Assignment 1

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Neuroscience of Learning, Memory, and Cognition

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Contents

Introduction

Brain signals include various neural activities and provide vital information about brain performance and condition. The way these signals are recorded varies but is generally divided into two categories:

1. **Non-invasive recording**: This does not require surgery and is often performed on the scalp close to the surface of the brain. **Electroencephalography (EEG)** is one of the most common and well-known non-invasive methods. EEG records brain electrical signals by placing electrodes on the scalp. EEG is widely used in sleep studies, diagnosing neurological diseases like epilepsy, and systems such as brain-computer interfaces (BCI). Other non-invasive techniques include **magnetoencephalography (MEG)**, which measures the magnetic fields generated by neural activity.

2. **Invasive recording**: In this method, brain signals are recorded via implanted electrodes inside the brain, which requires surgery. These methods provide highly accurate data on the activity of different parts of the brain and are used in animal research. Among these methods is **Local Field Potential (LFP) recording**, which records activity in specific parts of the brain with high spatial and temporal accuracy.

In recent years, neuroscience has advanced towards the preliminary diagnosis and analysis of mental disorders. EEG recordings, for instance, have shown that depression, a prevalent mental disorder today, affects a person's thoughts, emotions, behavior, and decision-making abilities. Depression symptoms include chronic sadness, anhedonia, fatigue, difficulty concentrating, and decreased decision-making capacity. Given the specific characteristics of depression, we can use EEG signals to analyze and describe it in a precise way that distinguishes affected individuals from healthy people.

One of the most common and critical tasks affected by depression is decision-making. Because this disorder influences the way affected individuals interact with their environment, EEG analysis can provide valuable insights into the distinctive characteristics of the decision-making and learning processes among depressed individuals. By receiving specific cues and feedback, individuals can choose to avoid them. Therefore, through EEG signal analysis, it is possible to extract different features related to depression and describe how affected individuals perform.

Dataset and Task Execution Method

The dataset provided includes EEG signals from both healthy individuals and those with depression while performing a reinforcement learning task. For more information on task execution and related details, refer to the video `CHW1_IntroToDataset.mp4`, which covers this part of the exercise. In the following section, to become familiar with the dataset structure, watch the video `CHW1_Sampledataset.mp4` in the first exercise section available in the course system.

Soloution

To become familiar with the dataset structure and for more information on task execution and related details we watch the video `CHW1_Sampledataset.mp4` and `CHW1_IntroToDataset.mp4` respectively.

Dataset Preprocessing

The EEG signals recorded from individuals contain specific types of noise and artifacts that need to be reduced to an acceptable level before applying various analysis methods. To become familiar with the preprocessing approach, watch the video `CHW1_Preprocessing.mp4`, which explains the preprocessing of EEG signals. Referring to **Table 1**, which is provided in the course system, it can be observed that the control and depressed subjects are listed in columns 3 and 4, respectively.

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Referring to the table which was provided in the course system, downloaded the data for the control and depressed subjects.

Preprocessing Steps

1. Load EEG Data

We began by loading all EEG data files into the processing environment, ensuring each dataset was correctly imported.

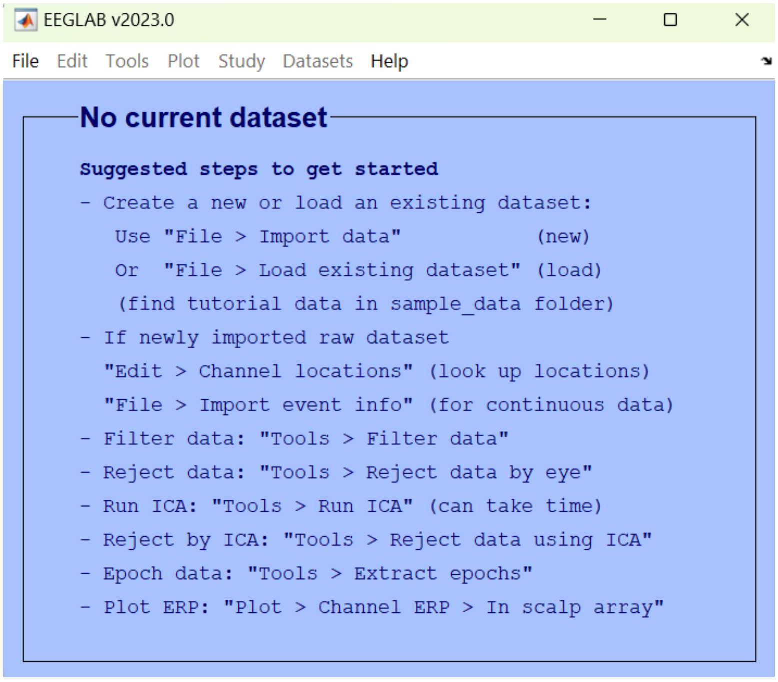

Figure 1: Loading the EEG data files

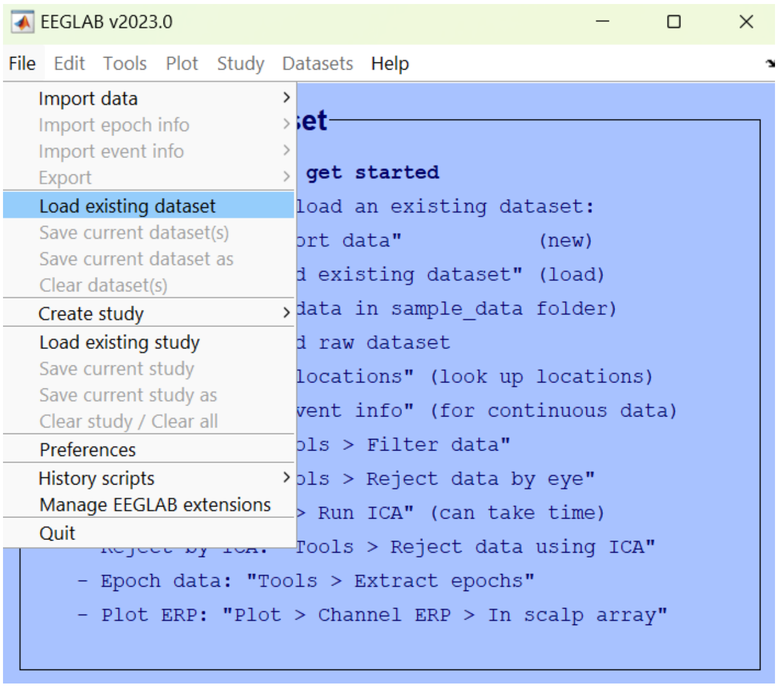

Figure 2: Loading the EEG data files

2. Load Channel Locations

Next, we loaded the standard channel locations to align with the 10-20 electrode placement system, which ensures spatial accuracy in the analysis.

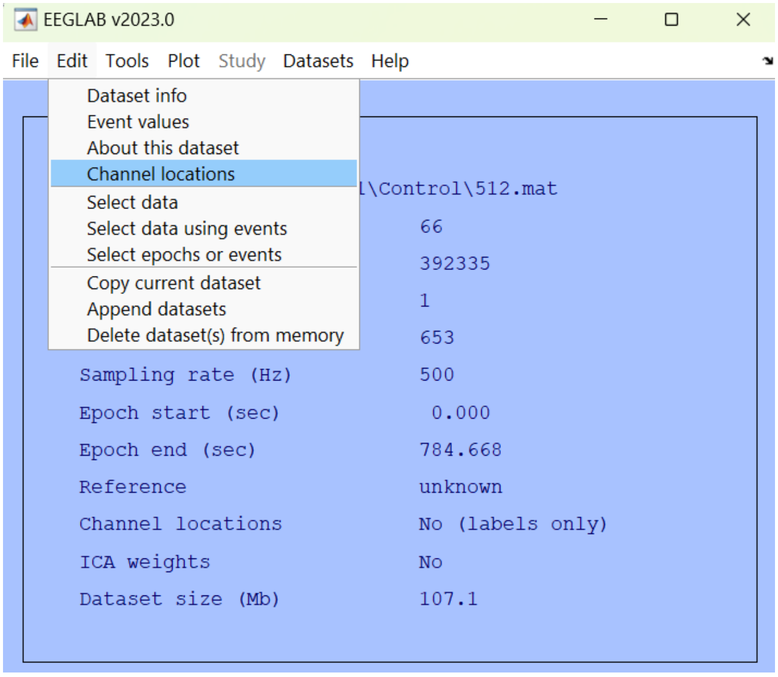

Figure 3: Loading channel location information

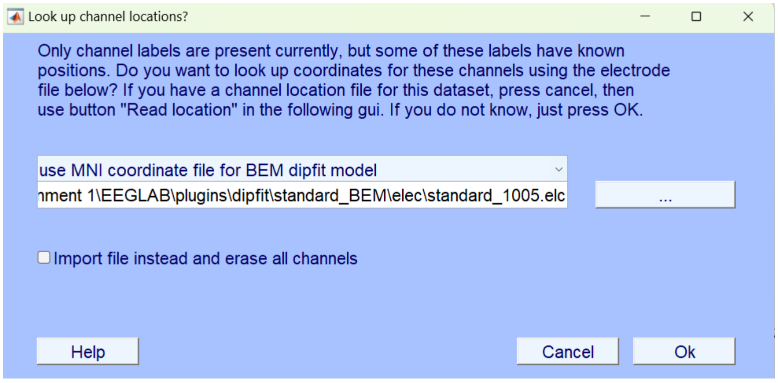

Figure 4: Loading channel location information

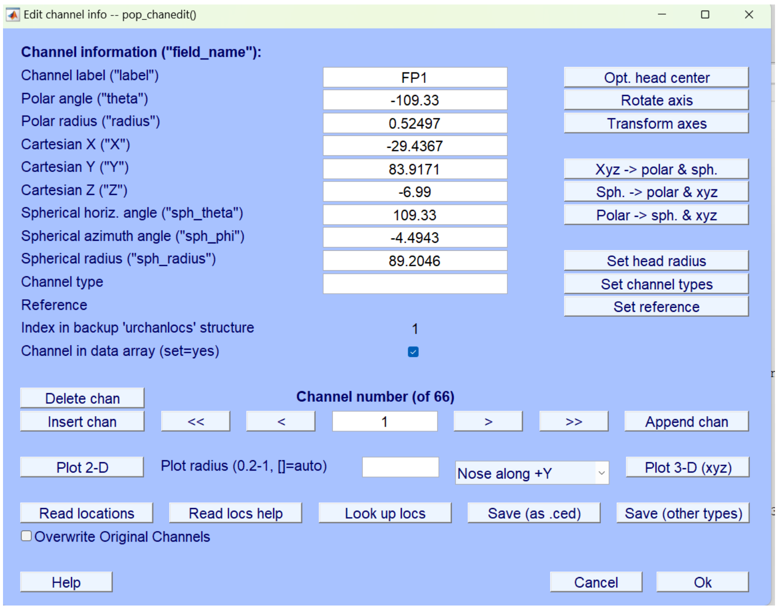

Figure 5: Loading channel location information

3. *Re-reference to Linked Mastoid*

To improve signal quality, we re-referenced the data to linked mastoid electrodes (M1 and M2), which can reduce noise in the recordings.

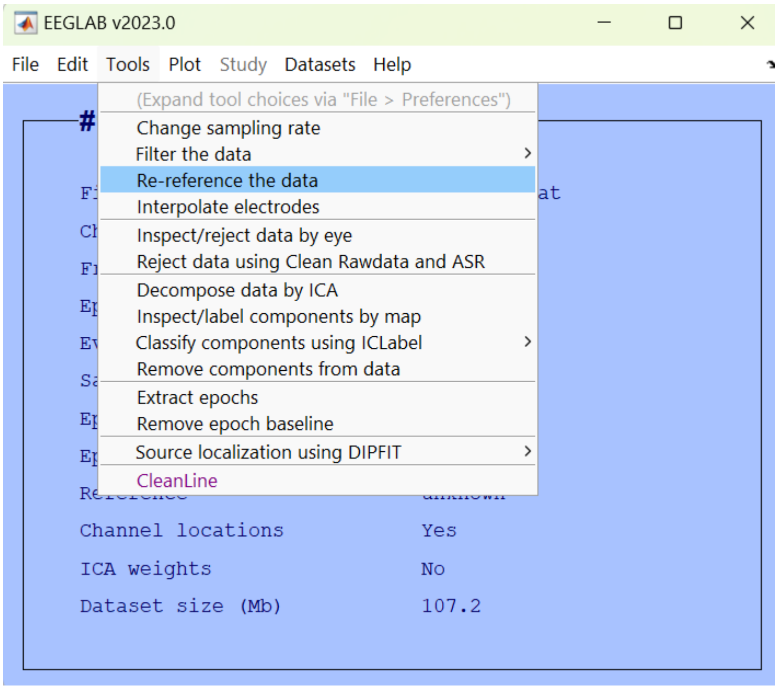

Figure 6: Re-referencing data to linked mastoids (M1 and M2)

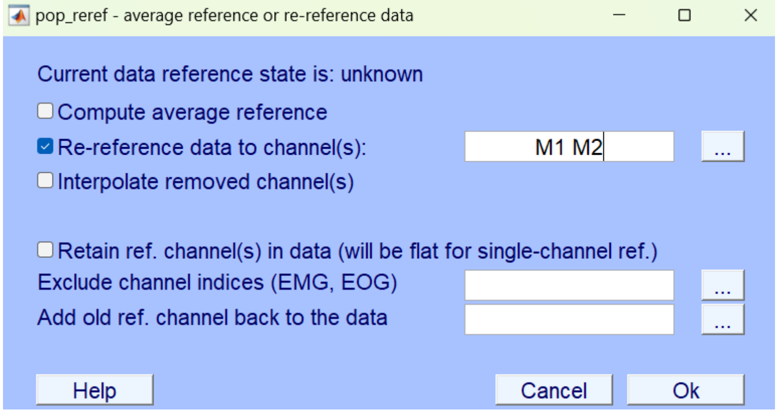

Figure 7: Re-referencing data to linked mastoids (M1 and M2)

4. *Select Data for Channel Removal*

We removed non-EEG channels (e.g., CB1, CB2, HEOG, VEOG, and EKG) that were not required for the analysis.

