دانشگاه تهران

پردیس دانشکده‌های فنی

دانشکده‌ی مهندسی برق و کامپیوتر

تمرین سوم درس مبانی علوم شناختی

نام و نام خانوادگی:

سینا پیرمرادیان

شماره دانشجویی:

۸۱۰۱۰۱۱۲۵

استاد:

دکتر محمدرضا ابوالقاسمی دهاقانی

Introduction:

The first part of the exercise is related to the preprocessing and EEG analysis using the EEGLAB toolbox.

Electroencephalography (EEG) is a widely used noninvasive brain imaging tool that measures the electrical activity of the brain through electrodes placed on the scalp. EEG provides valuable insights into brain function and has several advantages over other brain imaging techniques, including its non-invasiveness, portability, and high temporal resolution. In this report, we will discuss the preprocessing steps involved in analyzing EEG data using the EEGLAB toolbox. Specifically, we will cover the import of data, filtering, re-referencing, epoching, and artifact removal techniques.

The steps include filtering, spike detection, feature extraction, and clustering. Furthermore, this report addresses the effects of high-pass and notch filters, the rationale behind noise removal steps, and the logic behind removing components in ICA.

1. EEG Preprocessing Steps

In this section, we intend to preprocess the EEG data. We know that it is crucial for improving the quality, interpretability, and reliability of the results. The following steps were performed on the EEG data using the EEGLAB toolbox:

1.1. Data Preparation:

The data set consists of 7 files, each of which is a matrix of size 130*3170105, representing time, 126 channels of data, and triggers corresponding to the number of rows, with time points corresponding to the number of columns. The first row represents the corresponding time of the recording, which is not important for our analysis and can be deleted. The 65th rows contain the online reference electrode data do not represent brain data; they are recorded from A2 and Al, representing earlobe signals. The last row contains the trigger values. We must extract epochs for each trial based on this row.

For the epoching process, we should extract the time window that starts with the rising edge of the stimuli number. We know that successful are triggered by 223 values at the end of the epoch. Therefore, we keep these trials and remove others before epoching. Now the data is getting ready to import in the EEGLAB!
The sampling frequency is also considered to be 1200.

1.2. Identifying the event:

In this step, we import the events that are in the last line of the data, i.e. line 130, after this step we will have 4262 events. At the end, we can see the summary of what happened in Figure 1.

Figure 1-Summery report of EEG-Lab after event identifying until step 3

1.3. Channel Location:

In this section, the file related to the location of the channels is added. Therefore, we add the given location.txt file to EEG-LAB. At this stage, the locations of 128 relevant channels are specified. In the EEG data, the first line of data shows the time and the last line is the location of the trials that we do not need, in the previous step, the last line was automatically removed. But we delete the first line manually in Figure 2.

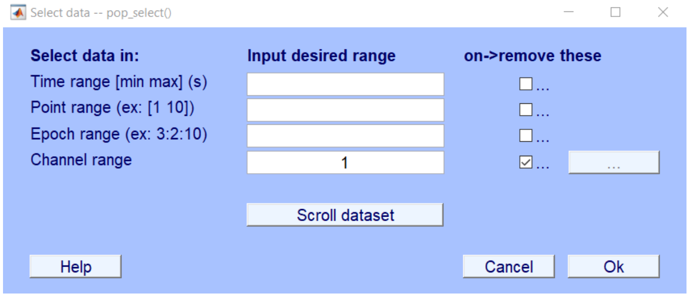


Figure 2- hand removing channel 1

At the end, we can see the summary of what happened in Figure 3.

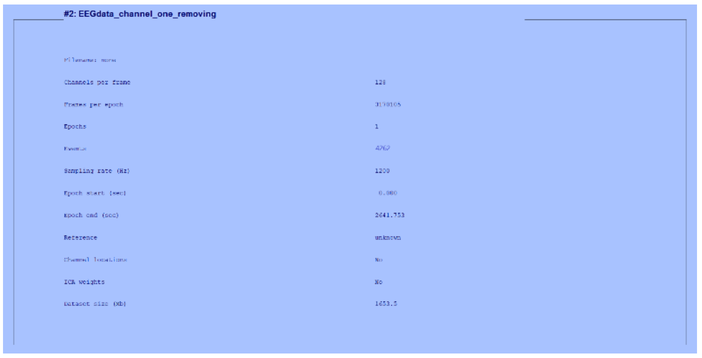


Figure 3- Summery report of EEG-Lab after removing until step 4

1.4. Filtering:

Filtering is an essential step in EEG preprocessing to remove unwanted noise and artifacts while preserving the frequency range of interest. In this case, we apply a high-pass filter with a cutoff frequency of 0.5 Hz and a low-pass filter with a cutoff frequency of 100 Hz.

- The high-pass filter removes low-frequency drifts and baseline fluctuations from the data. It helps eliminate slow changes in the signal that may not be relevant to the analysis. The frequency response of the filter can be seen in Figure 4.

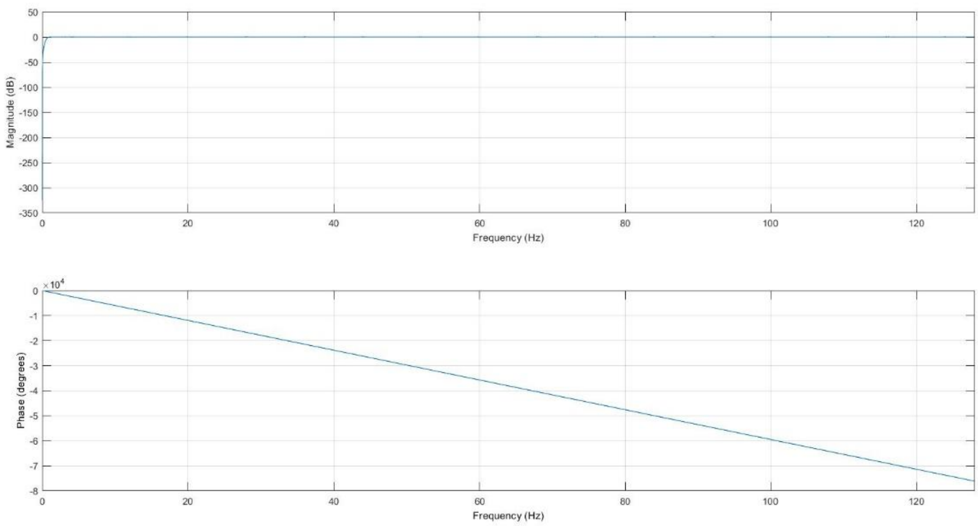


Figure 4- Frequency response of high-pass filter

The data after the high-pass filter, after removing the drift and small changes can be seen in Figure 5.

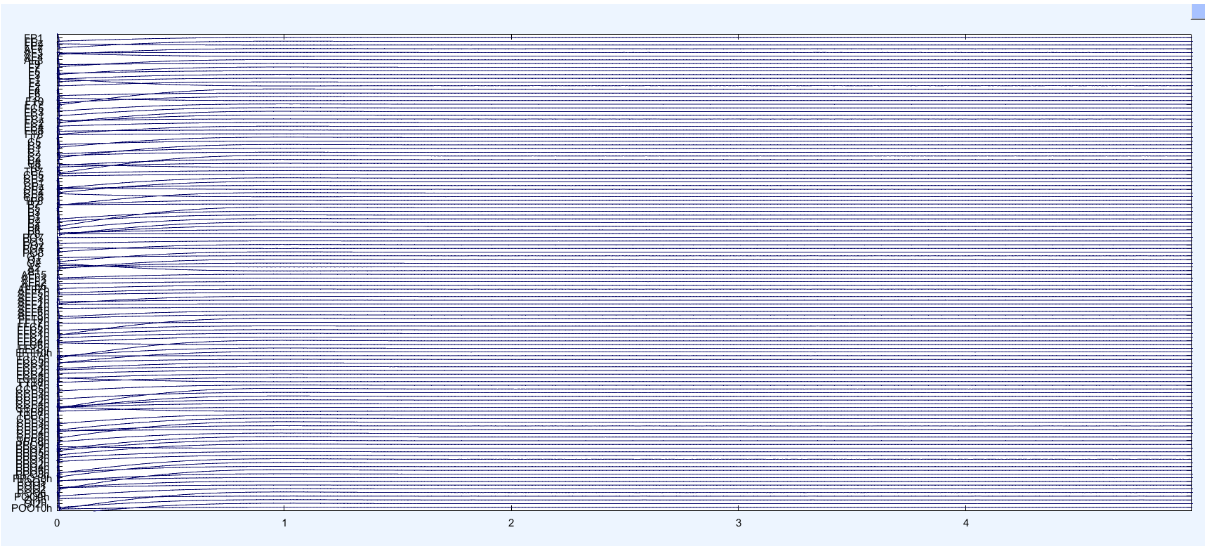


Figure 5- EEG signal after removing drifts

Using the resampling method, we reduce the sampling frequency from 1200 to 256.

1.5. Re-referencing

Re-referencing is the process of choosing an appropriate reference electrode based on the experimental design and analysis requirements. In this case, a common average reference (CAR) was used. The CAR calculates the average of all electrode signals and uses it as the reference for each channel. Re-referencing helps to remove the influence of common noise sources and enhances the ability to detect localized brain activity.

1.6 Notch Filtering:

We can apply a notch filter at a frequency of 50 Hz in order to remove the noise of city electricity which is 50 Hz in Iran. Therefore, we consider the 49 to 51 Hz band as the pass band of the filter. Also, the frequency response of the filter can be seen in Figure 6. The data output in the frequency domain is also shown in Figure 7.

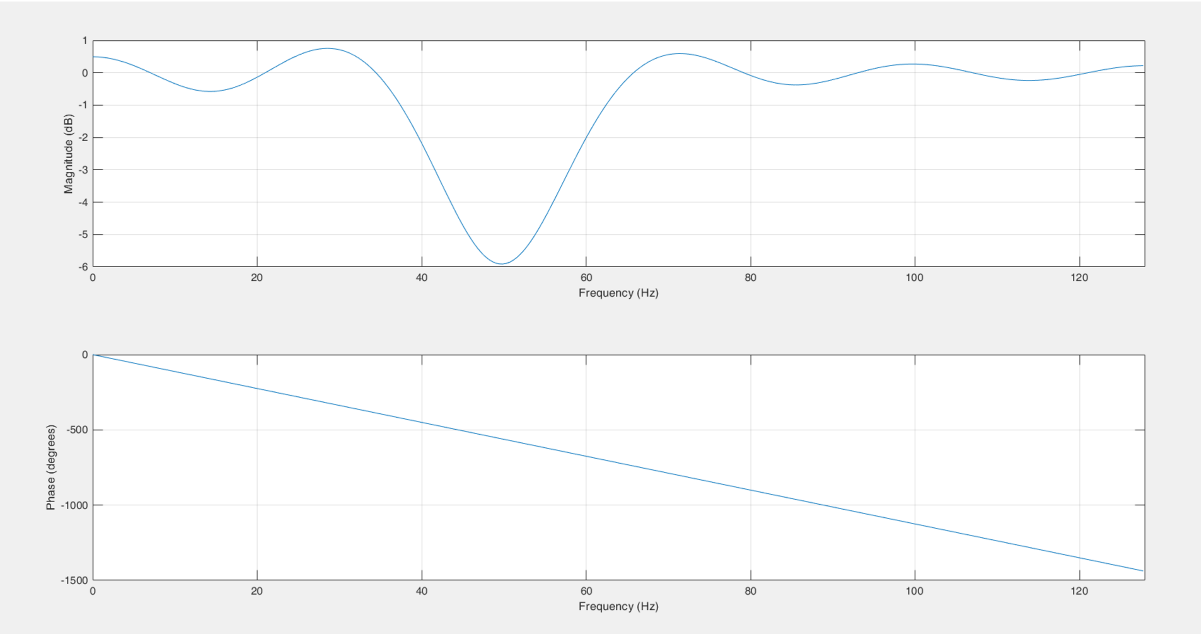


Figure 6- Frequency response of Notch filter

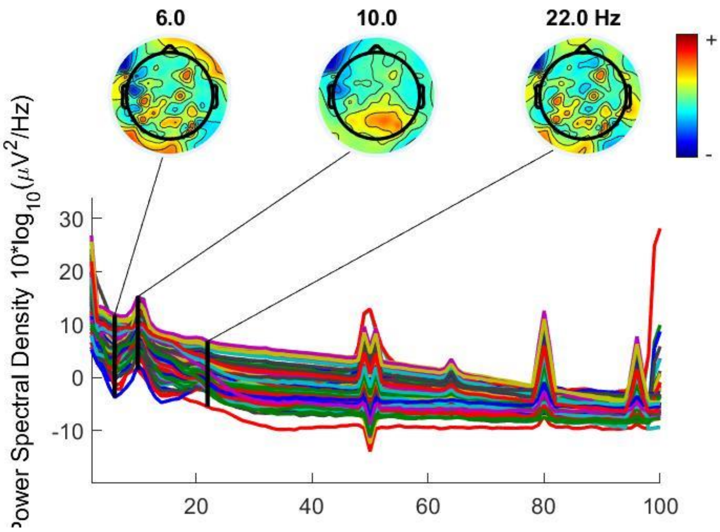


Figure 7- PSD of EEG after Notch filtering

At this stage, using a low-pass filter, we want to remove the noise in the signal at a frequency of 100 Hz. For this reason, we use a low-pass filter with a cutoff frequency of 100 Hz. The frequency response of the low-pass filter can be seen in Figure 8. Also, the output of the frequency domain of the data after applying the low-pass filter is shown in Figure 8.

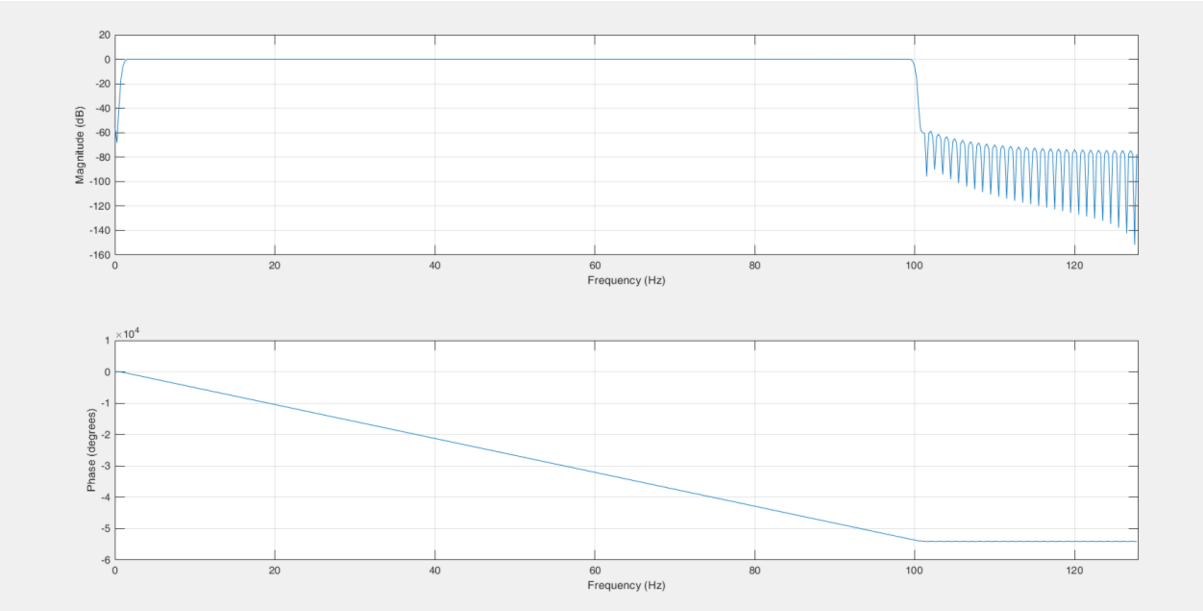


Figure 8- Frequency response of low-pass filter

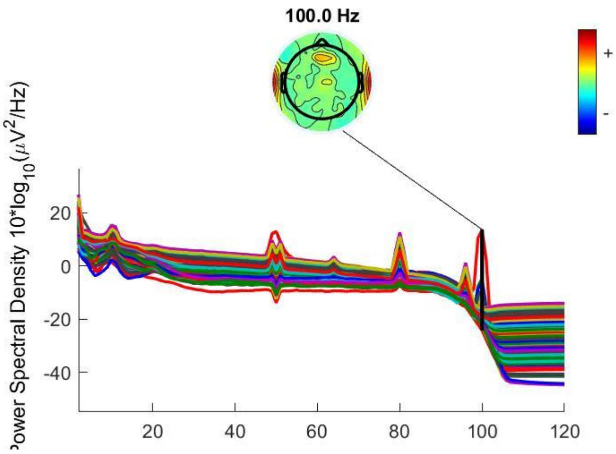


Figure 9- PSD of EEG after low-pass filtering

1.7. Epoching

Epoching involves segmenting the continuous EEG data into shorter epochs or time windows of interest. In this case, the epoch ranges were defined from -100 to 1000 ms relative to the stimulus onset. Epoching allows the analysis to focus on specific time intervals and facilitates the examination of event-related potentials (ERPs) or other time-locked brain responses.

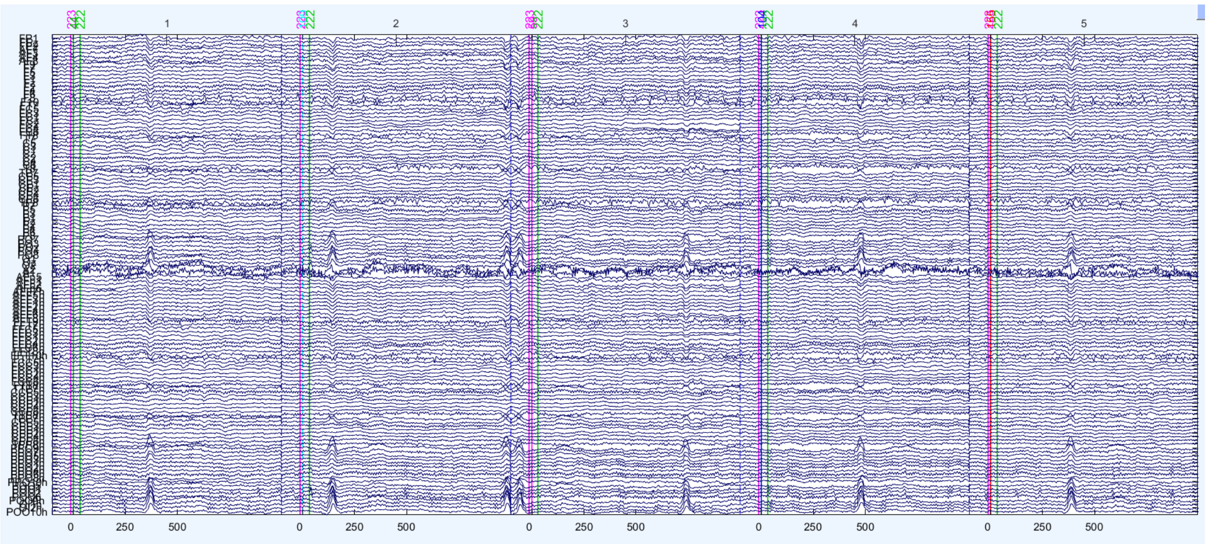


Figure 10- EEG signals after epoching

As can be seen in th Figure 10, the signal in channels A1 and A2 has a strong distortion and has no similarity with brain signals.

1.8. Baseline Normalization

Baseline normalization is performed by adjusting the baseline of each epoch. A pre-stimulus or pre-task interval, referred to as the baseline period, is chosen within each epoch. The mean amplitude of the pre-stimulus interval is subtracted from each epoch, effectively setting the baseline to zero. Baseline normalization removes the effects of baseline shifts and enhances the ability to detect changes in neural activity relative to the baseline. In this step, the data of 0.1 before the trigger has been deleted.

1.9. Bad Channel Interpolation

Bad channel interpolation is used to estimate the missing or bad channels based on neighboring electrodes. Electrodes with poor signal quality or significant artifacts are identified, and interpolation techniques (e.g., spherical spline interpolation) are applied to estimate their values. Bad channel interpolation helps to maintain data integrity and ensures the inclusion of all available information.

At this stage, noisy and distorted channels are removed. As seen in Figure 10, A1 and A2 channels, which were considered as reference electrodes during the interpolation process, are shown in Figure 11 and 12, are removed from the EEG data.

