Visual Oddball Task EEG Preprocessing

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Contents

1 Introduction

This project focuses on the preprocessing and analysis of EEG data collected during a visual oddball task. The primary objectives are to preprocess the data, apply artifact removal techniques using Independent Component Analysis (ICA), and conduct a comprehensive analysis of event-related potentials (ERPs), specifically focusing on the P3 and Error-Related Negativity (ERN) components. Various steps, such as downsampling, re-referencing, channel removal, filtering, and ICA-based artifact rejection, are applied to ensure clean data. Additionally, we perform ERP analysis for cognitive components, including statistical comparisons and grand-averaged waveform generation. The project utilizes MATLAB with the EEGLAB toolbox for EEG processing, ICA decomposition, and ERP analysis.

2 Preprocessing Steps

2.1 Loading the Data and Initial Setup

First, we load the EEG data for each participant. The data for each subject is stored in their respective folder, which includes both the EEG data files and metadata such as channel locations and event markers. The code snippet below demonstrates how the data is loaded and stored in the EEGLAB environment.

```
% Initialize EEGLAB
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;

% Base directory containing the data
baseDir = 'P3 Raw Data2';

% List all subject folders (15 subjects)
n = 15;
subjects = cell(1, n);
for i = 1:n
    subjects{i} = sprintf('sub-%03d', i);  % Format subject names
end

for i = 1:length(subjects)
    subjectDir = fullfile(baseDir, subjects{i}, 'eeg');
    eegSetFile = fullfile(subjectDir, [subjects{i} '_task-P3_eeg.set']);

    if exist(eegSetFile, 'file')
        EEG = pop_loadset('filename', eegSetFile);
        [ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, 0);
        fprintf('EEG data for %s loaded successfully.\n', subjects{i});
    end
end
```

Explanation: This code initializes EEGLAB, sets up the base directory for the data, and loops over 15 subjects to load their EEG datasets. For each subject, it checks if the '.set' file exists and then loads the data into EEGLAB.

2.2 Loading Channel Locations and Events

Next, we load the channel locations and event markers. These files are crucial for mapping the EEG data onto the correct electrode positions and ensuring the correct event timing for analysis.

```
% Load the channel locations (.tsv file)
channelsFile = fullfile(subjectDir, [subjects{i} '_task-P3_channels.tsv']);
if exist(channelsFile, 'file')
```

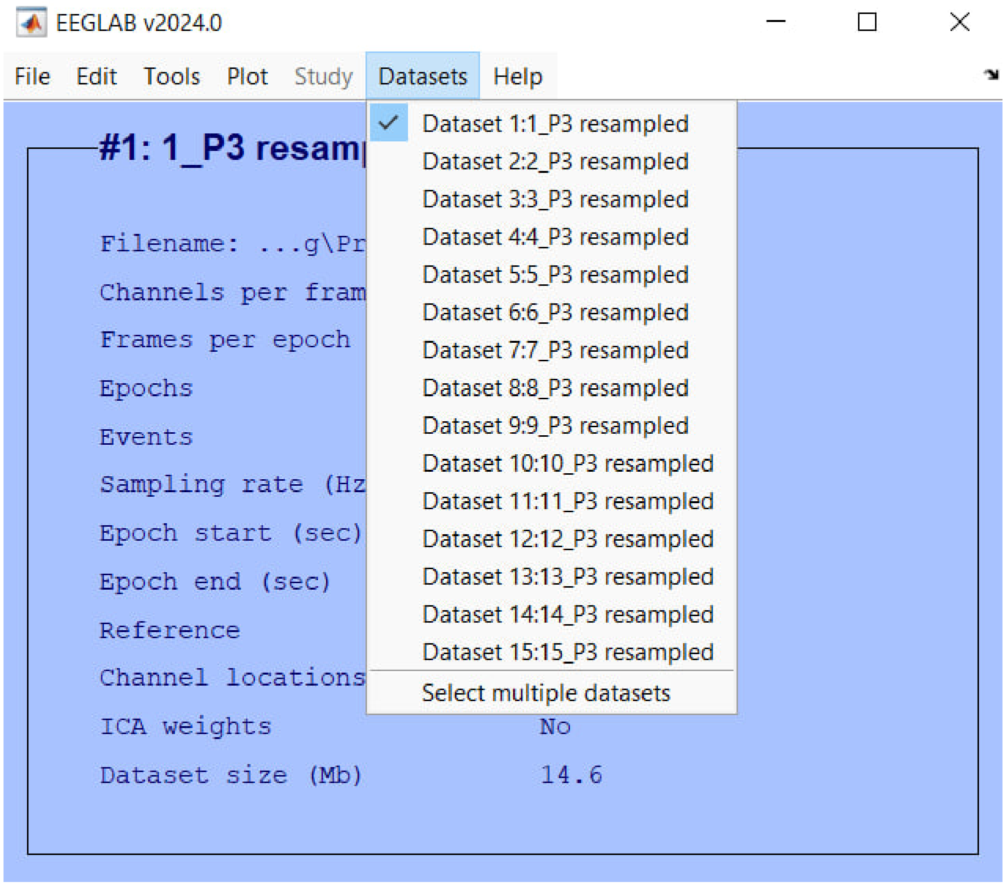

Figure 1: EEGLAB view of imported datasets.

```
    EEG = pop_chanedit(EEG, 'load', {channelsFile 'filetype' 'tsv'});
    [ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, CURRENTSET);
    fprintf('Channel locations loaded for %s.\n', subjects{i});
end

% Load the event markers
eventsFile = fullfile(subjectDir, [subjects{i} '_task-P3_events.tsv']);
if exist(eventsFile, 'file')
    eventData = tdfread(eventsFile, 'tab');  % Read the event file
    EEG = pop_importevent(EEG, 'event', eventData, 'fields', {'latency', '
        type'}, 'timeunit', 1e-3);
    [ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, CURRENTSET);
    fprintf('Events loaded for %s.\n', subjects{i});
end
```

Explanation: This code block handles loading the channel locations and event data from the respective '.tsv' files for each subject. The channel locations are important for electrode positioning, while the event markers are used to identify the time points of interest in the EEG data (e.g., stimulus onset and responses).

2.3 Downsampling and Re-referencing

The next step in preprocessing is to downsample the data to 256 Hz to reduce the file size and computational load. After that, we re-reference the data to the average of electrodes P9 and P10.

```
% Step 1: Downsample to 256 Hz
EEG = pop_resample(EEG, 256);
fprintf('Data downsampled to 256 Hz for %s.\n', subjects{i});

% Step 2: Re-reference to average of P9 and P10 electrodes
if any(strcmp({EEG.chanlocs.labels}, 'P9')) && any(strcmp({EEG.chanlocs.labels}, 'P10'))
    EEG = pop_reref(EEG, {'P9', 'P10'});
    fprintf('Data re-referenced to average of P9 and P10 for %s.\n', subjects{i});
end
```

Explanation: The downsampling step reduces the sampling rate to 256 Hz, a common practice to make data processing faster. Re-referencing to the P9 and P10 electrodes is used to adjust the data so that signals are interpreted relative to the average of these electrodes, which helps in eliminating noise.

2.4 Removing HEOG and VEOG Channels, and Filtering

After re-referencing, we remove the horizontal and vertical EOG (HEOG and VEOG) channels to reduce noise, followed by applying a high-pass filter to eliminate slow drifts in the data.

```
% Step 3: Remove HEOG and VEOG channels
EEG = pop_select(EEG, 'nochannel', {'HEOG_left', 'HEOG_right', 'VEOG_lower'});
fprintf('HEOG and VEOG channels removed for %s.\n', subjects{i});

% Step 6: Apply a high-pass filter of 0.1 Hz
EEG = pop_eegfiltnew(EEG, 0.1, []);
fprintf('High-pass filter (0.1 Hz) applied for %s.\n', subjects{i});
```

Explanation: The HEOG and VEOG channels are often removed when their contribution to the overall signal is not needed for the analysis. The high-pass filter with a cutoff at 0.1 Hz is applied to remove low-frequency noise and drifts from the EEG data.

2.5 DC Offset Removal and Saving Preprocessed Data

Finally, the DC offset is removed to further clean the signal, and the preprocessed data is saved.

```
% Step 5: Remove DC offset
EEG = pop_rmbase(EEG, []);
fprintf('DC offset removed for %s.\n', subjects{i});

% Save the preprocessed dataset
outputFile = fullfile(subjectDir, sprintf('Preprocess_P3_%s.set', subjects{i}));
EEG = pop_saveset(EEG, 'filename', sprintf('Preprocess_P3_%s.set', subjects{i}), 'filepath', subjectDir);
fprintf('Preprocessed dataset saved for %s.\n', subjects{i});
```

Explanation: The removal of the DC offset ensures that the baseline of the EEG data is properly adjusted. The preprocessed data is then saved into a new '.set' file for each subject.

3 Bad Channel Identification

The bad channels for each subject were identified using both the frequency-domain representation (power spectral density) and the time-domain EEG signals. Below are the details for each subject based on our analysis of these two domains.

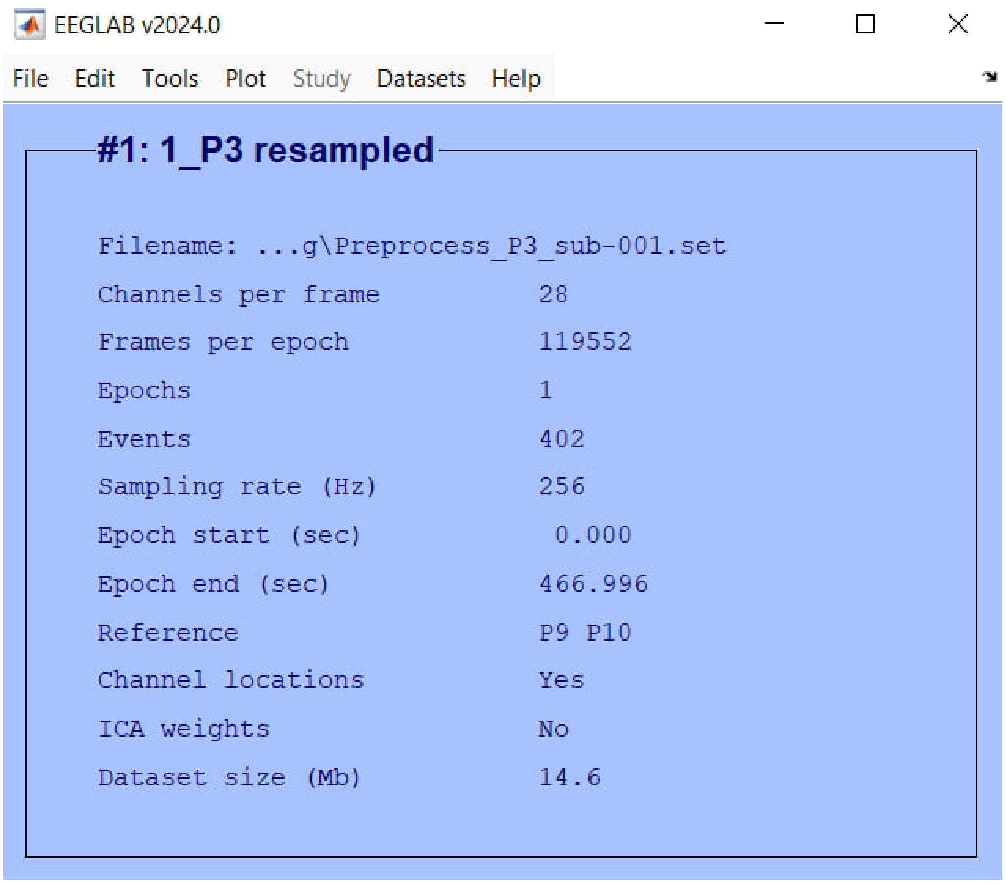

Figure 2: EEGLAB description of a preprocessed dataset.