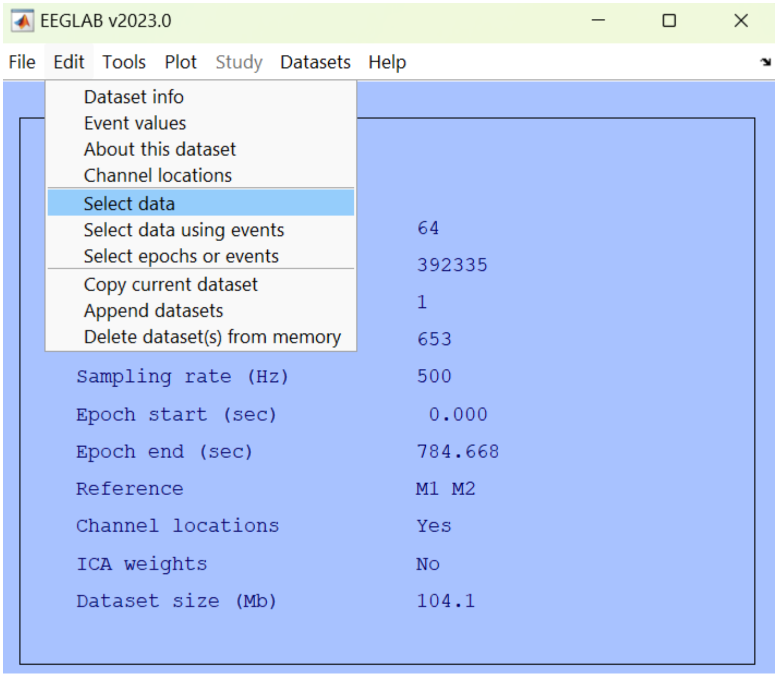

Figure 8: Selecting channels to retain and exclude

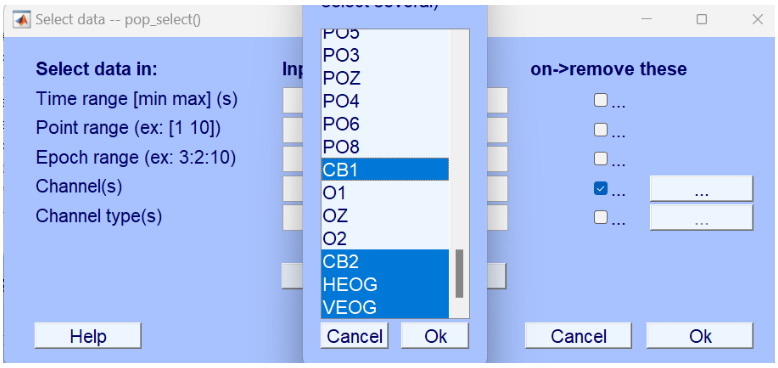

Figure 9: Selecting channels to retain and exclude

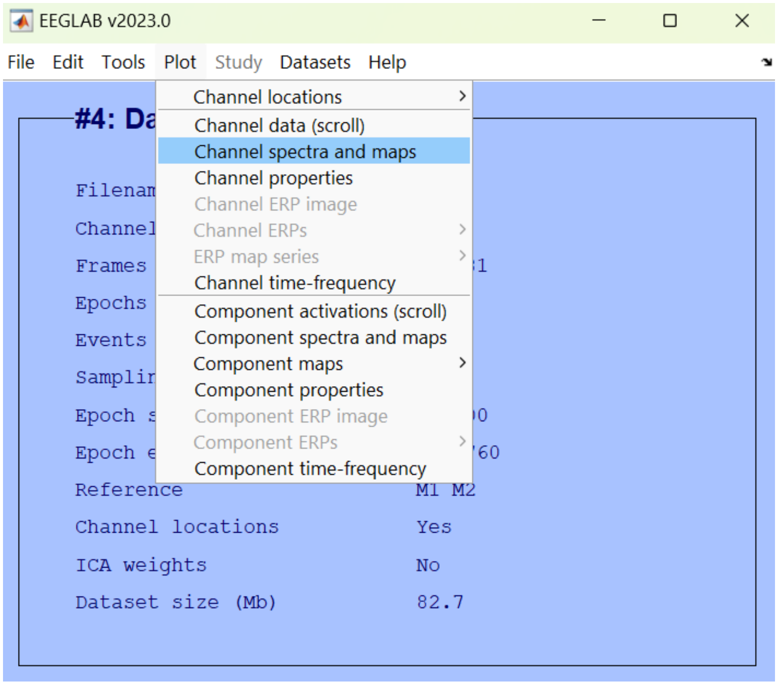

Figure 10: Selecting channels to retain and exclude

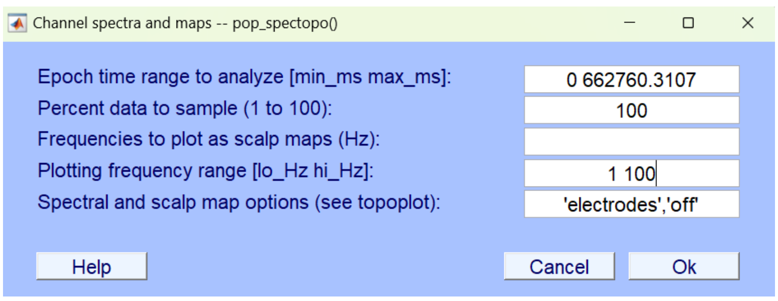

Figure 11: Selecting channels to retain and exclude

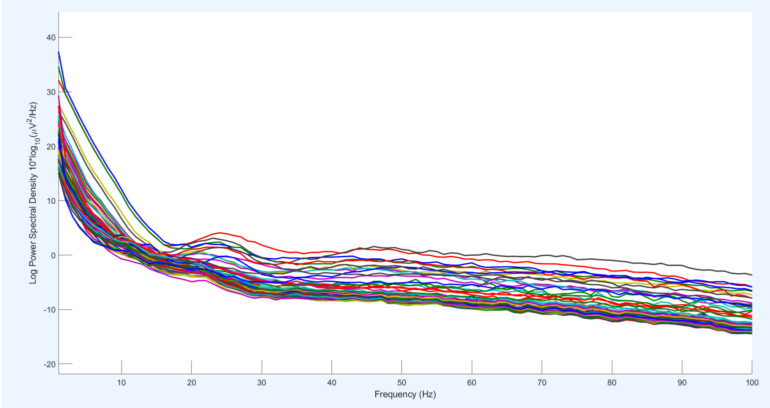

Figure 12: Selecting channels to retain and exclude

5. *Apply High-pass Filter*

We applied a high-pass filter at 1 Hz to remove slow drifts in the signal, which stabilized the baseline of the data.

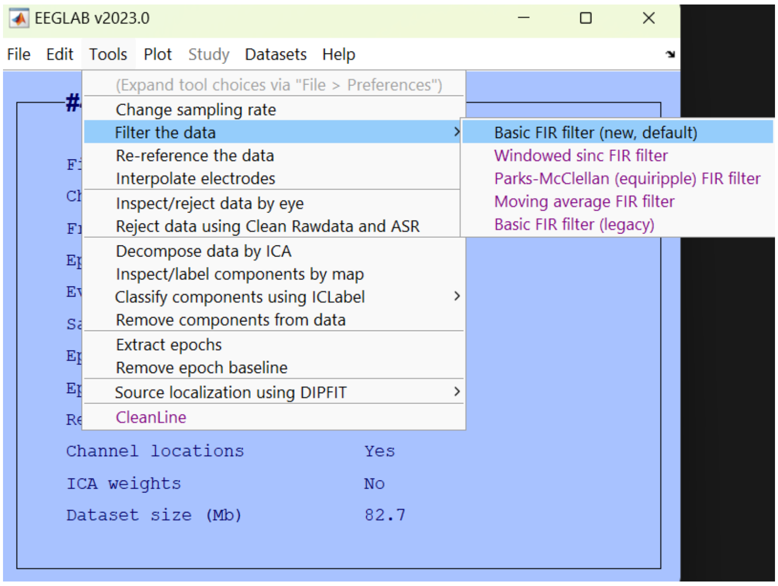

Figure 13: High-pass filtering at 1 Hz

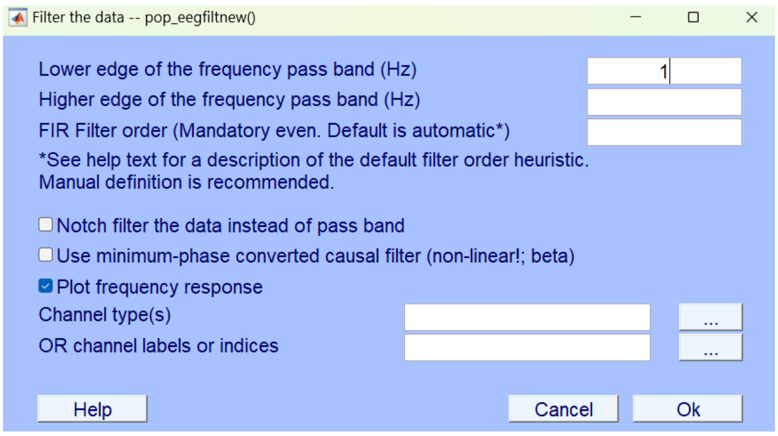

Figure 14: High-pass filtering at 1 Hz

6. Apply Notch Filter (CleanLine)

To remove line noise, we applied a notch filter around 60 Hz (or 50 Hz as appropriate) using CleanLine, targeting the specific frequency range of the line noise (59.5 Hz to 60.5 Hz).

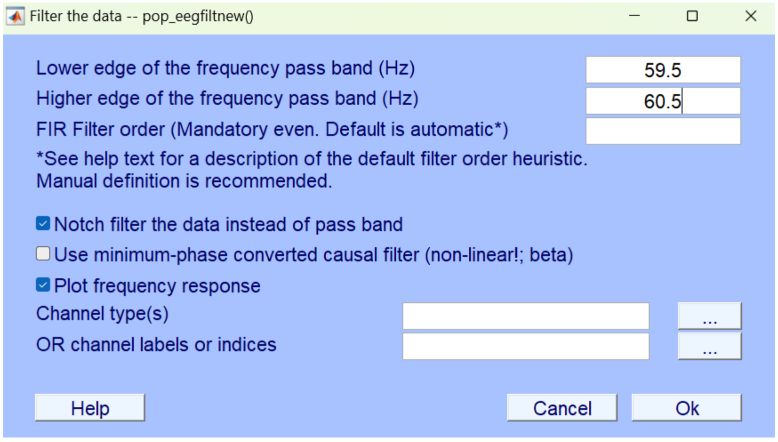

Figure 15: Applying notch filter to remove line noise

7. Visual Inspection of Temporal Channels

We visually inspected the temporal channels (e.g., TP7 and TP8) to check for any artifacts or anomalies that may affect further analysis.

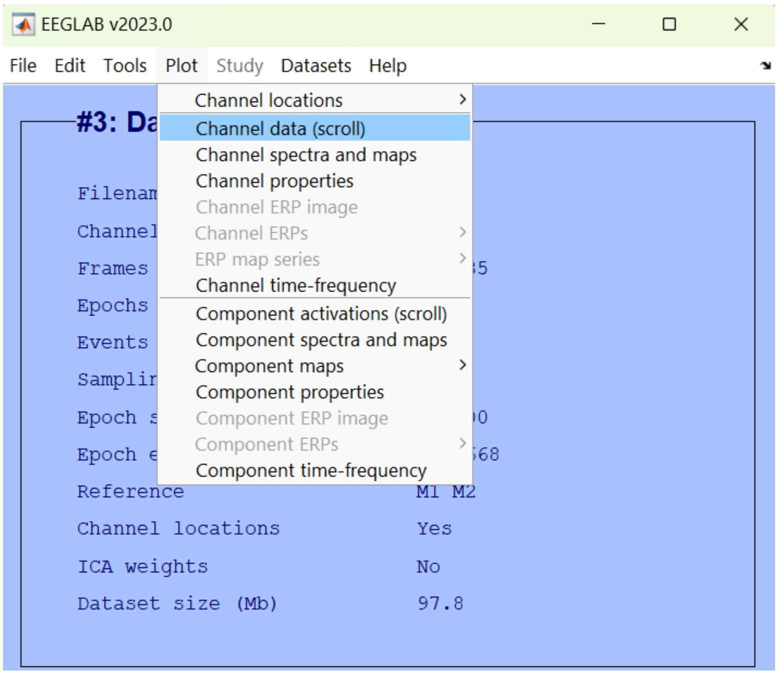

Figure 16: Inspecting channels TP7 and TP8

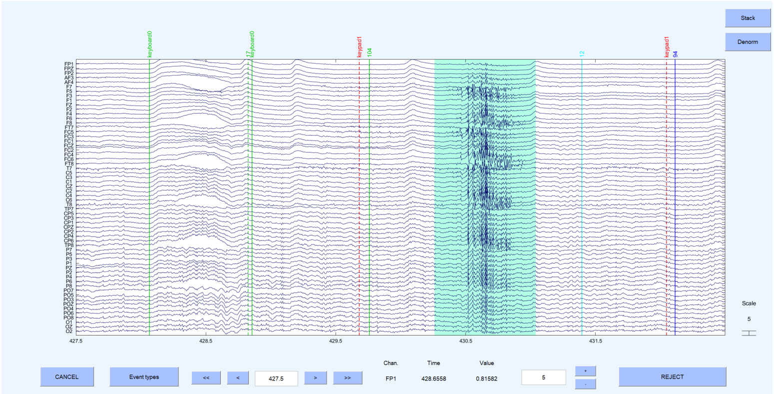

Figure 17: Inspecting channels TP7 and TP8

8. Remove Noisy Temporal Channels

To improve data quality, we removed noisy temporal channels (e.g., TP7 and TP8) that consistently showed artifacts.

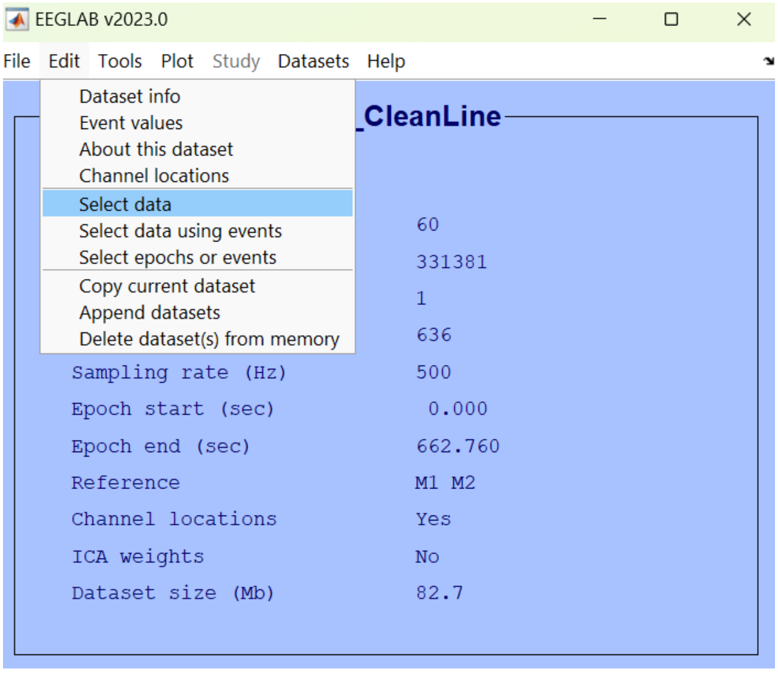

Figure 18: Removing noisy temporal channels

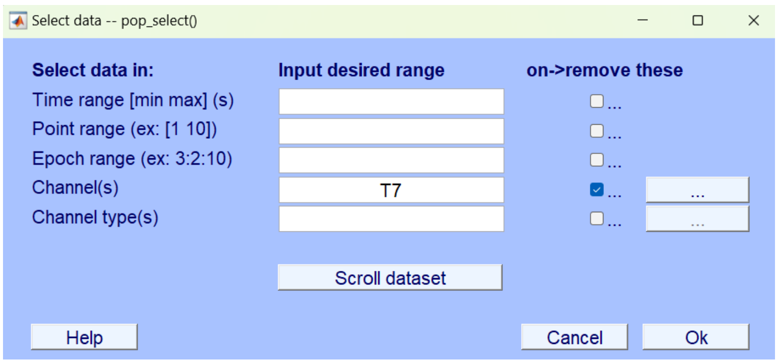

Figure 19: Removing noisy temporal channels

9. *Interpolate Removed Channels*

We interpolated the data for the removed channels to reconstruct their values based on surrounding channels, ensuring continuity in the dataset.