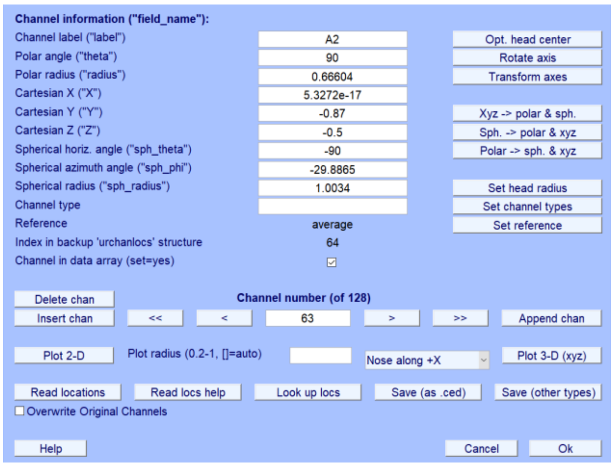


Figure 11- eliminate Bad Channel A1

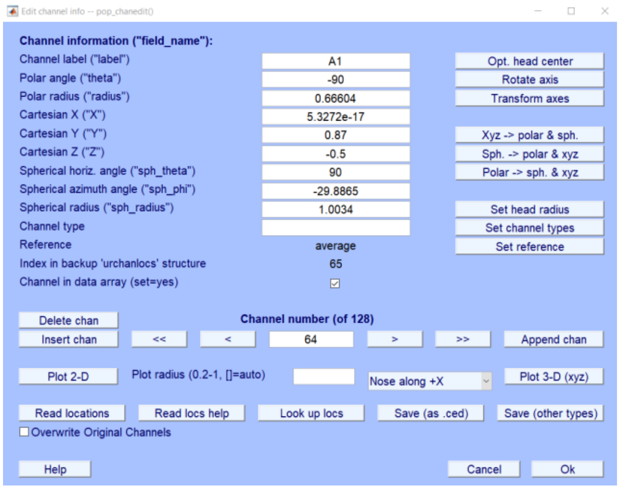


Figure 12- eliminate Bad Channel A2

1.10. Independent Component Analysis (ICA)

ICA is a data-driven technique used to decompose the EEG data into independent components. ICA identifies spatially and temporally independent components, some of which may correspond to non-brain sources (e.g., eye blinks, muscle artifacts). By analyzing the time and frequency domain signals of the components, it is possible to identify and remove or correct the components related to artifacts, thereby improving the quality of the EEG data.

Each electrode is affected by the neurons around it, which decreases as you move away from the electrode. By applying ICA, instead of our data being related to the space, they are related to the source, this is done by finding independent sources, and finally their sum gives the original signal. In Figure 13, from channel 1 to channel 35 Along with the signal type of each channel, it is specified after applying ICA.

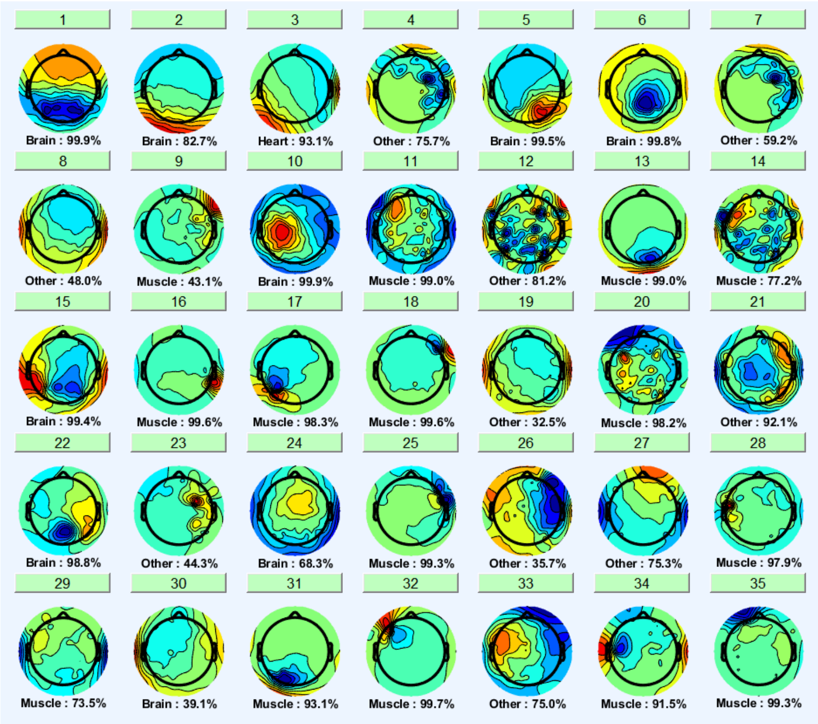


Figure 13- ICA from channel 1 to channel 35 with specifying signal type

2. Event-Related Potential (ERP) Study

Introduction:

Event-Related Potentials (ERPs) are widely used in electroencephalography (EEG) studies to investigate the neural processing of visual stimuli. In this report, we will focus on two important components of ERPs: the P100 and N170. The P100 component reflects early visual processing in the occipital cortex and occurs approximately 100 milliseconds after the onset of a visual stimulus. The N170 component, occurring around 170 milliseconds post-stimulus, is associated with the processing of facial and object recognition in the temporal cortex.

In this Section, we will analyze the ERPs recorded from multiple channels and compare the responses to face and non-face stimuli. Additionally, we will focus on the timing and amplitude differences of the N170 component between the two stimulus types and determine, there are statistically significant distinctions between timing, but not amplitude.

Method:

EEG data were collected from participants while they were exposed to visual stimuli, including both face and non-face stimuli. The ERPs were recorded from multiple channels. To analyze the ERPs, individual trials were averaged, and non-phase-locked activity was subtracted out during the averaging process.

2.1. Event-Related Potentials (ERPs) for all channels:

To analyze brain activity related to visual processing, event-related potential (ERP) studies often utilize EEG data. In this report, we focus on two commonly observed ERP components:

We plot ERPs for each 126 channel for face in Figure 14 and non-face in Figure 15.

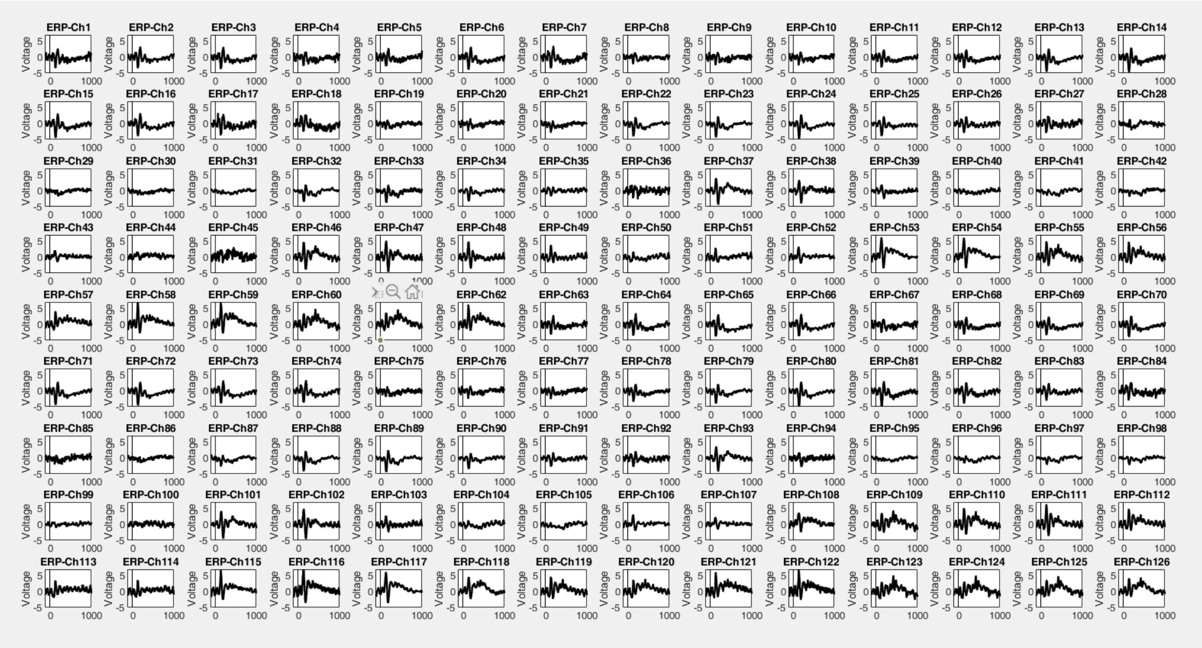


Figure 14- ERP of face condition for each 126 channel

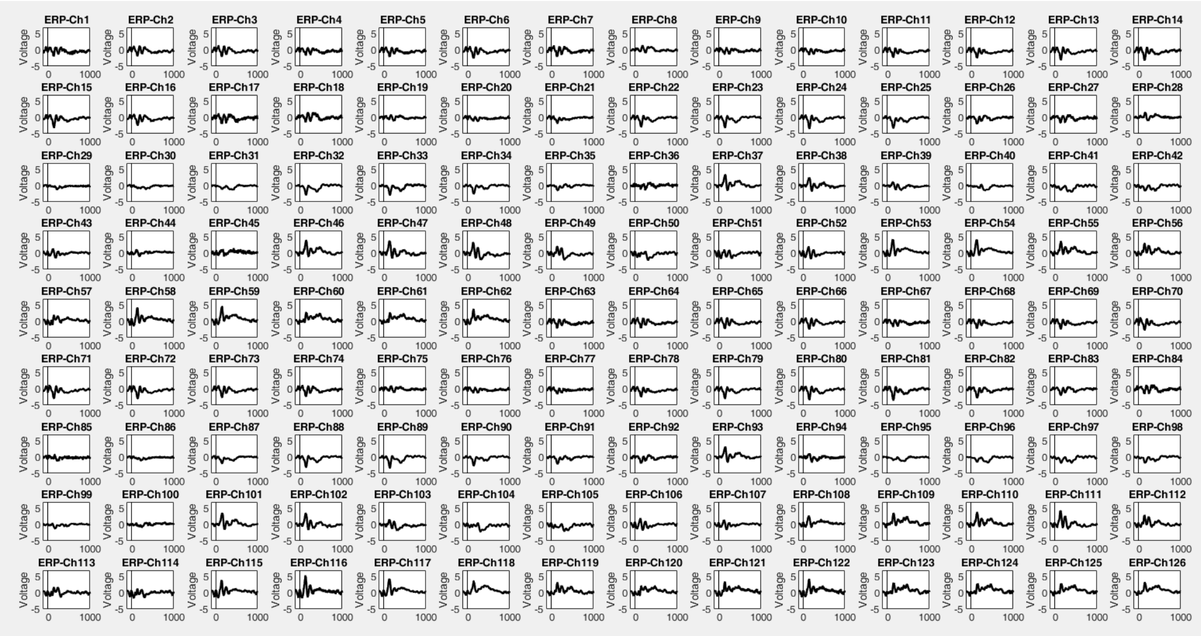


Figure 15- ERP of non-face condition for each 126 channel

2.2. Comparison of ERPs for face vs. non-face stimuli:

To compare the ERPs elicited by face and non-face stimuli, we recorded EEG data from multiple channels. Figure 4A displays a selection of randomly chosen trials from one electrode, while Figure 4B presents all trials from that electrode, superimposed with their average. Notably, the average ERP waveform exhibits a smaller magnitude compared to individual trials. This discrepancy arises from the removal of non-phase-locked activity, which typically has a larger amplitude, during the process of averaging.

As shown in Figure 16 and 17, ERPs for some random Trial for face data are plot together.

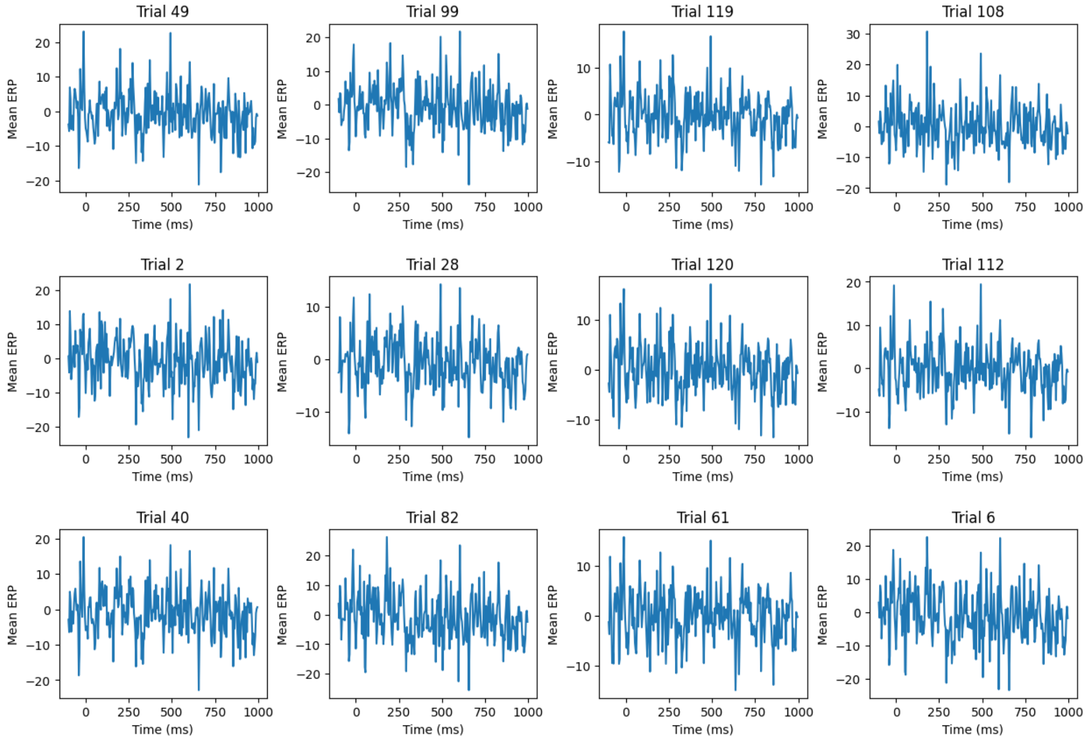


Figure 16- Random Selected ERP of face condition for Single Trials

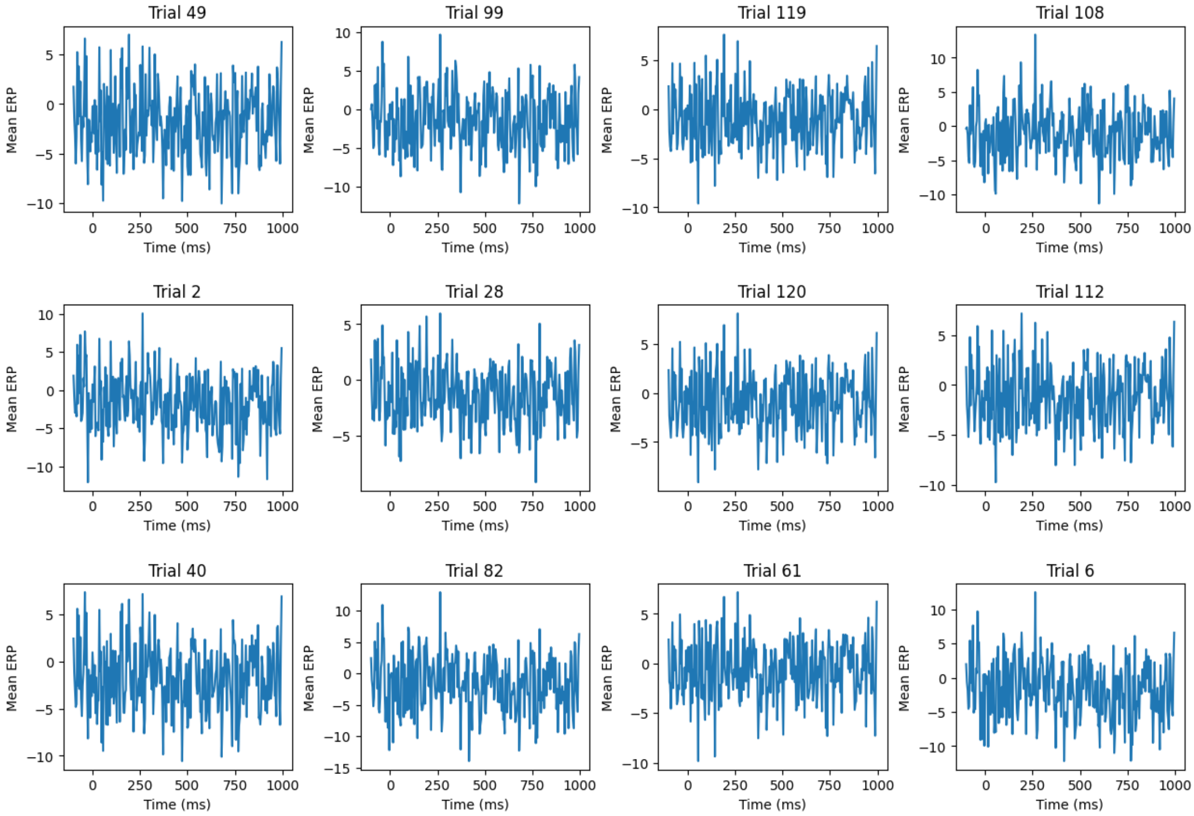


Figure 17- Random Selected ERP of non- face condition for Single Trials

To examine the differences between face and non-face stimuli, we computed the ERPs for both conditions across all channels. These ERPs provide an overview of the electrical brain responses evoked by each stimulus type. Confidence intervals are crucial for assessing the reliability of the observed effects.

As shown in Figure 18, ERPs for all channel for face data are plot together. In Figure 19 we plotted the Confidence Interval for face data.

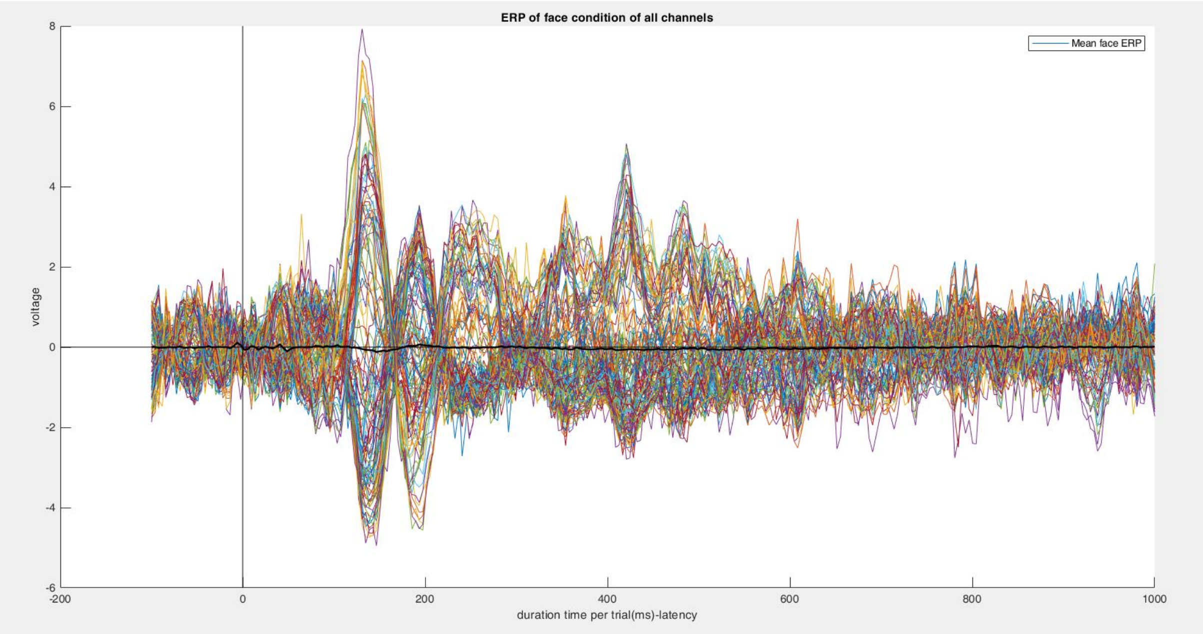


Figure 18- ERP of face condition for all 126 channel

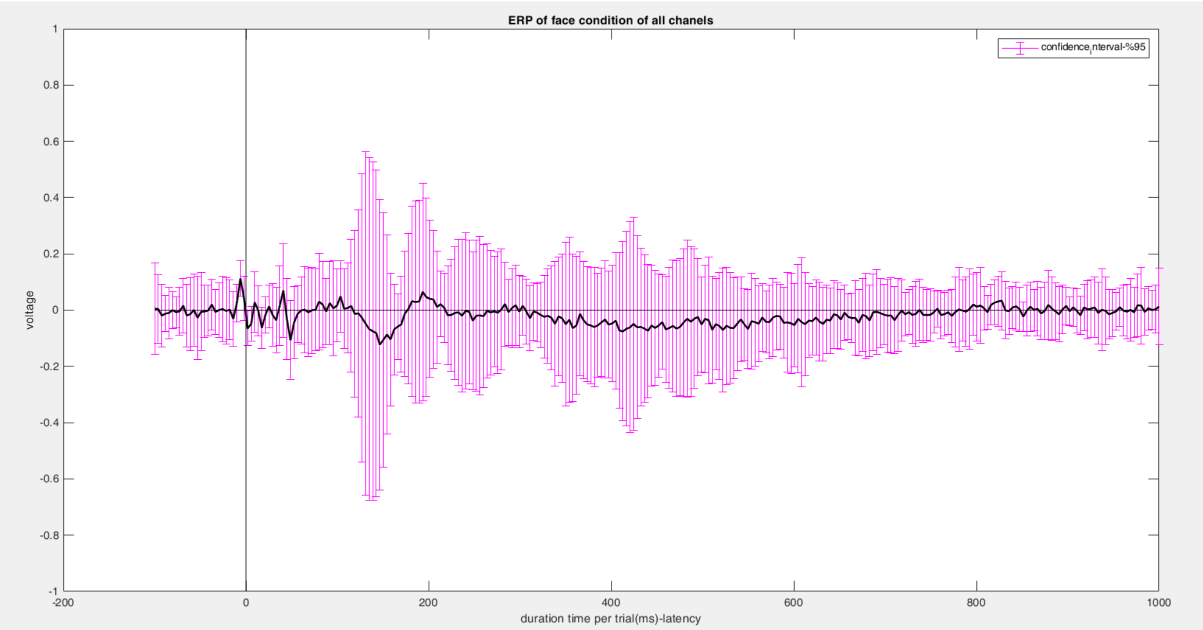


Figure 19- Mean ERP with CI of face condition for all 126 channel

As shown in Figure 20, ERPs for all channel for face data are plot together. In Figure 21 we plotted the Confidence Interval for face data.

