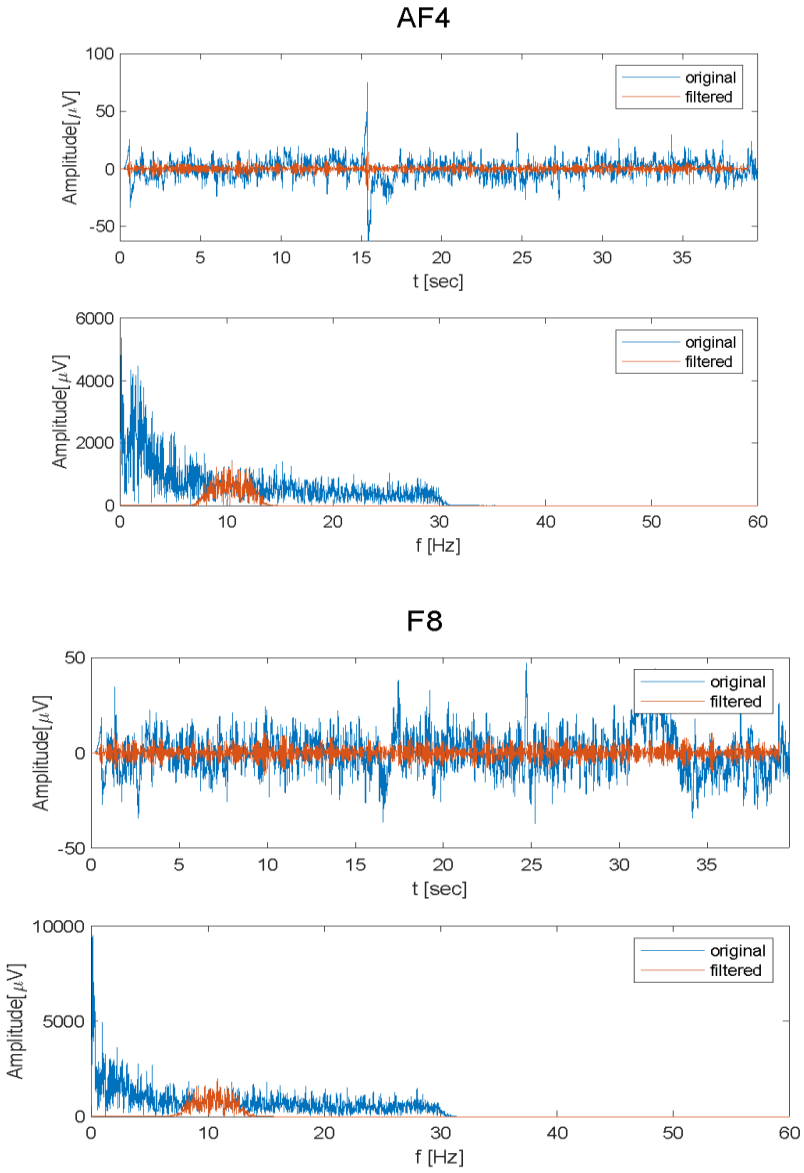
F3


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

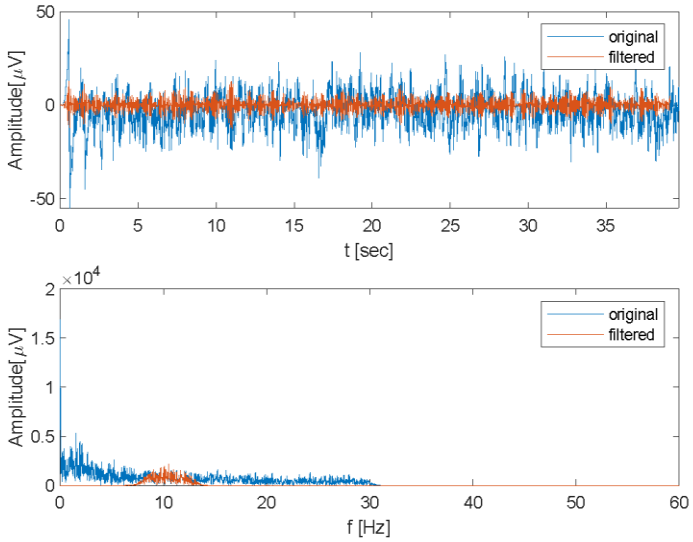
AF3


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

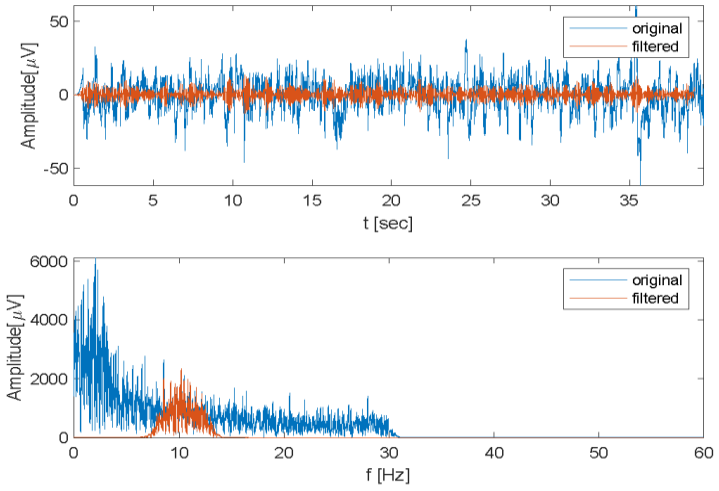