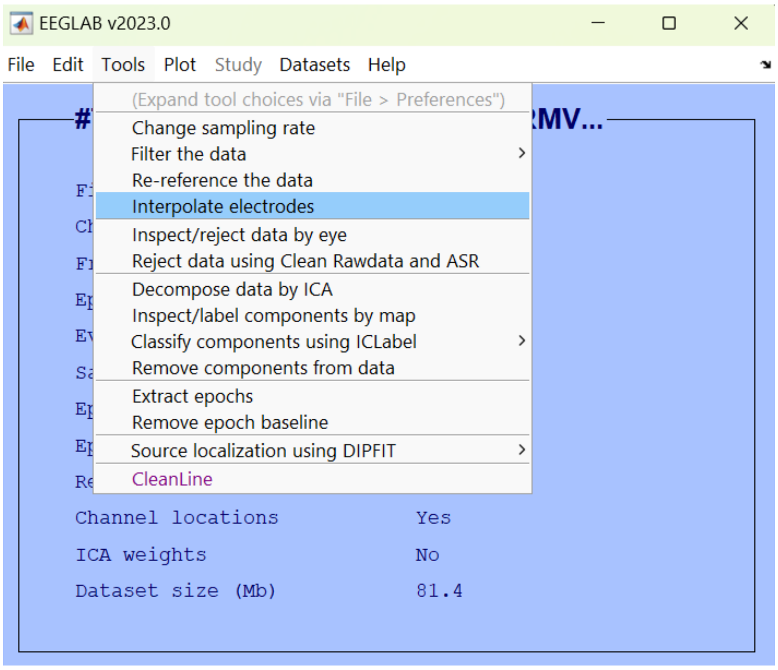

Figure 20: Interpolating data for removed channels

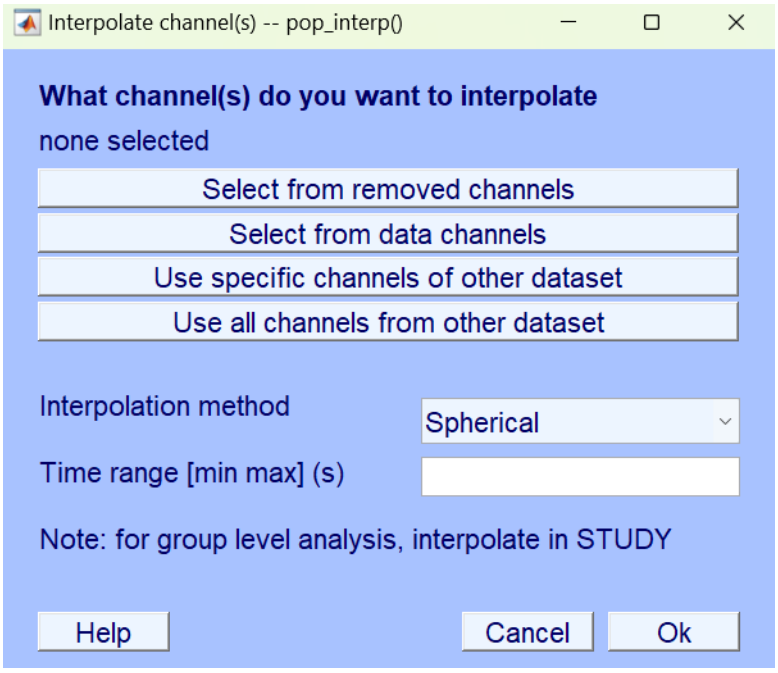

Figure 21: Interpolating data for removed channels

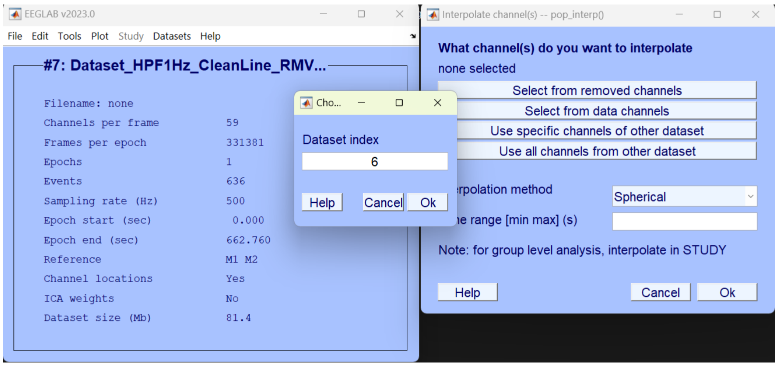

Figure 22: Interpolating data for removed channels

10. *Re-reference to Average*

The data was re-referenced to the average of all channels, a common approach to normalize the signals across the scalp.

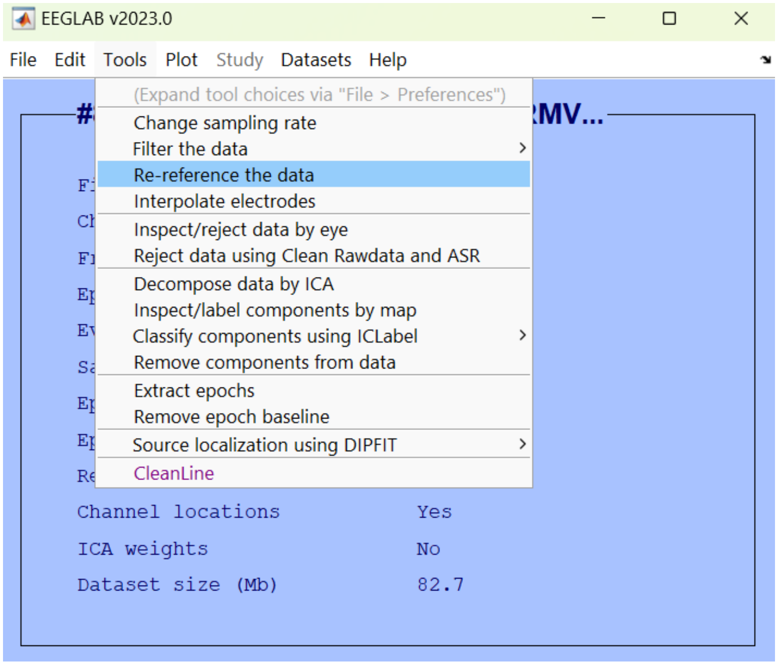

Figure 23: Re-referencing data to the average of all channels

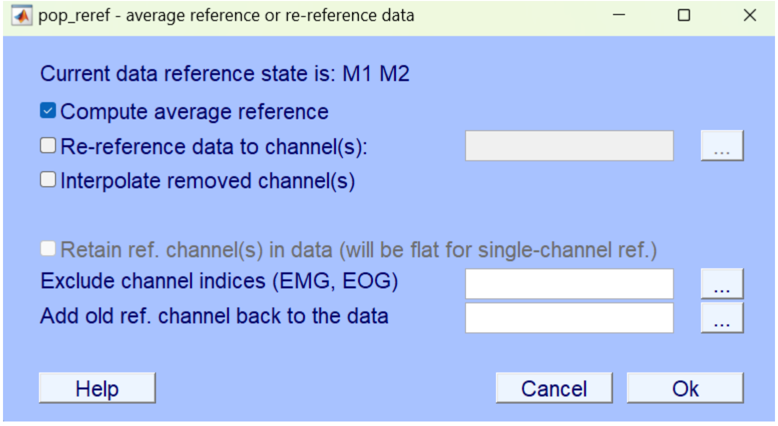

Figure 24: Re-referencing data to the average of all channels

11. Apply Artifact Subspace Reconstruction (ASR)

We applied ASR to remove transient high-amplitude artifacts. We set the artifact threshold to a reasonable maximum, focusing on performing artifact correction while preserving neural signal.

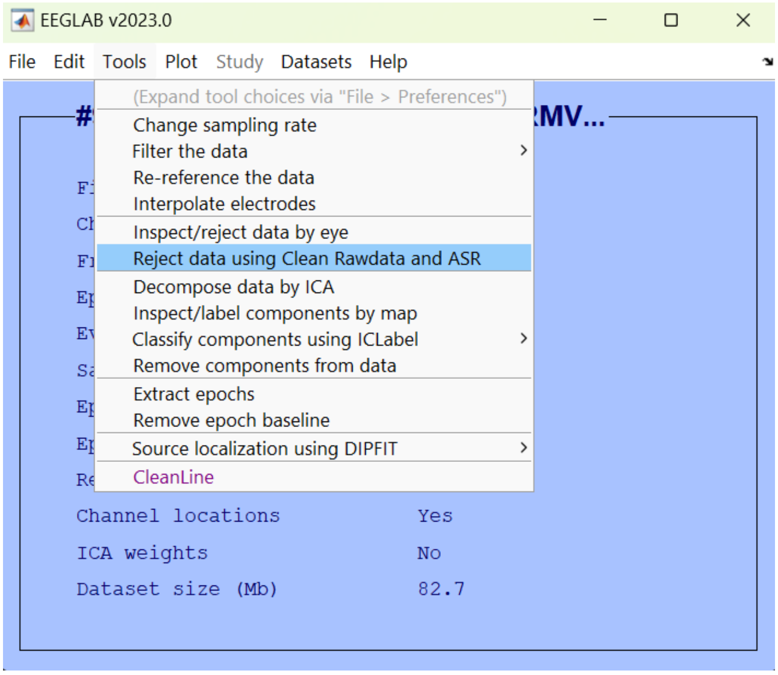

Figure 25: Applying ASR for artifact removal

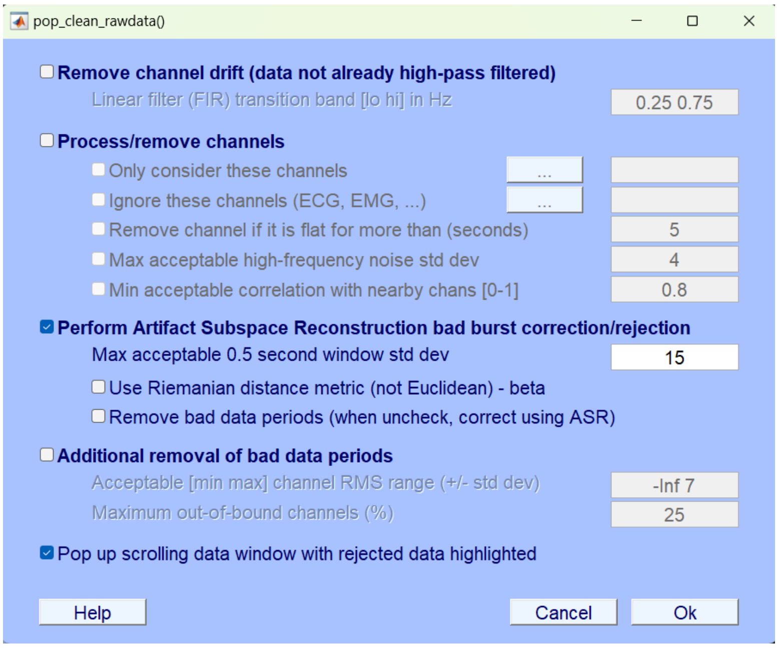

Figure 26: Applying ASR for artifact removal

12. *Re-reference Again to Average (Post-ASR)*

We re-referenced the data to the average again after ASR, to ensure a stable and consistent baseline across channels.

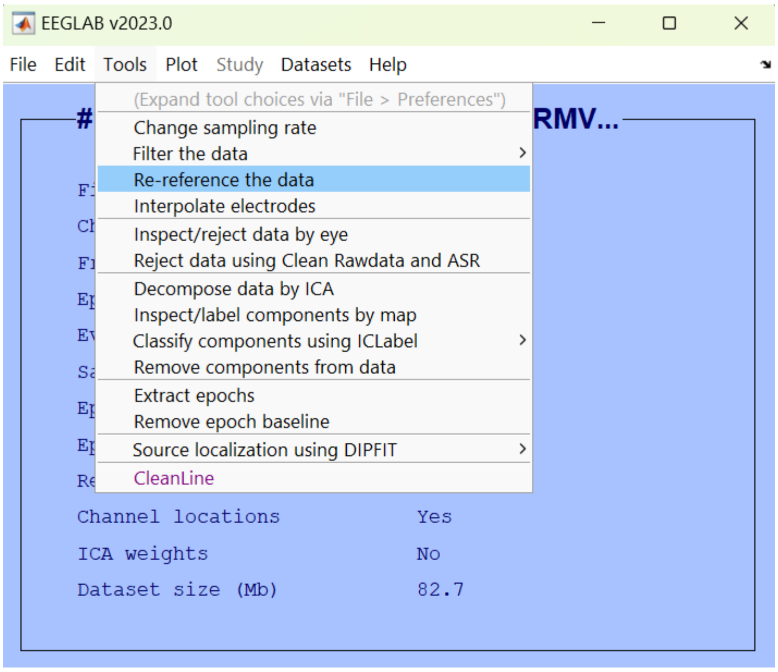

Figure 27: Second re-referencing to average after ASR

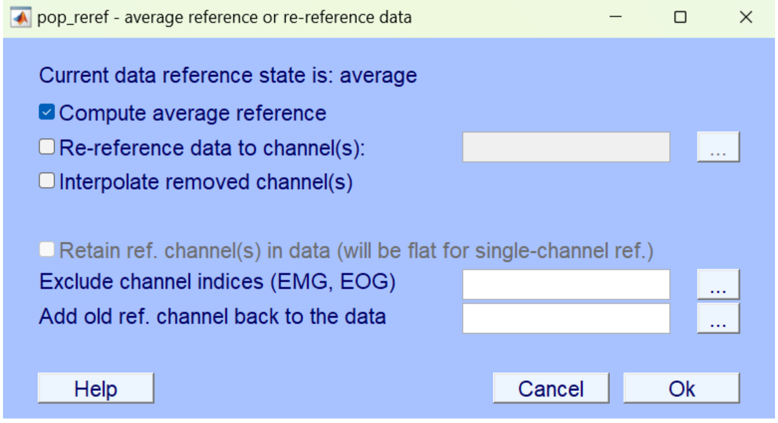

Figure 28: Second re-referencing to average after ASR

13. Perform Independent Component Analysis (ICA)

Using ICA, we decomposed the EEG data into independent components. This separation enabled us to identify and remove components representing non-neural artifacts.

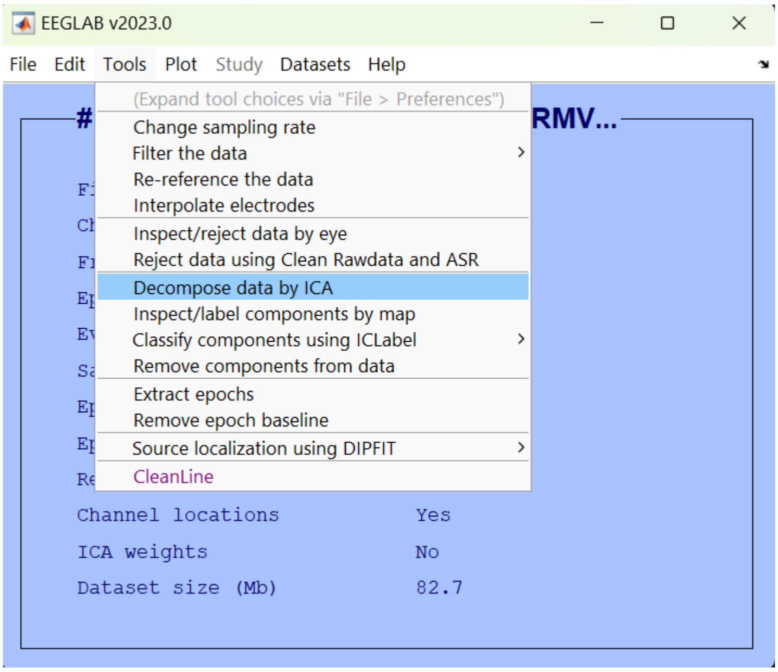

Figure 29: Performing ICA decomposition

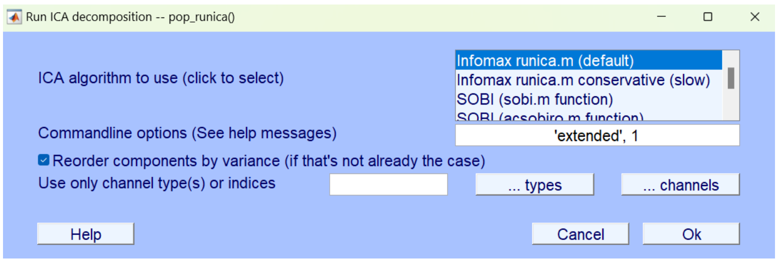

Figure 30: Performing ICA decomposition

14. Classify Components Using ICLabel

We used ICLabel to classify ICA components, identifying those corresponding to eye blinks, muscle artifacts, and other noise sources.