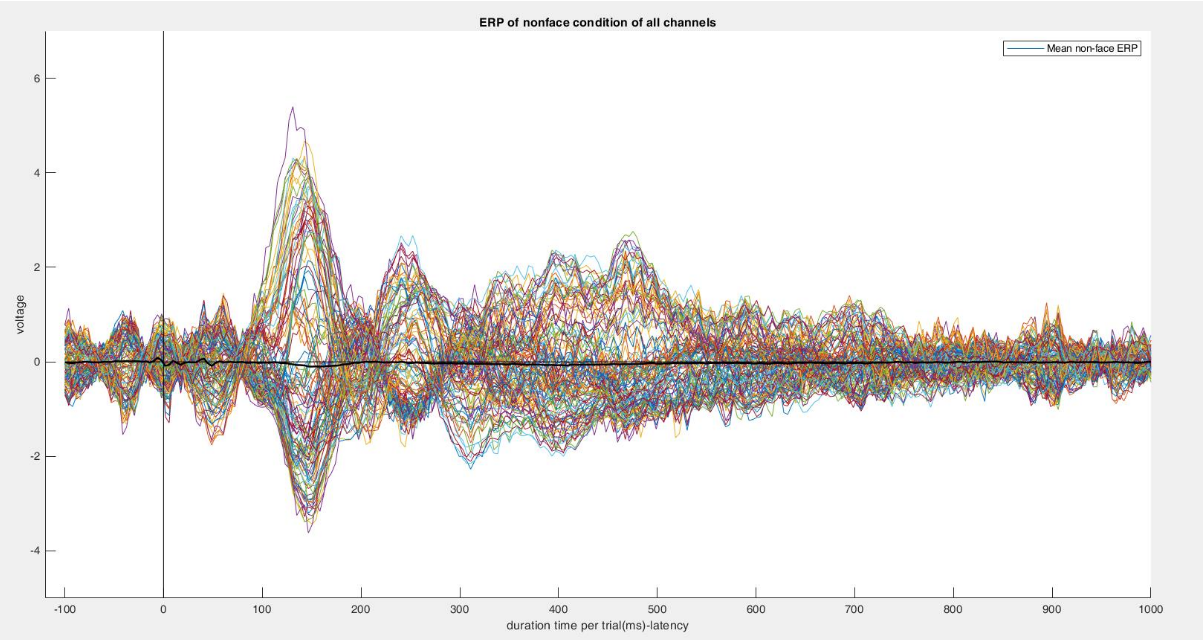


Figure 20- ERP of non-face condition for all 126 channel

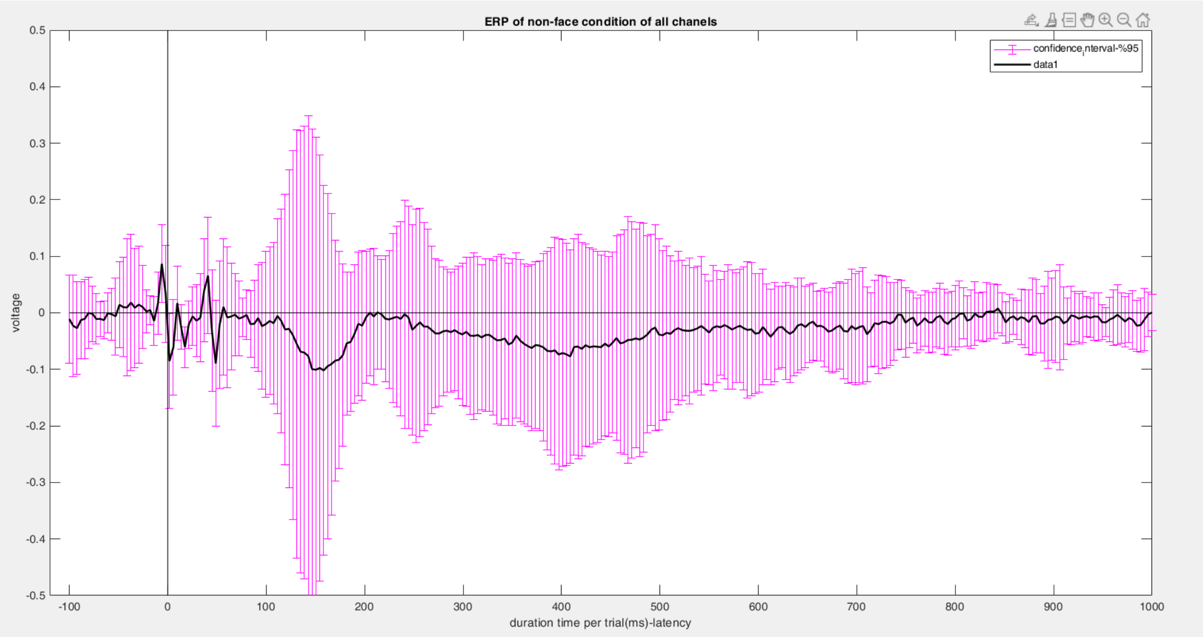


Figure 21- Mean ERP with CI of non-face condition for all 126 channel

In Figure 22 has shown the difference between face and non-face groups for each channel.

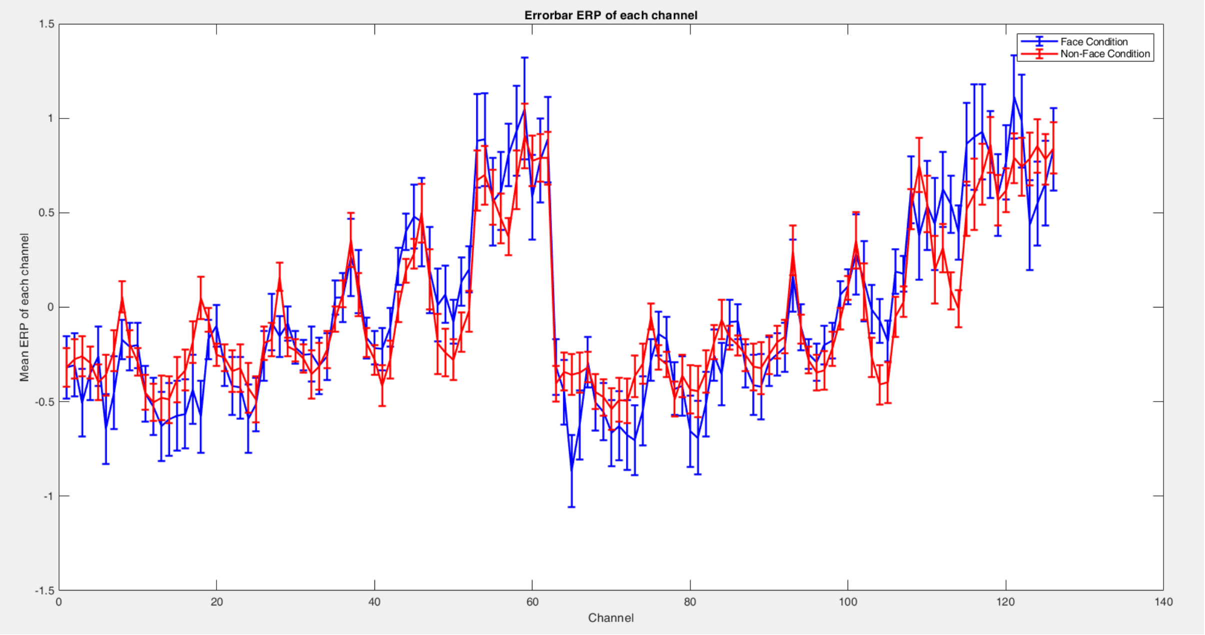


Figure 22- Error bar of the ERP for each channel

Figure 23 shows the scatter plot of face and non-face for each channel.

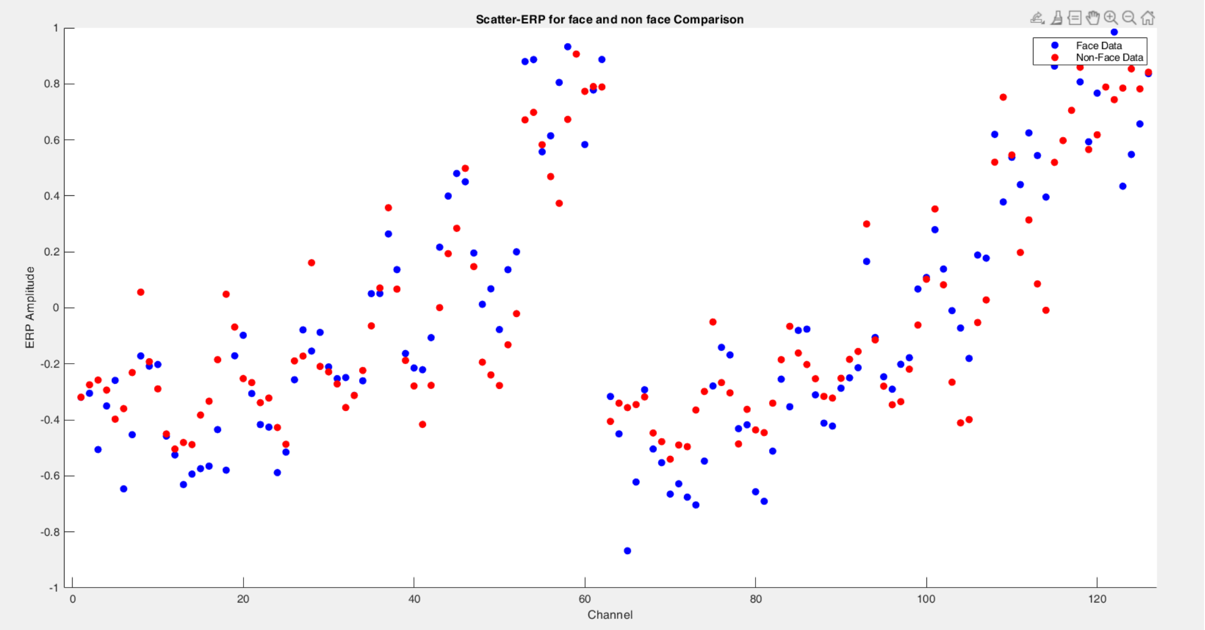


Figure 23- scatter plot of face and non-face for each channel

Figure 24 shows the output of the Wilcoxon statistical test for two categories of face and non-face for each channel.

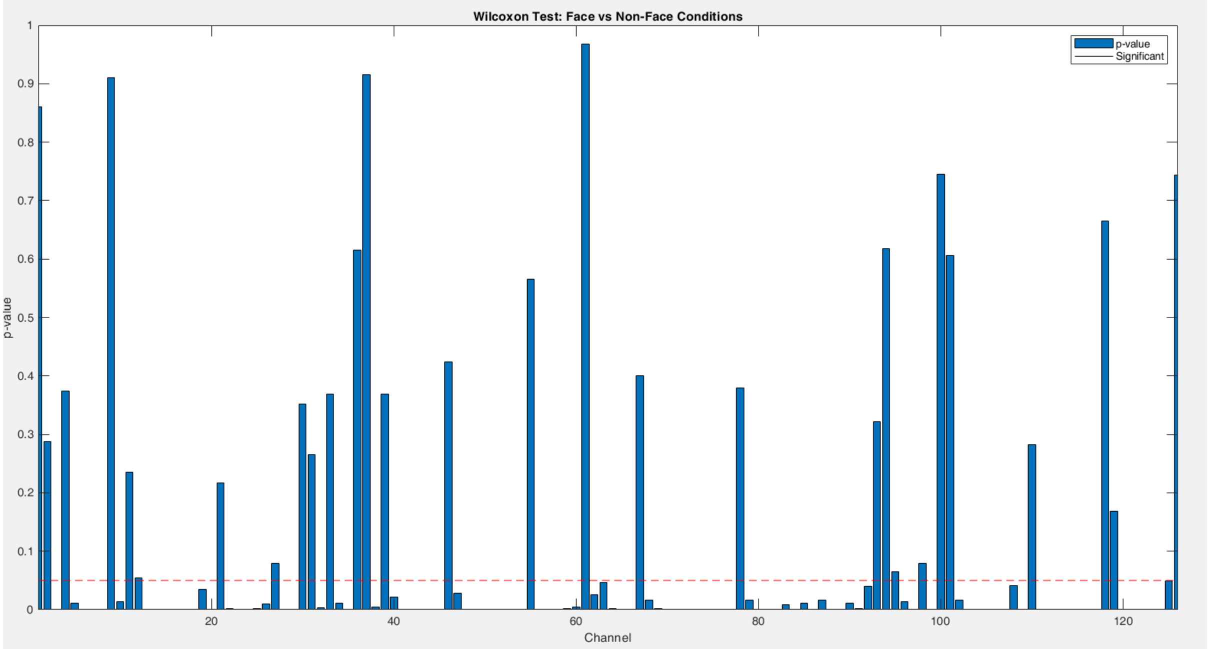


Figure 24- p-value for each channel for face and non-face

In the Wilcoxon statistical test, p-value indicates the probability of observing a difference equal to or greater than the observed difference between the two compared categories, as a random result. In fact, the p-value is the inverse of the power of the test.

The probability p-value shows how likely it is that the observed difference or greater would be obtained by chance if the null hypothesis (perfect correlation between categories, i.e., no difference between them) is true. If the p-value is less than the desired significance level (usually 0.05), we can reject the null hypothesis and say that the observed difference between the two groups is statistically significant. If the p-value is greater than the significance level, we cannot reject the null hypothesis and cannot confirm a significant difference between the two groups.

As it is known, the p-value for a number of channels such as 4, 40 and 60, etc. is less than 5%, in these channels there is a significant difference between the two categories of face and non-face. For about 24 channels, the p-value is greater than 5%, so we reject the null hypothesis and there is no significant difference between the face and non-face categories in these channels.

2.3. Timing and amplitude of the N170 component for face vs. non-face stimuli:

In Figure 25, the scatter-plot related to amplitude, timing related to N170 is displayed. As it is known, the accumulation of timings, especially in the Face data, occurred around the time of 170 milliseconds.

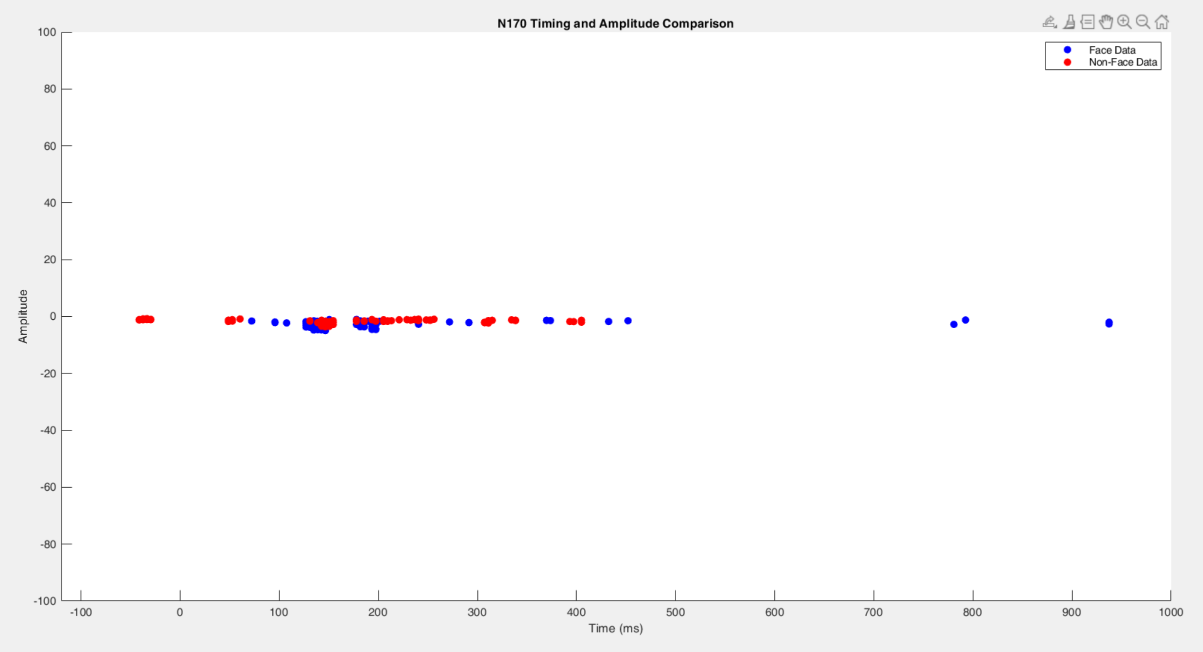


Figure 25- N170 Timing and amplitude comparisons

As shown in Figure 26, there are many changes in the face data in 170 milliseconds. Also, in 200 milliseconds, we have peak accumulation in Face data. In face data compared to non-face data, a lot of dispersion is observed in the data.

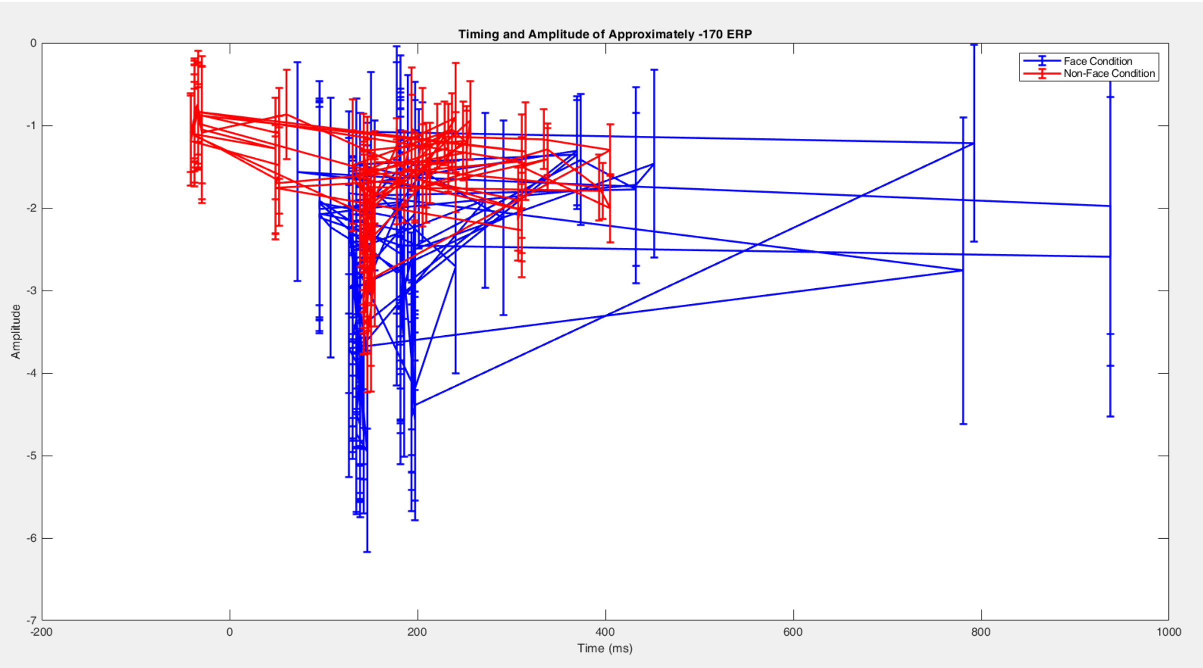


Figure 26- Error bar plot of N170 Timing and amplitude Comparisons

Figures 27 and 28 show the amplitude and approximate time of the N170 peak for each channel, respectively.

As can be seen, the non-face data has more time dispersion than the face data, and in almost both data, the peak occurred at 170 milliseconds.