3.1 Subject 1: Channel F8

For Subject 1, channel F8 showed high-frequency noise, indicating a potential issue. Based on both the frequency and time-domain data, we decided to remove this channel as it could introduce artifacts into the analysis.

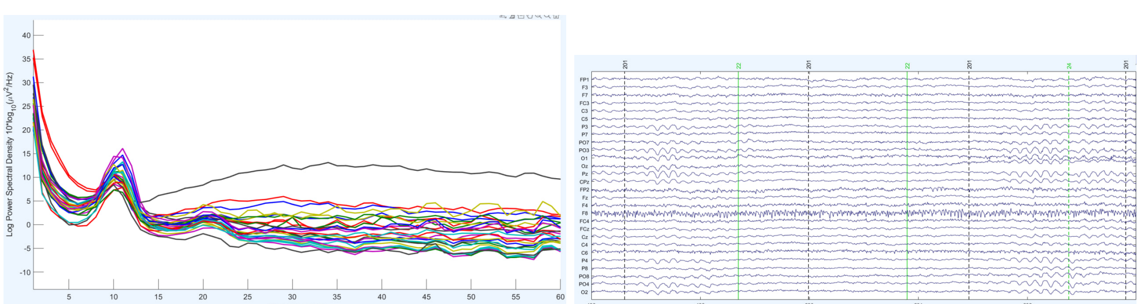

Figure 3: Subject 1: Frequency-domain (left) and time-domain (right) plots for. For channel f8, High-frequency noise was detected, leading to its removal.

3.2 Subject 4: Channel O2

For Subject 4, channel O2 displayed some high-frequency activity. However, it was not significant enough to warrant removal. We decided to retain this channel as it was still usable for analysis.

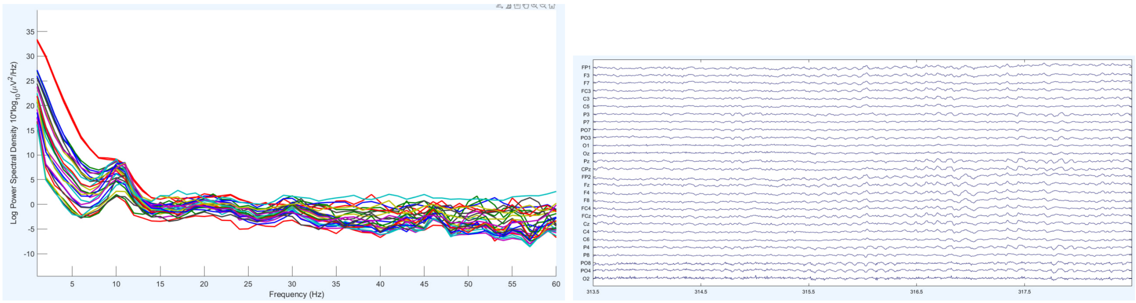

Figure 4: Subject 4: Frequency-domain (left) and time-domain (right) plots. In O2 channel slight high-frequency noise was observed but was not severe enough for removal.

3.3 Subject 5: Channel FP2

For Subject 5, channel FP2 was flagged for potential issues due to high-frequency noise. However, channels P8 and FP1, which showed some low-frequency activity and blink artifacts, were not classified as bad channels since they could be corrected later during ICA artifact removal.

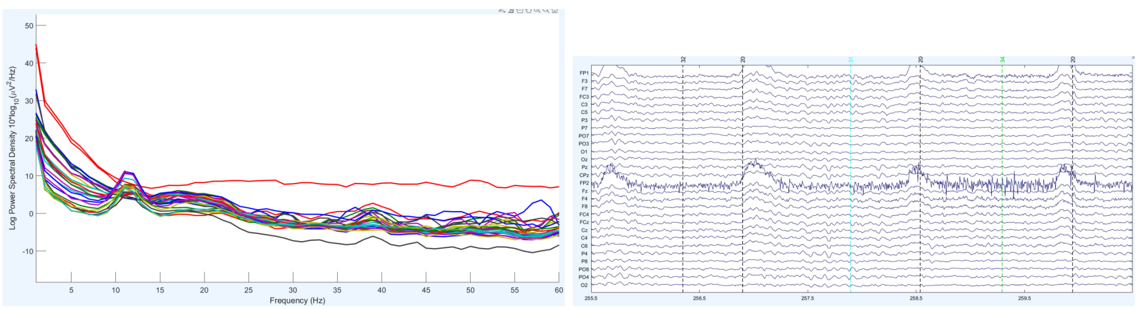

Figure 5: Subject 5: Frequency-domain (left) and time-domain (right) plots for. Channel FP2 The was flagged for potential issues, but FP1 and P8 were kept as they will be corrected later during ICA artifact removal.

3.4 Subject 6: Channel FC4

For Subject 6, channel FC4 displayed significant high-frequency noise and was therefore identified as a bad channel. This channel was removed from further analysis.

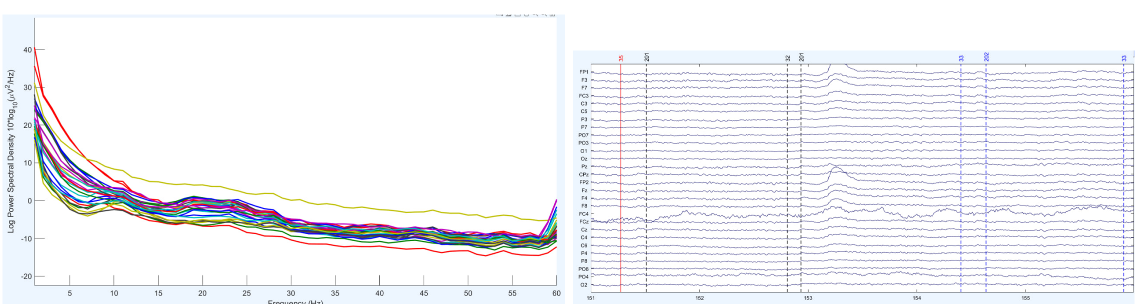

Figure 6: Subject 6: Frequency-domain (left) and time-domain (right) plots. In FC4 channel, High-frequency noise was detected, and the channel was removed.

3.5 Subject 9: Channels PO8 and PO3

For Subject 9, channel PO3 was removed due to high-frequency peaks in the frequency domain. However, channel PO8 was retained as the noise levels were not significant enough to impact the analysis.

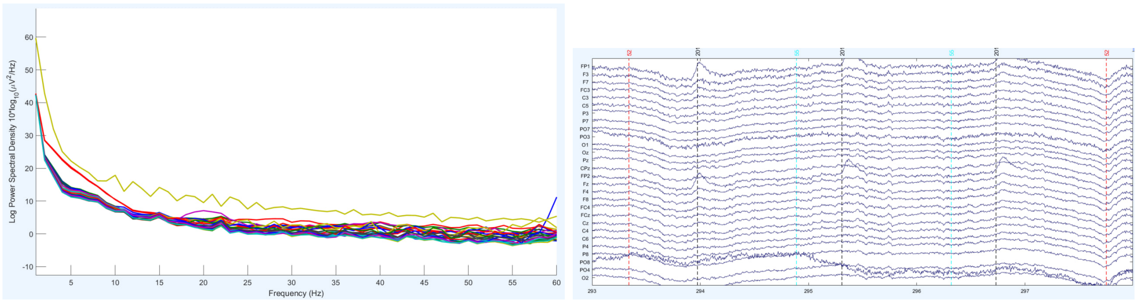

Figure 7: Subject 9: Frequency-domain (left) and time-domain (right) plots. PO3 and PO8 was removed due to high-frequency peaks.

3.6 Subject 10: Muscle Artifacts

In Subject 10, we identified repeating patterns of muscle artifacts. These will be addressed later during the ICA phase of artifact removal. Since in this project we are not going to cut any part of data, we will not manually remove these channels and will handle in ICA phase.

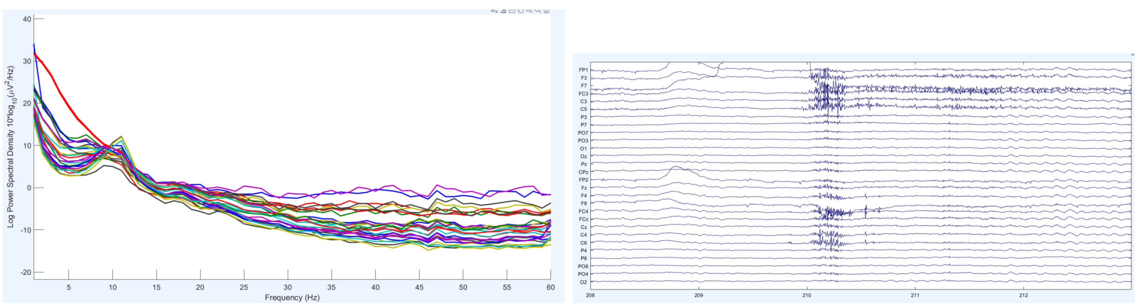

Figure 8: Subject 10: Frequency-domain (left) and time-domain (right) plots showing muscle artifacts. These will be handled during the ICA phase.

3.7 Subject 11: Channel P7

For Subject 11, channel P7 was identified as noisy. Channel F7 was also considered, but the noise level was not high enough to warrant removal, so we decided to retain it.

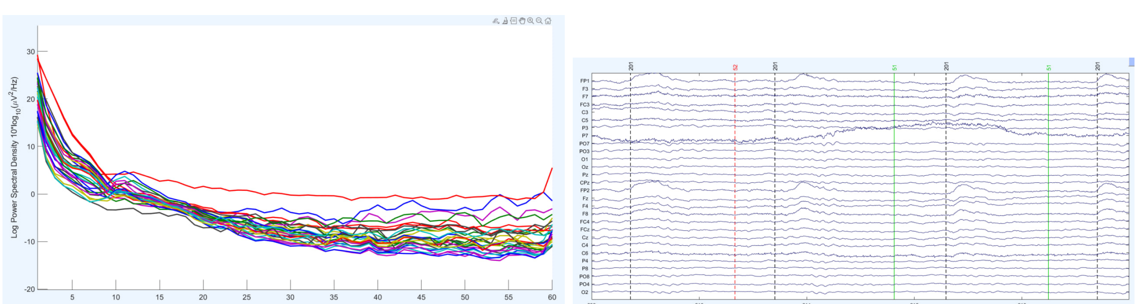

Figure 9: Subject 11: Frequency-domain (left) and time-domain (right) plots for channel P7. F7 was retained despite some noise, but P7 was removed.

3.8 Subject 12: Channels C6 and F8

Both channels C6 and F8 for Subject 12 showed high levels of noise. We decided to remove both of these channels from the analysis.