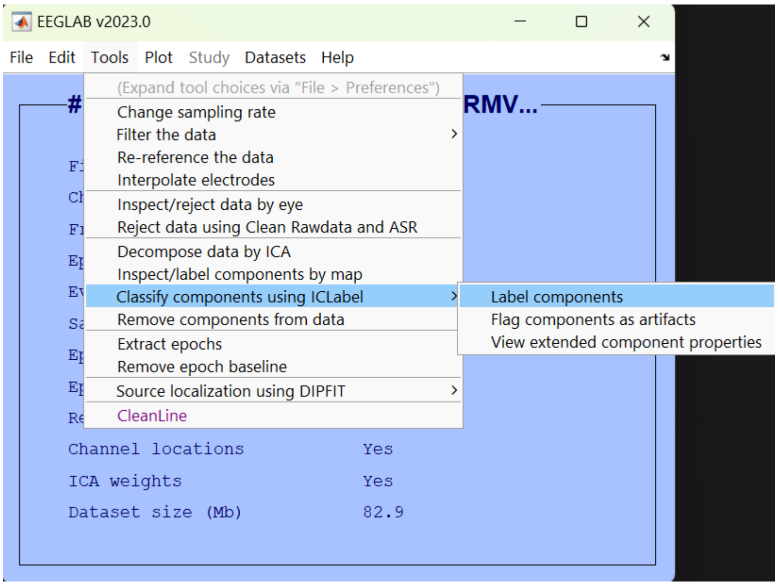

Figure 31: Classifying components using ICLabel

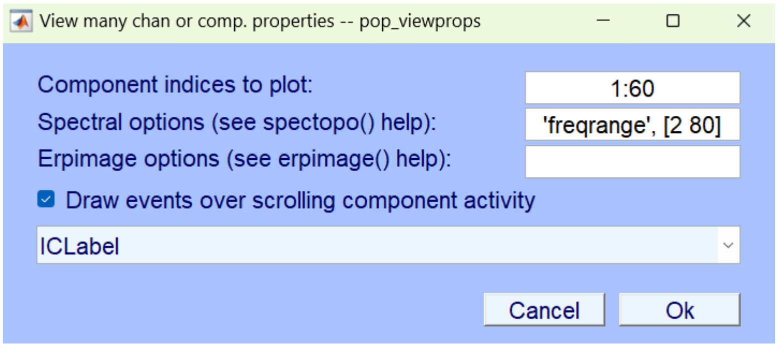

Figure 32: Classifying components using ICLabel

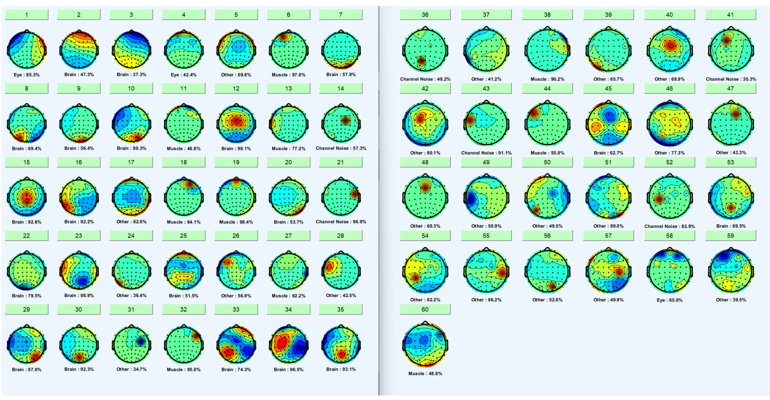

Figure 33: Classifying components using ICLabel

15. Remove Artifact Components

We removed the artifact components identified by ICLabel to retain only brain-related components in the data.

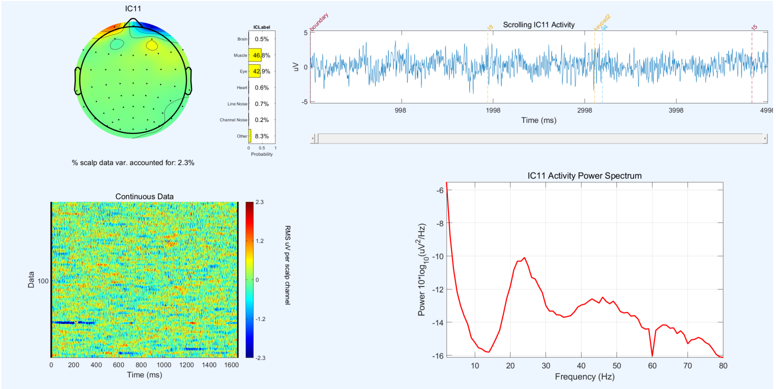

Figure 34: Removing artifact components from the data

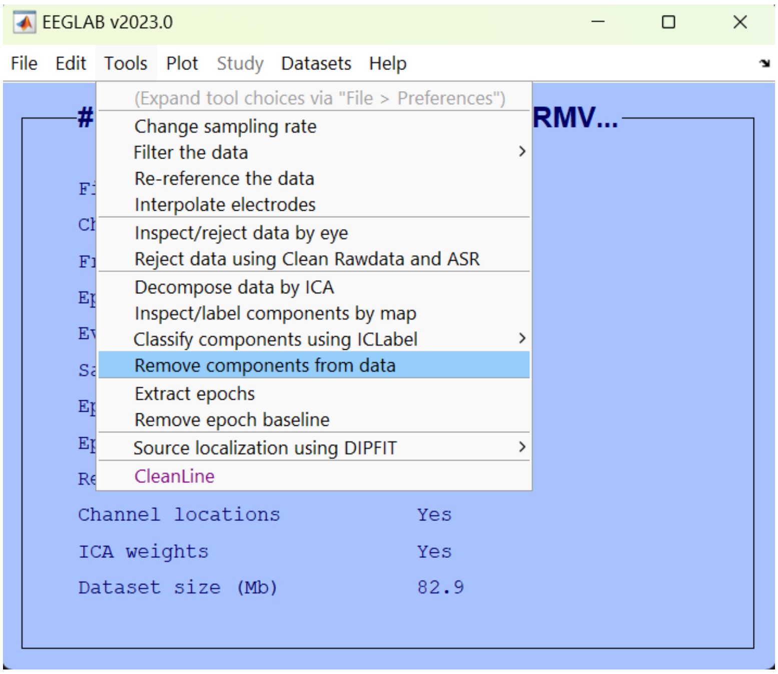

Figure 35: Removing artifact components from the data

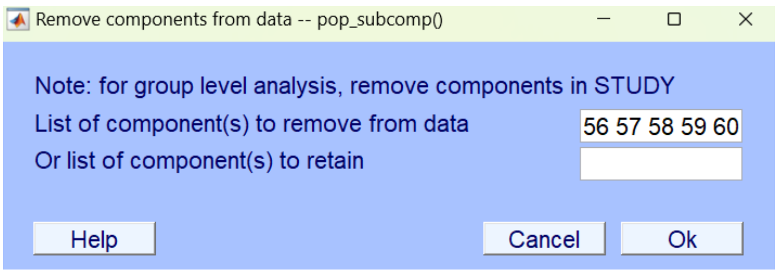

Figure 36: Removing artifact components from the data

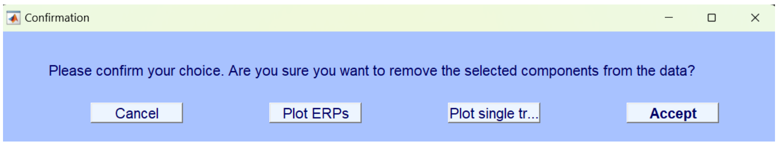

Figure 37: Removing artifact components from the data

16. *Extract Epochs*

After cleaning, we segmented the continuous data into epochs around specific events (see Table 1). Each epoch was defined by its start and end times based on the task's requirements.

Event Name	**Start Time (seconds)**	**End Time (seconds)**
Stimulus	-0.5	1
Reward (Positive Feedback)	-0.5	1
Punishment (Negative Feedback)	-0.5	1
Response (Action)	-1	0.5

Table 1: Epoch start and end times for each event type

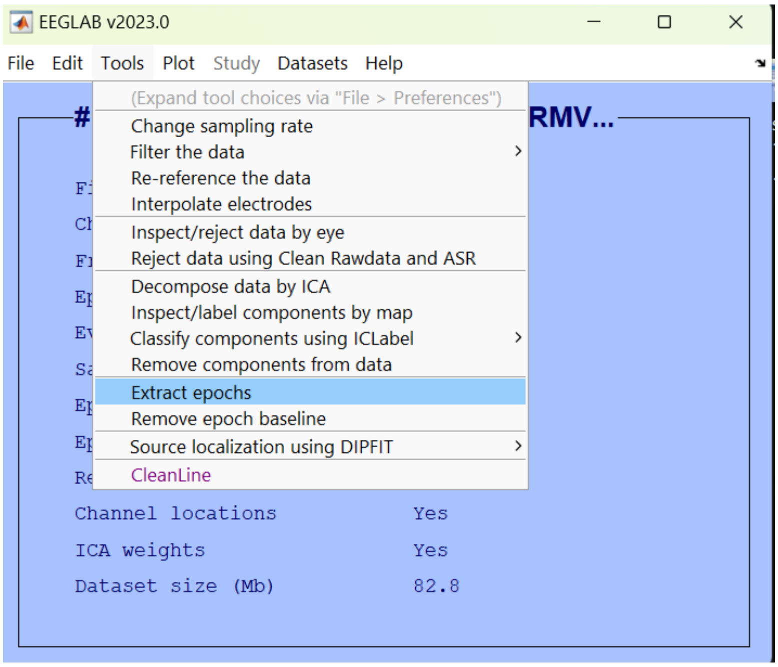

Figure 38: Extracting epochs based on events

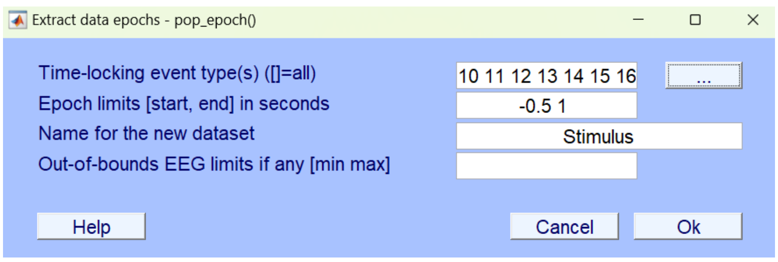

Figure 39: Extracting epochs based on events

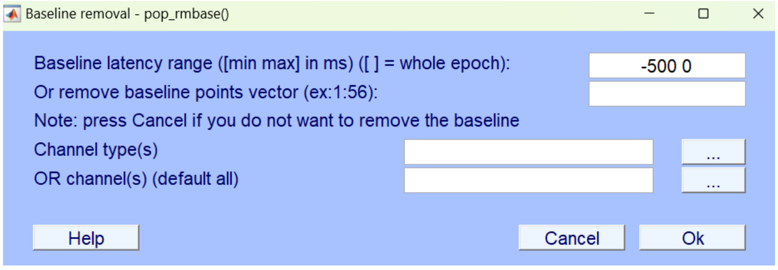

Figure 40: Extracting epochs based on events

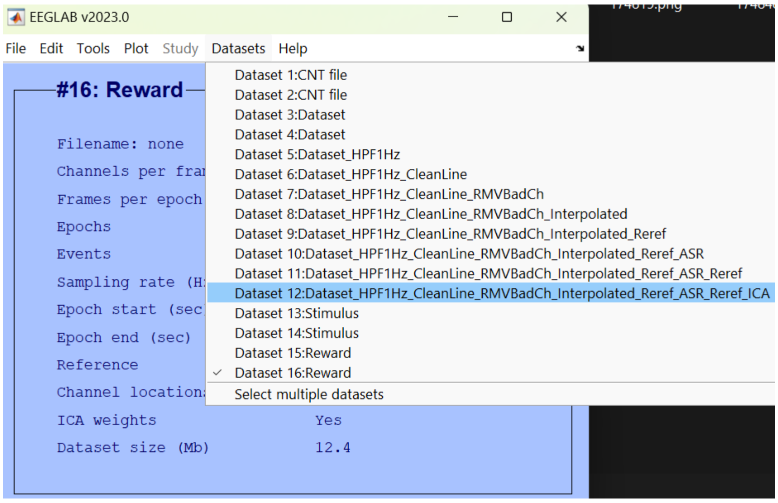

Figure 41: Extracting epochs based on events

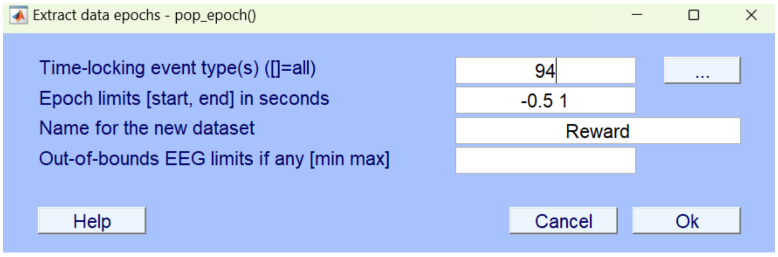

Figure 42: Extracting epochs based on events

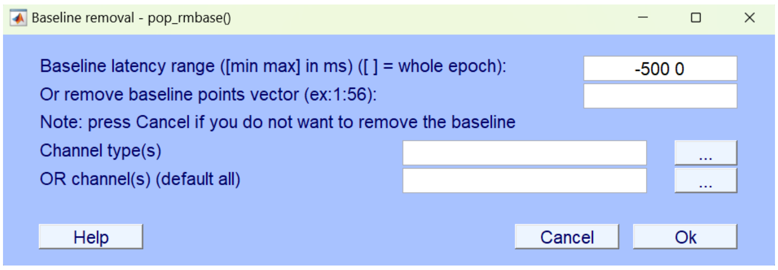

Figure 43: Extracting epochs based on events

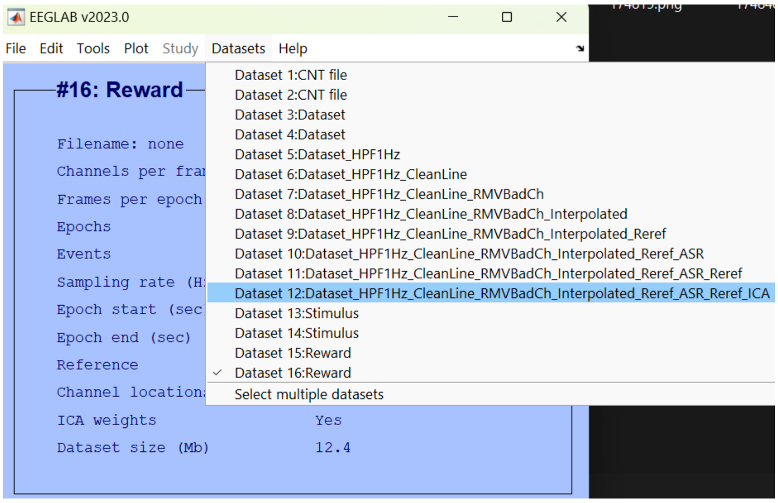

Figure 44: Extracting epochs based on events

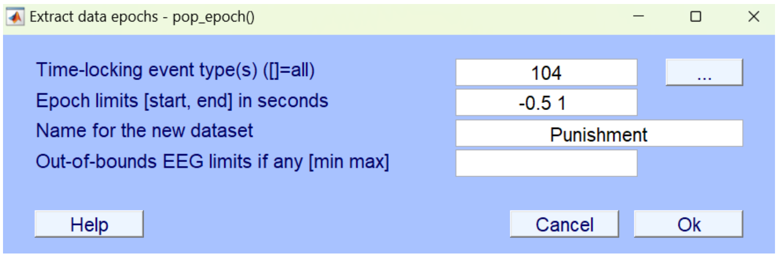

Figure 45: Extracting epochs based on events

17. Save the Epochs

Finally, we saved the cleaned and segmented epochs for further analysis.

Component Removal Justification

After completing the preprocessing steps, each ICA component was carefully reviewed to determine whether it should be retained or removed. The criteria for making this decision included the following common indicators:

1. **Absence of a peak at 10 Hz (Alpha Rhythm)**: Components that represent brain activity, especially from occipital areas, typically exhibit a peak around 10 Hz in the power spectrum. Components without this characteristic were considered for removal, as they are less likely to represent meaningful neural data.

2. **Deviation from a 1/f Spectral Pattern**: Neural data often display a 1/f pattern in the power spectrum, where power decreases as frequency increases. Components lacking this 1/f pattern, especially those with unusual spectral peaks, were marked for removal as they might represent artifacts rather than true brain signals.