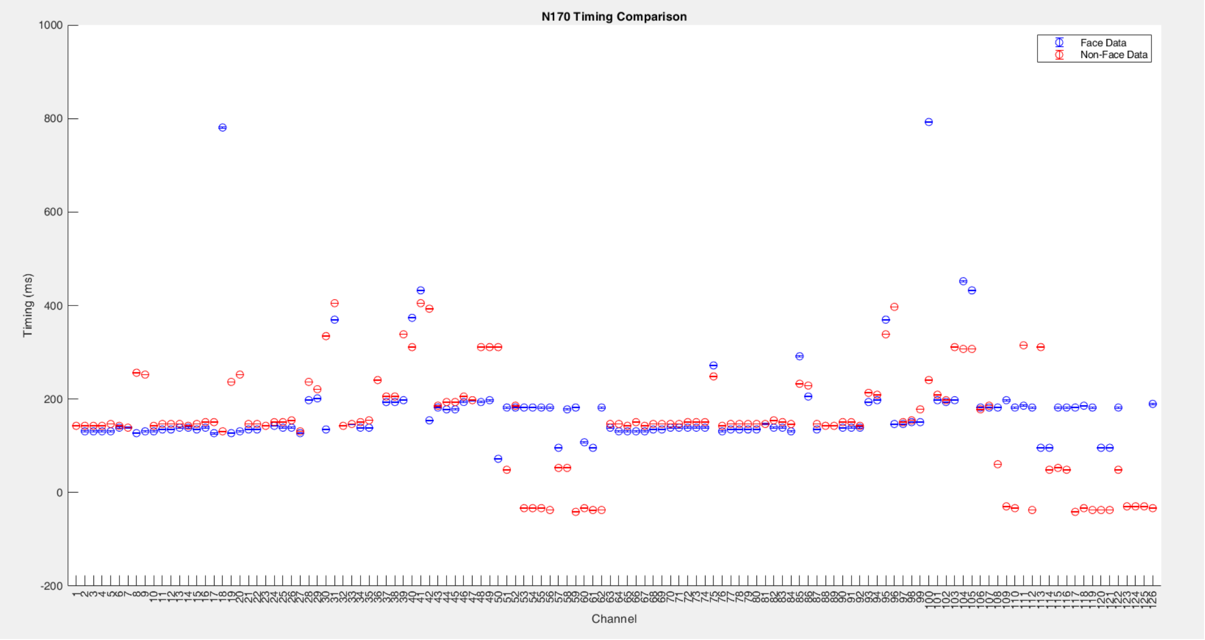


Figure 27- Error bar with CI plot of N170 Timing Comparisons in each channel

In Figure 28, as can be seen, the changes in the range of face data compared to non-face are much greater in the range of about 170 milliseconds, which means that by having a larger confidence interval in the range of face data, we statistically We are more confident that the actual value of the parameter is within this range.

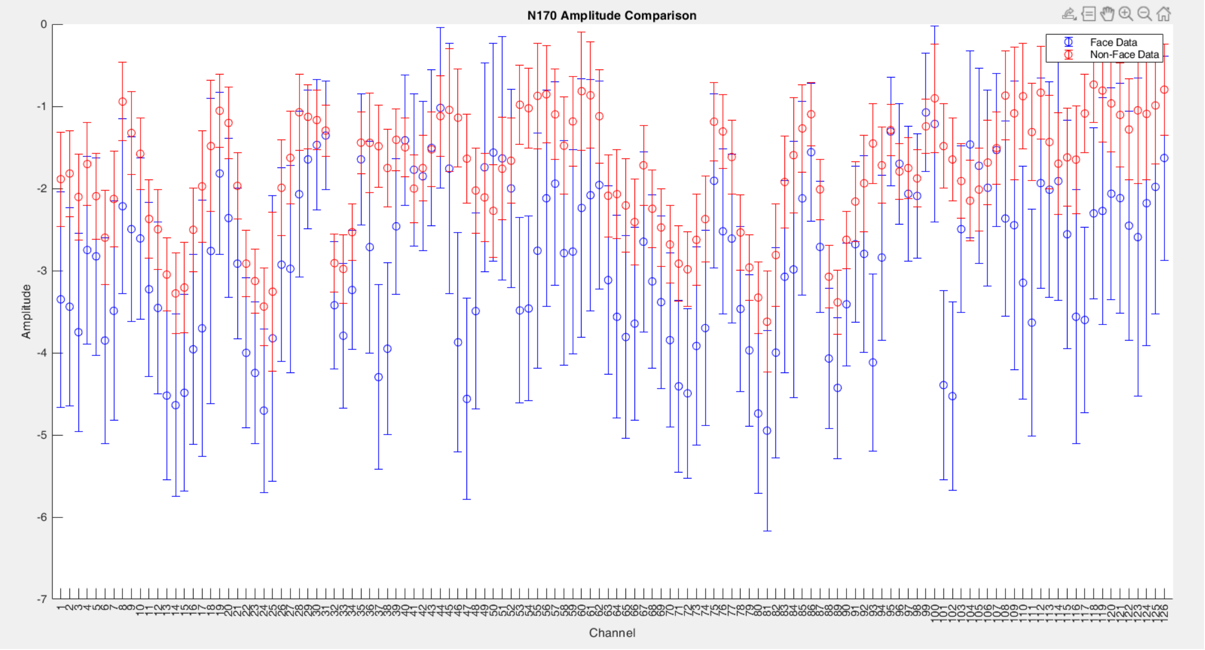


Figure 28- Error bar with CI plot of N170 amplitude Comparisons in each channel

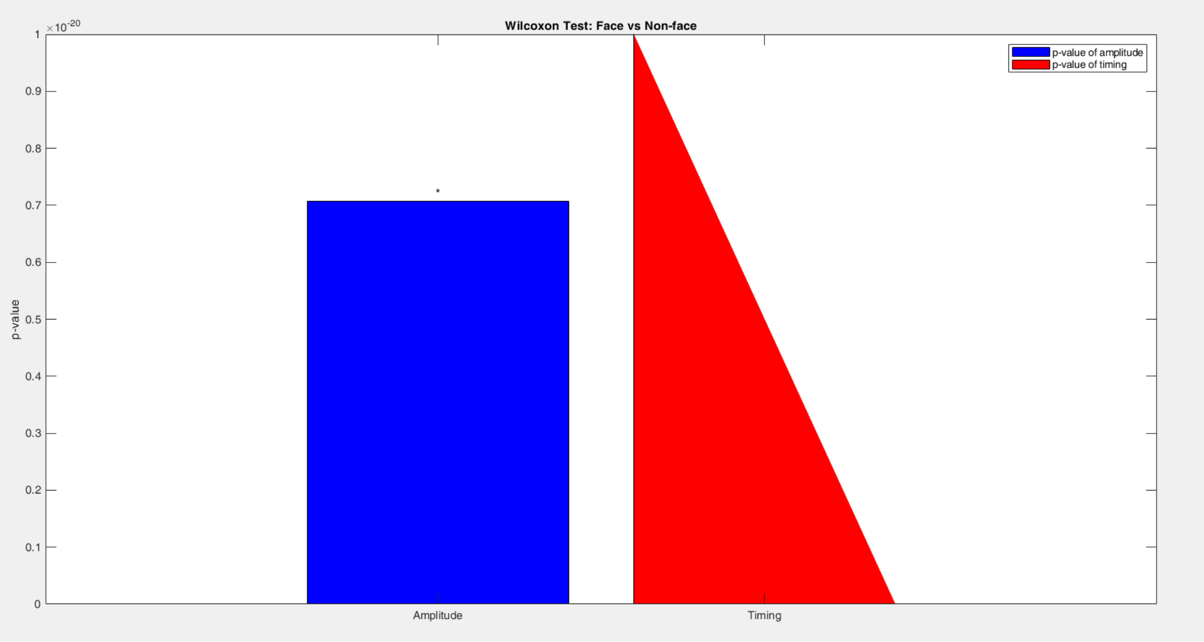


Figure 29- Wilcoxon test for face and non-face

The p-value related to amplitude is significantly lower than timing. We know that the p-value of both amplitude and timing is below the desired significance level (usually 0.05), so the null hypothesis is rejected and we conclude that the observed difference between the two categories is statistically significant. Therefore, between domains, because the P-value is smaller than Timing, the difference between face and non-face data is greater, and there is more correlation between face and non-face data Timing, as shown in the figures 27 and 28 concluded!

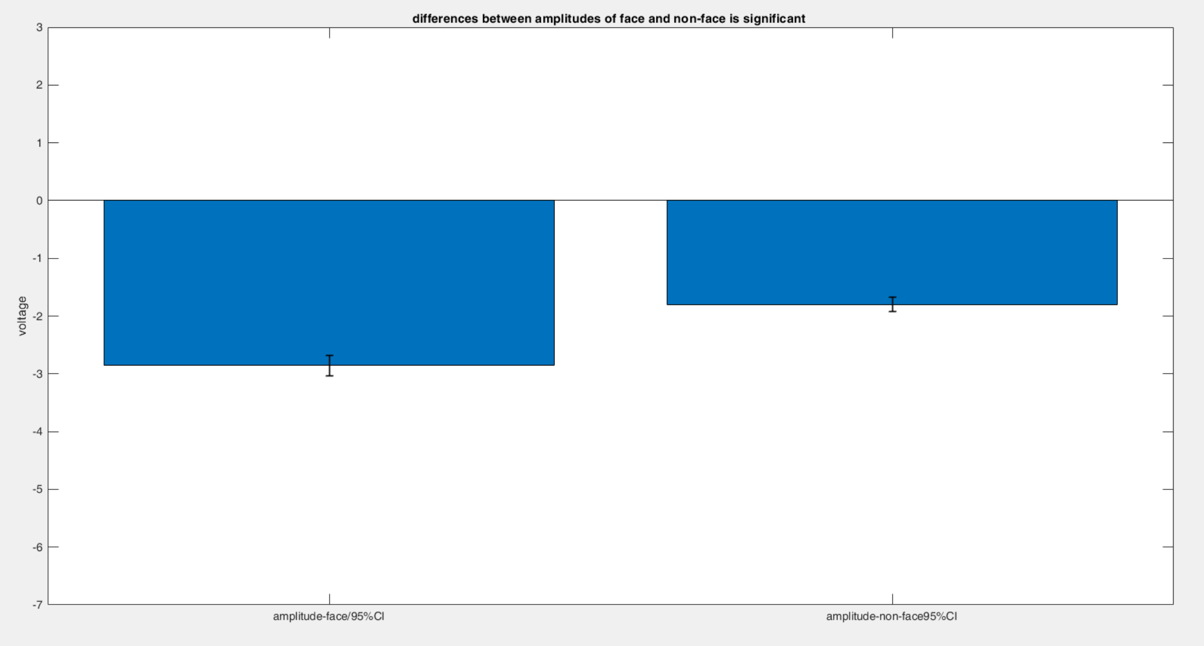


Figure 30- Comparison between amplitude of face and non-face

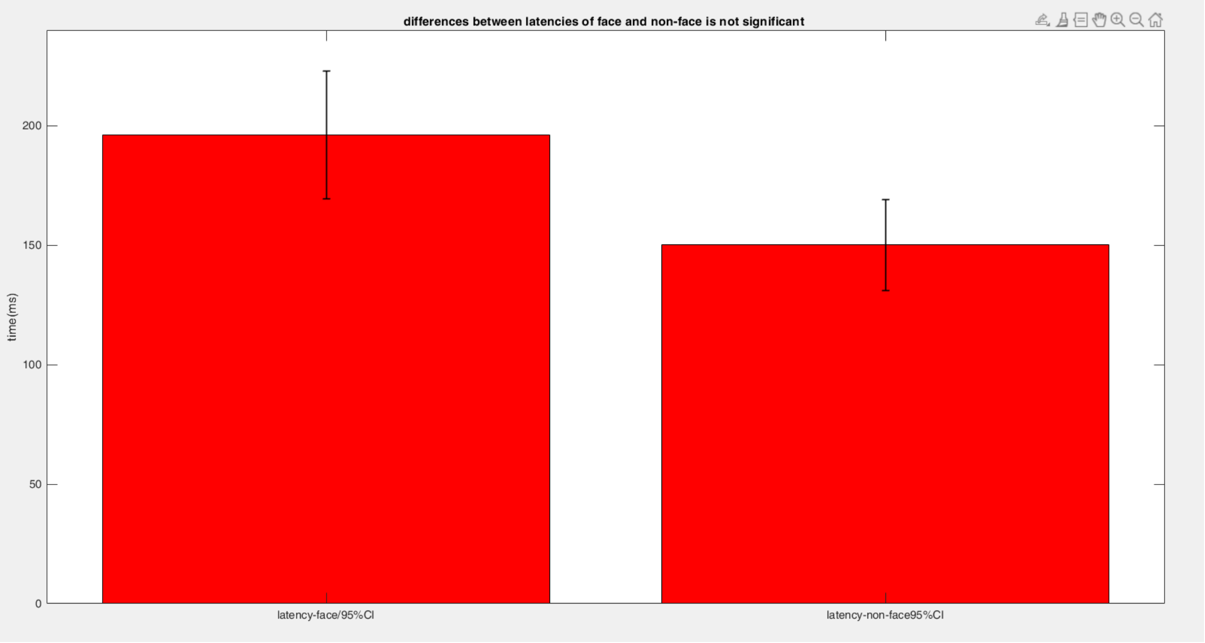


Figure 31- Comparison between Timing of face and non-face

As mentioned and shown in Figures 30 and 31, a significant difference is observed between the face and non-face data domains. But relatively less significant difference is observed between face and non-face data timings.

In conclusion, the ERP components N170 provide valuable insights into the neural processes underlying visual stimulus processing. By comparing ERPs and specific components like N170, researchers can gain a deeper understanding of how the brain responds to different types of visual stimuli, such as faces and non-face objects.

3. Spectral Analysis in EEG Signals:

Introduction:

Spectral analysis is a fundamental technique in the field of electroencephalography (EEG) that enables the examination of the frequency content of brain electrical activity. This section aims to provide an overview of spectral analysis in EEG signals.

By decomposing EEG signals into their frequency components, researchers gain insights into the underlying neural processes associated with different cognitive functions. It provides a means to extract valuable information from EEG data, aiding in the investigation of brain activity.

3.1. Power Spectral Density (PSD)

The power spectral density quantifies the relative contribution or strength of each frequency component to the overall EEG activity. Several common methods for estimating the PSD of

EEG signals include the Periodogram, Welch's Method, Multitaper Method, and Wavelet Transform. In this section, Multitaper Method is used in solving problems.

As it is clear from figures 33 to 34. The general shape of the power spectrum density of face and non-face data is the same.

By using t-test, we can see that the data of the two groups are not significantly different from each other.

Finally, according to the statistical test at each frequency, it is determined that the power spectrum density of the face and non-face data are close to each other.

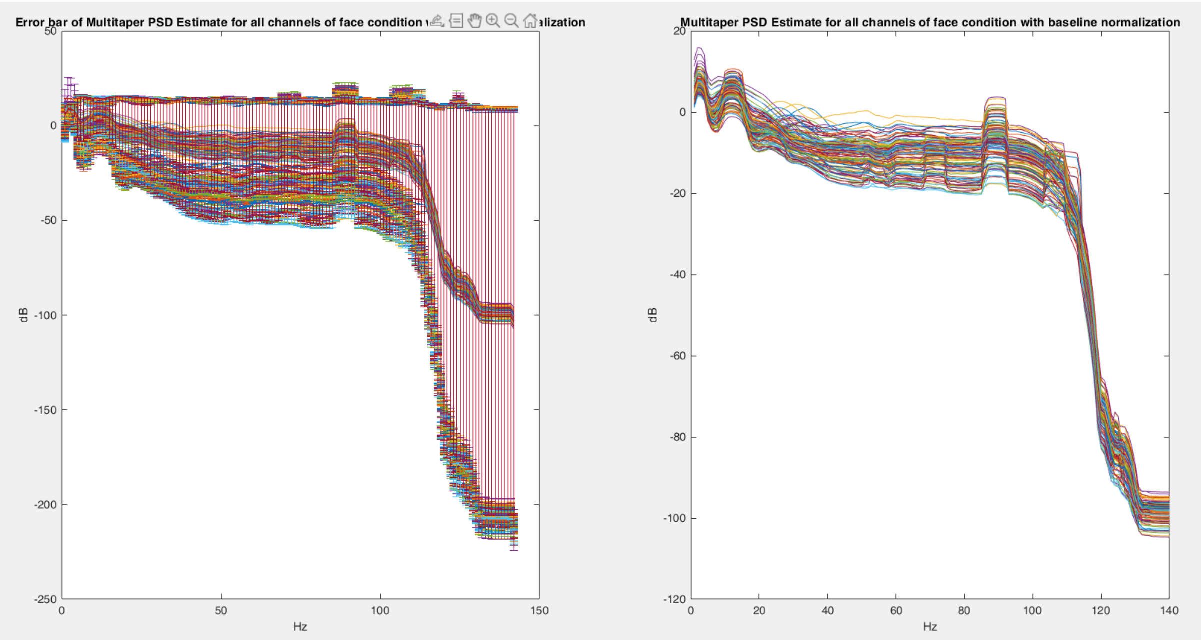


Figure 32- Error bar and Estimation of MT-PSD face with all Frequency points with baseline normalization

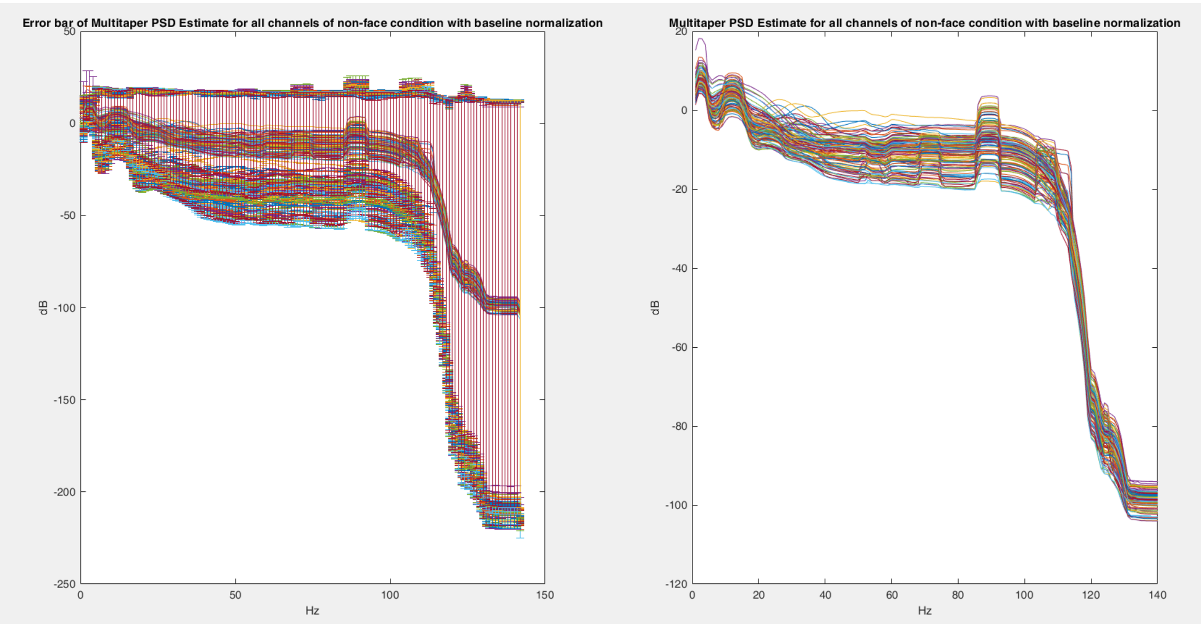


Figure 33- Error bar and Estimation of MT-PSD non-face with all Frequency points with baseline normalization