Appendix 2: alpha waves during the first segment (eyes open)



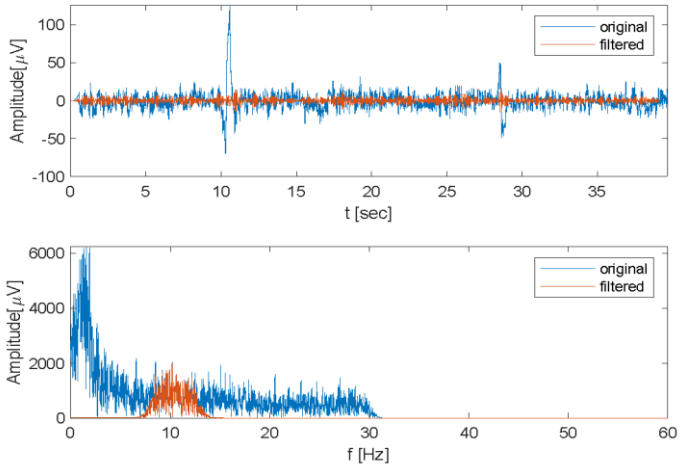
F4


original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

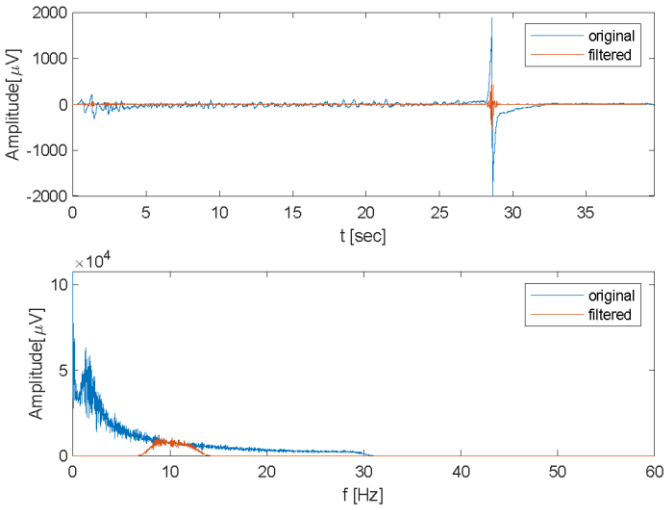
FC6


original
filtered
Amplitude[μV]
t [sec]
f [Hz]