3. **Eye Movement Artifacts (EOG contamination)**: Components showing strong activation patterns consistent with eye blinks or lateral eye movements (characteristic spikes around the frontal region in the spatial topography) were removed. These artifacts can be identified by their distinct patterns in both spatial and spectral domains, often with a high amplitude in lower frequencies.

4. **Muscle Activity (EMG contamination)**: Muscle artifacts typically appear in higher frequencies, often above 20 Hz, with irregular and high-power spectral peaks. Components with these characteristics were removed to prevent contamination of neural signals with muscle noise.

5. **Heartbeat (ECG contamination)**: Some ICA components may capture cardiac activity, which can often be identified by its distinct rhythmic pattern, typically around 1 Hz. Components with this characteristic were considered for removal to avoid interference from physiological noise.

6. **Artifacts from Head Movement or External Interference**: Components that displayed unusual spatial patterns or inconsistencies across time, likely due to head movements or external electronic interference, were also marked for removal to ensure cleaner data.

Each component was analyzed based on these criteria to ensure that only meaningful neural components were retained for further analysis. Components that did not meet these criteria were removed, as they were likely to represent noise or non-neural artifacts rather than genuine brain activity.

Here are the removed components for Depressed subject number 571 and the reasons:

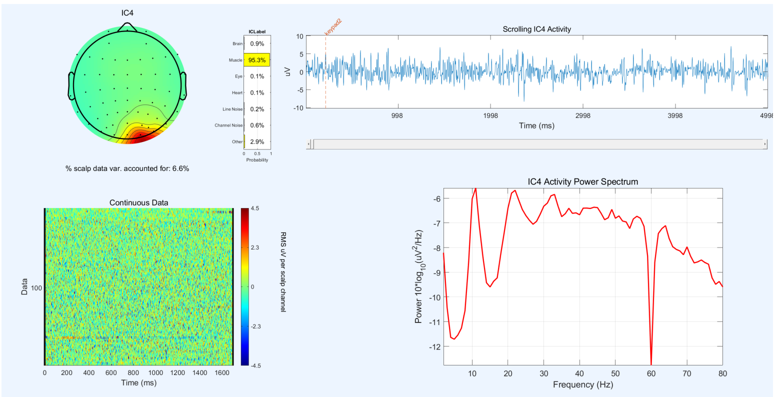

Figure 46: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern - Oscillation

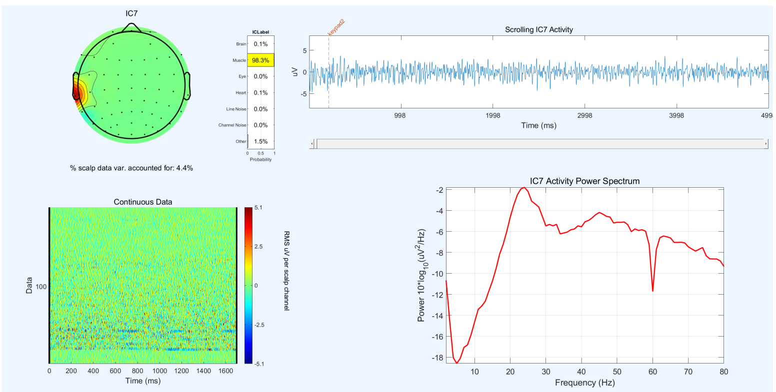

Figure 47: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

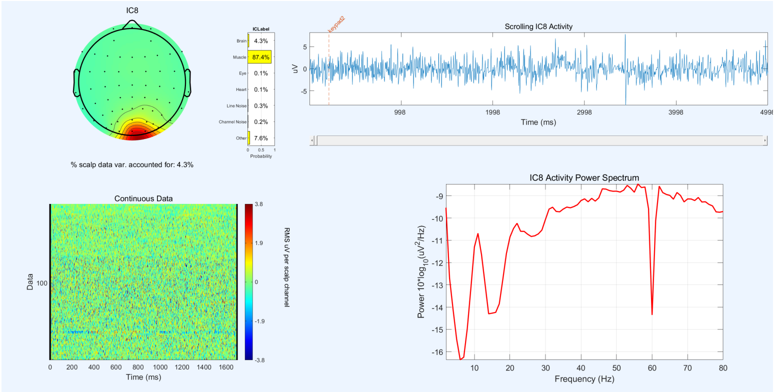

Figure 48: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

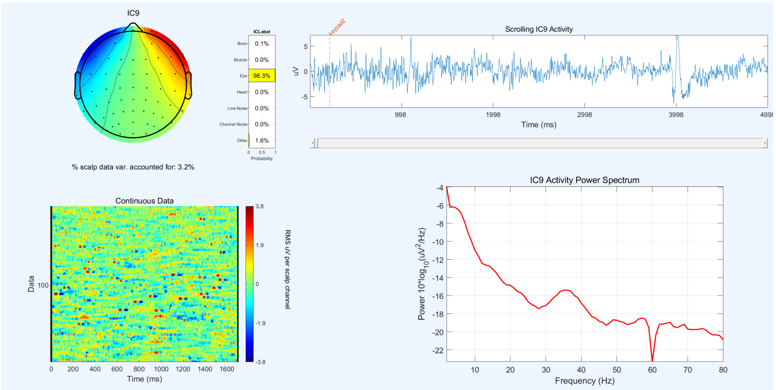

Figure 49: Absence of a peak at 10 Hz - Similar to Eye Movement Artifacts

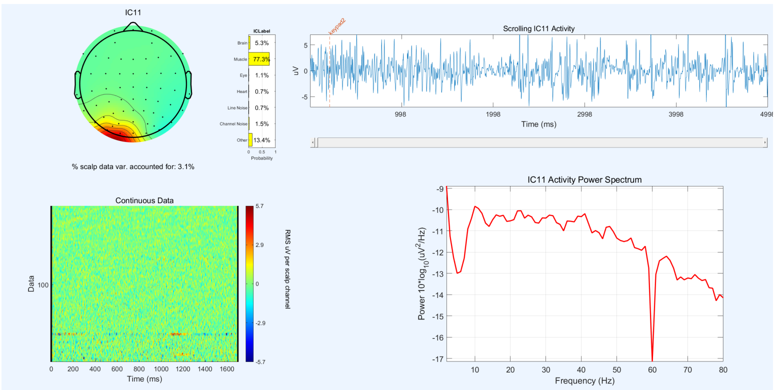

Figure 50: Deviation from a 1/f Spectral Pattern - Similar to Artifacts

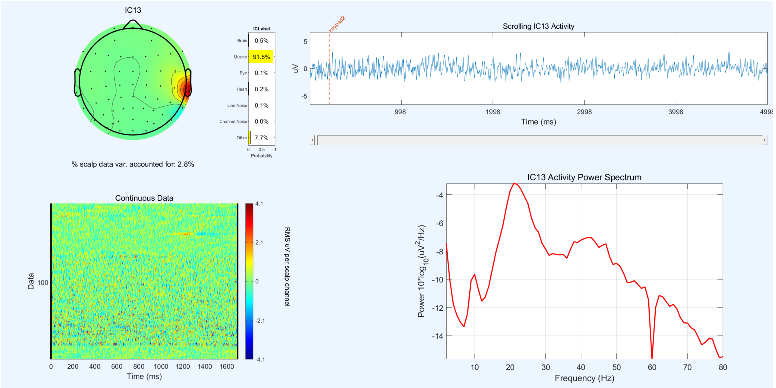

Figure 51: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

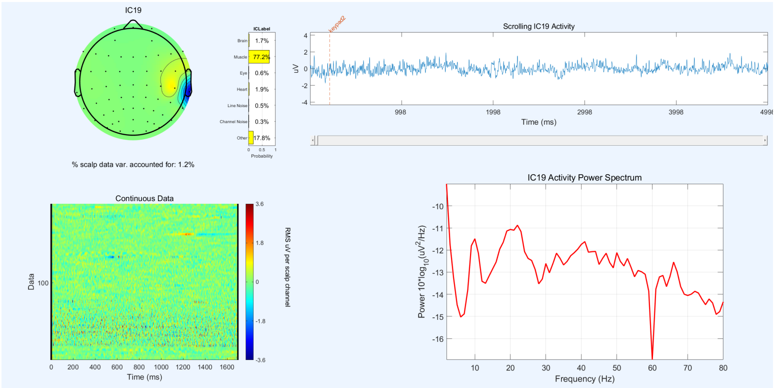

Figure 52: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

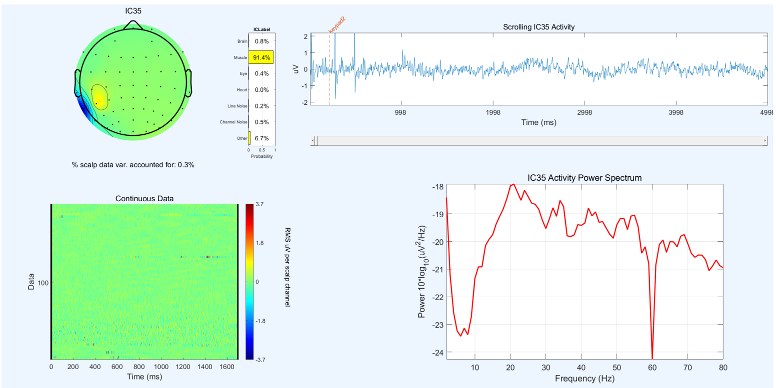

Figure 53: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

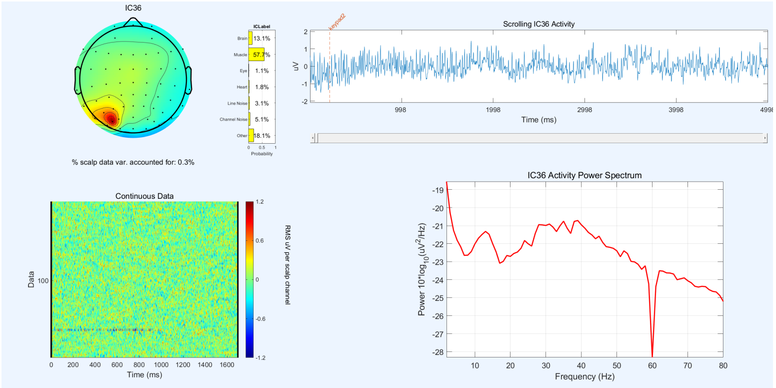

Figure 54: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern

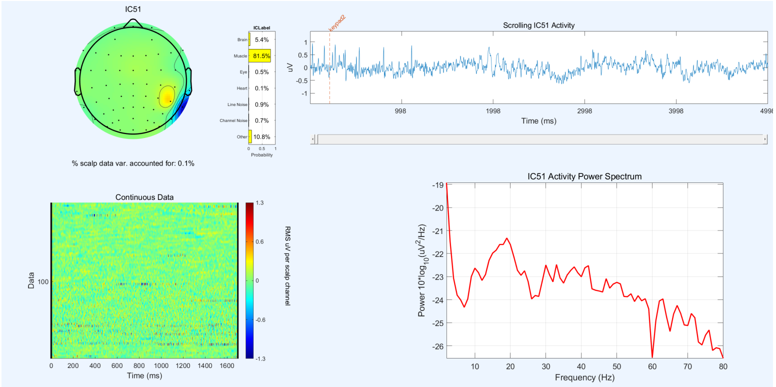

Figure 55: Absence of a peak at 10 Hz - Deviation from a 1/f Spectral Pattern - Oscillations

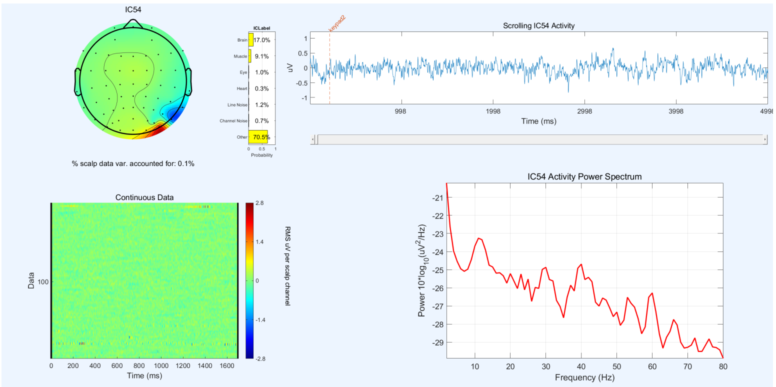

Figure 56: Absence of a peak at 10 Hz - Oscillations

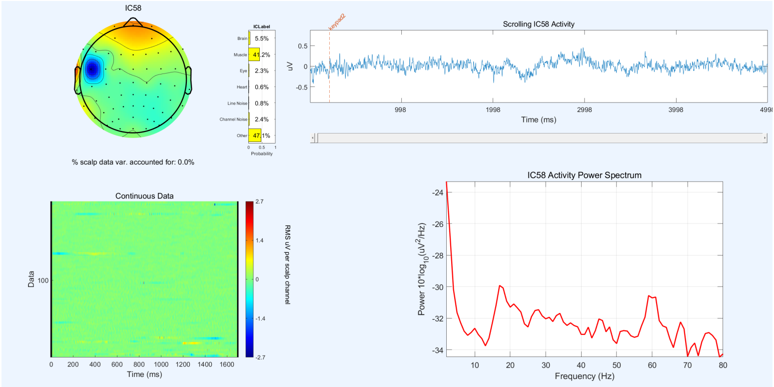

Figure 57: Absence of a peak at 10 Hz - Similar to Artifacts

Event-Related Potential (ERP)

All Codes are available in the `Assignment_1.ipynb` uploaded file.

Question 1

1. Research what event-related potential (ERP) means in EEG signals. How is it calculated, and why is ERP used in EEG signal analysis?

Soloution

Definition: An Event-Related Potential (ERP) is a measured brain response that is the direct result of a specific sensory, cognitive, or motor event. ERPs are small, time-locked voltage fluctuations in the EEG that reflect the brain's response to particular stimuli or tasks. They are widely used in cognitive neuroscience to study the timing and neural processes associated with various cognitive functions, such as perception, attention, and decision-making.

Calculation Methods: ERP calculation involves averaging EEG segments (epochs) that are time-locked to repeated presentations of the same stimulus or event. This process enhances the signal related to the event while reducing background noise and random activity. The typical steps for calculating ERP are:

1. Segment the continuous EEG data into epochs around the event of interest (e.g., stimulus onset) with a pre-defined time window (e.g., -200 ms to 800 ms).
2. Perform baseline correction for each epoch to remove slow drifts.
3. Average the epochs for each event type, aligning the time of the event onset in each segment. This averaging process emphasizes the brain's consistent response to the event while reducing unrelated noise.

Importance: ERPs are valuable in EEG analysis because they provide insights into how the brain processes stimuli. By analyzing ERP components (such as N100, P200, and P300), researchers can infer specific neural processes related to sensory processing, attention, and cognitive functions. ERPs allow researchers to measure the timing and amplitude of brain responses with high temporal precision, making them essential tools in cognitive and clinical neuroscience.

Question 2

1. Investigate the P300 and FRN, two well-known ERP features. What events in the brain do each of these features describe?

Soloution

P300: The P300 is a positive ERP component that typically peaks around 300 milliseconds after a stimulus. It is associated with attention and cognitive processing, often observed in tasks requiring stimulus discrimination. The P300 is commonly elicited in oddball paradigms, where subjects respond to infrequent, target stimuli. The amplitude and latency of the P300 provide insights into cognitive processes such as attention allocation and working memory.

Soloution

FRN (Feedback-Related Negativity): FRN is a negative deflection that occurs approximately 200-300 milliseconds after feedback, especially when feedback is unexpected or indicates an error. It reflects the brain's response to feedback and is often used to study reinforcement learning and decision-making processes. FRN amplitude is thought to correlate with the evaluation of prediction errors, making it a valuable indicator of reward processing in the brain.

Question 3

1. Load the preprocessed data into Python. You can use the MNE toolbox to load the EEG data files exported from EEGLAB.

Soloution

Loading Data in Python: To load the preprocessed EEG data into Python, we use the MNE toolbox, which provides efficient functions for reading '.set' files (EEGLAB format).