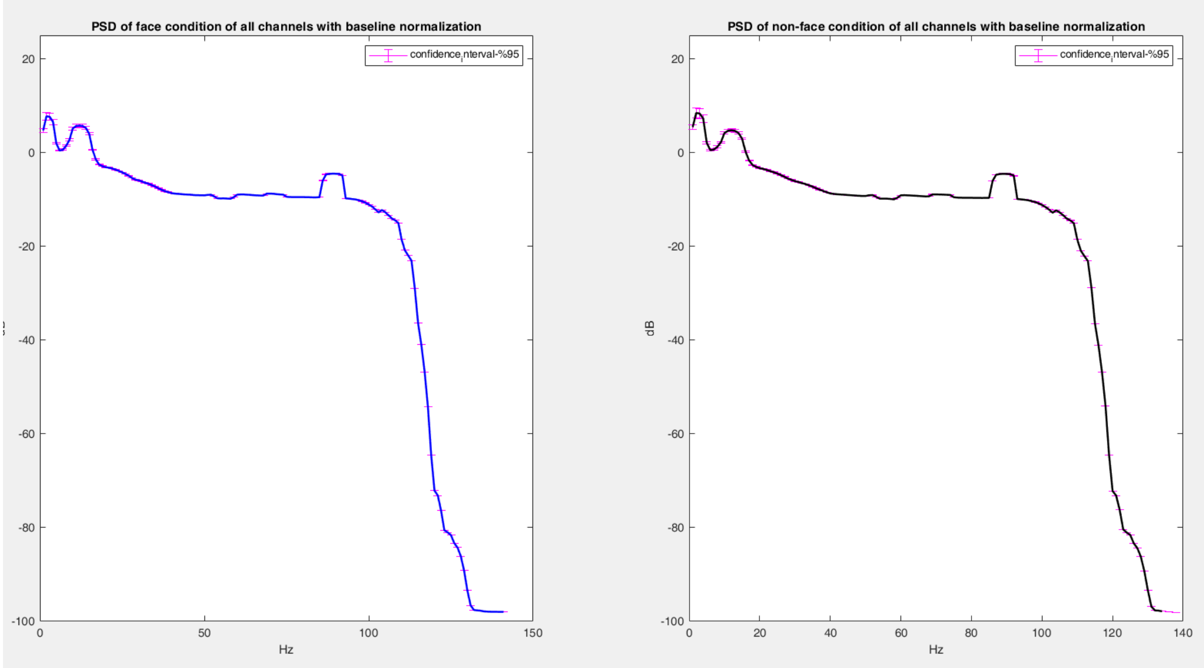


Figure 34-PSD with CI of face and non-face with all Frequency points with baseline normalization

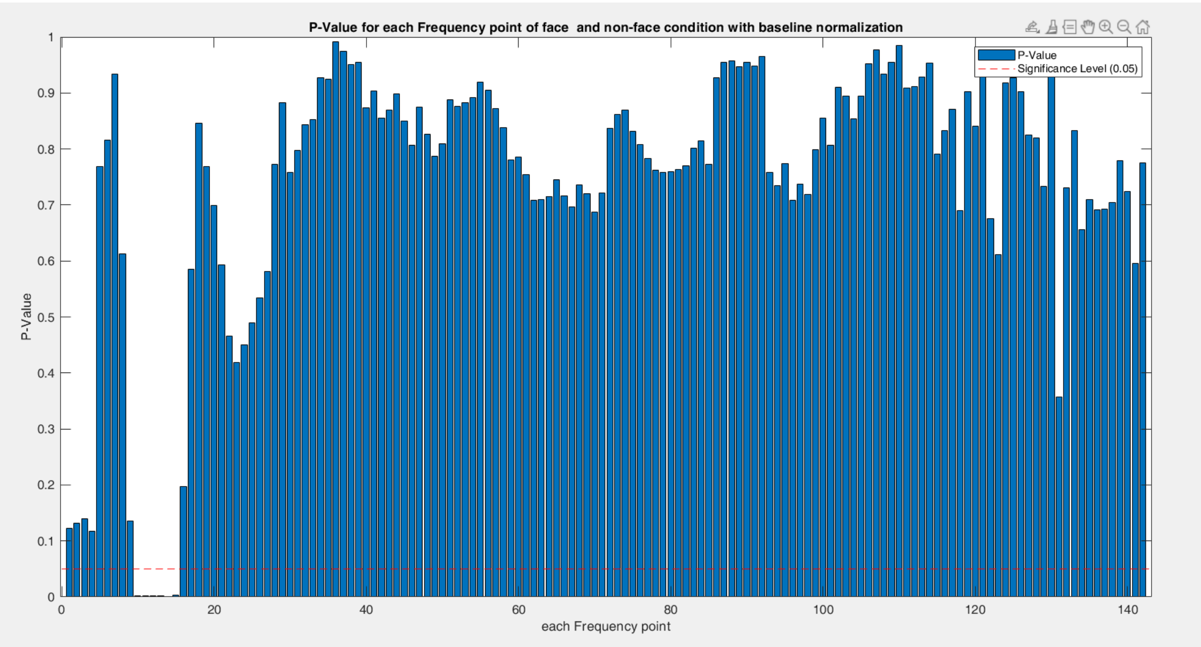


Figure 35-p-value for each Frequency points with baseline normalization

Hypothesis Test Result: Fail to reject the null hypothesis.

3.2. Baseline Normalization

Baseline normalization is a preprocessing step that involves adjusting the power values of EEG signals relative to a baseline period. By performing baseline normalization prior to applying the Multitaper method, we can control for individual differences and enhance the interpretability of the power spectral density estimates.

Prior to applying the Multitaper method, baseline normalization is performed. Baseline normalization involves adjusting the power values to a baseline reference level, often the mean power of a specific frequency band. By normalizing the data, it becomes possible to compare power changes within and across different frequency bands. This step allows for more accurate and meaningful interpretation of the results.

As Dear TA explained, it is enough to get data without baseline, don't do the baseline part in part 1. The results of the previous part were based on baseline data.

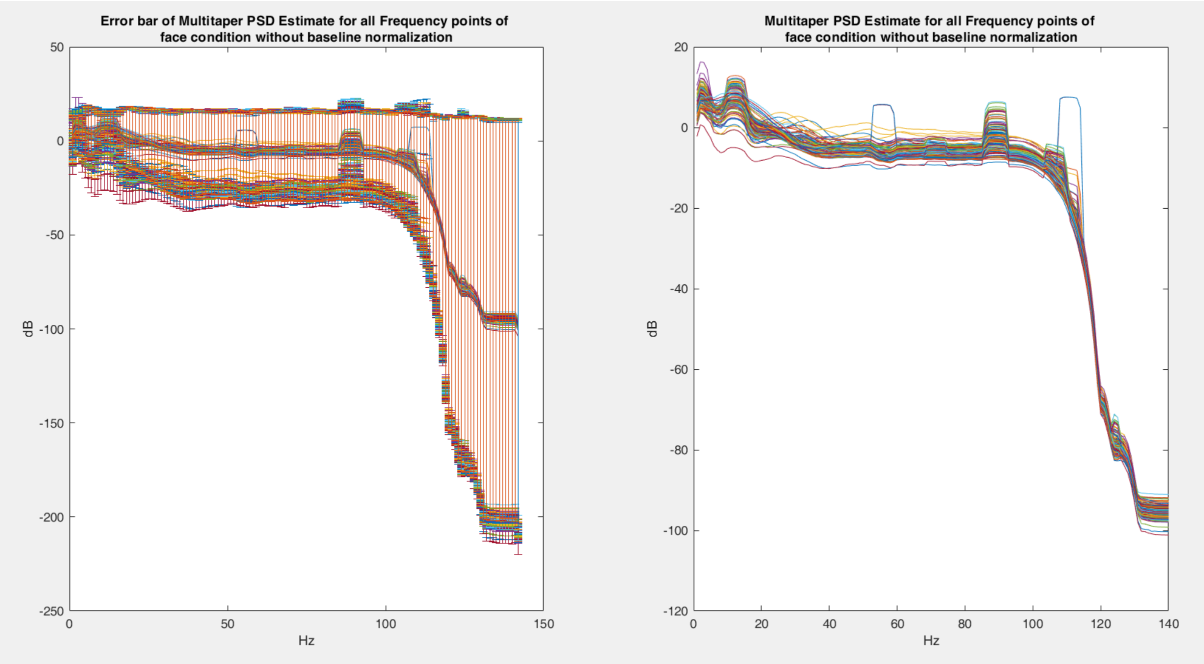


Figure 36- Error bar and Estimation of MT-PSD face with all Frequency points without baseline normalization

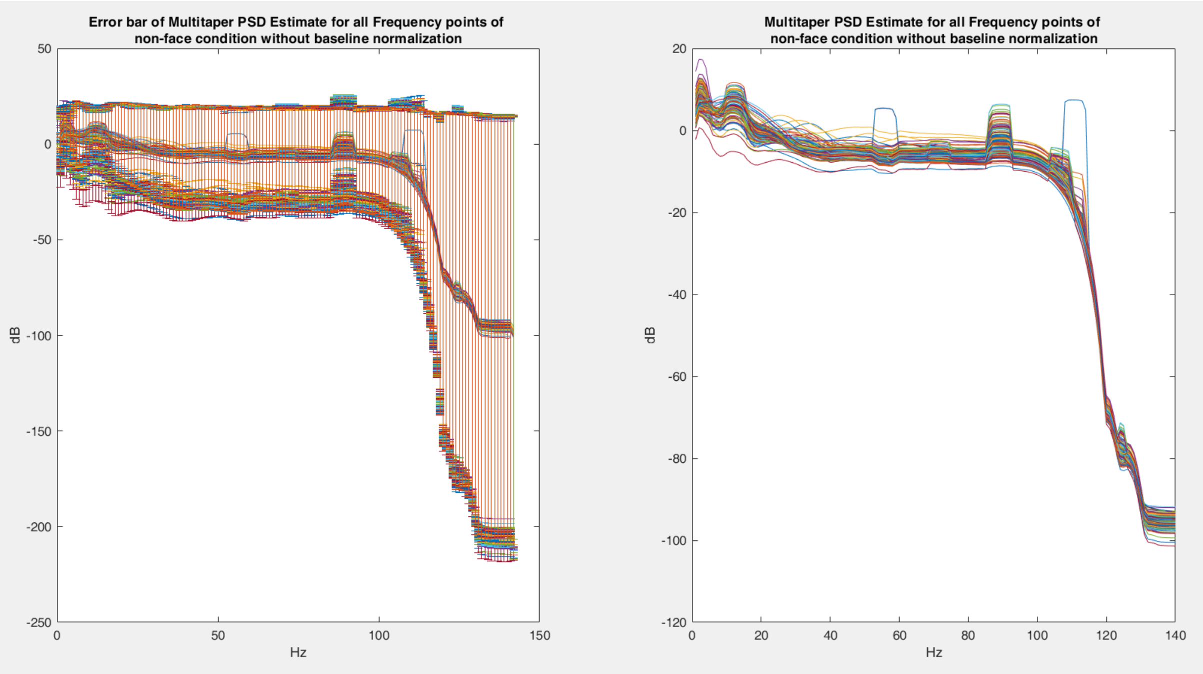


Figure 37- - Error bar and Estimation of MT-PSD non-face with all Frequency points without baseline normalization

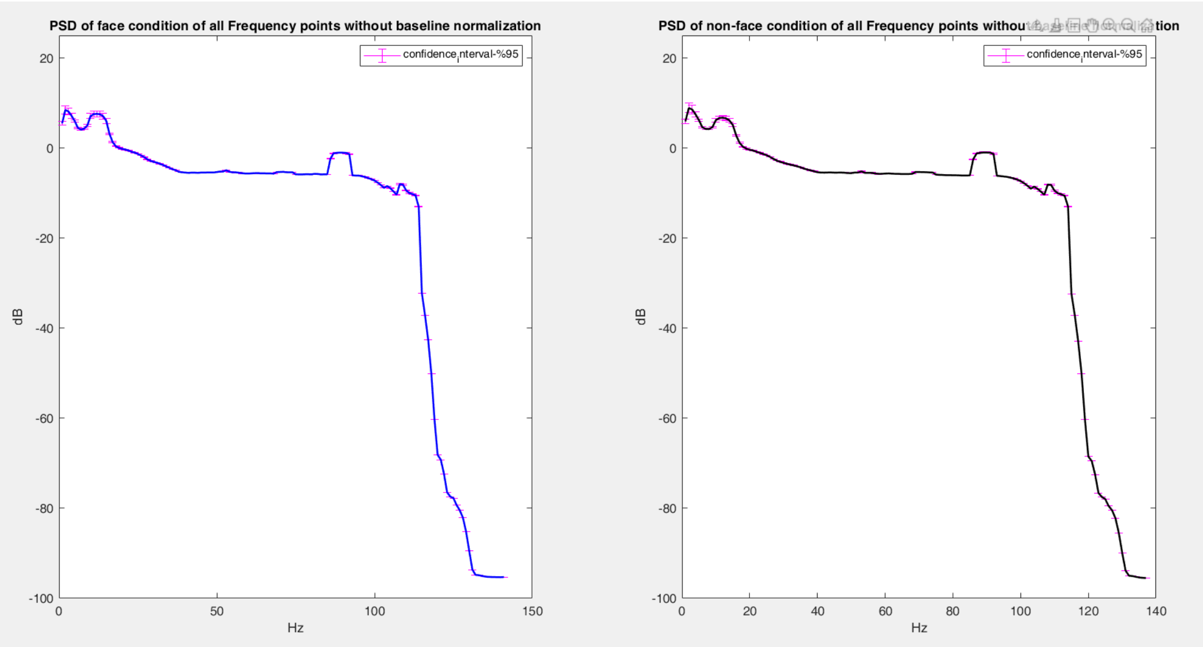


Figure 38-PSD with CI of face and non-face with all Frequency points without baseline normalization

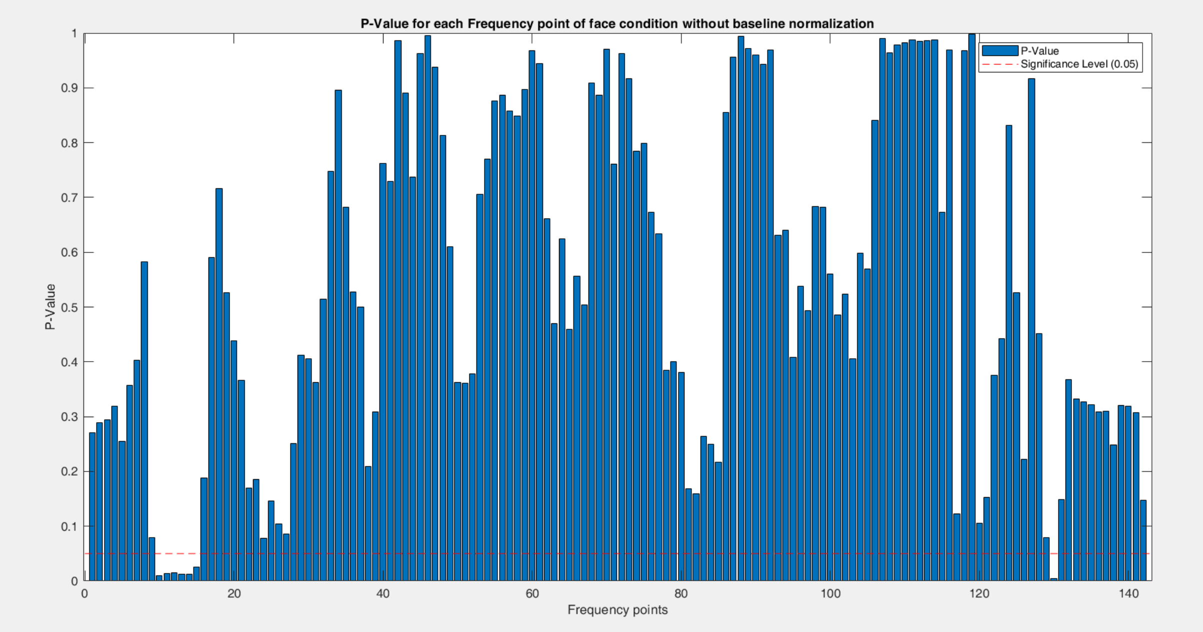


Figure 39-p-value for each Frequency points without baseline normalization

Hypothesis Test Result: Fail to reject the null hypothesis.

When the result of "Fail to reject the null hypothesis" is obtained in the t-test, it means that the data show that there is no significant difference between the two groups. In this case, the p-value is greater than the significance level and no significant difference can be inferred in the data.

Indeed, failure to reject the null hypothesis suggests that differences may be attributed to random factors.

By comparing figures 35 and 39, in the mode with baseline, there is more correlation between the two modes of face and non-face on the output frequencies of pmtm than the mode without baseline. It is true that in both cases the null hypothesis is rejected.

But the correlation level is higher in the mode with the baseline on the pmtm output frequencies between the face and non-face modes, with respect to without baseline normalization.

Therefore, there is a more significant difference between face and non-face data in the case without baseline normalization than in the case with baseline.

As it can be seen from the comparison of Figures 32 and 33 with Figures 36 and 37, respectively, that in the case without a baseline, strong distortions occur in the signal, for example, at the frequency of 120 Hz. Also, in the case of no baseline normalization in some frequencies, as can be seen from Figure 39, the p-value is less than 5%. Therefore, there is a significant difference between face and non-face data.

3.3. Re-evaluation of PSD within Frequency Bands

The power spectral density within different frequency bands, such as delta, theta, alpha, beta, and gamma, is evaluated to understand their associations with specific cognitive and physiological processes.

In Figure 40, different frequency bands in the first channel for the data that used baseline normalization are compared between face and non-face data. As can be seen from the figure, there is no significant difference between face and non-face data. As inferred from Figure 53. There is no significant difference between normalization with baseline and without baseline.

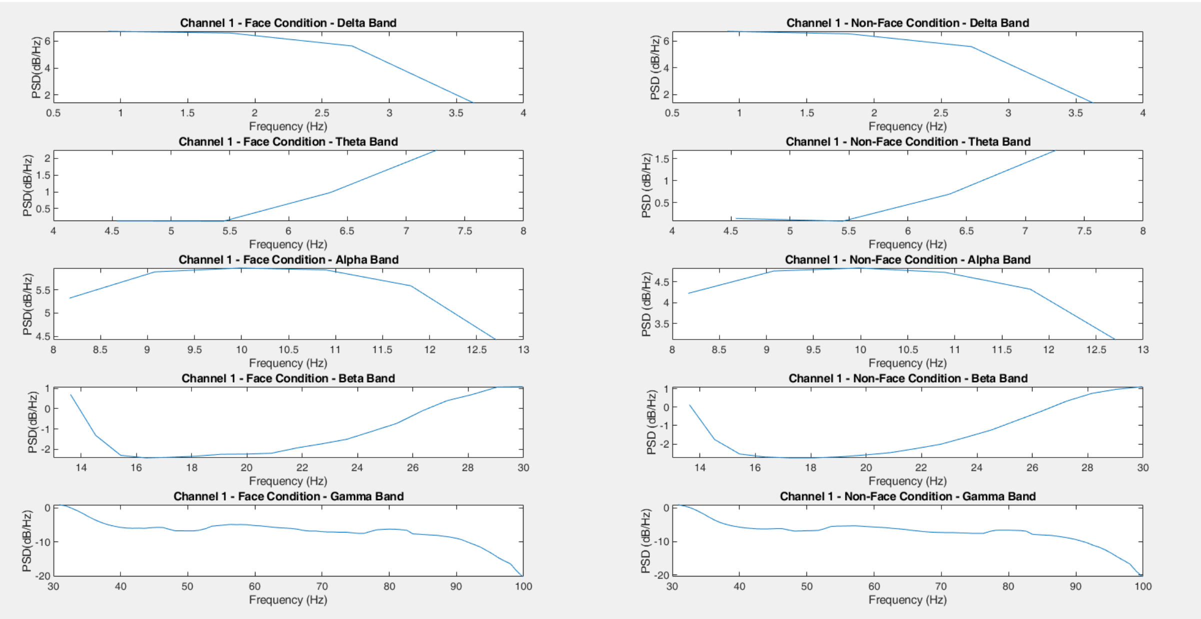


Figure 40- Sample Channel 1 face and non-face condition for different Band with baseline

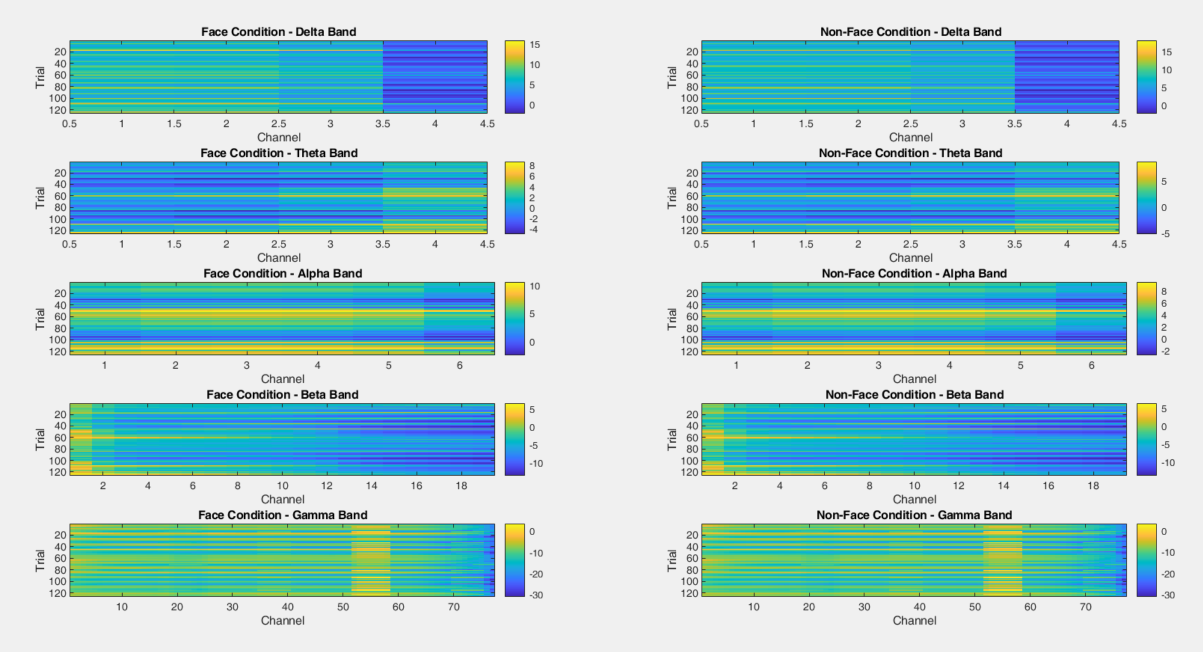


Figure 41-Image of face and non-face condition for different Band with baseline

As can be seen in Figure 41, in the case of using baseline normalization, there is no significant difference between the face and non-face groups.