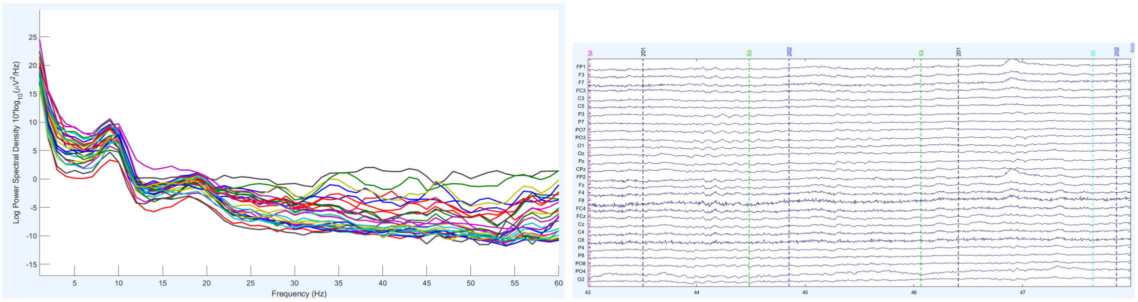

Figure 10: Subject 12: Frequency-domain (left) and time-domain (right) plots for channels C6 and F8. Both channels were removed due to high noise levels.

3.9 Subject 15: Channels F8 and FP2

In Subject 15, both channels F8 and FP2 showed considerable noise. Although channels F7 and FP1 also exhibited some noise, it was not as severe as in F8 and FP2. These two channels were therefore removed from the analysis.

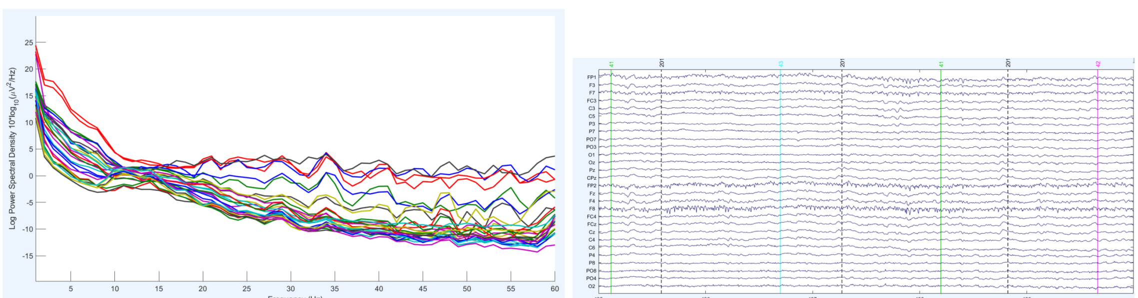

Figure 11: Subject 15: Frequency-domain (left) and time-domain (right) plots. The F8 and FP2 channels were removed due to significant noise, while F7 and FP1 were retained.

4 MATLAB Code Analysis

In this section, we analyze the following MATLAB code:

```
EEG = pop_epochbin(EEG, [-1800.0  800.0],  '-1800 -1600');
[ALLEEG, EEG, CURRENTSET] = pop_newset(ALLEEG, EEG, 2, ...
    'setname', ['response_locked_file'],
    'savenew', ['response_locked_file'], ...
    'gui', 'off');
```

Code Analysis:

1. `EEG = pop_epochbin(EEG, [-1800.0 800.0], '-1800 -1600');`

   - This line of code segments (epochs) the EEG data around an event or trigger with a time window of −1800 ms to 800 ms. The epoching window is centered around the event of interest, with the data being time-locked to that event.

- The third argument, `'-1800 -1600'`, specifies the baseline period for baseline correction. The time window of −1800 ms to −1600 ms relative to the event is used to correct the data and remove any DC offsets, ensuring the signals are correctly centered before stimulus onset.

2. `[ALLEEG, EEG, CURRENTSET] = pop_newset(ALLEEG, EEG, 2, ... 'setname', ['response_locked_file'], 'savenew', ['response_locked_file'], ... 'gui', 'off');`

   - This line creates a new EEG dataset in the EEGLAB environment. The function `pop_newset` stores the new EEG data in the global `ALLEEG` structure, assigning it the name `'response_locked_file'`.
   - The parameter `'savenew'` ensures the dataset is saved as a file named `'response_locked_file.set'`.
   - The parameter `'gui', 'off'` runs this function without the graphical user interface, allowing for automated batch processing.

5 Independent Component Analysis (ICA) and Artifact Removal

We performed ICA on the preprocessed dataset to identify and remove components associated with artifacts, such as eye movement, muscle activity, and line noise. Below are the removed components with explanations of why they were classified as artifacts.

5.1 Example 1 - Non-Brain Source

Because the resource of signal in the scalp map seems to be outside of the brain, we considered this component as a removable independent component.

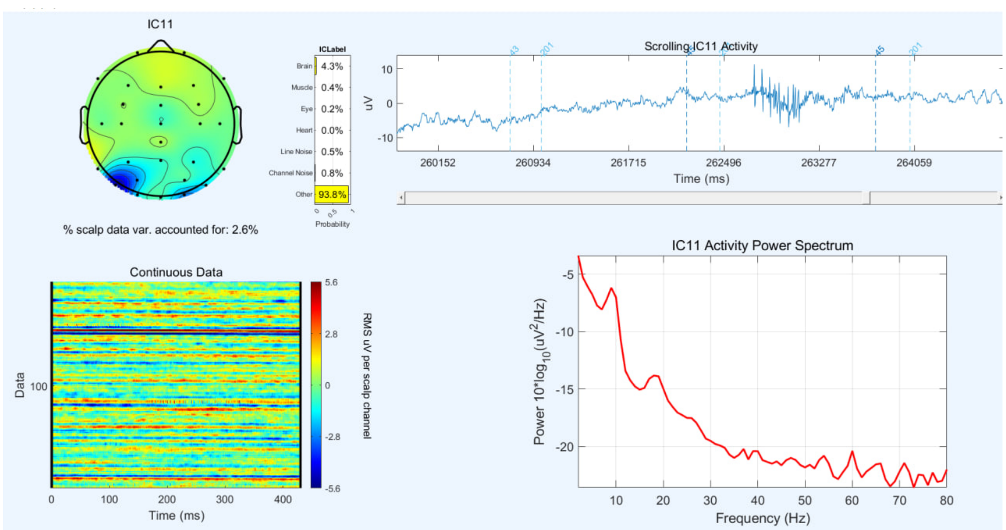

Figure 12: Example 1: Removed due to its origin outside of the brain.

5.2 Example 2 - Low Amplitude in 60 Hz (Not Line Noise)

Initially, we considered this component as line noise due to the peak at 60 Hz, but since the amplitude is low, we decided to maintain it and handle the artifact in the next phases (ICA and low-pass filters).

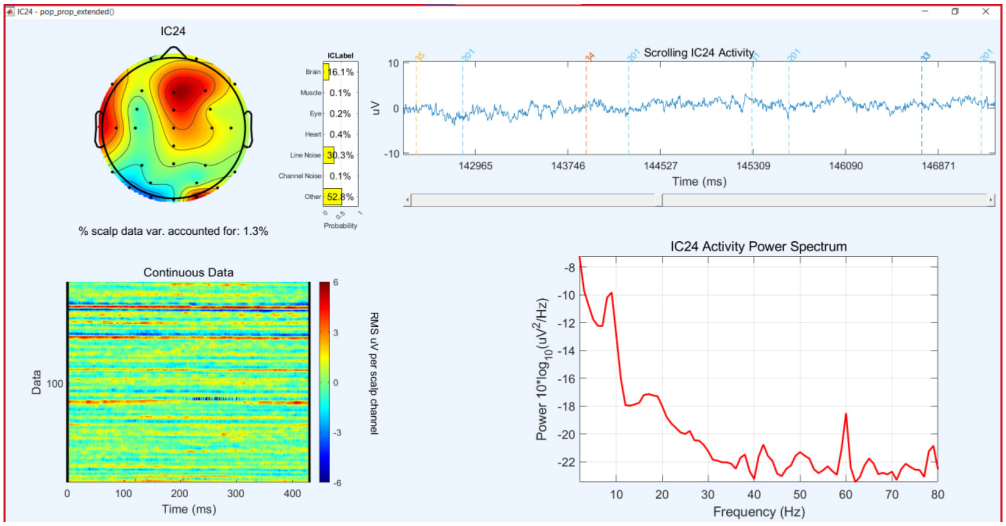

Figure 13: Example 2: Maintained and addressed in later phases despite a small peak at 60 Hz.

5.3 Example 3 - Eye Blinking Artifact

The pattern of blinking in this signal and the most activity in the front of the scalp map indicated that this component is related to eye blinking.

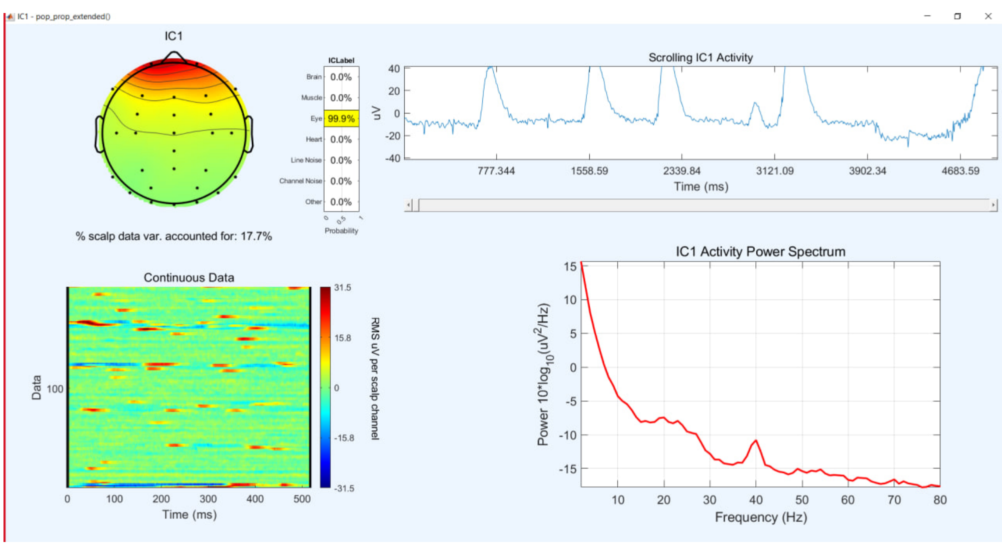

Figure 14: Example 3: Classified as an eye blinking artifact, removed.

5.4 Example 4 - Eye Movement Artifact

In this case, we have two main activated areas on the right and left front of the scalp map. The rise and fall in the signal correspond to eye movements.

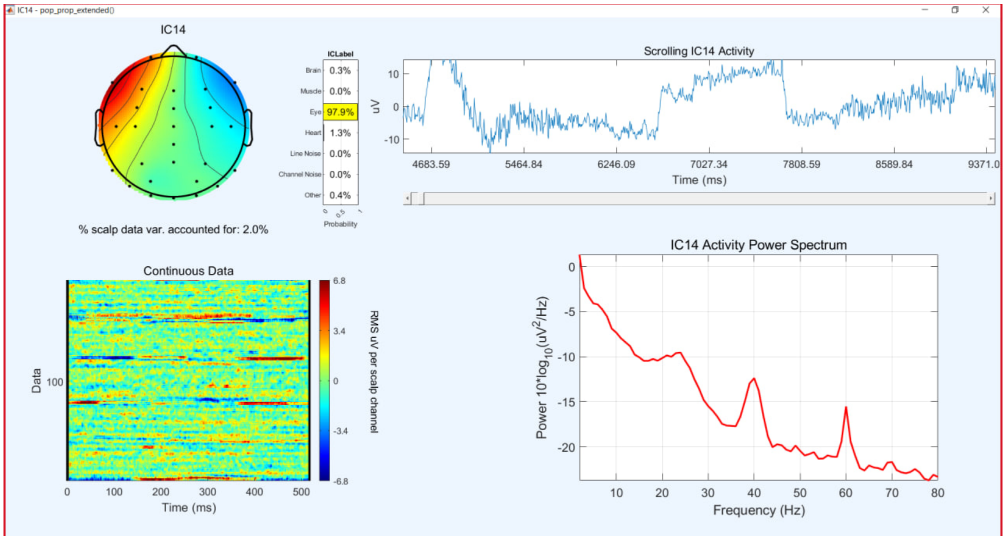

Figure 15: Example 4: Eye movement artifact, removed.