Question 4

1. Based on the figure below, retain only the highlighted channels and discard the rest.

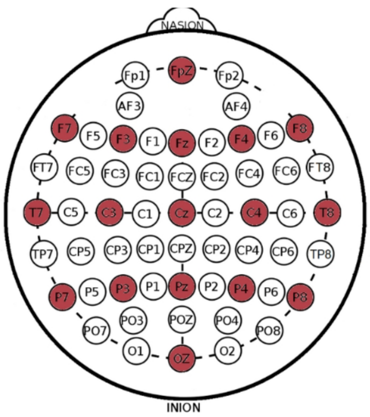

Figure 58: Selected channels for analysis (highlighted in red)

Soloution

Channel Selection: Using the highlighted channels in the figure below, we selected only these channels for further analysis, discarding the rest. This allows us to focus on relevant regions of interest in the EEG data.

Question 5

1. To improve the comparison of ERP signals, normalize the data using the **z-score** calculation across time, for each trial, and for each channel. The z-score formula is given below:

$$x_{zscore}(n) = \frac{x(n) - \text{mean}(x(n))}{\text{std}(x(n))} \tag{1}$$

Soloution

This function calculates the mean and standard deviation along the time axis (axis=2) for each trial and channel, then applies the z-score formula to normalize the data accordingly.

```
def normalize_with_zscore(data_dict):
    for group in data_dict:
        for subj in data_dict[group]:
            epochs = data_dict[group][subj]
            data = epochs.get_data()

            normalized_data = zscore(data, axis=-1)
            epochs._data = normalized_data
```

Question 6

Calculate and plot the preprocessed ERP data for the **Stimulus** event on channels **Fz** and **Pz** for the first 5 trials from the data of one healthy individual and one individual with depression.

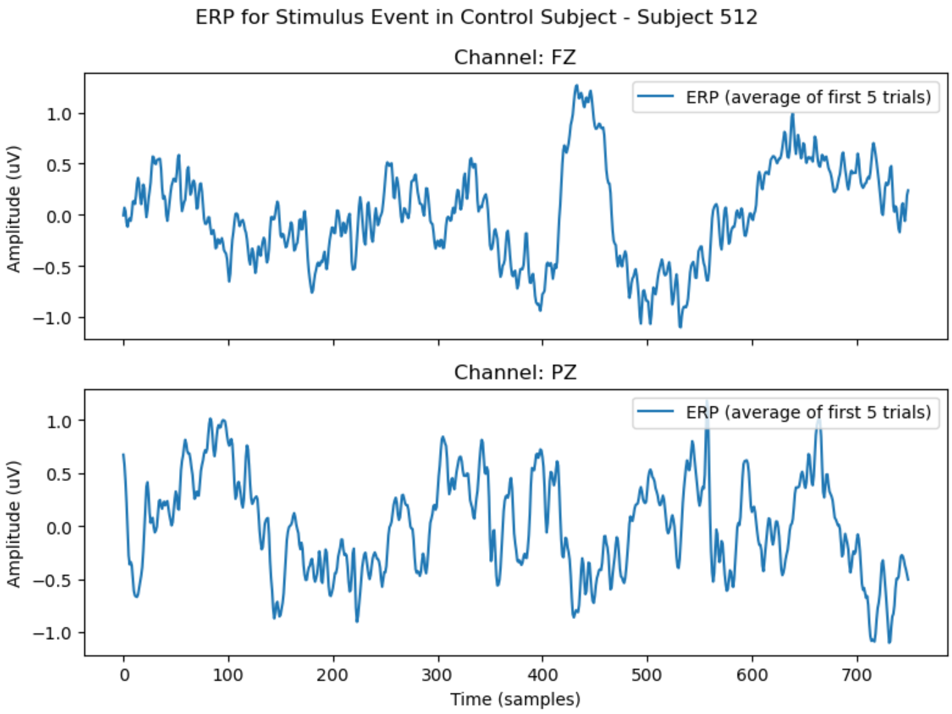

Figure 59: ERP for Stimulus Event in Healthy Individual

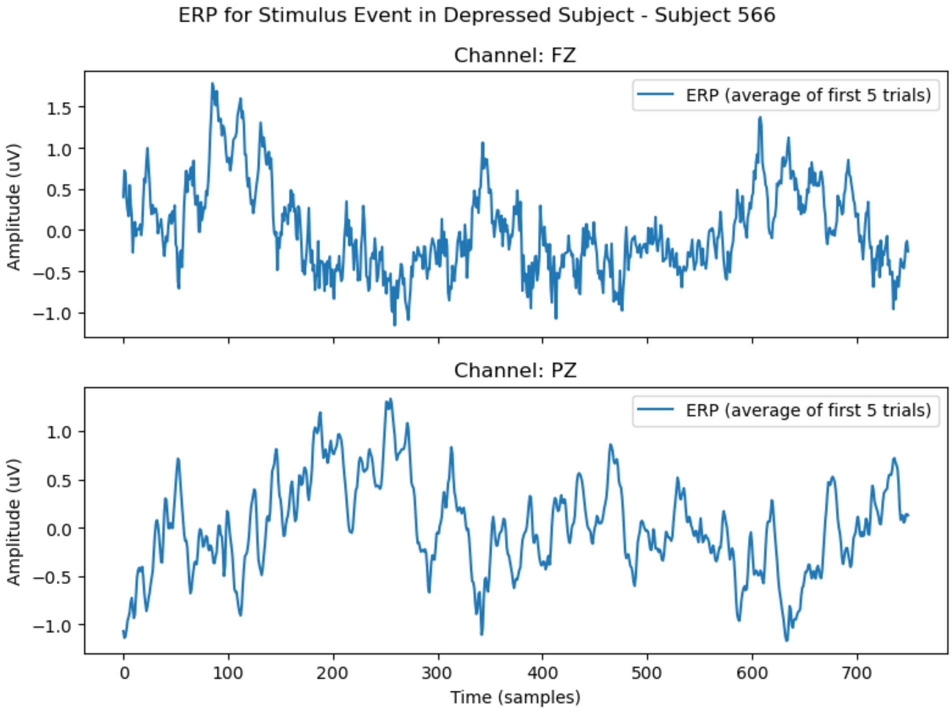

Figure 60: ERP for Stimulus Event in Depressed Individual

Question 7

Calculate and plot the ERP on channels **Fz** and **Pz** for the first 10, 15, and 20 trials from the same data of the same individuals, and compare the results with the previous section. Explain how increasing the number of trials affects the ERP.

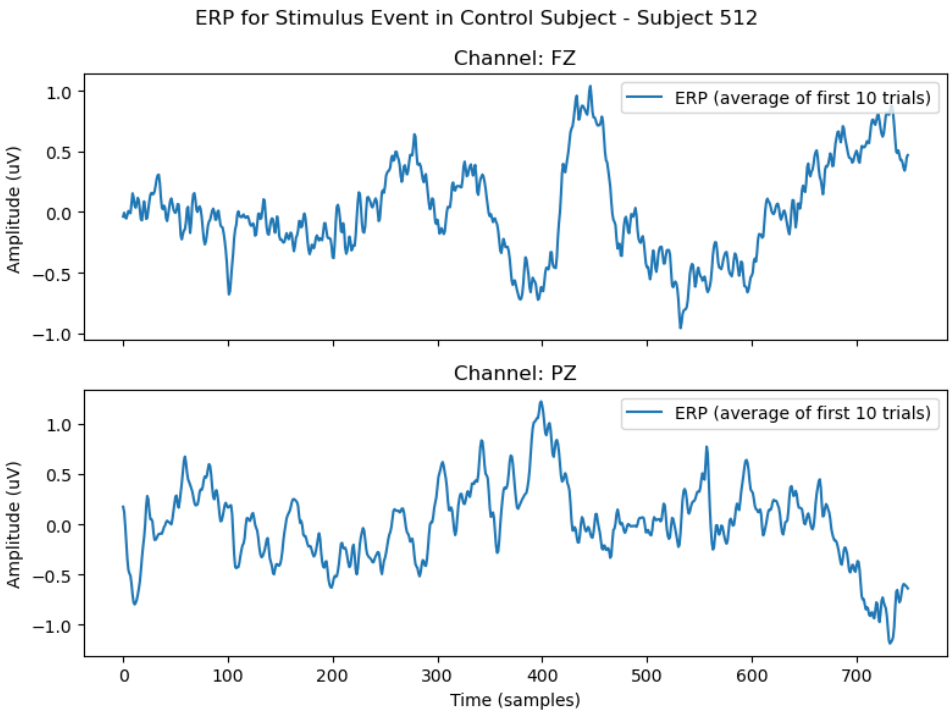

Figure 61: ERP for Stimulus Event on Channels Fz and Pz (Healthy Individual - 10 Trials)

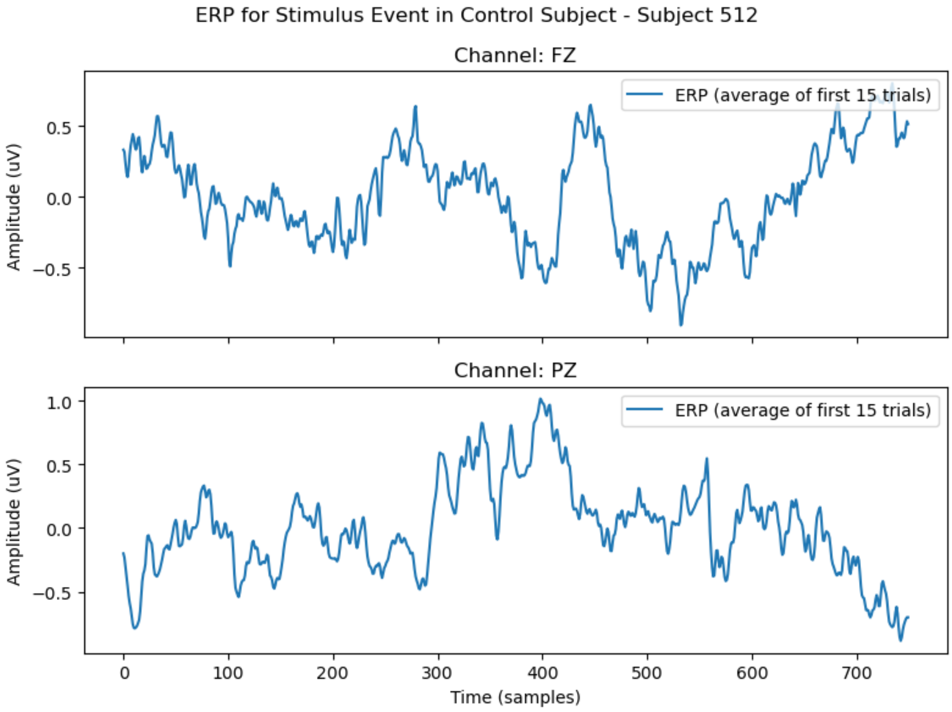

Figure 62: ERP for Stimulus Event on Channels Fz and Pz (Healthy Individual - 15 Trials)

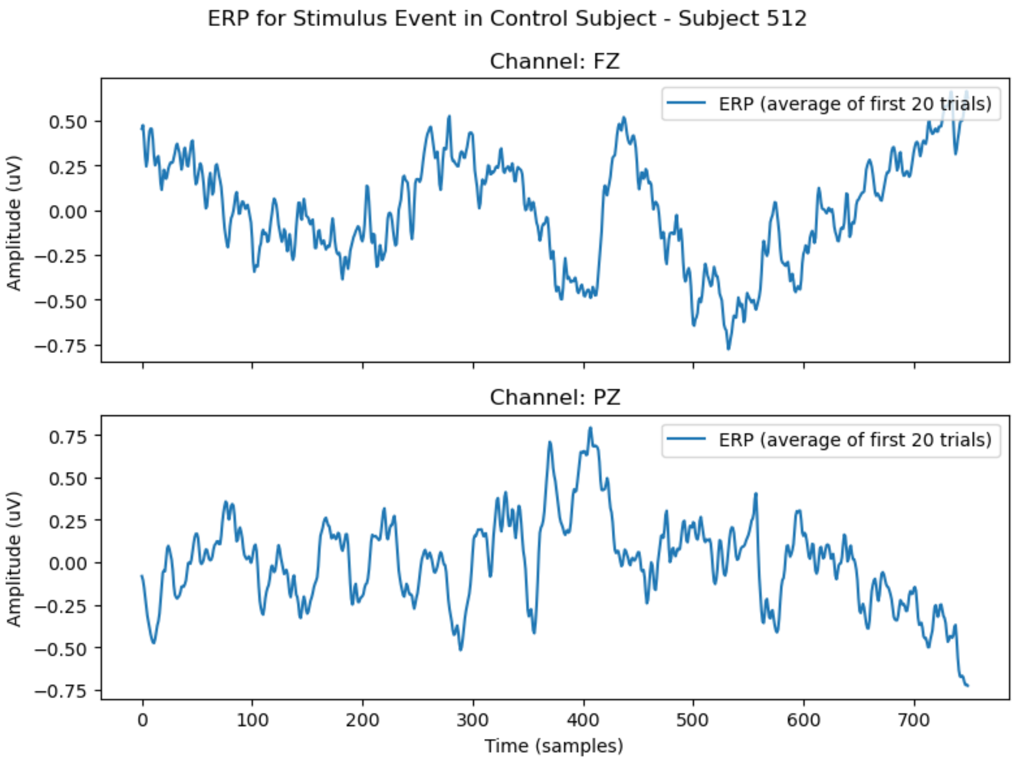

Figure 63: ERP for Stimulus Event on Channels Fz and Pz (Healthy Individual - 20 Trials)

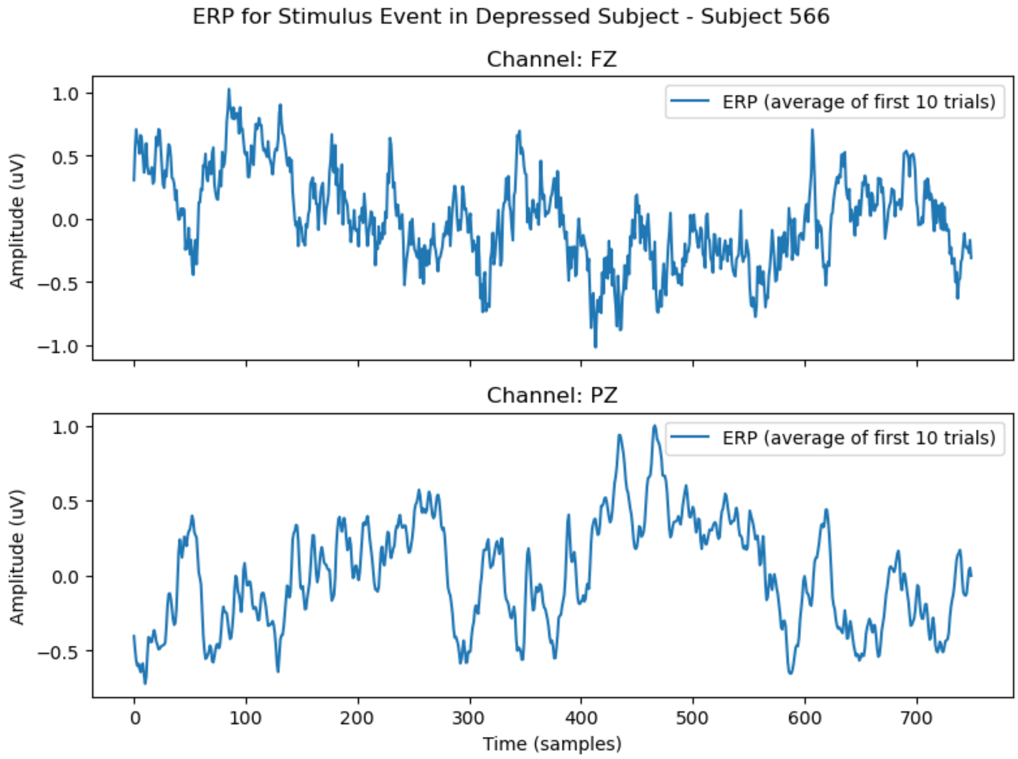

Figure 64: ERP for Stimulus Event on Channels Fz and Pz (Depressed Individual - 10 Trials)