But when we compare Figure 41 with Figure 54, we see that when drawing the frequency image of the channel in terms of trials, we have a significant difference between the mode with normalization and without normalization.

Power Spectral Density (PSD) are shown in Figure 41 to 54 using baseline normalization.

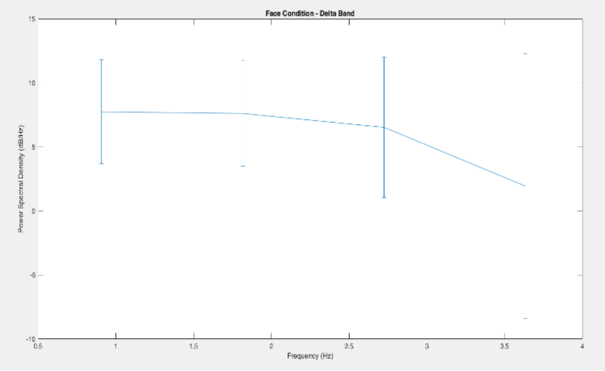


Figure 42- face condition Delta Band with baseline

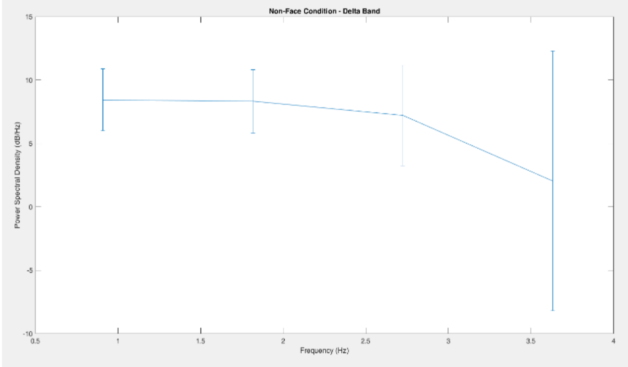


Figure 43- non-face condition Delta Band with baseline

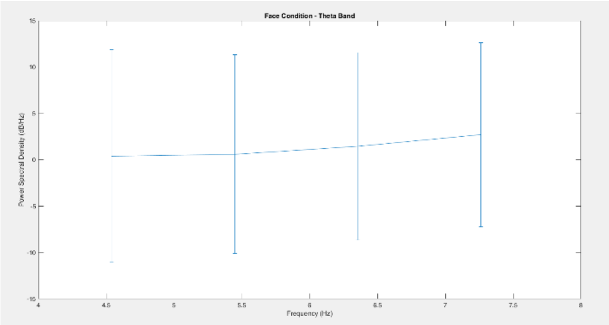


Figure 44- face condition Theta Band with baseline

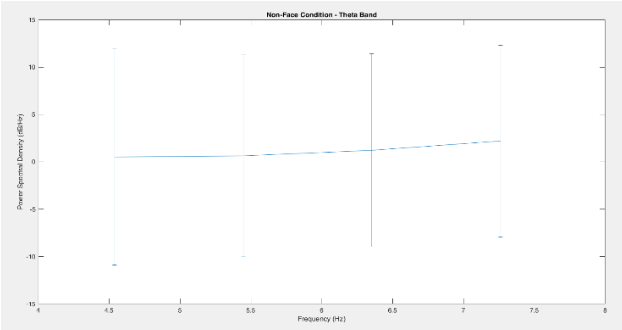


Figure 45- non-face condition Theta Band with baseline

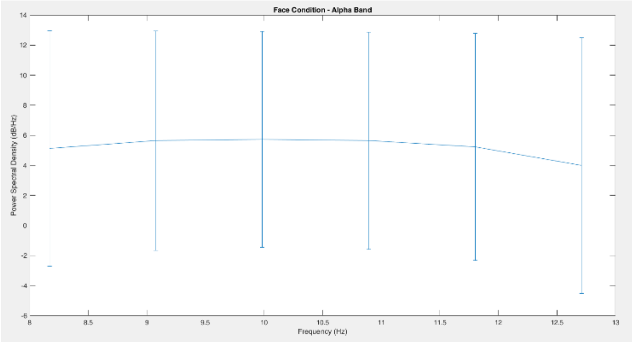


Figure 46- face condition Alpha Band with baseline

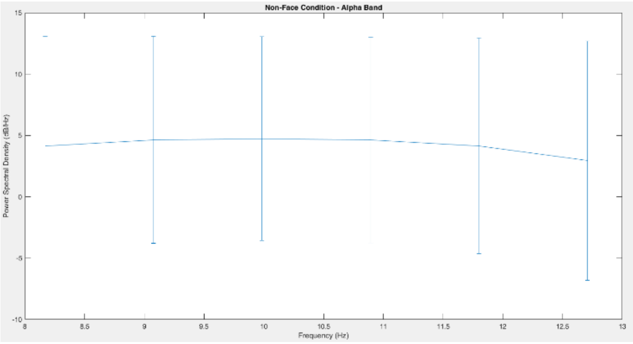


Figure 47- non-face condition Alpha Band with baseline

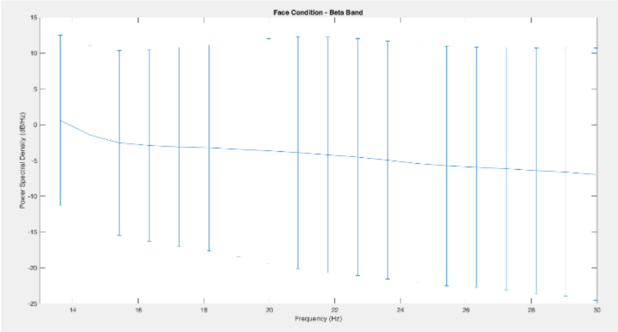


Figure 48- face condition Beta Band with baseline

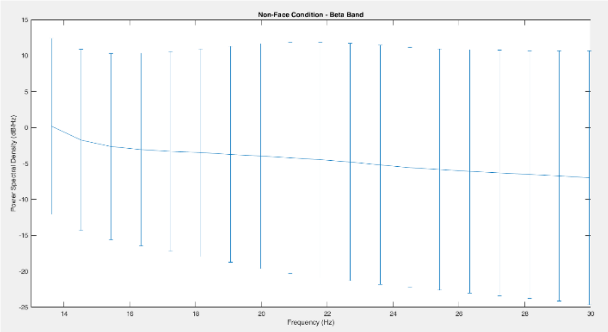


Figure 49- non-face condition Beta Band with baseline

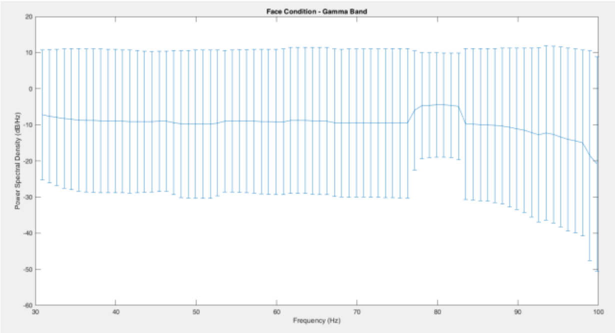


Figure 50- face condition Gamma Band with baseline

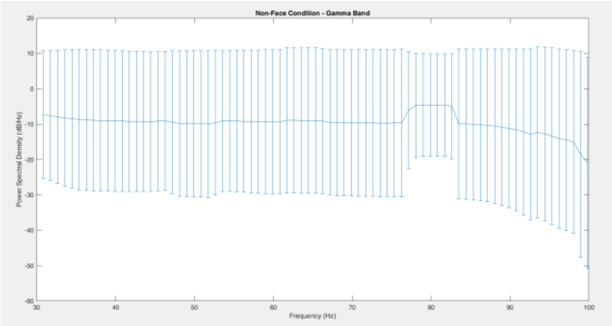


Figure 51- non-face condition Gamma Band with baseline

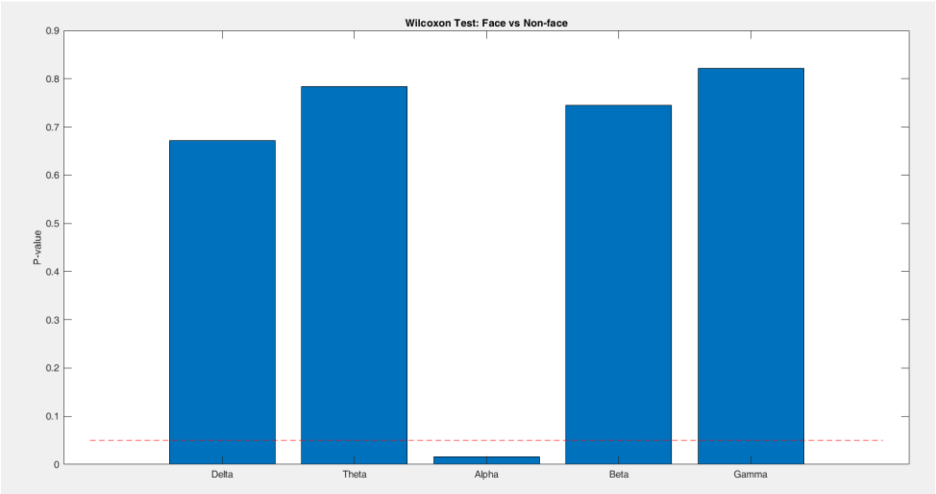


Figure 52- Wilcoxon-test: face and non-face with baseline

In Figures 42 to 51, the power spectrum density is plotted in different bands. As can be seen in these forms and especially in Figure 52, which specifies the result of the statistical test, no significant difference can be seen between all frequency bands, except for the alpha band.

In Wilcoxon's statistical test if the p-value is less than the desired significance level (usually 0.05), here only the alpha band we can reject the null hypothesis and say that the observed difference between the two groups is statistically significant. If the p-value is greater than the significance level, here the rest of the bands except for the alpha band, we cannot reject the null hypothesis and we cannot confirm the significant difference between the two groups. In Figure 65, which is related to the state without normalization, the same conclusion is also valid.

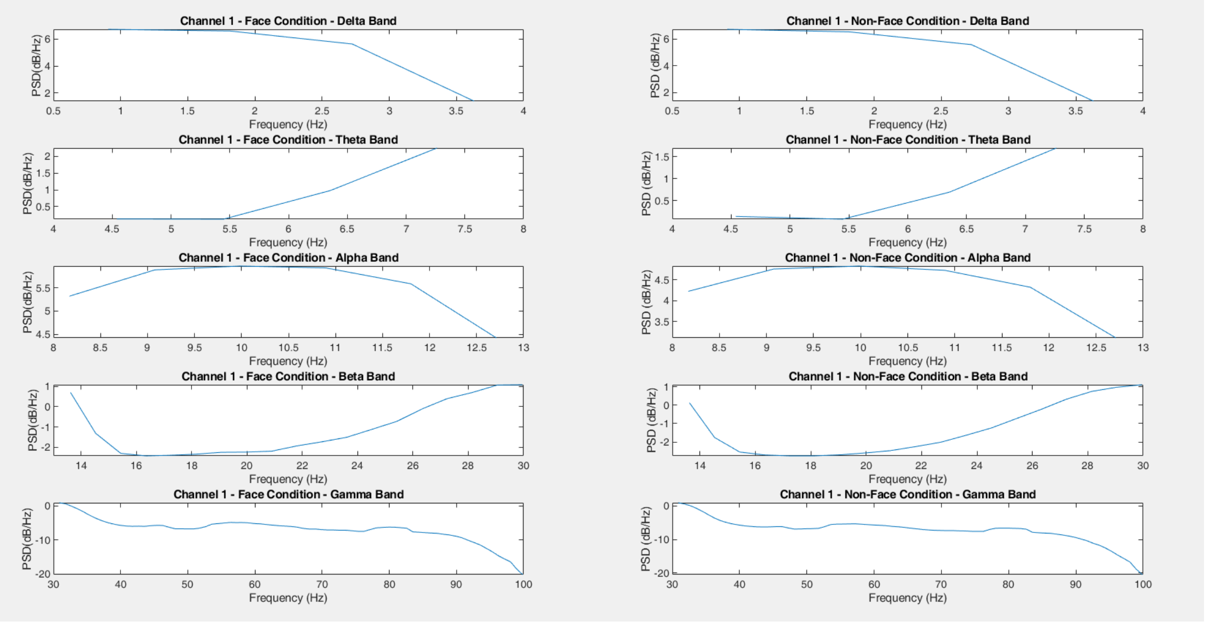


Figure 53- Sample Channel 1 face and non-face condition for different Band without baseline

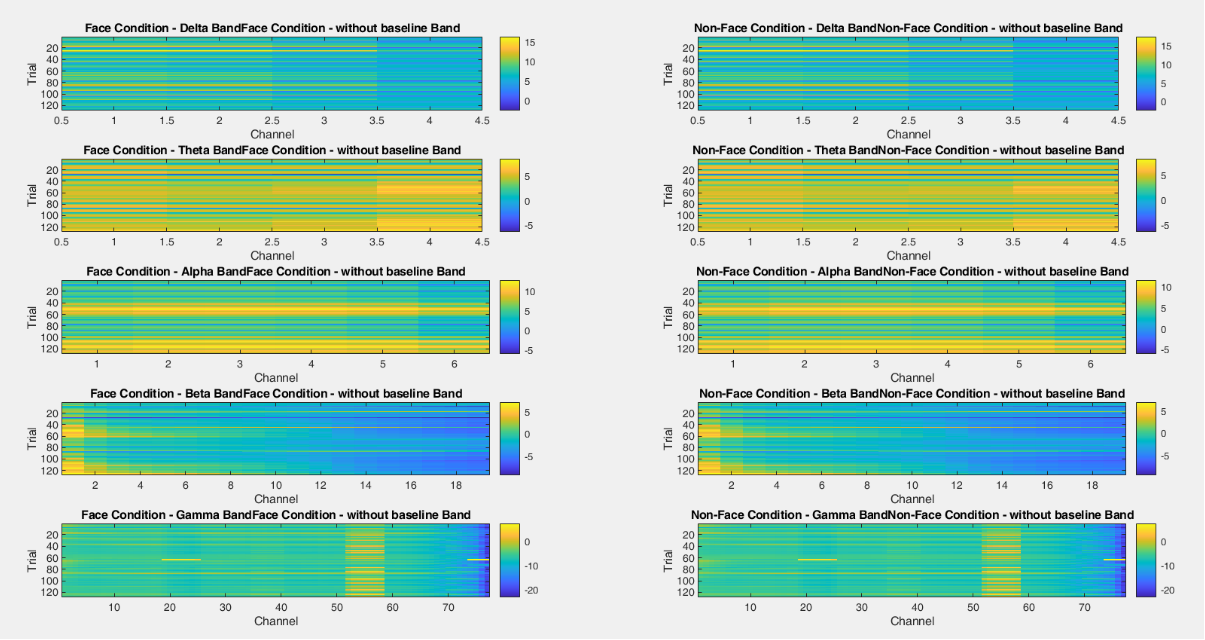


Figure 54-Image of face and non-face condition for different Band without baseline

Power Spectral Density (PSD) are shown in Figure 55 to 64 using without baseline normalization.