5.5 Example 5 - Peak at 23 Hz (Not Typical 1/f Pattern)

Although this component should have peaked around 10 Hz, it peaked at approximately 23 Hz, which is incompatible with the 1/f rule, suggesting it is not brain-related.

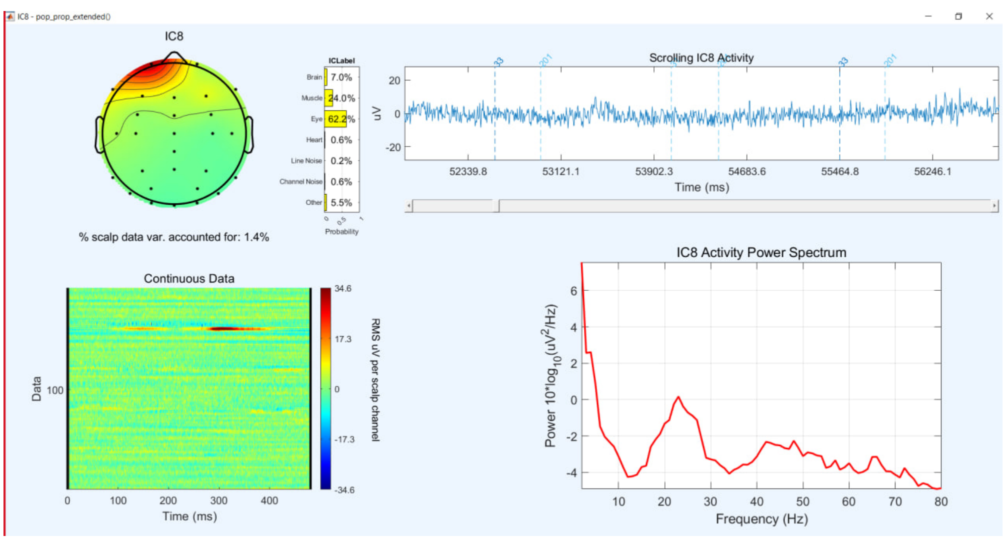

Figure 16: Example 5: Atypical peak at 23 Hz, removed.

5.6 Example 6 - Muscle Artifact

In the frequency domain, the high amplitude at high frequencies suggests this component is related to muscle activity.

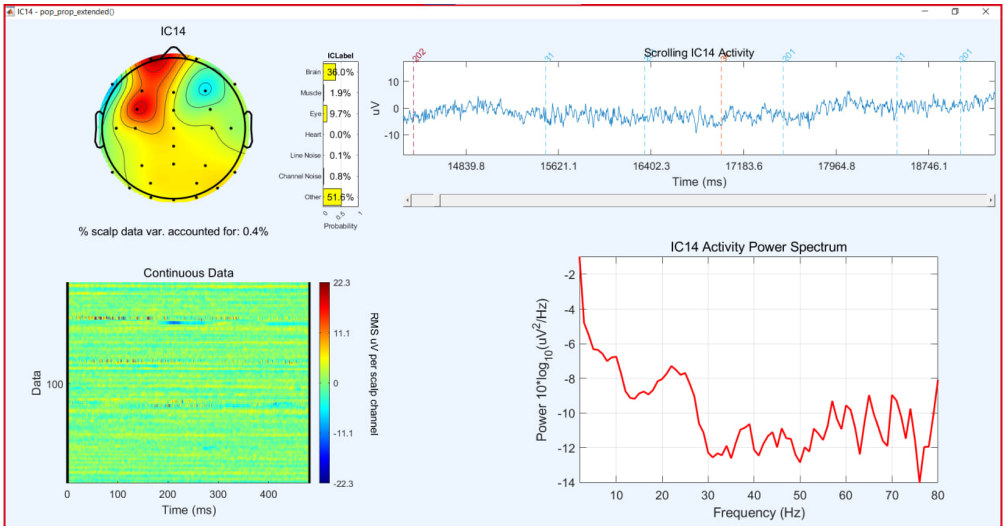

Figure 17: Example 6: Classified as muscle activity due to high-frequency noise, removed.

5.7 Example 7 - Muscle Artifact

Similar to the previous component, this one is also classified as muscle activity and removed.

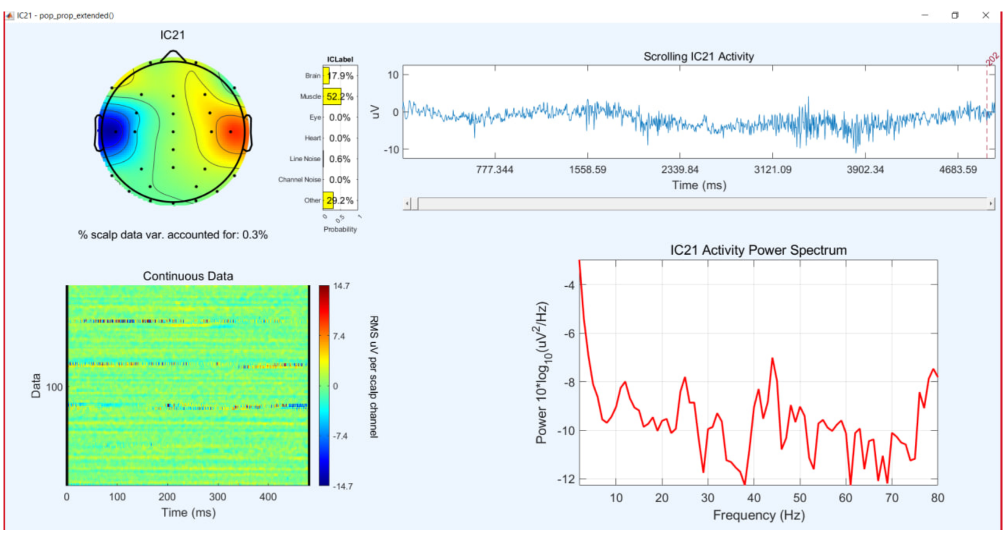

Figure 18: Example 7: Classified as muscle activity, removed.

5.8 Example 8 - Eye Blinking Artifact

Looking at the signal in the time domain, the repetitive pattern of eye blinking is clear. The scalp map also shows most of the activity in the frontal area, which is consistent with eye movements.

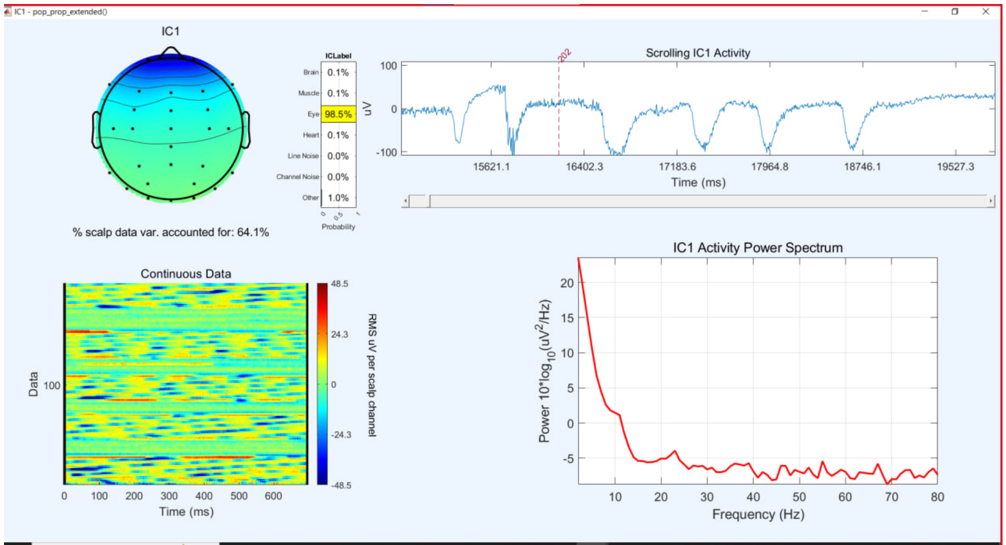

Figure 19: Example 8: Eye blinking artifact, removed.

5.9 Example 9 - Line Noise Artifact

This component exhibited a strong peak at 60 Hz. Unlike Example 2, this peak is more prominent, and we removed this component as line noise.

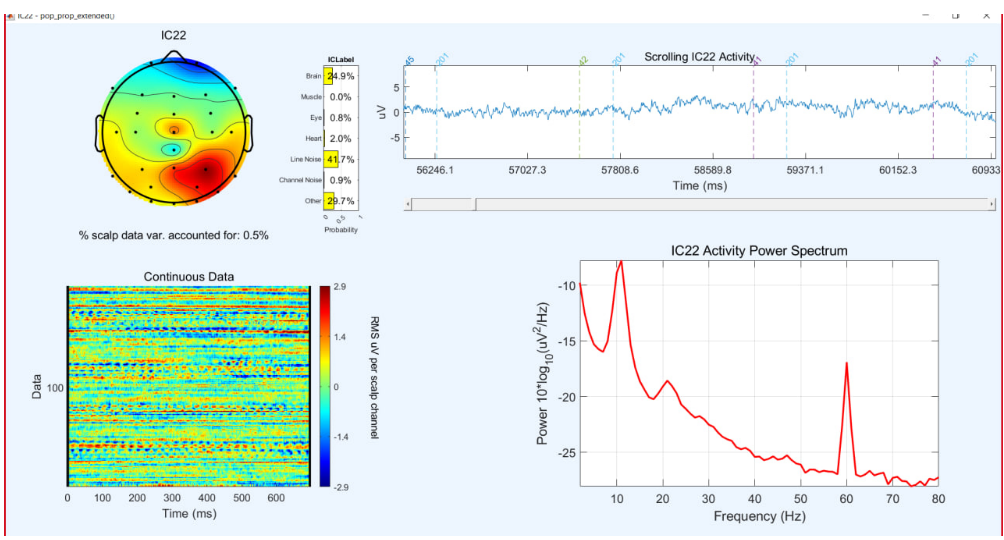

Figure 20: Example 9: Classified as line noise due to a strong peak at 60 Hz, removed.

5.10 Example 10 - Muscle Artifact

Both in the frequency and time domains, high-frequency activity related to muscle movements is apparent. This component was removed.