T8

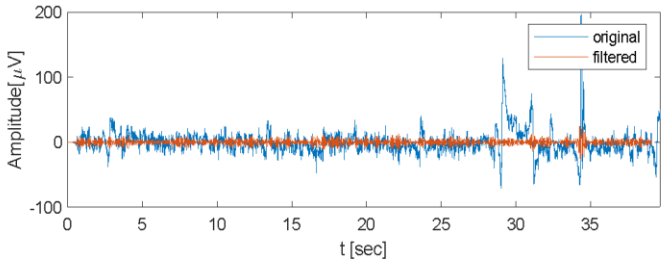

original
filtered
Amplitude[μV]
t [sec]
f [Hz]

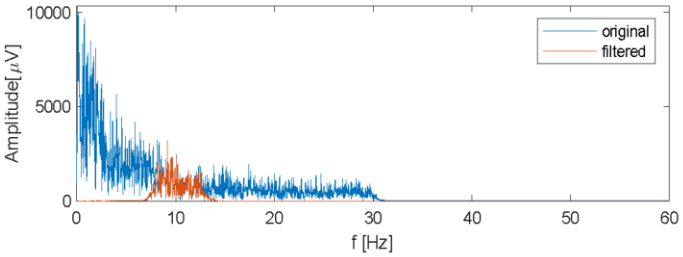
P8


original
filtered
Amplitude[μV]
t [sec]

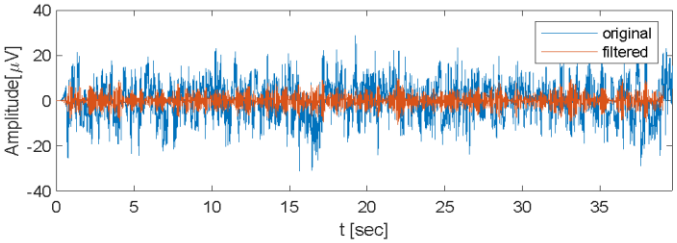
$\times 10^4$
original
filtered
Amplitude[μV]
f [Hz]

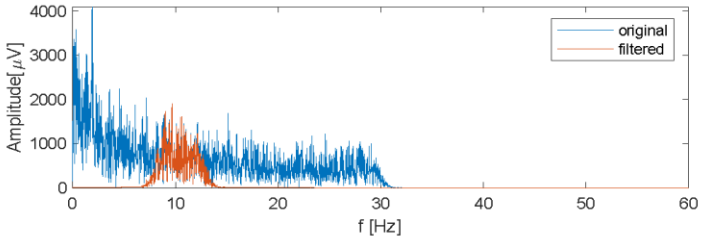
o2


original
filtered
Amplitude[μV]
t [sec]

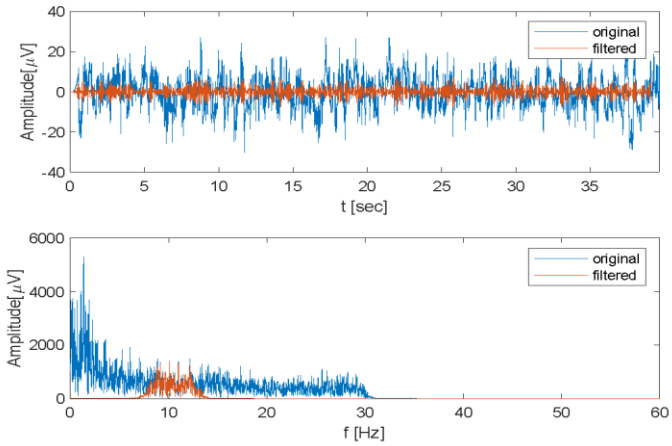

original
filtered
Amplitude[μV]
f [Hz]

o1

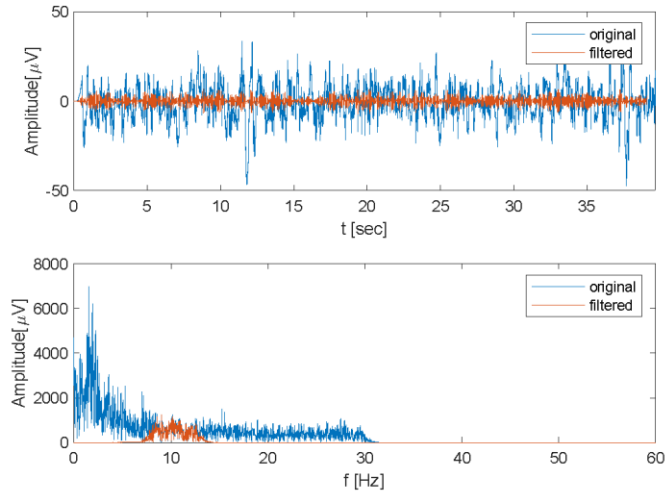

original
filtered
Amplitude[μV]
t [sec]


original
filtered
Amplitude[μV]
f [Hz]