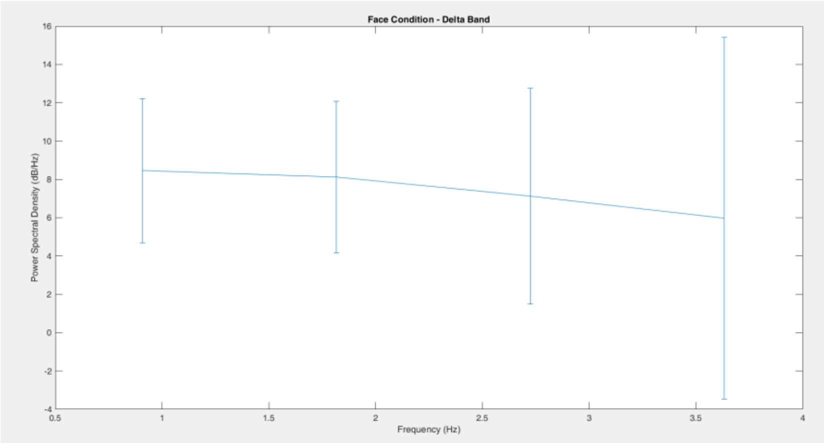


Figure 55- face condition Delta Band without baseline

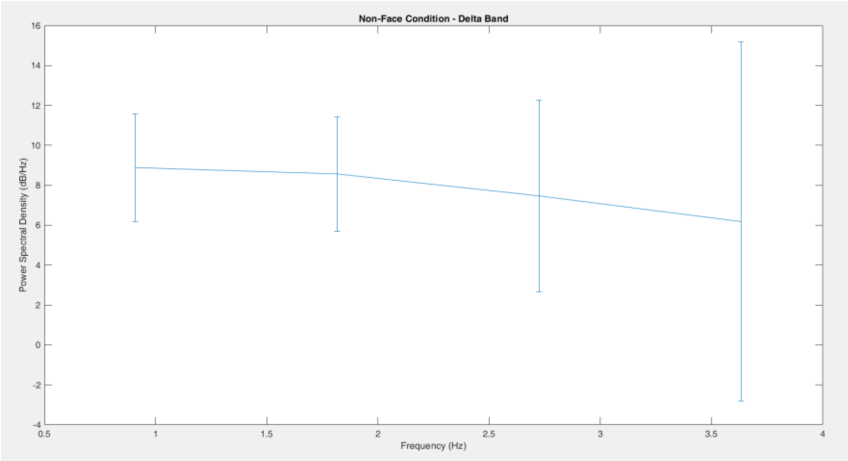


Figure 56- non-face condition Delta Band without baseline

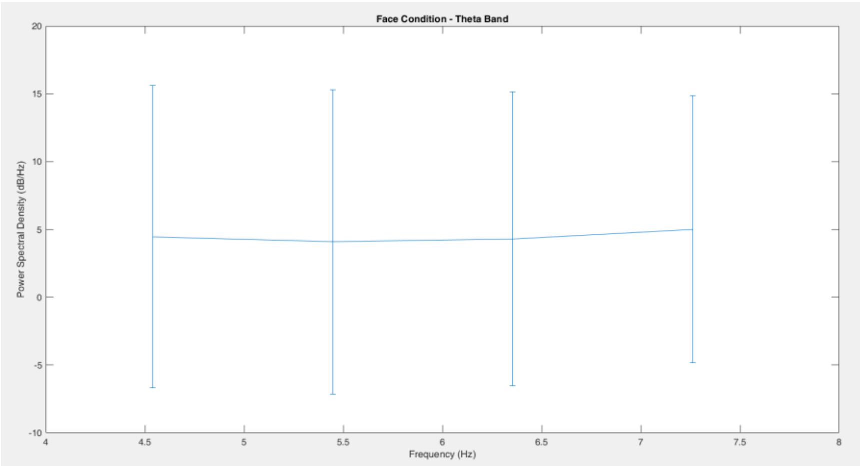


Figure 57- face condition Theta Band without baseline

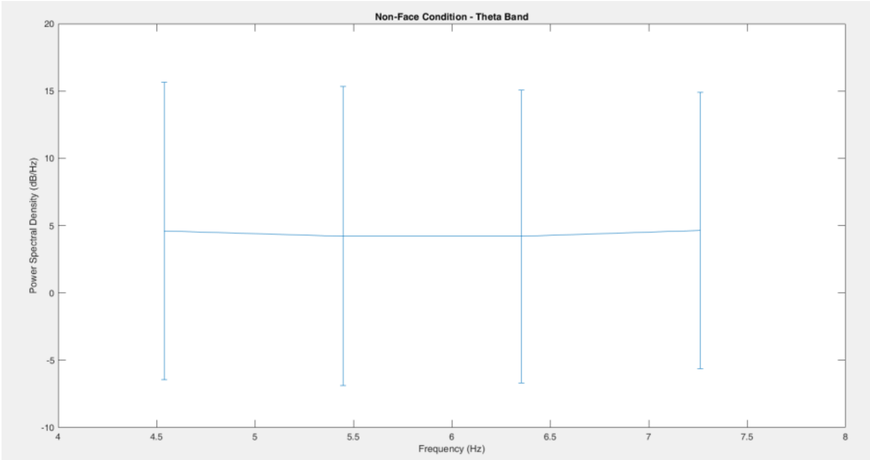


Figure 58- non-face condition Theta Band without baseline

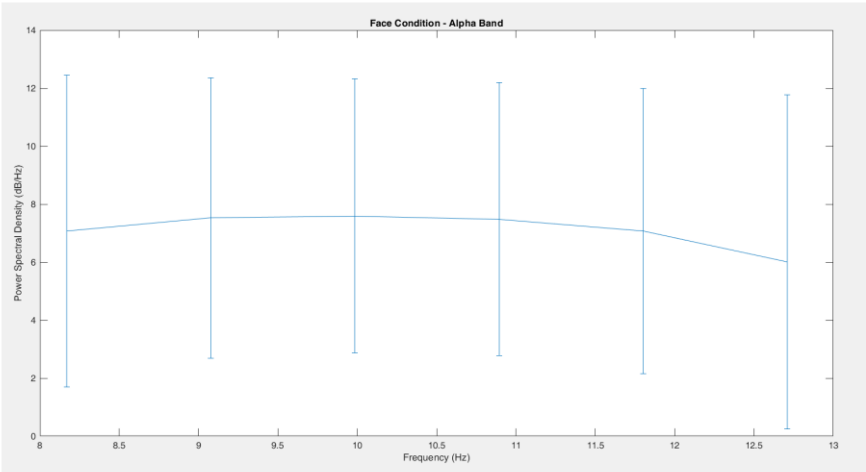


Figure 59- face condition Alpha Band without baseline

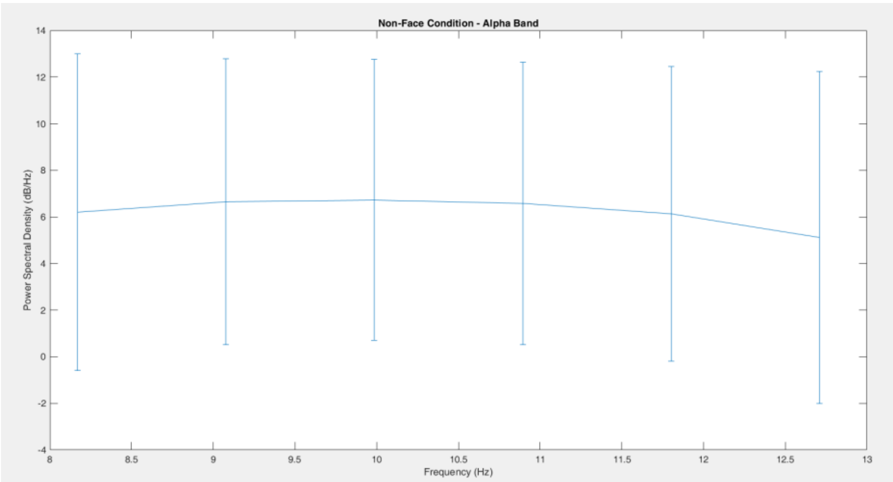


Figure 60- non-face condition Alpha Band without baseline

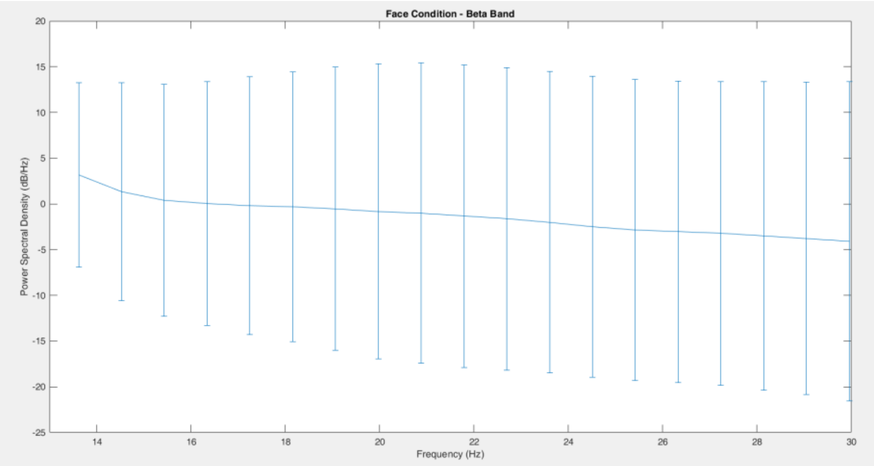


Figure 61- face condition Beta Band without baseline

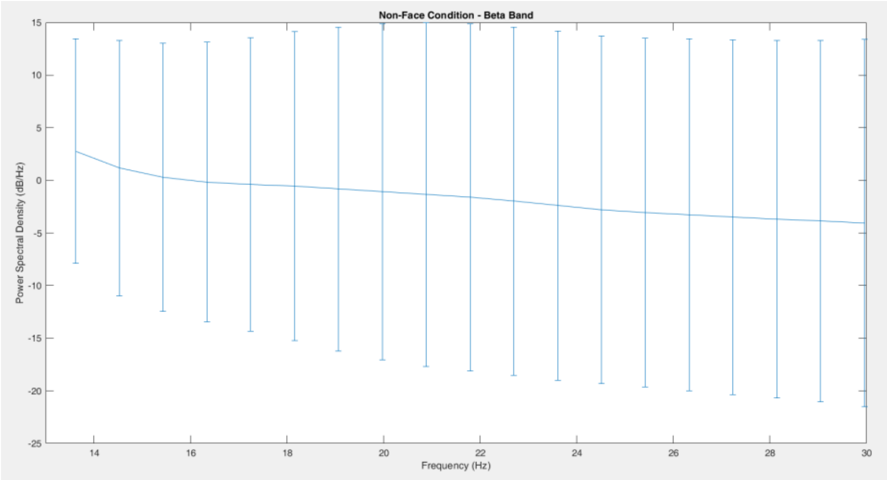


Figure 62- non-face condition Beta Band without baseline

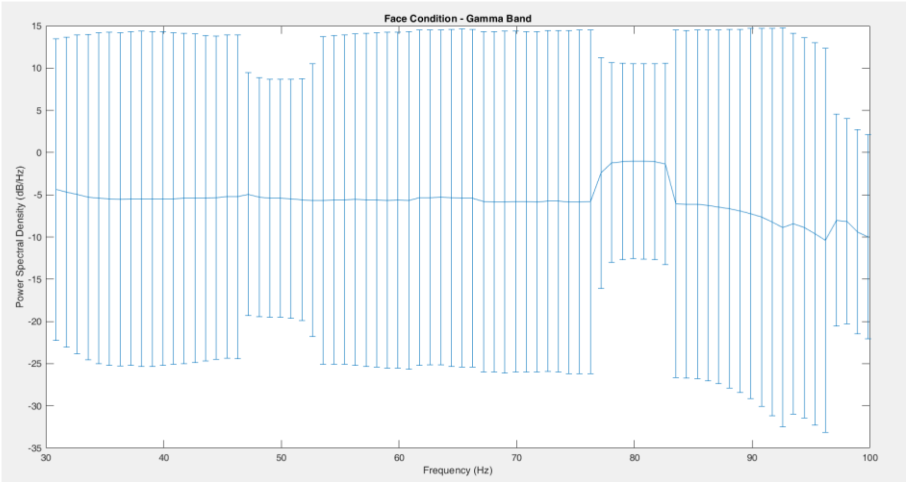


Figure 63- face condition Gamma Band without baseline

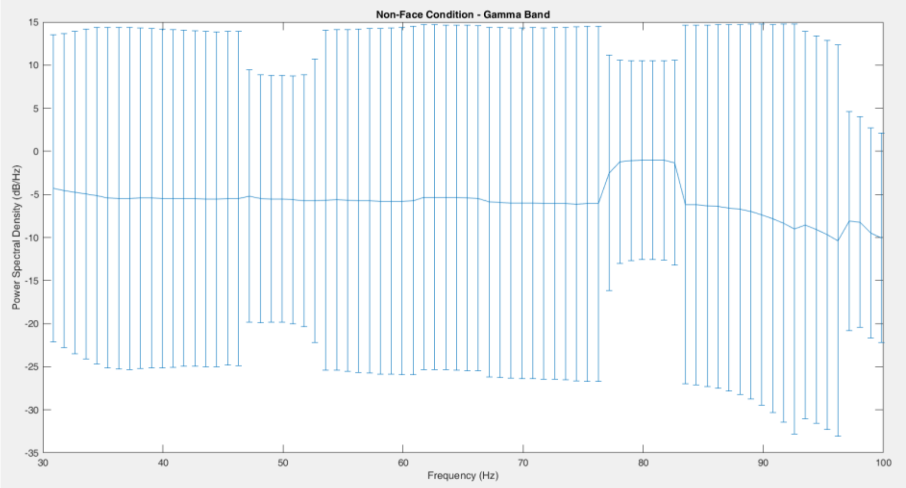


Figure 64- non-face condition Gamma Band without baseline

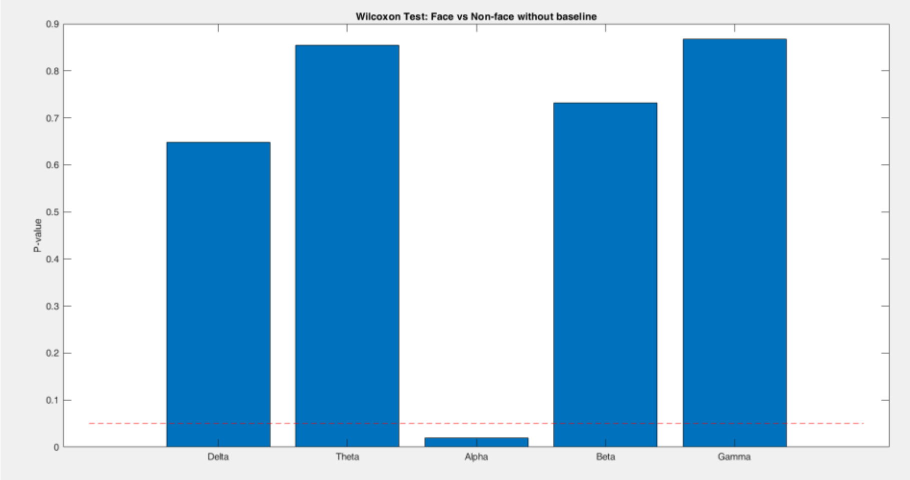


Figure 65- Wilcoxon-test: face and non-face without baseline

In Figures 55 to 64, the power spectrum density is plotted in different bands. As can be seen in these forms and especially in Figure 65, which specifies the result of the statistical test, no significant difference can be seen between all frequency bands, except for the alpha band.

In Wilcoxon's statistical test if the p-value is less than the desired significance level (usually 0.05), here only the alpha band we can reject the null hypothesis and say that the observed difference between the two groups is statistically significant. If the p-value is greater than the significance level, here the rest of the bands except for the alpha band, we cannot reject the null hypothesis and we cannot confirm the significant difference between the two groups.

If we look at figures 65 and 52 more closely. We can see that there is less difference in the gamma and theta bands in the case without baseline normalization and they have a higher correlation than the case with normalization.

4. EEG-Phase

Introduction:

Phase analysis of EEG signals provides valuable insights into the temporal dynamics and synchronization patterns of neural activity in the brain. This section focuses on two key aspects: utilizing the Hilbert transform to extract phase information from different frequency bands and evaluating inter-trial phase clustering (ITPC) to assess the consistency of phase values across trials.

At first, general explanations about the different parts of the exercise and the written code are provided:

1. Preprocess the data by filtering it into different frequency bands using the desired low and high cutoff frequencies.
2. Apply the Hilbert transform to extract the phase information from the filtered data in each frequency band.
3. Calculate the ITPC for each group (face and non-face) by quantifying the consistency of phase values across trials.
4. Compare the ITPC results between the groups by reporting the mean ITPC values along with confidence intervals.
5. Evaluate the statistical difference between the two groups using the bootstrap method.
6. Apply shuffle correction to the data by randomly reassigning trial labels while preserving the original spectral characteristics of the data.
7. Re-calculate the ITPC after shuffle correction.
8. Compare the results from the shuffled data with the previous results to determine if the observed clustering is genuinely related to the stimulus set.

In this section, we intend to calculate the phase and ITPC for face and non-face datasets using Hilbert transform in the time domain and make a comparison between them.

For the first question of this part, we intend to draw the phase using Hilbert transformation for face and non-face datasets in different frequency bands, which is done for faces and non-faces respectively in Figure 66 and 67.

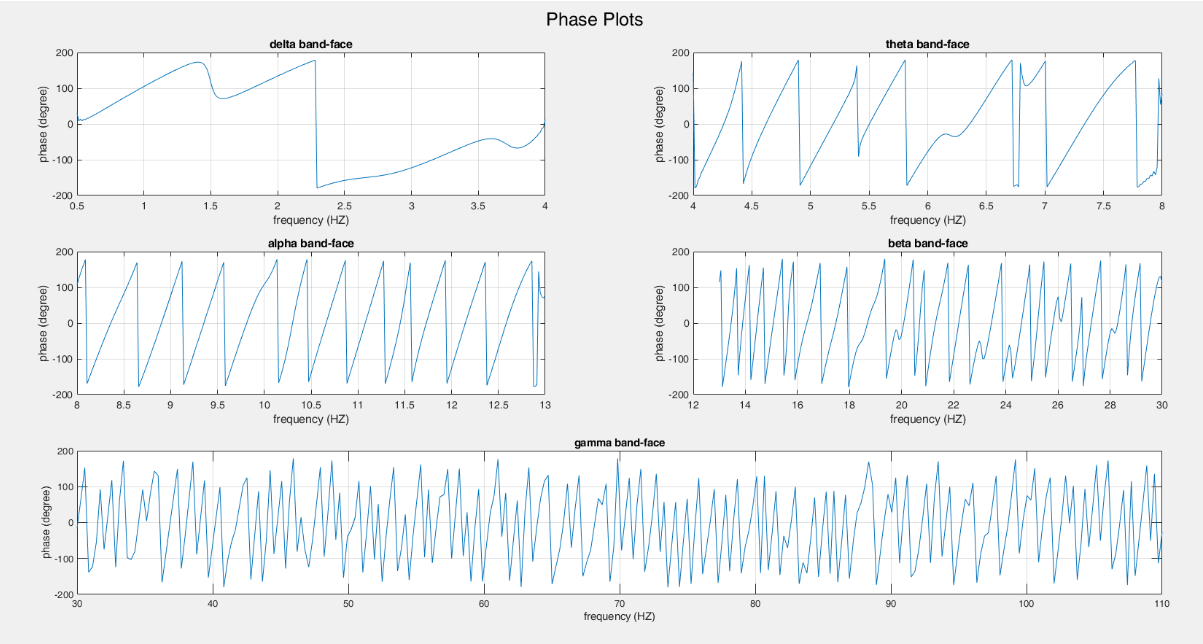


Figure 66-phase plot for different bands for face data

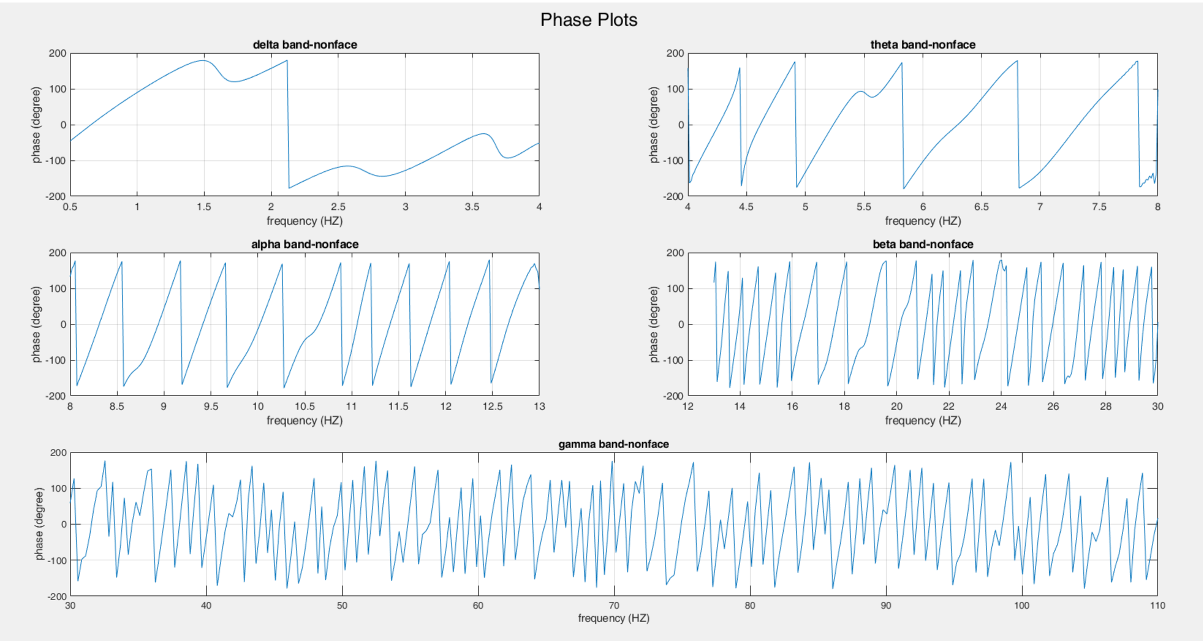


Figure 67-phase plot for different bands for non- face data

As it can be seen, for both datasets face and non-face, the more the frequency band increases, the more the phase changes.

For the second question, we plan to draw the ITPC for each dataset in different frequency bands, for this we average the original data which is in three dimensions on the channel and trial.

The face and non-face ITPC datasets are shown in Figure 68 and Figure 69, respectively.

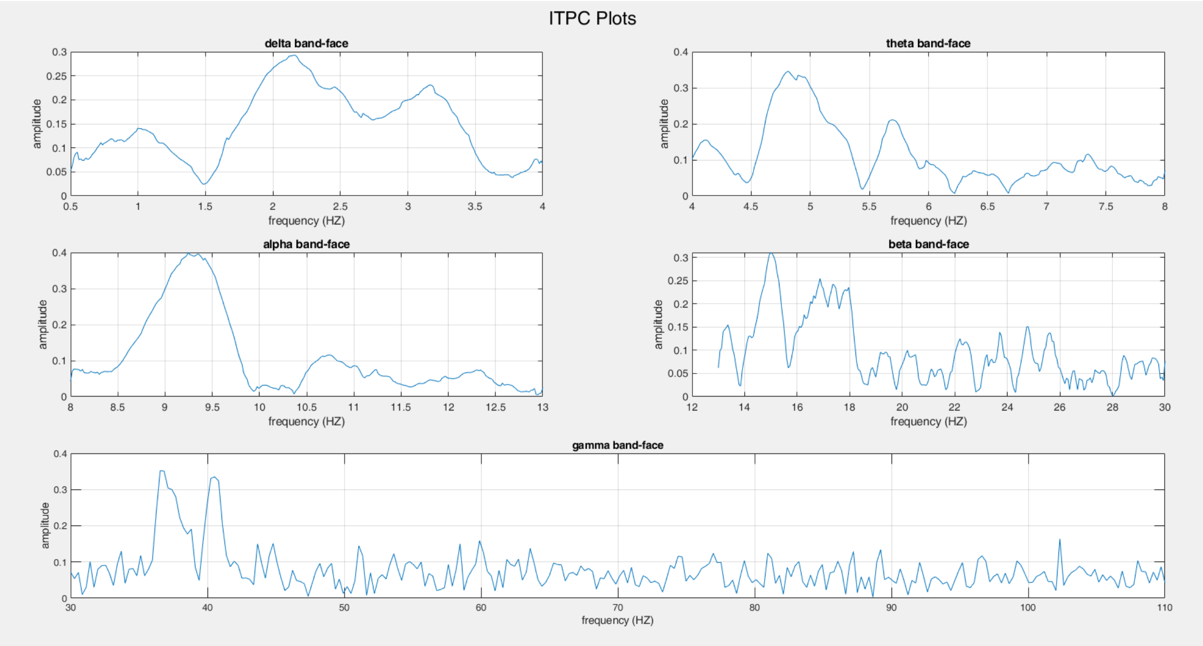


Figure 68-ITPC plot for different bands for face data

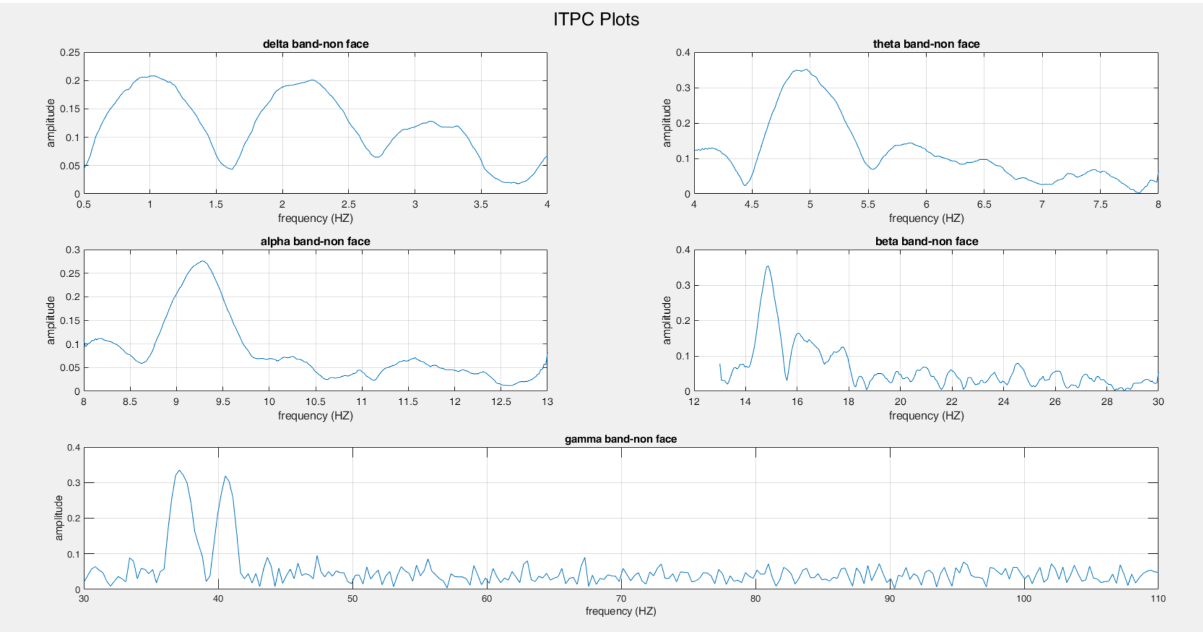


Figure 69-ITPC plot for different bands for non- face data

Also, by using the bootstrap method, we have obtained the ITPC distributions for each dataset in each frequency band, which is shown in Figure 70. Also, the average of each part is shown in the title of each frequency band.