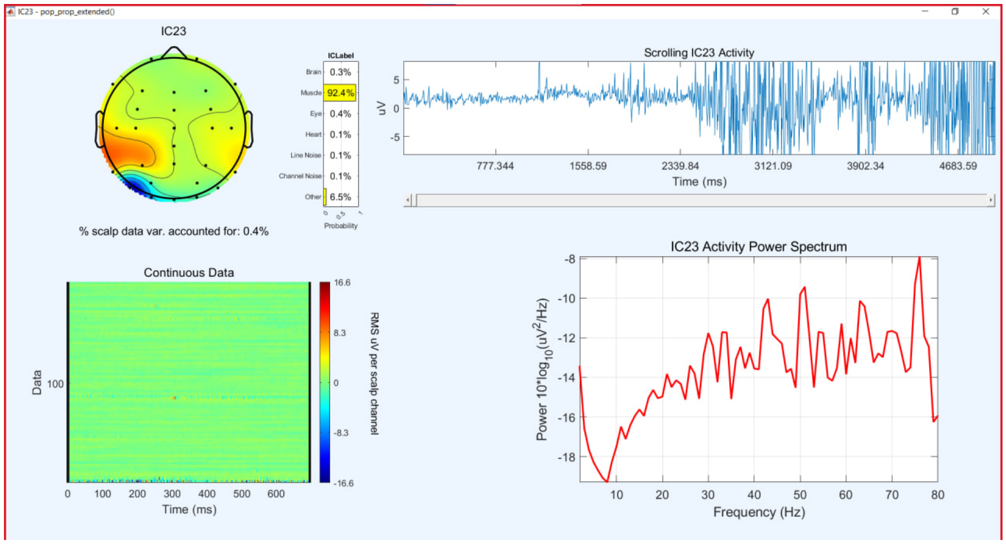

Figure 21: Example 10: Muscle activity, removed.

5.11 Example 11 - Eye Artifact (Special Case)

In this case, we observe a pattern of eye blinking in the time domain, but the main activity is not located in the front of the scalp map. Although it could be an artifact, it is clearly not brain activity. These high amplitudes in the time domain suggest non-brain activity, so it was removed.

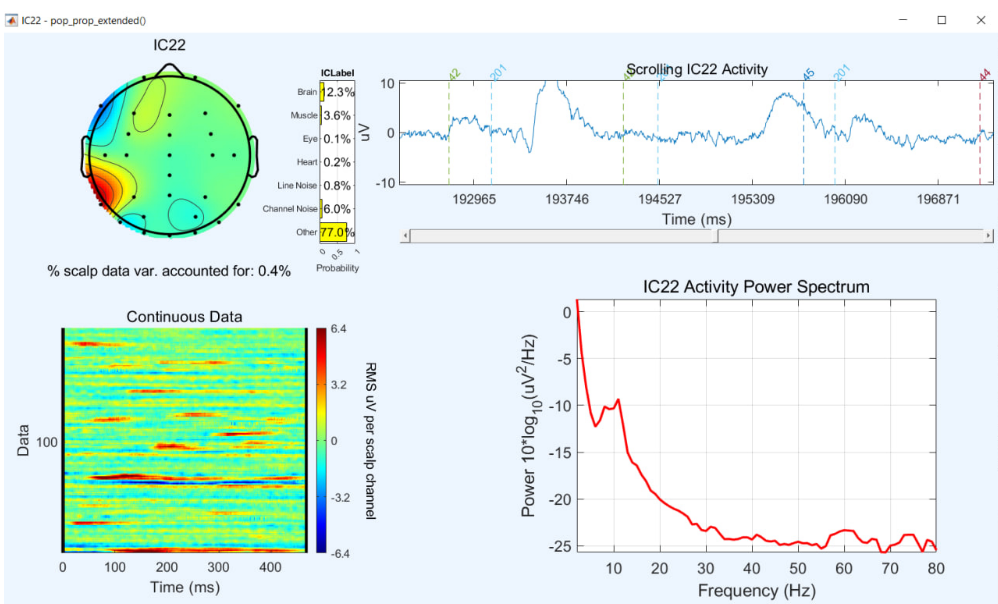

Figure 22: Example 11: Eye blinking pattern observed, removed due to non-brain activity.

5.12 Example 12 - Rhythmic Artifact

A rhythmic pattern was observed in the signal, which is a clear indicator of an artifact unrelated to brain activity.

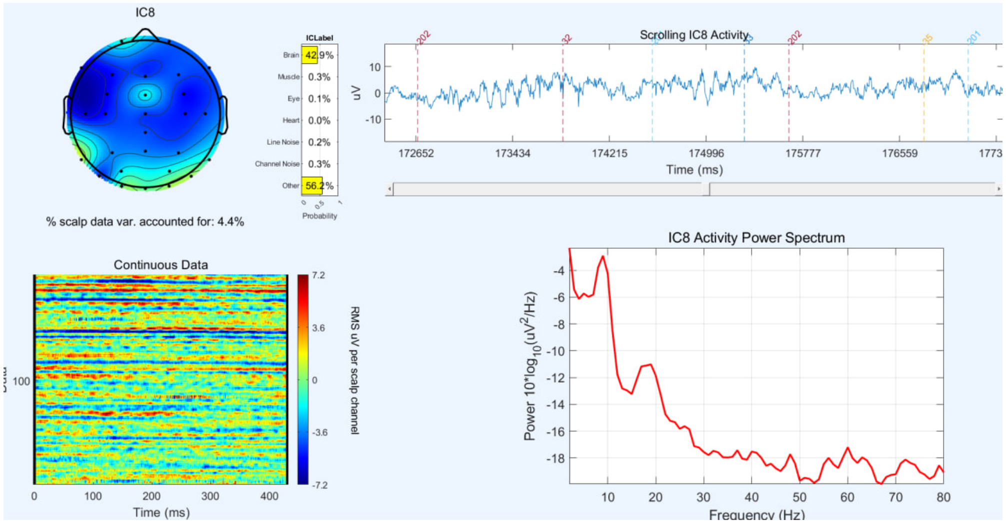

Figure 23: Example 12: Rhythmic artifact, removed.

5.13 Example 13 - Muscle Artifact

This component was identified as muscle activity due to the high amplitudes in the higher frequencies of the frequency spectrum.

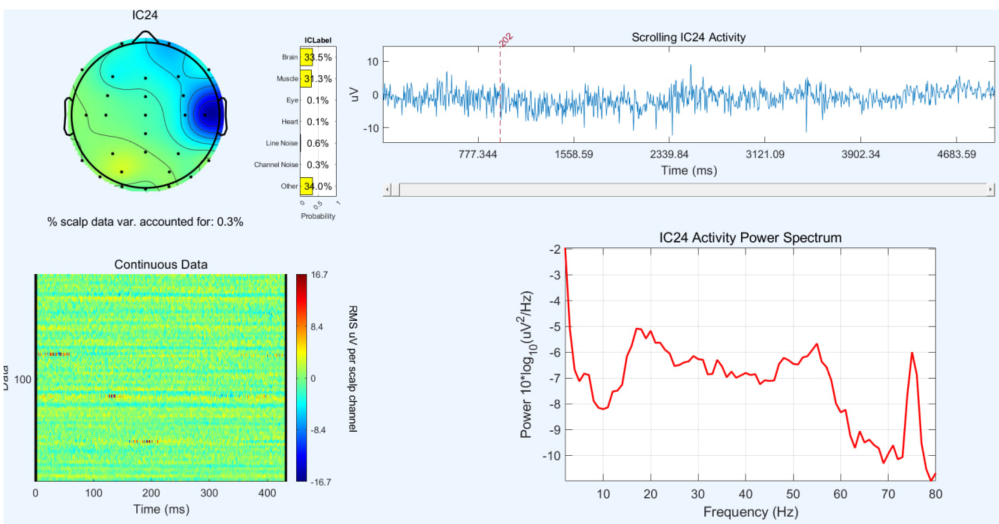

Figure 24: Example 13: Muscle activity, removed.

5.14 Signal Comparison Before and After ICA (Subject 12)

The figure below demonstrates the difference between the signal before and after applying ICA for subject 12. Notice the cleaner signal after artifact removal, which eliminates significant noise artifacts such as eye movements, muscle activity, and line noise.

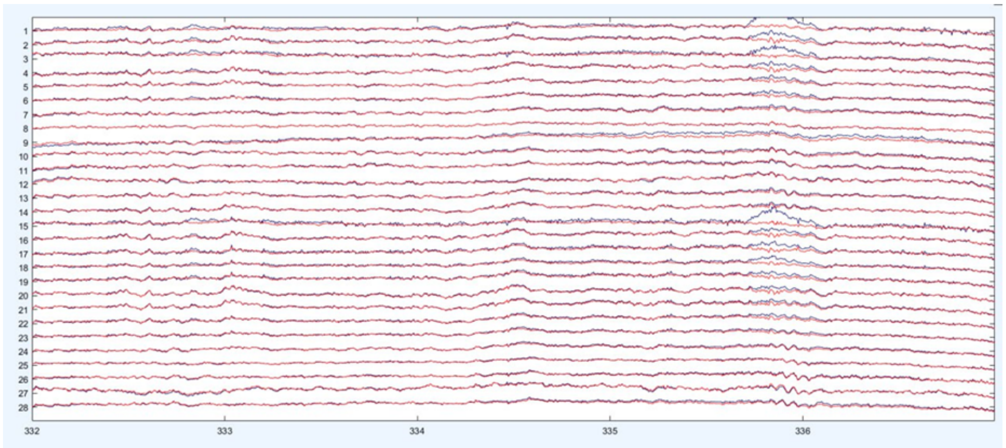

Figure 25: Comparison of the EEG signal before and after ICA for subject 12. The cleaned signal exhibits reduced noise, particularly around eye movement and muscle-related artifacts.

6 Overview of IC Components for All Subjects

In this section, we present the scalp maps of independent components (ICs) from all 15 subjects. The components highlighted with **green boxes** represent ICs that were accepted as brain-related activity, while those with **red boxes** were identified as noise or artifacts (such as eye movement, muscle activity, or line noise) and subsequently removed. The maps are arranged in a 5x3 grid for each subject, showing the status of all ICs.

Figure 26: Scalp maps showing IC components for all 15 subjects. Green boxes indicate accepted components, while red boxes indicate rejected components (artifacts or noise).

7 Event List and Epoching

This section outlines the steps taken to preprocess the EEG data for P3 and ERN analyses, including assigning event codes, creating bin descriptor files, epoching the data, and applying baseline correction.

7.1 Event Codes Assignment

For each subject, event codes were assigned to the EEG data using the `pop_creabasiceventlist` function in EEGLAB. This function cleaned and structured the events to align with the stimulus-response paradigm.

```
% Assign event codes to the EEG data
EEG = pop_creabasiceventlist(EEG, 'AlphanumericCleaning', 'on', ...
    'BoundaryNumeric', { -99 }, 'BoundaryString', { 'boundary' });
[ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, CURRENTSET);
fprintf('Event codes assigned for %s.\n', subjects{i});
```

This ensures that the event codes in each subject's data are properly formatted for the subsequent binning process.

7.2 Bin Descriptor Files

We created bin descriptor files to categorize the data into four key conditions:

- Correct Target
- Correct Non-Target
- Incorrect Target
- Incorrect Non-Target

Each bin was assigned to the EEG data using the following structure:

```
Bin 1
Correct Target
.{11;22;33;44;55}{t<200-1500>201}

Bin 2
Correct Non-Target
.{12;13;14;15;21;23;24;25;31;32;34;35;41;42;43;45;51;52;53;54}{t
    <200-1500>201}

Bin 3
Incorrect Target
.{11;22;33;44;55}{t<200-1500>202}

Bin 4
Incorrect Non-Target
.{12;13;14;15;21;23;24;25;31;32;34;35;41;42;43;45;51;52;53;54}{t
    <200-1500>202}
```

These bins were then assigned to the EEG data using the `pop_binlister` function:

```
% Assign bins to the data using the bin descriptor file
binDescriptorFile = 'Bin_Dicriptor.txt';
EEG = pop_binlister(EEG, 'BDF', binDescriptorFile, 'IndexEL', 1, ...
    'SendEL2', 'EEG', 'Voutput', 'EEG');
[ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, CURRENTSET);
fprintf('Bins assigned for %s.\n', subjects{i});
```

This allowed the data to be categorized according to the correct and incorrect responses for both target and non-target stimuli.