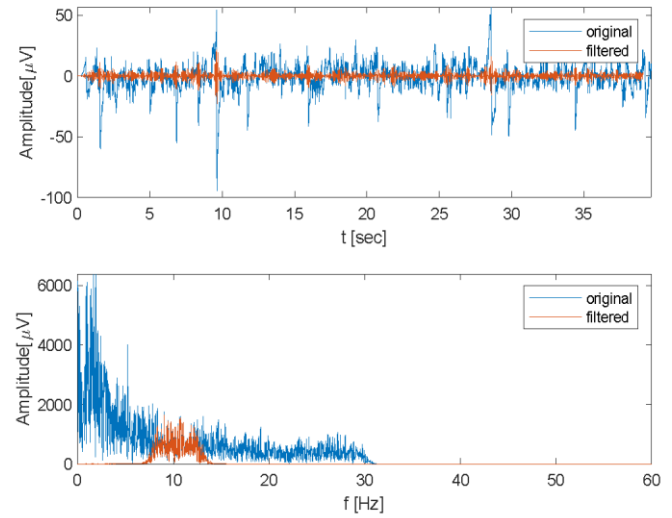
P7

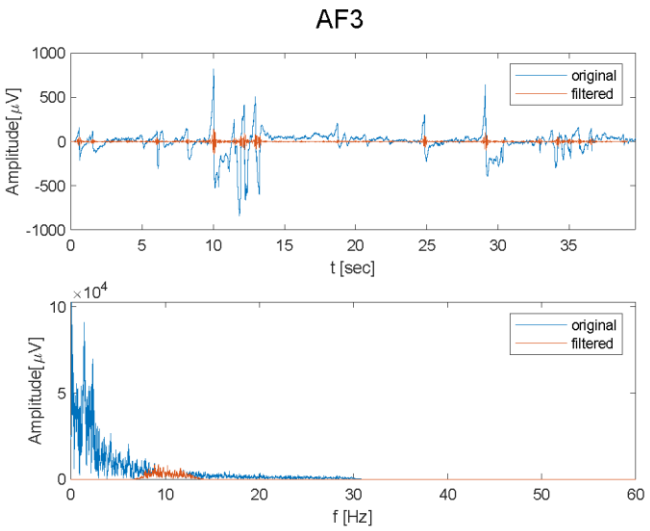

original
filtered
Amplitude[μV]
t [sec]
original
filtered
Amplitude[μV]
f [Hz]