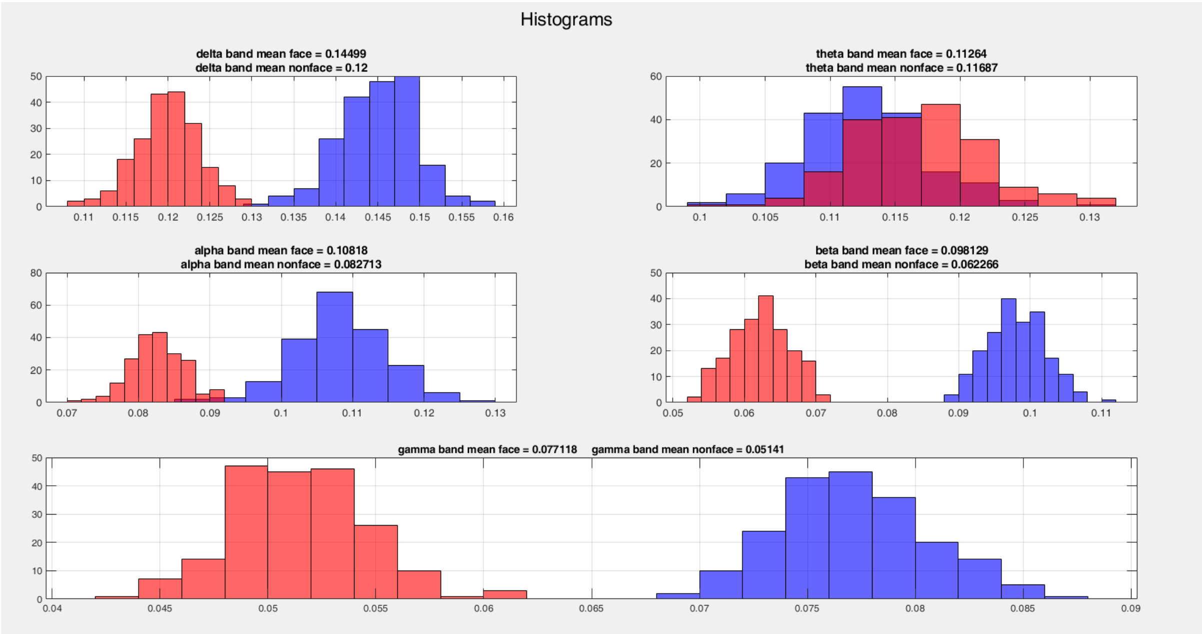
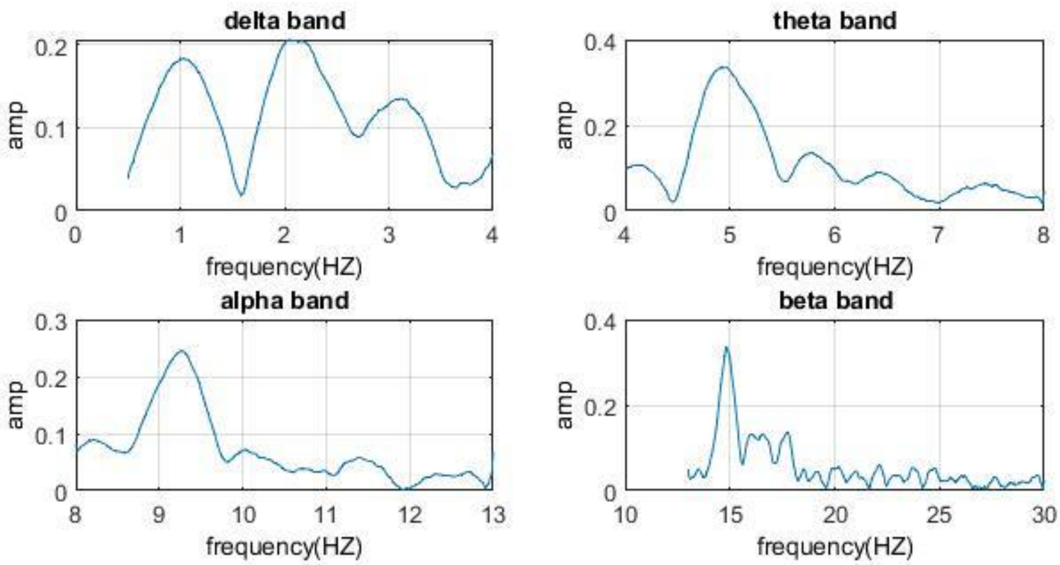


Figure 70- ITPC distributions for each dataset in each frequency band

As can be seen from Figure 70, face and non-face distributions do not overlap in any frequency band except for the theta band. And except for theta band, we can have a classifier with good accuracy between face and non-face.

For the third question, we plan to shuffle the trials first and draw the ITPC in each frequency band to see if the ITPC is robust compared to the TRIALS or not. This is done in Figure 71.



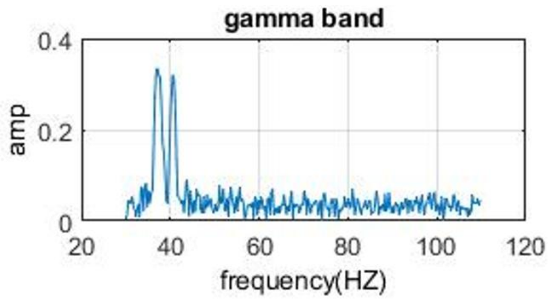


Figure 71- ITPC in each frequency band with shuffling cross the Trials

As can be seen, ITPC in this case does not have any particular difference with face and non-face data, so ITPC is robust compared to the type of trials.

Next, the FIR filters and the frequency response of the different bands introduced in figures 72 to 76 are shown.

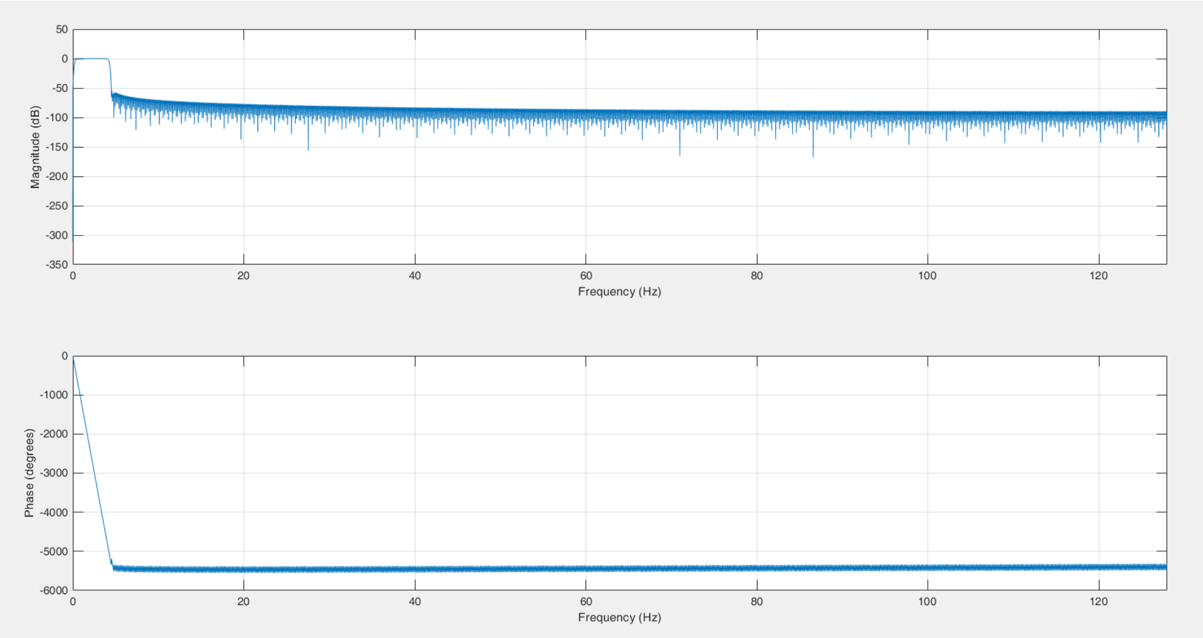


Figure 71- FIR-Filter frequency response

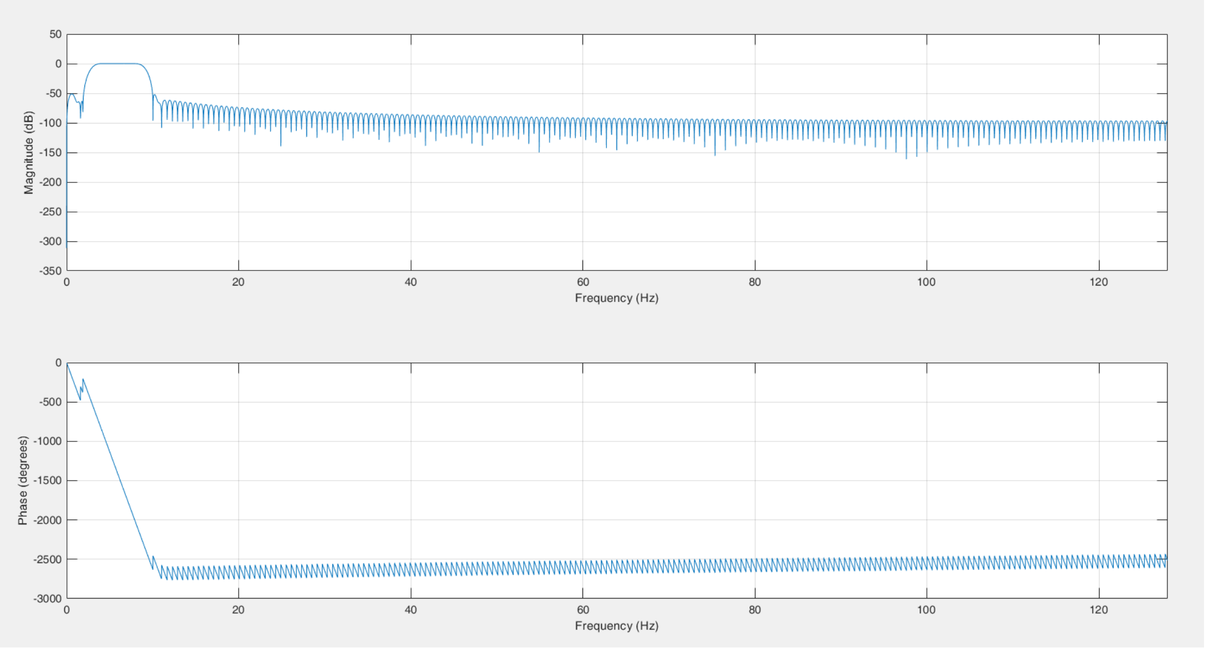


Figure 72- FIR-Filter frequency response

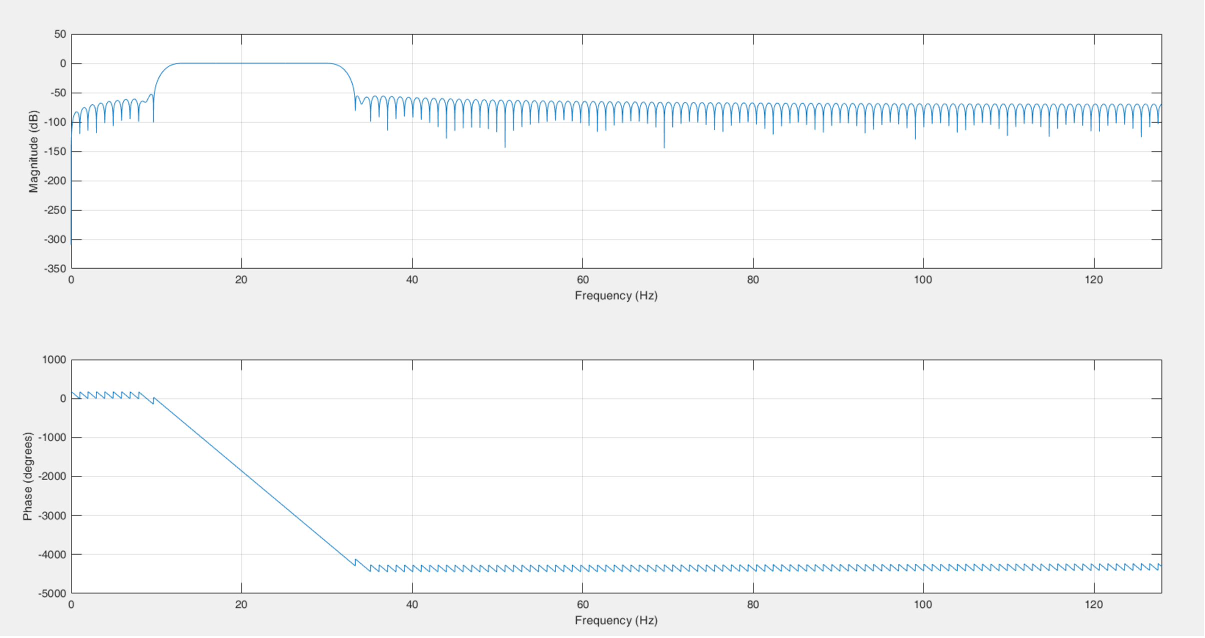


Figure 73- FIR-Filter frequency response

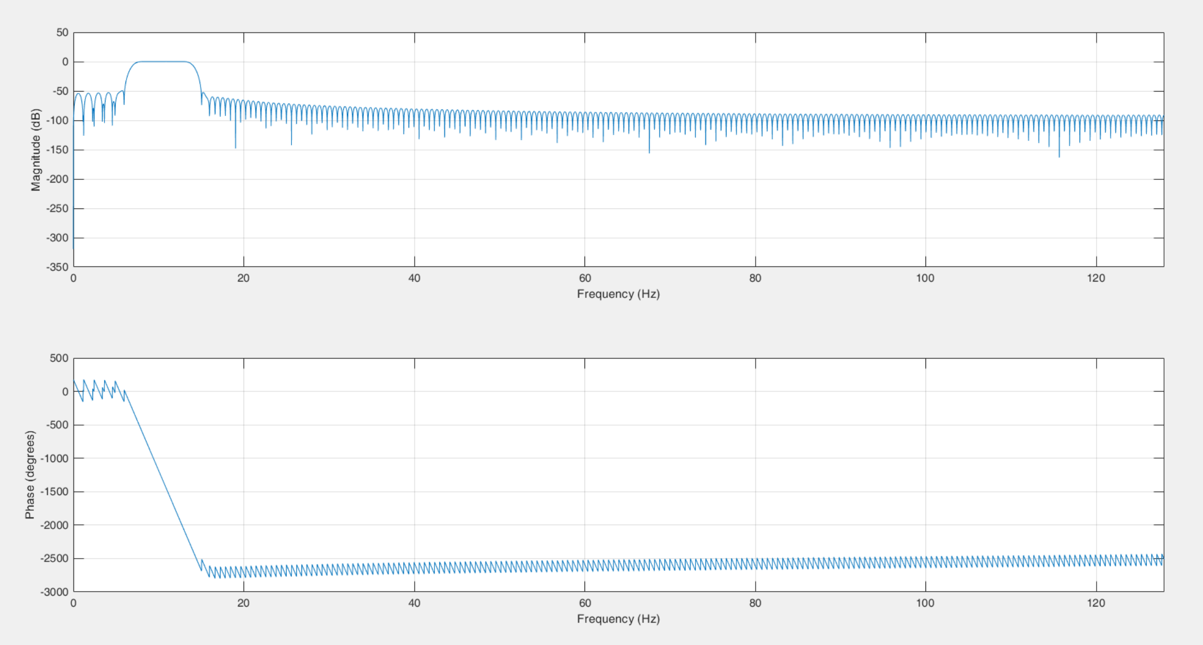


Figure 74- FIR-Filter frequency response

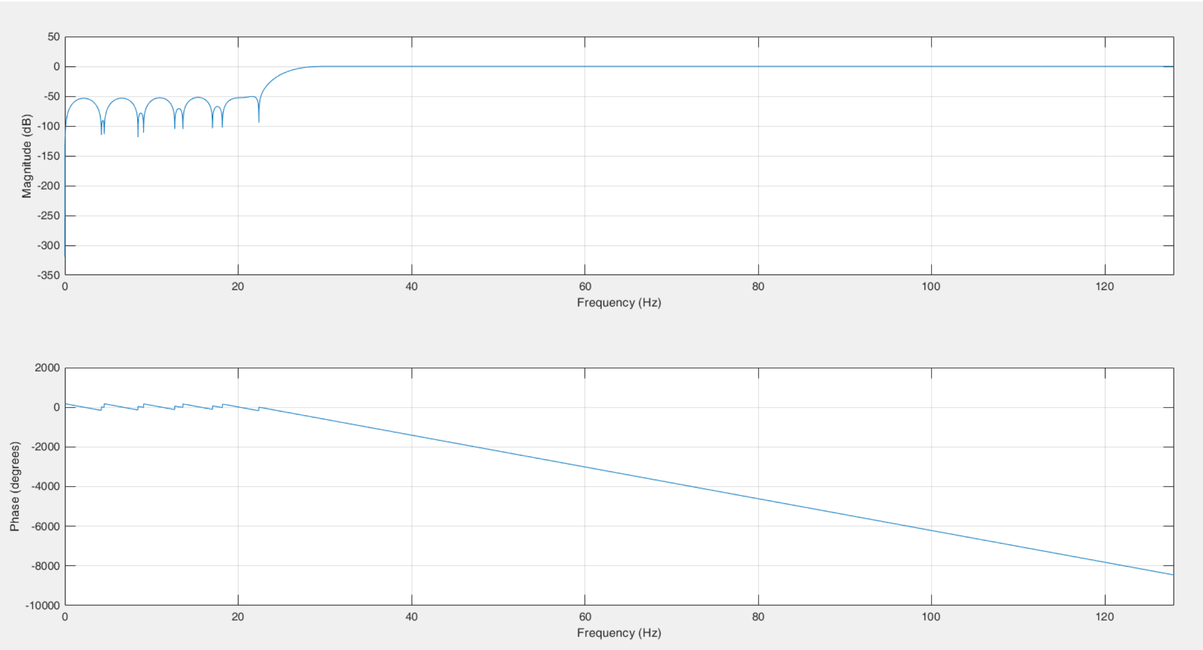


Figure 75- FIR-Filter frequency response

In conclusion, this section explored the phase analysis of EEG signals using the Hilbert transform and examined the inter-trial phase clustering (ITPC) measure. The analysis revealed distinct phase clustering patterns between face and non-face trials, with face trials exhibiting stronger phase alignment. The statistical difference was confirmed using the bootstrap method. Additionally, shuffle correction analysis demonstrated that the observed phase clustering was genuinely related to the underlying neural dynamics, rather than being an artifact of the stimulus set.