7.3 Epoching

The EEG data were epoched into segments time-locked to the stimulus onset for P3 analysis, and response onset for ERN analysis. Specifically:

- **P3 Analysis:** Epochs were created from -200 ms to 800 ms, time-locked to the stimulus onset.
- **ERN Analysis:** Epochs will be created from -600 ms to 400 ms, time-locked to the response onset.

For P3 analysis, baseline correction was applied using the pre-stimulus period. The following code shows the epoching process for P3 analysis:

```
% Epoch the EEG data for P3 analysis (-200 ms to 800 ms)
EEG_P3 = pop_epochbin(EEG, [-200.0 800.0], 'pre');  % Baseline correction
    using pre-stimulus interval
[ALLEEG, EEG_P3, CURRENTSET] = eeg_store(ALLEEG, EEG_P3, CURRENTSET);
fprintf('P3 epochs created for %s.\n', subjects{i});
```

The epoched dataset was saved as:

```
% Save the epoched dataset
outputFileName_P3 = sprintf('Preprocess_Epoch_P3_%s.set', subjects{i});
EEG_P3 = pop_saveset(EEG_P3, 'filename', outputFileName_P3, 'filepath',
    outputDir);
fprintf('P3 epoched dataset saved for %s.\n', subjects{i});
```

This process was repeated for all subjects, and the datasets were saved in the `bin_epoch` directory.

7.4 Baseline Correction

Baseline correction was applied using the pre-stimulus interval (-200 ms to 0 ms) for P3 analysis.

The final output for this section includes a set of epoched datasets saved under the format:

`Preprocess_Epoch_P3_[YourName].set`.

8 ERP Waveforms

8.1 P3 Analysis: Correctly Answered Target vs Correct Non-Target Conditions

For subject 12, we generated averaged ERP waveforms for both correctly answered target (Bin 1) and correct non-target (Bin 2) conditions. The ERPs were computed across all channels. In the figure below, it is clear that at the 300 ms mark (corresponding to the P3 component), there is a significant difference between the correct target and correct non-target conditions. This difference is a key indicator of the P3 response, which reflects cognitive processes involved in target detection. Especially in CPz, FCz, PO4, Cz and F3 the difference is more significant.

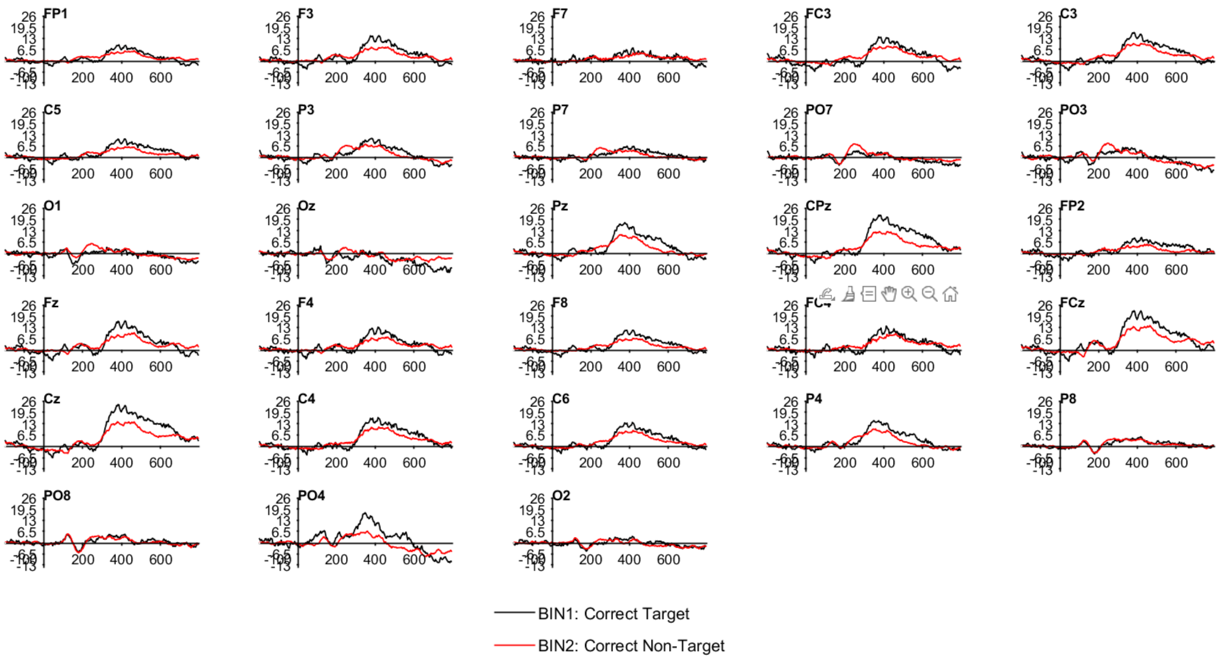

Figure 27: ERP Waveforms for Subject 12: Correctly answered target vs correct non-target conditions (P3 Analysis)

8.2 Quality Comparison: Correct Non-Targets vs Target Incorrect Responses

To compare the quality of data between correct non-targets and target incorrect responses, we analyzed the ERP waveforms. From the heatmap and numeric comparison (SNR) of ERP amplitudes (shown in the following figures), it is clear that the target incorrect responses (Bin 3) contain more noise compared to correct non-targets (Bin 2).

	-100 : 0	0 : 100	100 : 200	200 : 300	300 : 400	400 : 500	500 : 600	600 : 700
FP1	0.37137	0.72079	0.77801	0.78074	1.3783	1.2768	1.2482	1.2794
F3	0.45395	1.0019	1.1192	1.0928	1.6481	1.7699	1.5044	1.355
F7	0.30619	0.76367	0.94218	0.87322	1.4142	1.5288	1.5508	1.8193
FC3	0.59533	1.4222	2.0251	2.1325	2.4802	2.5693	2.6842	2.6856
C3	0.48182	0.82515	1.0582	0.95978	1.9094	1.4992	1.4333	1.3675
C5	0.34872	0.72398	0.86684	0.98392	1.5484	1.3781	1.3232	1.3617
P3	0.39242	0.9283	1.0711	1.2322	1.9122	1.5553	1.5396	1.5783
P7	0.19421	0.56847	0.632	0.75028	1.0584	0.96376	1.0528	1.1618
PO7	0.31469	0.68721	0.74536	1.012	1.2561	1.3856	1.4107	1.654
PO3	0.34882	0.9984	0.9984	1.3285	1.6569	1.6353	1.6035	1.7388
O1	0.33531	1.0281	1.3279	1.4776	1.7169	1.8247	1.7792	1.9205
Oz	0.68925	2.1207	2.3235	2.3812	2.5667	2.4512	2.7911	2.8198
Pz	0.42196	1.1344	1.387	1.4327	2.2062	1.793	1.8002	1.662
CPz	0.45128	0.9094	1.243	1.1808	2.2367	1.594	1.5626	1.4681
FP2	0.41966	0.8326	0.98993	1.2306	1.7667	1.5405	1.4814	1.7102
Fz	0.61667	1.226	1.3033	1.3367	2.1224	2.0175	1.7631	1.7449
F4	0.44262	0.99431	1.14	1.155	1.6136	1.7069	1.4569	1.3931
F8	0.35836	0.74531	0.88976	0.91597	1.5413	1.339	1.2398	1.139
FC4	0.44667	1.0289	1.1353	1.1289	1.7465	1.6935	1.7197	1.5245
FCz	0.63869	1.2967	1.5096	1.436	2.5314	2.065	1.8266	1.8794
Cz	0.52336	0.98136	1.3336	1.26	2.3724	1.681	1.6727	1.542
C4	0.35979	0.91268	1.1287	1.148	1.8638	1.6021	1.535	1.2665
C6	0.31506	0.80136	0.9955	1.0341	1.6826	1.4863	1.4267	1.1766
P4	0.30362	0.94751	1.0436	1.2255	1.8555	1.6538	1.6346	1.5149
P8	0.20402	0.58184	0.76635	0.93755	1.2558	1.3145	1.3089	1.3397
PO8	0.30532	0.92687	1.0238	1.2492	1.5034	1.6373	1.4245	1.3248
PO4	0.76843	2.0149	2.4295	2.9162	3.7479	3.9017	4.0919	3.7745
O2	0.35277	0.83549	1.1006	1.2985	1.644	1.8281	1.8045	1.7509

Figure 28: ERP Heatmap for Correct Non-Targets

	-100 : 0	0 : 100	100 : 200	200 : 300	300 : 400	400 : 500	500 : 600	600 : 700
FP1	0.5946	0.90816	1.5349	2.6872	2.688	3.6358	2.6124	3.1789
F3	0.88476	1.1	1.8799	3.256	2.9044	3.8083	2.7896	3.7234
F7	0.42505	1.2141	2.0466	2.2658	3.0411	3.7413	3.811	3.5086
FC3	1.0434	1.787	2.3429	3.1739	3.137	4.1439	3.5719	4.5961
C3	0.70657	1.4476	1.9039	3.3605	3.1841	3.575	3.1725	4.1707
C5	0.44919	0.73646	1.4933	2.534	2.0743	3.0223	2.4485	2.0396
P3	0.68631	1.4678	1.5329	2.4583	1.8952	2.3737	2.0109	2.2479
P7	0.49592	0.64108	0.9773	1.5537	1.2703	1.4738	1.5786	1.2392
PO7	0.4908	1.0879	1.8011	1.7912	2.2272	2.5266	2.4617	1.9436
PO3	0.81527	1.5419	2.063	2.7511	2.6437	2.8568	2.5098	2.2068
O1	0.65834	1.3827	1.8865	2.698	2.8227	3.1931	2.9301	2.8926
Oz	1.1301	2.1029	1.9759	1.9801	3.9312	3.0541	2.8296	2.9
Pz	1.039	1.811	2.0885	2.3148	2.0897	2.9372	1.9437	2.4301
CPz	0.71175	1.615	2.5499	3.2116	2.9873	4.1286	3.0587	3.4221
FP2	0.60734	1.143	1.2109	2.39	2.1243	3.3326	2.5637	3.0033
Fz	1.0571	1.4025	2.62	3.9617	3.9387	4.9479	3.7886	5.2905
F4	0.74155	1.0774	1.9868	3.2193	3.0054	3.646	3.2654	3.9941
F8	0.6506	1.0896	1.2079	2.4443	2.1289	3.0411	2.2261	2.6684
FC4	0.68064	1.2148	1.9273	3.5799	3.7885	4.6598	3.8682	4.5678
FCz	1.031	1.6695	2.9453	3.9677	3.7487	4.8967	4.5235	5.4628
Cz	0.80575	1.8165	3.1126	4.0796	4.1568	5.0968	3.7865	4.8051
C4	0.63257	0.98268	1.9297	2.7368	2.6396	3.2759	2.2226	2.8467
C6	0.70507	1.1439	1.5065	2.4568	2.3528	3.0239	1.9968	2.465
P4	1.0267	1.8228	2.1633	2.2429	2.3111	3.2128	2.3456	1.8169
P8	0.59251	1.108	1.2784	1.0161	1.3161	1.9162	1.9639	2.0858
PO8	0.68454	1.3736	1.4257	0.95402	1.2548	2.2326	1.8571	1.6842
PO4	1.5455	4.5943	4.4296	3.921	5.6724	7.3022	7.5334	9.3955
O2	0.67959	1.5383	1.7205	1.3712	1.8426	2.3662	2.249	2.2176

Figure 29: ERP Heatmap for Target Incorrect Responses (more noise present)

8.3 ERN Analysis: Target Incorrect Responses vs Target Correct Answers

9 Low-pass Filter Application

For the ERP waveforms of subject 12, we applied a low-pass filter using a non-causal Butterworth filter with a 20 Hz cut-off and a 48 dB/octave roll-off. The filter was set up in the GUI based on these specifications. The filtered ERP waveform for subject 12 was saved as `P3_FilteredWave_YourName.erp`.