FC5

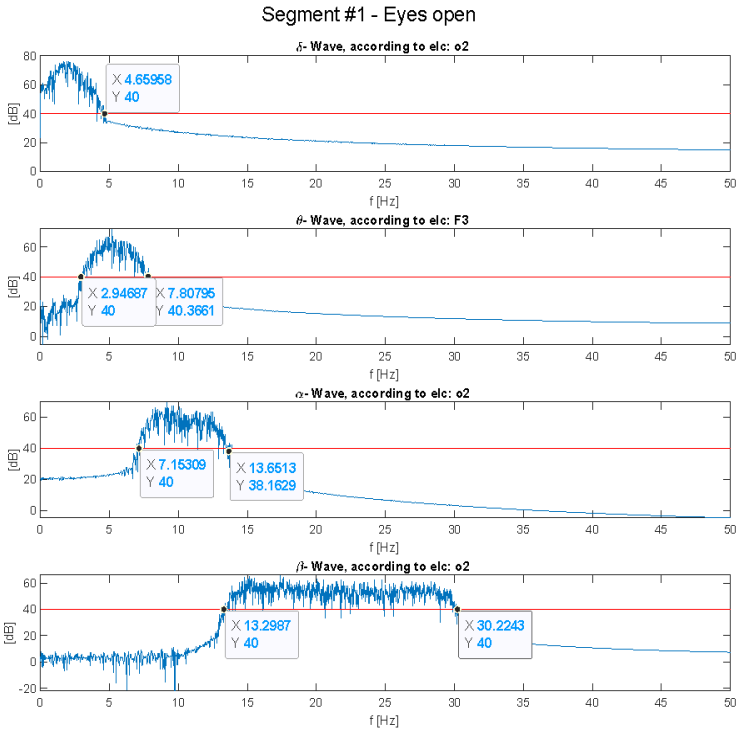

original
filtered
Amplitude[μV]
t [sec]
original
filtered
Amplitude[μV]
f [Hz]

F3

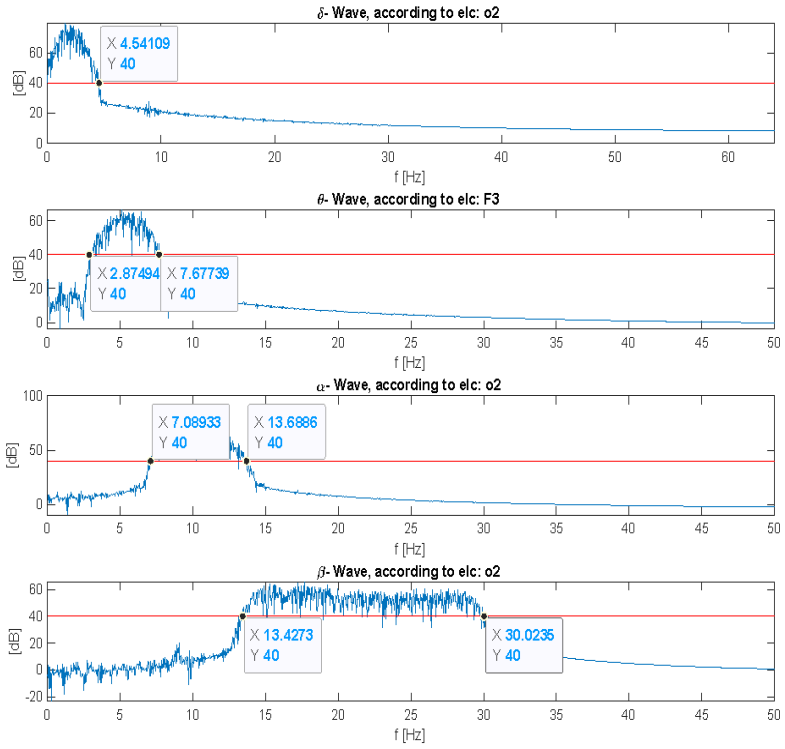

original
filtered
Amplitude[μV]
t [sec]
original
filtered
Amplitude[μV]
f [Hz]


AF3
original
filtered
Amplitude[μV]
t [sec]
$\times 10^4$
f [Hz]

Appendix 3:


Segment #1 - Eyes open
δ- Wave, according to elc: o2
X 4.65958
Y 40
θ- Wave, according to elc: F3
X 2.94687
Y 40
X 7.80795
Y 40.3661
α- Wave, according to elc: o2
X 7.15309
Y 40
X 13.6513
Y 38.1629
β- Wave, according to elc: o2
X 13.2987
Y 40
X 30.2243
Y 40
[dB]
f [Hz]

Segment #2 - Eyes closed



MATLAB CODE:

PART 1:

```
%% part 1-A %%
close all; clear all; clc
%%load electrodes data:
% elc_names=["AF3","F7","F3","FC5","T7","P7","O1","02","P8","T8","FC6","F4","F8","AF4"];
elc_names=["AF3","F3","FC5","P7","o1","o2","P8","T8","FC6","F4","F8","AF4"]; %took out
F7 &T7
not_green=[1,12,4,5,7];
num_of_electrodes= length(elc_names);
for i=1:num_of_electrodes
   j=i-1;
   Elc(:,i)= csvread('Part-A-25.03.20.08.59.27.csv',0,j,[0,j,8999,j]);
   Elc(:,i)=Elc(:,i)-mean(Elc(:,i));
end
%%setup parameters:
N=9000;
fs= 128; %Hz;
Ts= 1/fs; %sec
Tmax= (N-1)*Ts; %the total time.  (accurding to the video it is 1.08 min)
t= 0:Ts:Tmax;
eyes_open_time= 39.7; %sec;  (accurdint to the video)
eyses_closed_time=Tmax-eyes_open_time; %sec;
N_eyes_open= int16(eyes_open_time*fs);
%
%% alpha beta theta delta waves
% filter noise:
fl= 1; %Hz;
fh= 30; %Hz;
Elc_f= get_desired_wave(Elc,fl,fh,elc_names,fs,t,num_of_electrodes,not_green);
%segment 1:
Elc_eyes_open= Elc_f((1:N_eyes_open),:);
t_eo= t(1:N_eyes_open);
[delta_waves, delta_dominent_elc]=
get_desired_wave(Elc_eyes_open,1,3.5,elc_names,fs,t_eo,num_of_electrodes,not_green);
[theta_waves, theta_dominent_elc]=
get_desired_wave(Elc_eyes_open,4,7,elc_names,fs,t_eo,num_of_electrodes,not_green);
[alpha_waves, alpha_dominent_elc]=
get_desired_wave(Elc_eyes_open,8,13,elc_names,fs,t_eo,num_of_electrodes,not_green);
[beta_waves, beta_dominent_elc]=
get_desired_wave(Elc_eyes_open,14,30,elc_names,fs,t_eo,num_of_electrodes,not_green);
waves_seg1=[delta_waves(:,delta_dominent_elc), theta_waves(:,theta_dominent_elc),
alpha_waves(:,alpha_dominent_elc), beta_waves(:,beta_dominent_elc)];
```

```
selected_elc_names=
[elc_names(delta_dominent_elc),elc_names(theta_dominent_elc),elc_names(alpha_domin
ent_elc),elc_names(beta_dominent_elc)];
plot_waves(waves_seg1,selected_elc_names,t_eo,fs,1)

std_seg1=[std(waves_seg1(:,1)),std(waves_seg1(:,2)),std(waves_seg1(:,3)),std(waves_seg1(:,
4))]

%segment 2:
Elc_eyes_closed= Elc_f((N_eyes_open+1:end),:);
t_ec= t(N_eyes_open+1:end);
delta_waves=
get_desired_wave(Elc_eyes_closed,1,3.5,elc_names,fs,t_ec,num_of_electrodes,not_green);
theta_waves=
get_desired_wave(Elc_eyes_closed,4,7,elc_names,fs,t_ec,num_of_electrodes,not_green);
alpha_waves=
get_desired_wave(Elc_eyes_closed,8,13,elc_names,fs,t_ec,num_of_electrodes,not_green);
beta_waves=
get_desired_wave(Elc_eyes_closed,14,30,elc_names,fs,t_ec,num_of_electrodes,not_green)
;

waves_seg2=[delta_waves(:,delta_dominent_elc), theta_waves(:,theta_dominent_elc),
alpha_waves(:,alpha_dominent_elc), beta_waves(:,beta_dominent_elc)];
plot_waves(waves_seg2,selected_elc_names,t_ec,fs,2)

std_seg2=[std(waves_seg2(:,1)),std(waves_seg2(:,2)),std(waves_seg2(:,3)),std(waves_seg2(:,
4))]

%change between segments
change= (std_seg2-std_seg1)./std_seg1.*100

%% ------------ part 1.B (salt bridge)----------%%
clear all; close all; clc;

%%Opening the Elc file
Elc=load('partIII_Group6.txt','r');
Elc_names={'AF3', 'F7', 'F3', 'FC5', 'T7', 'P7', 'O1', 'O2', 'P8', 'T8','FC6', 'F4','F8',
'AF4'};%defining Elc_names' name by the Elc's order

%%setup parameters:
N=3000;
fs= 128; %Hz
Ts=1/fs; %sec
Tmax= (N-1)*Ts; %the total time.
t= 0:Ts:Tmax;

%%find the SB suspects:
for i=1:13
 P(:,i) =abs(Elc(:,i)-Elc(:,i+1));            %the potential diff between niegboring electrodes.
 %ED(i)=sum((P(:,i)-mean(P(:,i))).^2)./Tmax;     %temporal variance
 similarity(i)=length(find(P(:,i)<=100))/N;     %the relative similarity between niegboring
electrodes potentials.
end
```

```
suspects= find(similarity> mean(similarity));
SB_moments= zeros(size(P));

for i =1:length(suspects)
   j=suspects(i);
   locs= find(P(:,j)<=100);