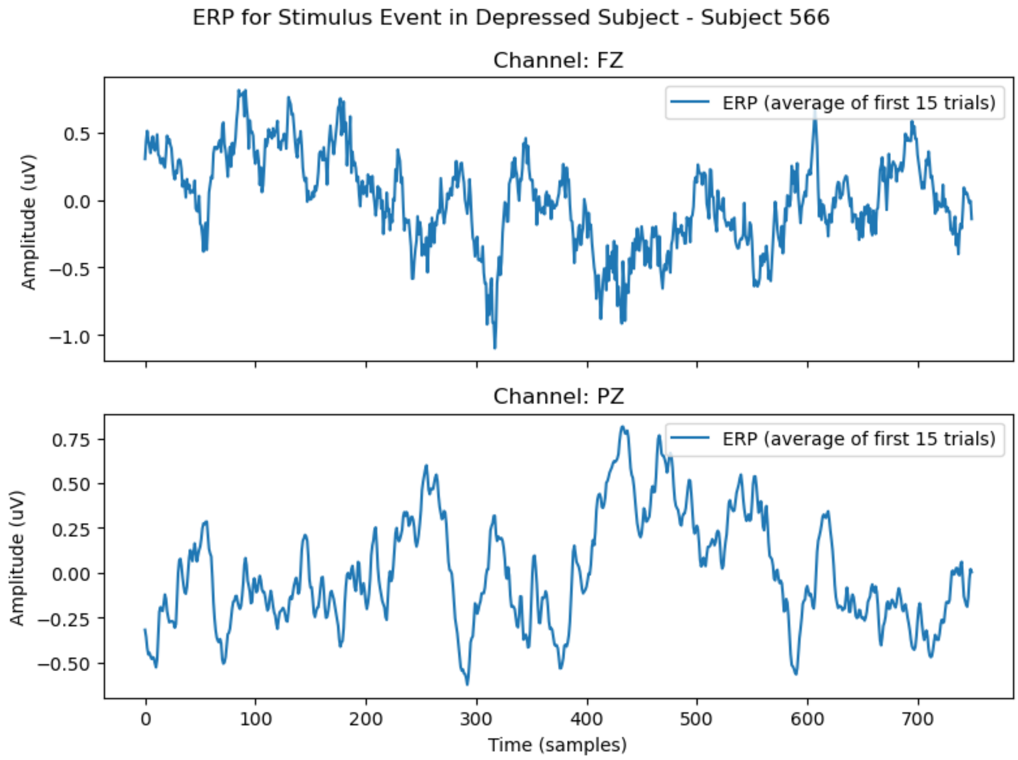

Figure 65: ERP for Stimulus Event on Channels Fz and Pz (Depressed Individual - 15 Trials)

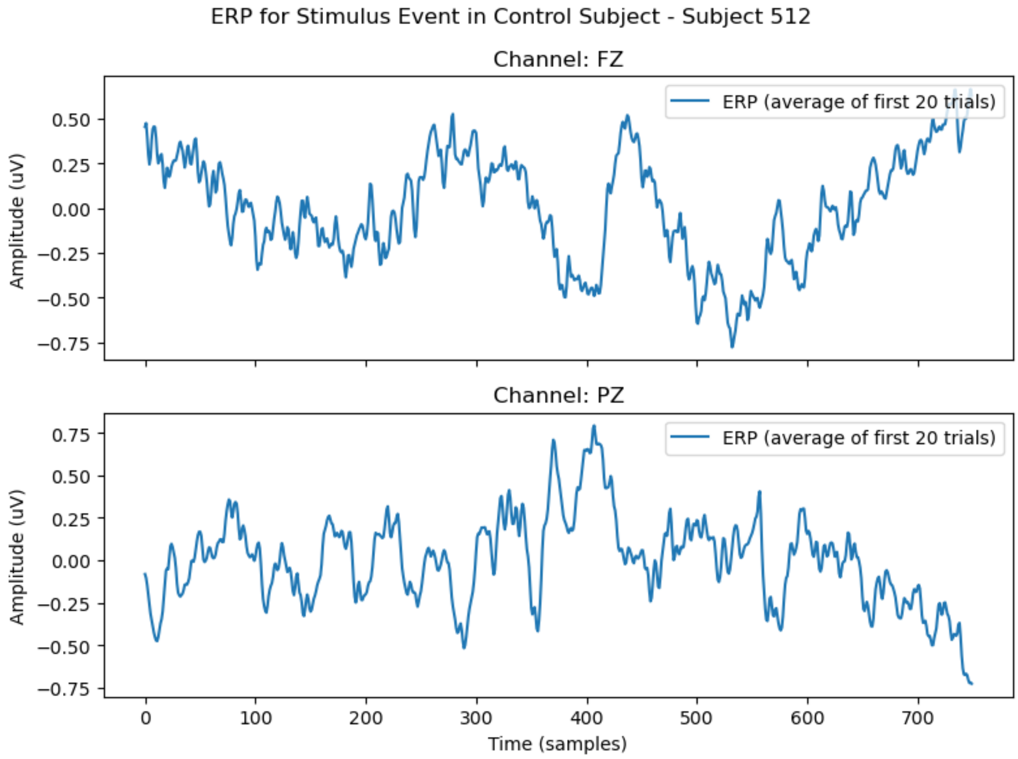

Figure 66: ERP for Stimulus Event on Channels Fz and Pz (Depressed Individual - 20 Trials)

Soloution

Explanation: Calculating the ERP for increasing numbers of trials helps to stabilize the signal by reducing the influence of noise. As more trials are averaged, random noise tends to cancel out, making the ERP waveform clearer and more representative of the brain's response to the stimulus. Below are the ERP plots for channels Fz and Pz, averaged over the first 5, 10, 15, and 20 trials, comparing both a healthy individual and a depressed individual.

Analysis: - Effect of Increasing Trials: As the number of trials increases (5, 10, 15, 20), the ERP waveform becomes more stable, and the amplitude fluctuations due to random noise decrease. This results in a cleaner ERP signal, where the underlying brain response is more distinct.
- Comparison with Previous Section: Comparing these plots with the results from Question 6 (using fewer trials) shows that a higher number of trials improves the clarity of ERP components, such as the P300 and N100 peaks.
- Depressed vs. Healthy Individual: There are notable differences in ERP characteristics between the healthy and depressed individuals, especially as more trials are averaged, which may reflect differences in neural processing or attention.

Question 8

Calculate the ERP signal for the **Reward** and **Punishment** events on channels **Fz** and **Pz** for 10 subjects.

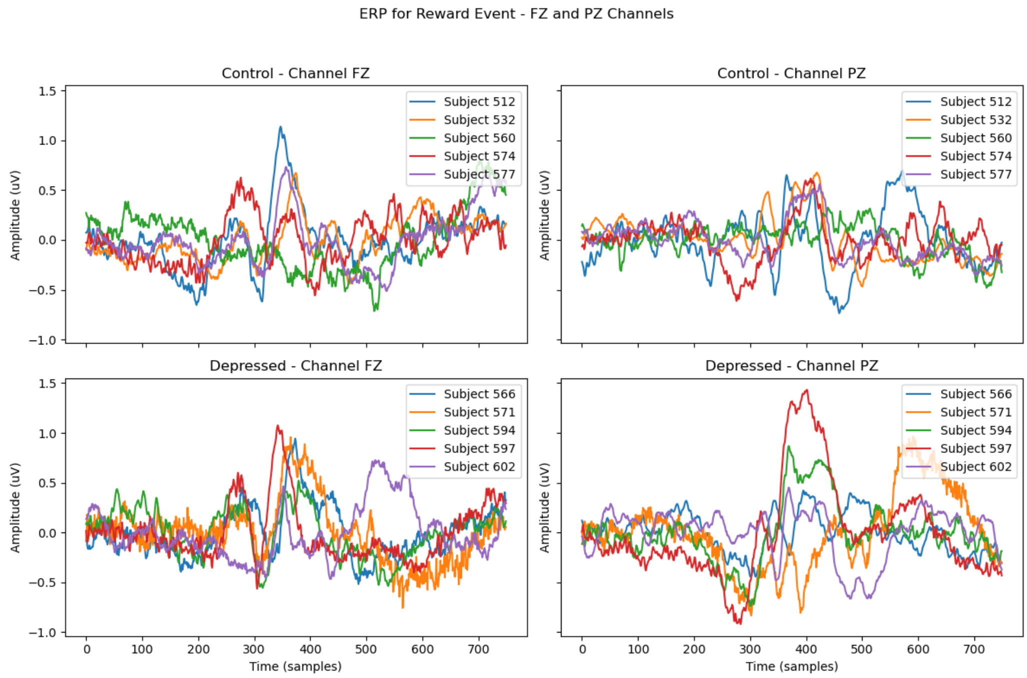

Figure 67: ERP for Reward Event - FZ and PZ Channels

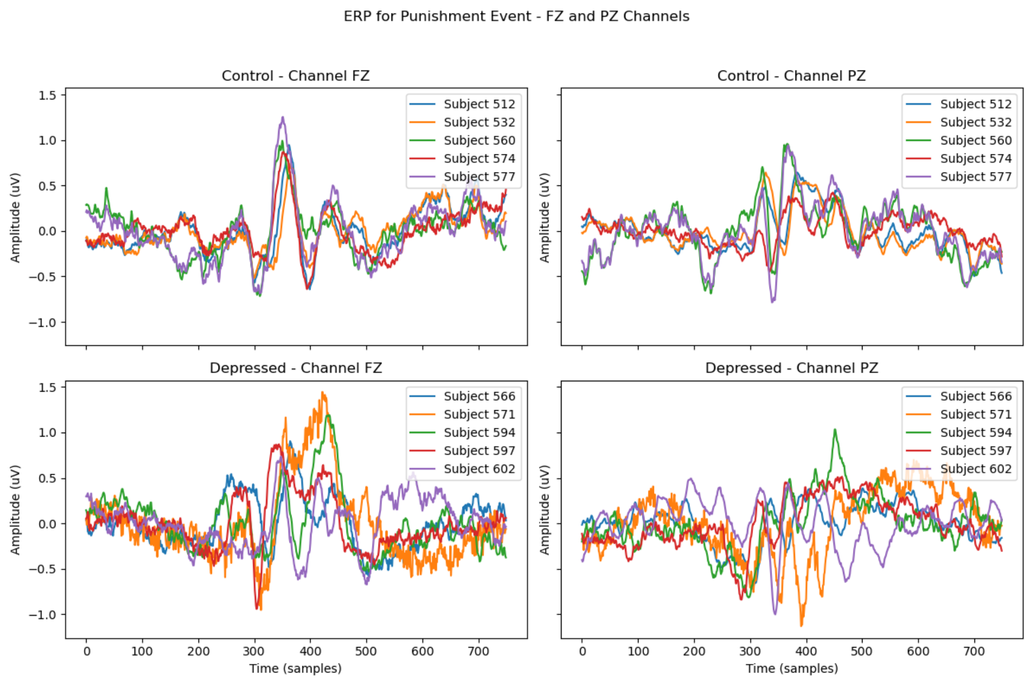

Figure 68: ERP for Punishment Event - FZ and PZ Channels

Question 9

Plot the ERP signals separately for each channel and event, for all subjects (all healthy and all depressed). Ensure that the ERP for all subjects is plotted on the same graph to identify common features. Is there any difference between the ERPs related to the **Reward** and **Punishment** events? Is there a difference between channels **Fz** and **Pz** in response to Reward or Punishment events? Interpret the results.

Soloution

Figures are plotted in the previous question.

Analysis and Observations

- Reward Event: In the Reward ERP, healthy Individuals tend to show a more consistent pattern of positive deflections across both channels (Fz and Pz), indicating a stable response to positive feedback. Depressed Individuals, however, display greater variability in their ERP responses, particularly in the Pz channel, where the amplitude and timing of peaks differ significantly between individuals.
- Punishment Event: The Punishment ERP results exhibit distinct patterns between the two groups. Healthy Individuals again show more uniform ERP responses, especially in channel Fz. Depressed Individuals, however, demonstrate higher amplitude variability and less defined ERP components, particularly in the Fz channel, which may indicate different cognitive or emotional processing of negative feedback.
- Channel Differences (Fz vs. Pz): Across both events, channel Fz shows larger amplitude responses compared to Pz, particularly in the Reward condition. This may indicate that the frontal region (represented by Fz) is more responsive to feedback processing, possibly due to its involvement in cognitive and emotional regulation.
- Group Differences (Healthy vs. Depressed): Depressed subjects exhibit higher variability in their ERP responses compared to healthy subjects, with less consistent ERP peaks. This variability may reflect differences in cognitive processing or emotional response to feedback in depressed individuals.
- Common Features: Both groups show some shared features in their ERPs for the Reward and Punishment events, such as a general positive deflection for Reward around 300-500 ms post-stimulus. However, the variability in amplitude and timing between subjects, especially in the depressed group, suggests individual differences in response to feedback events.

Conclusion

These observations suggest that ERP responses for Reward and Punishment events can provide insights into neural processing differences between healthy and depressed individuals. Differences in channel response (Fz vs. Pz) further indicate region-specific processing in response to feedback, with the frontal region being particularly active.

Question 10

Calculate the ERP signal separately for all healthy and depressed subjects on channel Fz for the Reward and Punishment events, and then average the ERP of all subjects within each group to obtain the Grand Average. To show the variability, calculate the standard error (SE) of the ERP for each group. Finally, plot the Grand Average signal for each event and channel along with the standard error. Is there a difference between healthy and depressed individuals in response to Reward or Punishment events? Interpret the results.

$$SE = \frac{std(x)}{\sqrt{n}} \tag{2}$$

where $std(x)$ represents the standard deviation of the ERP signal across subjects, and n is the number of individuals in the group.