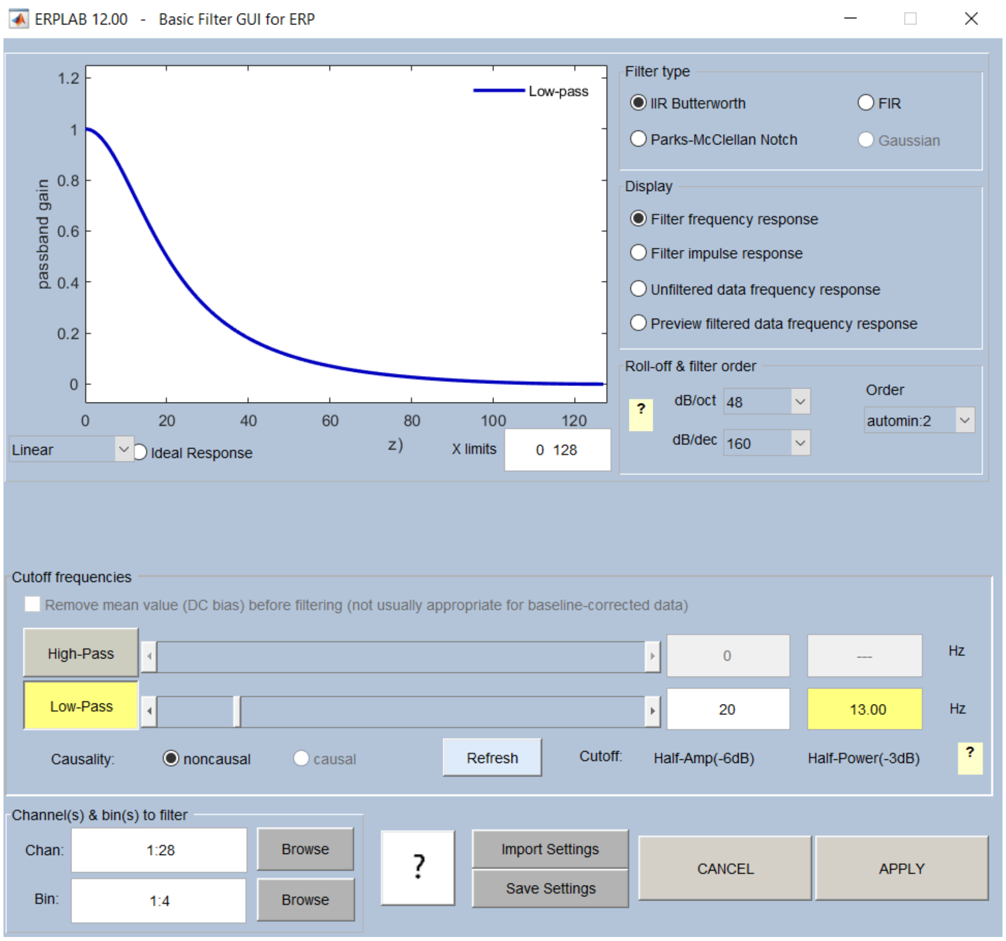

Figure 30: Screenshot of Low-pass Filter GUI Settings (20 Hz cut-off, 48 dB/octave roll-off)

The filtered ERP dataset for subject 12 was successfully.
The figure below shows the low-pass filtered waveform for subject 12:

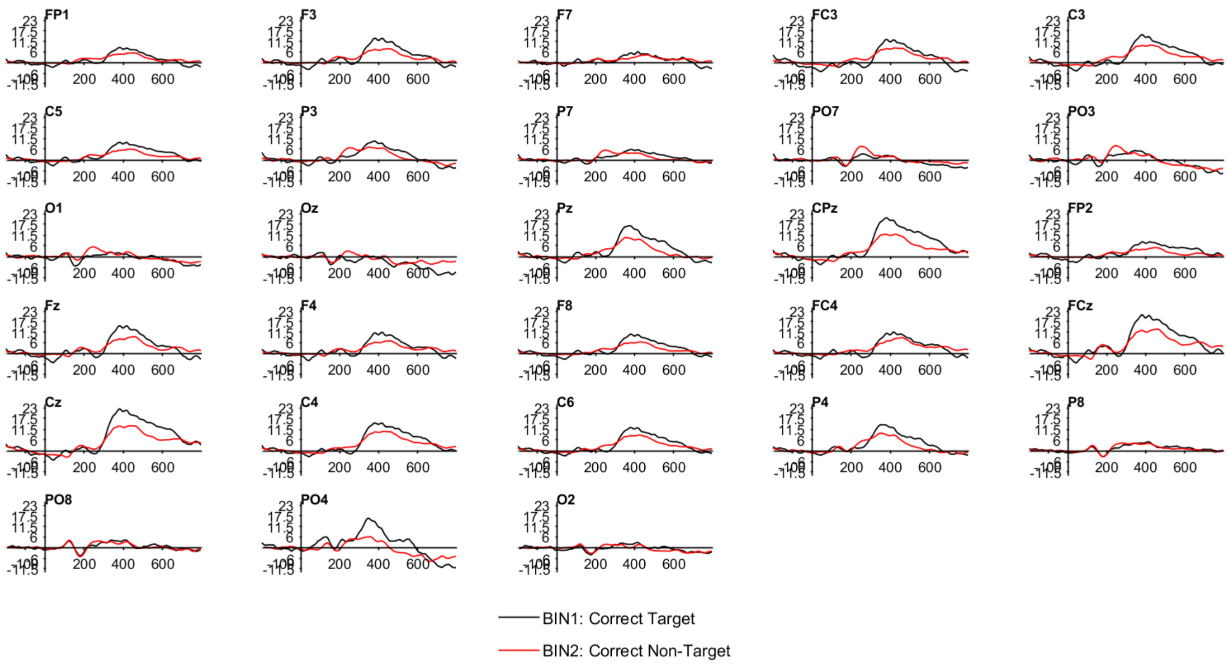

Figure 31: Low-pass filtered ERP waveforms for Subject 12

The low-pass filter applied at 20 Hz resulted in smoother ERP waveforms, especially for channels where high-frequency fluctuations were previously more pronounced. In both conditions (correct non-targets and target incorrect responses), the post-filter ERP waveforms show a reduction in noise, which is especially evident in the channels Fz, FCz, and Cz, where the P3 component is more distinct after filtering.

10 P3 and ERN Plot and Interpretation

10.1 P3 Analysis for Fz Electrode

The figure below shows the P3 component, calculated as the difference between the ERP waveforms for correct target (Bin 1) and correct non-target (Bin 2) conditions for the Fz electrode. The P3 component is associated with attention and working memory processes, typically peaking around 300-400 ms post-stimulus onset.

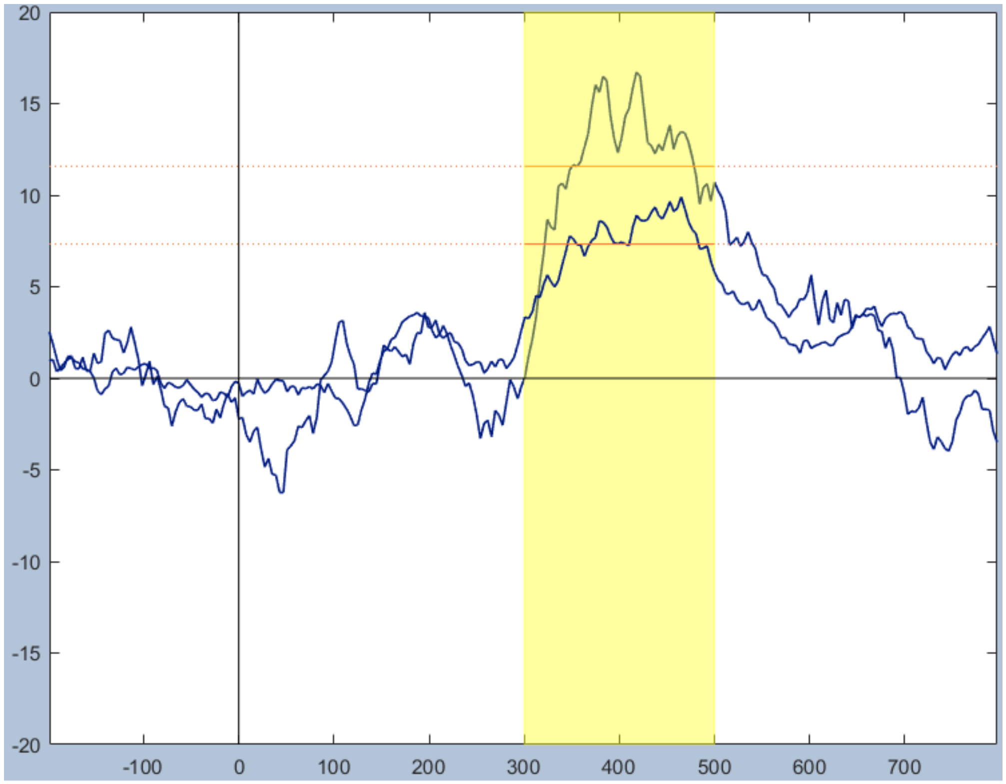

Figure 32: P3 Difference Waveform for Fz Electrode: Correct Target vs Correct Non-Target conditions. A clear P3 component is visible, with higher amplitude for the correct target condition.

10.1.1 Interpretation of P3 Component

The P3 waveform at the Fz electrode shows a significant positive deflection around 300-500 ms post-stimulus onset, particularly in the correct target condition (Bin 1). This is consistent with typical P3 activity observed in healthy individuals during target detection tasks. The higher amplitude in the correct target condition compared to the non-target condition suggests heightened cognitive processing, likely related to target recognition and evaluation.

The difference waveform highlights the increased P3 amplitude for correct targets, which is expected in typical P3 responses. There is no evidence of any abnormalities suggesting atypical cognitive processing in this data.

11 Group-level Analysis

11.1 Mean Amplitude of the P3 Peak ($\pm$50 ms Window Around the Peak)

To calculate the mean amplitude of the P3 peak for both **correct target (Bin1)** and **correct non-target (Bin2)** conditions, the peak amplitude was averaged across all participants and channels in a window of $\pm$50 ms around the peak. The resulting values are presented in the form of heatmaps:

- **Figure 33** shows the mean P3 amplitude for both Bin1 (correct target) and Bin2 (correct non-target) conditions across all participants and channels.
- The rows correspond to individual subjects, and the columns correspond to EEG channels. The heatmap shows that **Bin1** has generally higher amplitudes than **Bin2**, especially in the central-parietal regions (e.g., *Pz, Cz, Fz*).