   SB_moments(locs,j)=1000;  % the moments on time where the electrodes are bridging.
end

%%plot
for i =1:length(suspects)
   j=suspects(i);
   figure;
   plot(t,Elc(:,j))
   hold on
   plot(t,Elc(:,j+1))
   hold on
   plot(t,SB_moments(:,j),'g')
   hold on
   plot(t,P(:,j),'r')
   title(Elc_names(j)+" & "+ Elc_names(j+1))
   ylabel('Amplitude [\muV]');
   xlabel('Time [sec]');
   legend(Elc_names{j},Elc_names{j+1},'Bridge moments','potential diff');
end



function [Elc_f,dominent_elc] =
get_desired_wave(Elc,fl,fh,elc_names,fs,t,num_of_electrodes,not_green)
   close all
   %% filter
   f = linspace(0, 1, fix(length(t)/2)+1)*(fs/2); % frequency vector
   Iv = 1:length(f); %the relevent indexes
   fft_Elc= abs(fft(Elc));
   [a,b] =fir1(150, [fl fh]/(fs/2));
   delay = mean(grpdelay(a));
   filtered_t=(t*fs-delay)/fs;

   Elc_f= filter(a,b,Elc);
   fft_Elc_f=abs(fft(Elc_f));
   %% find diminent electrode
   S= max(fft_Elc_f);
   for i=1:length(not_green)
      S(not_green(i))=0;
   end

   [max_eng ,dominent_elc] = max(S);
   dominent_elc_name= elc_names(dominent_elc);

   %%plot
   for i=1:num_of_electrodes
      figure();
```

```
        %time domain
        subplot(2,1,1)
        plot(t,Elc(:,i))
        hold on
        plot(filtered_t,Elc_f(:,i))
        legend('original','filtered')
        xlim([0 t(end)]);
        xlabel('t [sec]');
        ylabel('Amplitude[\muV]');
        %freq domain
        subplot(2,1,2)
        plot(f,fft_Elc(Iv,i))
        xlabel('f [Hz]');
        ylabel('Amplitude [\muV]');
        hold on
        plot(f,fft_Elc_f(Iv,i))
        xlabel('f [Hz]');
        ylabel('Amplitude[\muV]');
        legend('original','filtered')
        xlim([0 60]);
%       ylim([0 500])
        sgtitle(elc_names(i))
    end
end


function [] = plot_waves(W,elc_names,t,fs,seg)
%% time domain:
    names =["\delta",'\theta','\alpha','\beta'];
    figure()
    for i=1:4
        subplot(4,1,i)
        plot(t,W(:,i))
        hold on
        plot(t,ones(size(W(:,i)))*mean(W(:,i)),'r')
        hold on
        plot(t,ones(size(W(:,i)))*std(W(:,i)),'g')
        hold on
        plot(t,ones(size(W(:,i)))*-std(W(:,i)),'g')
        title(names(i)+"- Wave, according to elc: "+elc_names(i))
        xlabel('t [sec]');
        ylabel('[\muV]');
        xlim([t(1) t(end)]);
        legend('the wave','mean','\sigma','-\sigma')
        if seg==1
            sgtitle('Segment #1 - Eyes open');
        else
            sgtitle('Segment #2 - Eyes closed');
        end
```

```
    end
%% freq domain
    figure()
    fft_W= abs(fft(W));
    f = linspace(0, 1, fix(length(t)/2)+1)*(fs/2); % freq vec
    If = 1:length(f); %the relevent indexes
    for i=1:4
      subplot(4,1,i)
      plot(f,db(fft_W(If,i)))
      hold on
      plot(f,ones(size(fft_W(If,i)))*40,'r')
      title(names(i)+"- Wave, according to elc: "+elc_names(i))
      xlabel('f [Hz]');
      ylabel('[dB]');
      xlim([0 50]);
      if seg==1
         sgtitle('Segment #1 - Eyes open');
      else
        sgtitle('Segment #2 - Eyes closed');
      end
    end
end


function [s_delta,s_theta,s_alpha,s_beta] = get_std_of_4_brain_waves(X,fs)
    elc_names=["AF3","F3","FC5","P7","o1","o2","P8","T8","FC6","F4","F8","AF4"];
    delta_waves= get_desired_wave(X,1,3.5,elc_names,fs,0,0,[]);
    theta_waves= get_desired_wave(X,4,7,elc_names,fs,0,0,[]);
    alpha_waves= get_desired_wave(X,8,13,elc_names,fs,0,0,[]);
    beta_waves= get_desired_wave(X,14,30,elc_names,fs,0,0,[]);
    s_delta= std(delta_waves);
    s_theta= std(theta_waves);
    s_alpha= std(alpha_waves);
    s_beta= std(beta_waves);
end
```