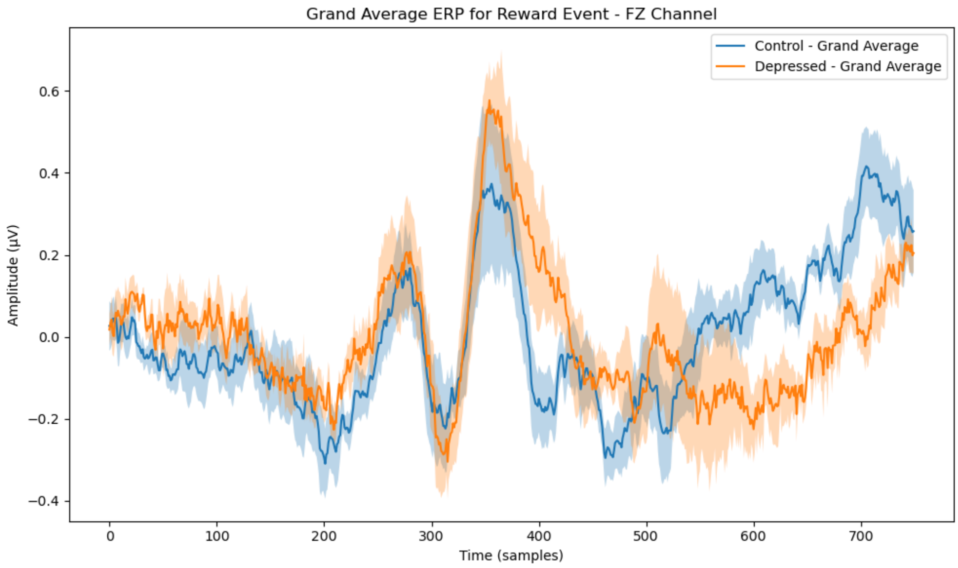

Figure 69: Grand Average ERP for Reward Event - FZ Channel with Standard Error

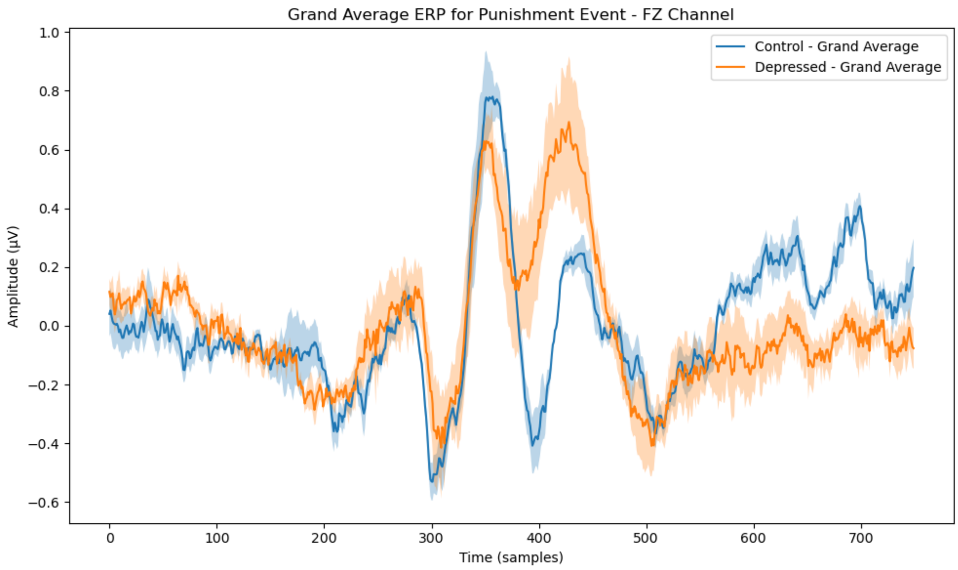

Figure 70: Grand Average ERP for Punishment Event - FZ Channel with Standard Error

Soloution

Analysis and Observations

- Reward Event: The Grand Average ERP for the Reward event shows a clear positive deflection in both healthy and depressed groups, with the healthy Individuals generally having a higher amplitude response. The standard error shaded area indicates less variability in the healthy group, suggesting more consistent responses to the Reward stimulus.
- Punishment Event: For the Punishment event, both groups display a similar pattern with a significant deflection. However, the healthy Individuals shows a more pronounced response amplitude compared to the depressed group. The standard error is larger for the depressed individuals, indicating more variability in their responses to Punishment.
- Comparison Between Groups: Overall, healthy subjects exhibit higher consistency (lower SE) in their ERP responses for both Reward and Punishment, while depressed subjects show more variability and generally lower response amplitudes. These differences could indicate variations in cognitive or emotional processing of feedback in depressed individuals compared to healthy controls.

Conclusion

These observations suggest that ERP responses for Reward and Punishment events reveal distinct patterns between healthy and depressed individuals, with the former showing stronger and more consistent ERP components. The variability in the depressed group may reflect underlying differences in neural or emotional responses to these stimuli.

Time-Frequency Characteristics

All calculations and results observed so far were done without frequency-specific analysis. However, another important method in EEG signal analysis is the examination of activity within specific frequency bands. Frequency-based analysis provides insight into different types of brain activity. Typically, EEG activity observed at the scalp can be categorized by its frequency into specific bands, each associated with unique behavioral characteristics.

In EEG signals, key frequency bands are defined as follows:

Band Name	**Frequency Range**
Delta	0.5 – 4 Hz
Theta	4 – 8 Hz
Alpha	8 – 12 Hz
Beta	12 – 30 Hz
Gamma	30 – 80 Hz

Table 2: Frequency Bands in EEG Signals

Each of these bands is associated with different types of cognitive and behavioral functions. For instance, the Delta band is often linked to deep sleep and regenerative processes, while the Alpha band is associated with relaxation and calm focus. Theta and Beta bands are typically linked to different stages of attentiveness and cognitive processing, while the Gamma band is involved in high-level cognitive functions.

Investigate how each of these frequency bands relates to different types of brain activities. One of the main methods for time-frequency analysis is through short-time Fourier transform (STFT), which allows us to compute and extract the temporal and spectral characteristics of EEG signals. Unlike traditional Fourier analysis, STFT enables the observation of frequency changes over time, converting a time-domain signal into a time-frequency representation.

To apply this, STFT is calculated by using a short sliding window (e.g., 500 ms) to compute the signal spectrum in each segment. This technique allows for a windowed analysis that provides insights into the temporal dynamics of the EEG signal. For a more detailed overview of STFT, you can refer to this video.

In this exercise, we aim to examine temporal changes across frequency bands during Reward and Punishment events. We first normalize the data in each trial using the z-score method over the time axis. Then, we focus on channel Fz for all healthy and depressed subjects and calculate the STFT across each trial in both groups (healthy and depressed) for each event (Reward and Punishment). This results in a 4D tensor of the following shape:

$$(\text{number of subjects}) \times (\text{number of trials}) \times (\text{frequency points}) \times (\text{time points})$$

Next, we calculate the average for each subject across all trials to obtain a 3D tensor for each group and each event. This tensor is defined as:

$$(\text{number of subjects}) \times 5 \times (\text{time points})$$

Finally, we examine the frequency axis across these bands (Delta, Theta, Alpha, Beta, and Gamma) by averaging to observe time-frequency changes.

Frequancy Bands

Investigate how each frequency band relates to different types of brain activities.

Soloution

Each EEG frequency band is associated with specific types of cognitive and behavioral processes:
- Delta (0.5 – 4 Hz): Linked with deep sleep stages and regenerative processes. It is most commonly observed during deep, restorative sleep, where brain activity is slow and synchronized. - Theta (4 – 8 Hz): Associated with drowsiness, light sleep, and relaxation. Theta activity often increases during meditation, daydreaming, and creativity.
- Alpha (8 – 12 Hz): Often observed when an individual is in a relaxed, calm, and focused state. It is associated with the resting state of the brain and often appears in calm and wakeful states with closed eyes.
- Beta (12 – 30 Hz): Related to active thinking, problem-solving, and concentration. Beta waves are more pronounced when a person is awake, alert, and engaged in focused mental activity.
- Gamma (30 – 80 Hz): Associated with higher-level cognitive functions, such as perception, problem-solving, and consciousness. Gamma waves are thought to be involved in processes that require attention and memory integration.

Frequency Band Power Analysis

Calculate the mean and standard error (SE) of the power on all subjects (healthy and depressed) for each frequency band. In the end, plot the changes in power for each frequency band (Delta, Theta, Alpha, Beta, and Gamma) with confidence intervals for different events (Reward and Punishment) for both control and depressed groups. Display the results for better comparison between the two groups.

Soloution

Analysis and Observations
- Delta and Theta Bands: For both Reward and Punishment events, healthy subjects generally display a higher power in the Delta and Theta bands compared to depressed subjects, with relatively lower SE, indicating consistency across control subjects. Depressed subjects show lower power and greater variability.
- Alpha Band: In the Alpha band, healthy subjects exhibit a slightly higher power during the Reward event, while depressed subjects have more consistent power levels across both events. The Alpha band is often associated with relaxation and cognitive readiness, and these differences might reflect variations in cognitive and emotional responses between the two groups.
- Beta and Gamma Bands: Depressed subjects exhibit greater power in the Beta and Gamma bands, particularly during the Punishment event. These bands are typically associated with active cognitive processing and attention, and the elevated power may suggest increased cognitive effort or emotional response in depressed individuals when facing negative feedback.

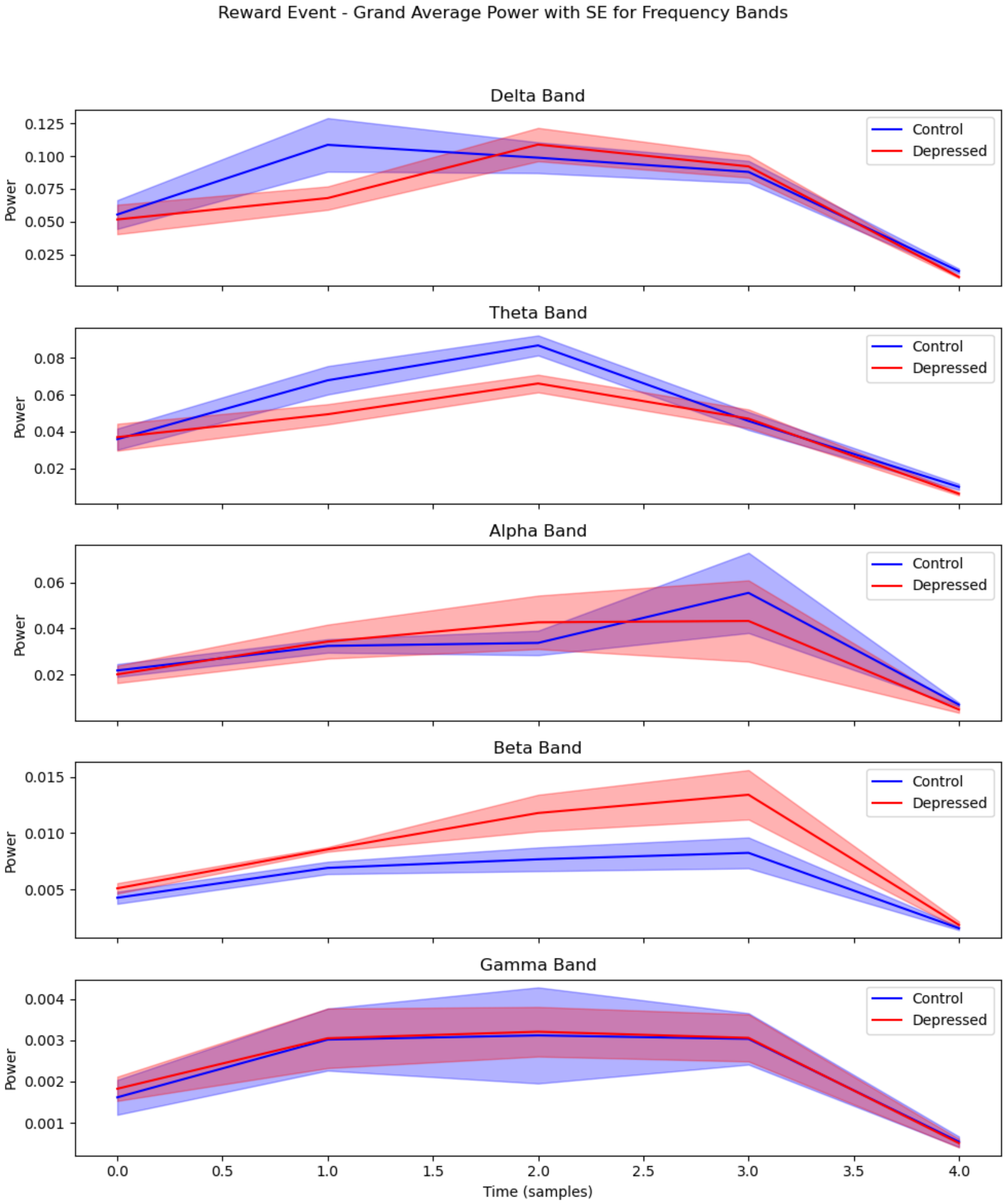

Figure 71: Reward Event - Grand Average Power with SE for Frequency Bands

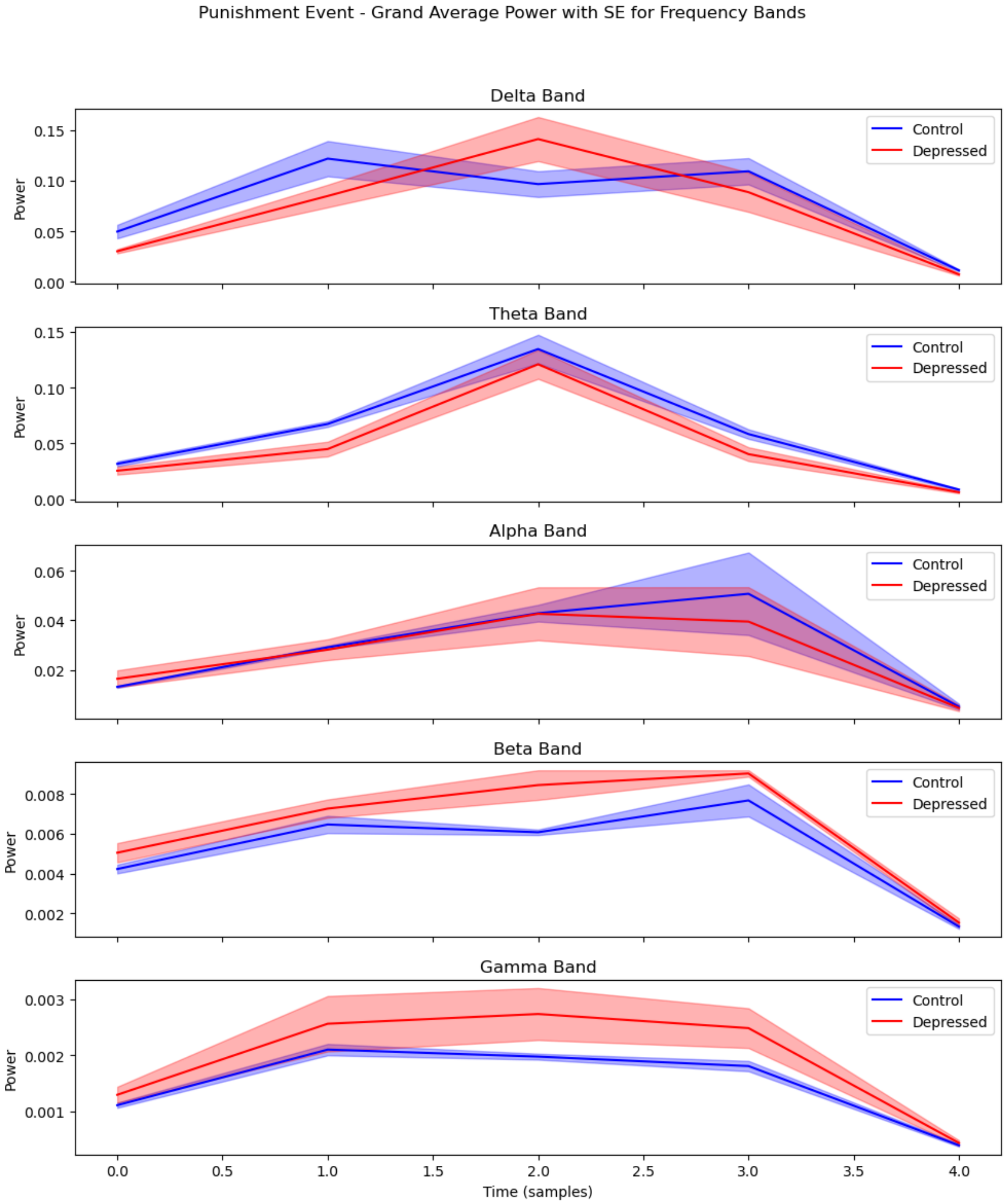

Figure 72: Punishment Event - Grand Average Power with SE for Frequency Bands

Conclusion

1. In which frequency band is the difference between the healthy and depressed groups greater during the **Reward** event?

Soloution

Based on the plots in the previous part, for the Reward event, the most prominent difference between healthy and depressed groups appears in the **Delta** and **Alpha** bands. In the Delta band, healthy subjects generally exhibit higher power than depressed subjects across time points, which suggests a stronger underlying response in the low-frequency range. In the Alpha band, however, depressed subjects show slightly higher power compared to the healthy group, particularly in the middle time points. This contrast in the Alpha band may indicate variations in cognitive or relaxation states in response to positive feedback.

Thus, the **Delta** and **Alpha** bands reveal the most significant differences during the Reward event.

2. In which frequency band is the difference between the healthy and depressed groups greater during the **Punishment** event?

Soloution

For the Punishment event, the **Gamma** and **Beta** bands exhibit the most substantial differences between the two groups. The depressed group shows a notably higher power in the Gamma band throughout the time samples, suggesting an intensified response to negative stimuli, which could be associated with heightened cognitive or emotional processing. In the Beta band, depressed subjects also display higher power than the control group, indicating increased cognitive engagement or stress response when facing punishment stimuli.

Consequently, the **Gamma** and **Beta** bands display the greatest differences between the healthy and depressed groups during the Punishment event.