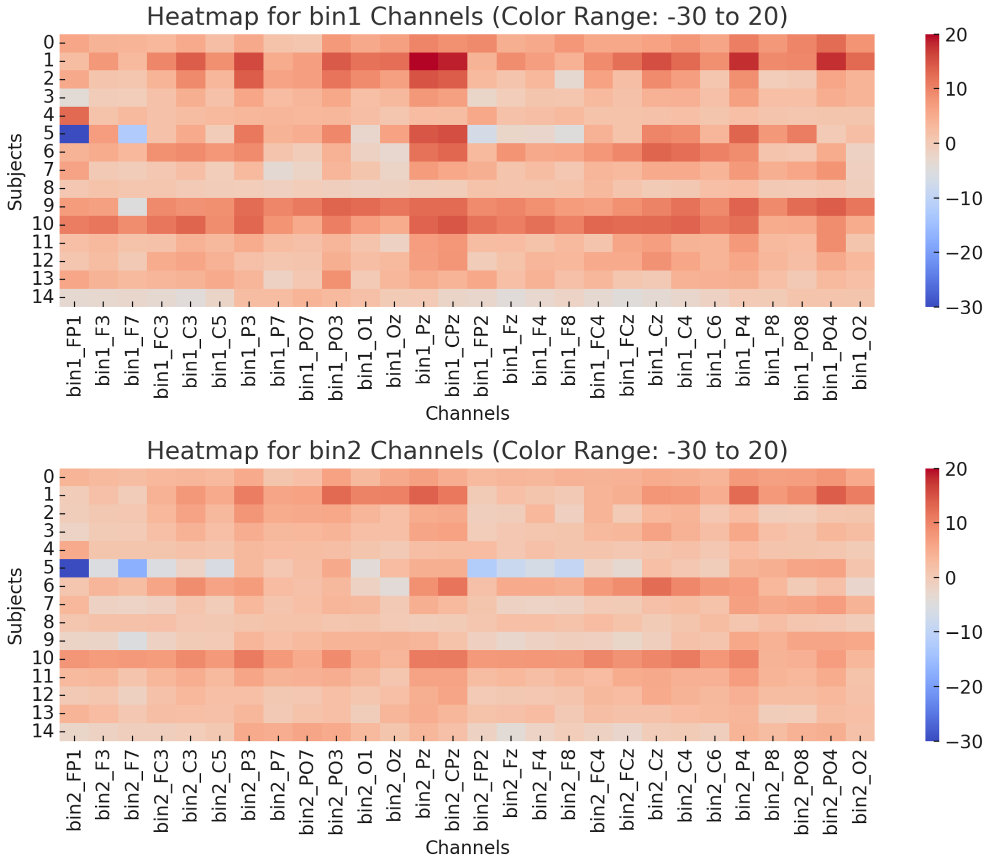

Figure 33: Heatmaps of mean P3 amplitude for Bin1 (correct target) and Bin2 (correct non-target) across all subjects and channels.

11.2 Difference Between Correct Target and Correct Non-target Conditions

The difference between Bin1 and Bin2 was also calculated for each subject and channel, resulting in the heatmap shown in **Figure 34**.

- The largest differences are observed in the central-parietal regions, particularly in *Pz, Cz, Fz*, which is consistent with typical P3 activity.
- This suggests that the P3 component is stronger in response to targets compared to non-targets.

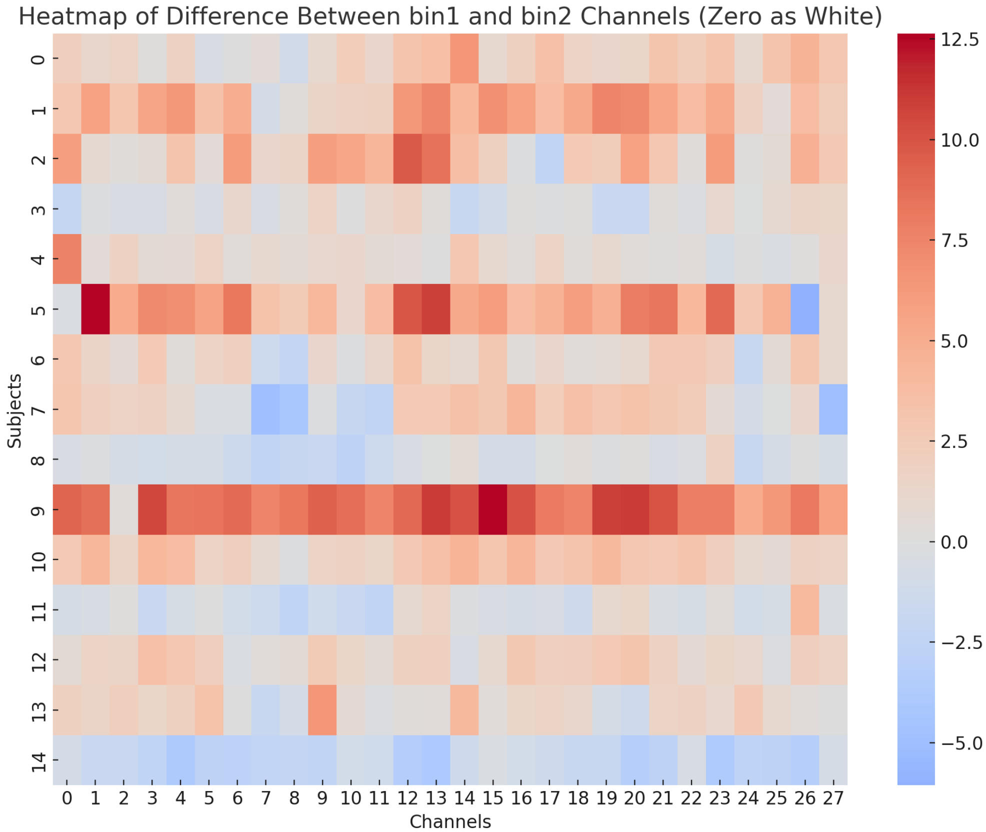

Figure 34: Heatmap showing the difference in P3 amplitude between Bin1 and Bin2 conditions across all subjects and channels.

11.3 Grand-averaged ERP Waveforms

Additionally, the grand-averaged ERP waveforms for Bin1 and Bin2 were computed across all participants and channels. As shown in **Figure 35**, there is a clear difference in the P3 component between the two conditions:

- **Bin1** (correct target) exhibits a stronger P3 peak, particularly around the 300-400 ms time window post-stimulus.
- **Bin2** (correct non-target) has a weaker P3 component, which aligns with the expectation that non-target stimuli do not elicit the same level of cognitive processing as target stimuli.

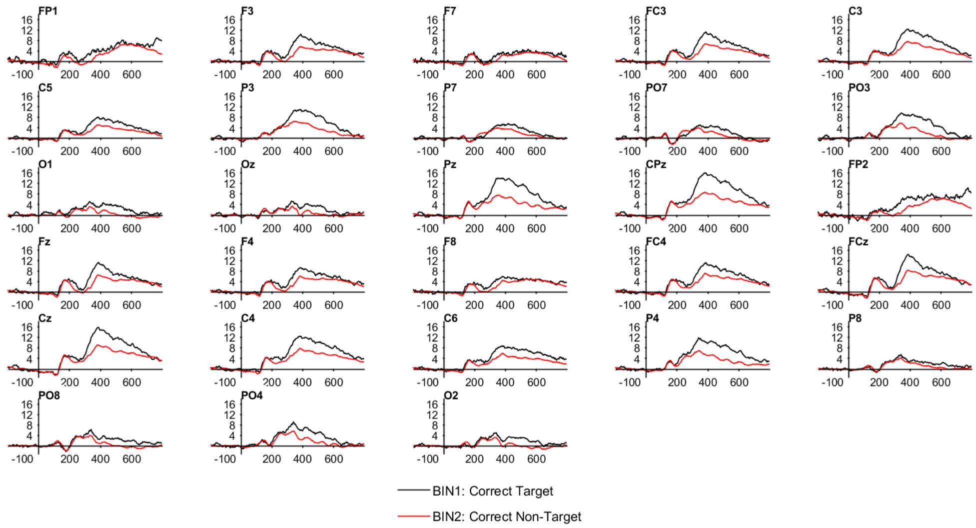

Figure 35: Grand-averaged ERP waveforms for Bin1 (correct target) and Bin2 (correct non-target) across all participants.

In summary, the group-level P3 analysis reveals significant differences between correct target and correct non-target conditions. The heatmaps and grand-averaged ERP plots show that the P3 component is more pronounced in response to target stimuli, particularly in the central-parietal electrodes.

12 Statistical Analysis: Paired T-Test (P3 Analysis)

For the P3 analysis, a paired t-test was conducted to compare the mean amplitudes of Bin1 (correct target) and Bin2 (correct non-target) conditions across all subjects in the time window [300 ms, 500 ms]. The results of the t-tests are displayed in Figure 36.

12.1 Explanation of Paired T-Test Results

The plot in Figure 36 illustrates the p-values obtained from the paired t-tests for each EEG channel:

- The p-values are displayed on the y-axis, while the corresponding EEG channels are on the x-axis.
- A red dashed line is placed at the threshold of $p = 0.05$, representing the cutoff for statistical significance. Channels with p-values below this threshold indicate a significant difference between the mean amplitudes of Bin1 and Bin2.
- Channels with p-values above 0.05 do not show statistically significant differences, implying that any observed differences between the two conditions are likely due to random variation.

12.2 Interpretation of Results

- Channels such as F3, FC3, and C3 show significant differences between the correct target and correct non-target conditions, as their p-values fall below the 0.05 threshold.
- Channels like FP1 and F7 exhibit p-values above 0.05, indicating no significant difference in the P3 response between the two conditions for these channels.
- Most of channels have p-value below 0.05 which indicated the meaningful difference between two bins.

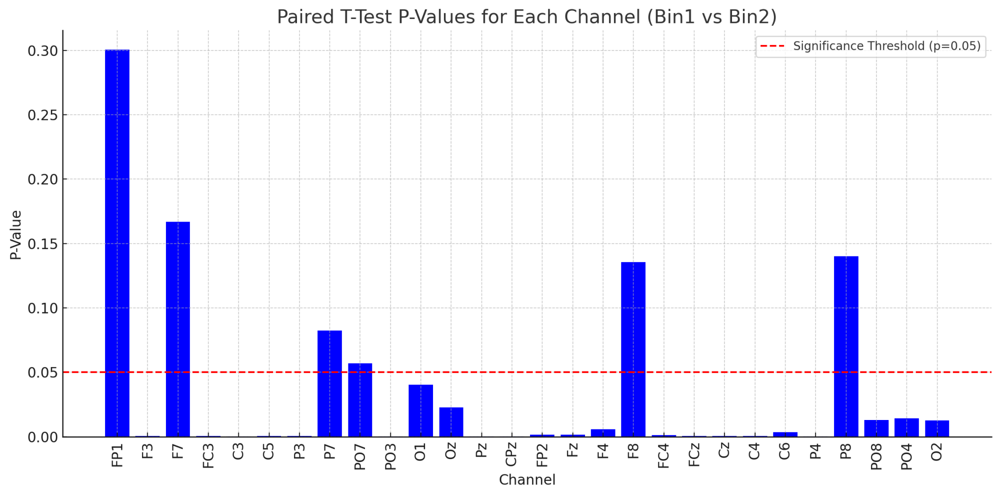

Figure 36: Paired T-Test P-Values for Each Channel (Bin1 vs Bin2). The red dashed line represents the significance threshold at $p = 0.05$.