PART 2:

```
fs =100;
relax_time_windows= zeros(10,2);
fear_time_windows= zeros(10,2);
for i =1:10
    if i==10
       file='sub-10_eeg_sub-10_task-ImaginedEmotion_events.tsv';
```

```
    else
        file= sprintf('sub-0%d_eeg_sub-0%d_task-ImaginedEmotion_events.tsv',i,i);
    end
    events=tdfread(file);
    event_val= deblank(string(events.value));
    event_t= events.onset;
    relax_idx= find(event_val(:,1) == "relax");
    anger_idx= find(event_val(:,1) == "fear");
    exit_idx= find(event_val(:,1) == "exit");
    exit_idx= exit_idx(exit_idx > anger_idx);
    relax_time_windows(i,1)= event_t(relax_idx);
    relax_time_windows(i,2)= event_t(relax_idx+1);
    fear_time_windows(i,1)= event_t(anger_idx+1);
    fear_time_windows(i,2)= event_t(exit_idx(1));
end
%% extract Features:
Features(1:10,9)= "Relaxation";
Features(11:20,9)= "Fear";
for i=1:10
    switch i
        case 1
            sub= sub1(:,:);
        case 2
            sub= sub1(:,:);
        case 3
            sub= sub3(:,:);
        case 4
            sub= sub4(:,:);
        case 5
            sub= sub5(:,:);
        case 6
            sub= sub6(:,:);
        case 7
            sub= sub7(:,:);
        case 8
            sub= sub8(:,:);
        case 9
            sub= sub9(:,:);
        otherwise
            sub= sub10(:,:);
    end
    sub_times= sub.Time;
    sub_CI1= sub.VarName2;
    sub_CI2= sub.VarName3;
    %%relax:
```

```
   idx= find(and(sub_times>= relax_time_windows(i,1),sub_times<=
relax_time_windows(i,2)));
   sub_CI1_r =sub_CI1(idx);
   sub_CI2_r= sub_CI2(idx);
   [Features(i,1),Features(i,2),Features(i,3),Features(i,4)]=
get_std_of_4_brain_waves(sub_CI1_r,fs);
   [Features(i,5),Features(i,6),Features(i,7),Features(i,8)]=
get_std_of_4_brain_waves(sub_CI2_r,fs);
   %%fear:
   j=10+i;
   t_start= fear_time_windows(i,1);
   t_end=fear_time_windows(i,2);
   idx= find(and(sub_times>= t_start,sub_times<= t_end));
   sub_CI1_a =sub_CI1(idx);
   sub_CI2_a= sub_CI2(idx);
   [Features(j,1),Features(j,2),Features(j,3),Features(j,4)]=
get_std_of_4_brain_waves(sub_CI1_a,fs);
   [Features(j,5),Features(j,6),Features(j,7),Features(j,8)]=
get_std_of_4_brain_waves(sub_CI2_a,fs);
end
writematrix(Features,'Features.csv')
```