Assignment 4

Mahdi Tabatabaei - Heliya Shakeri

Biomedical Signal and Image Processing Lab

Nastaran Nouri

October 30, 2024

Contents

Contents **1**

Evoked Related Potential **2**

Question 2 **8**
Question 1 8
Question 2 11
Question 3 11
Question 4 12
Question 5 13
Question 6 14

Event Related synchronization/desynchronization **15**

Evoked Related Potential

The EEG signal (`ERP_EEG` stored in `EEG_ERP.mat`) is recorded from one EEG channel (Pz). The signal is a response to a visual stimulus and includes baseline periods, a stimulus event, and a P300 response.

The experiment consists of 2550 trials, with an inter-trial interval of 240 Hz (approximately 4.17 ms) from the stimulus onset until the signal is recorded.

Assuming that all trials have a constant delay for the stimulus response, we will average the trials to extract the P300 response from the signal by averaging a sufficient number of trials.

(a) Average response obtained for different values of N: $N = 100 : 100 : 2500$. Plot the patterns in one figure and compare them as N increases.

```
load('ERP_EEG.mat', 'ERP_EEG');  % Assumes the EEG data is stored in ERP_EEG

% Sampling frequency
fs = 240; % Hz

% Define the values of N for averaging
N_values = 100:100:2500;

% Time vector for 1 second (assuming data starts from stimulus onset)
t = (0:size(ERP_EEG, 1)-1) / fs;

% Initialize a figure for plotting
figure;
hold on;
title('Averaged EEG Response for Different N Values');
xlabel('Time (seconds)');
ylabel('Amplitude (V)');

% Loop over different values of N
for N = N_values
    % Randomly select N trials from the 2550 available trials
    selected_trials = ERP_EEG(:, [1:N]);

    % Compute the average response across the N selected trials
    avg_response = mean(selected_trials, 2);

    % Plot the averaged response
    plot(t, avg_response, 'DisplayName', sprintf('N = %d', N), LineWidth=1.5);
end

% Add legend and display the plot
legend show;
hold off;
```

Source Code 1: 1-1

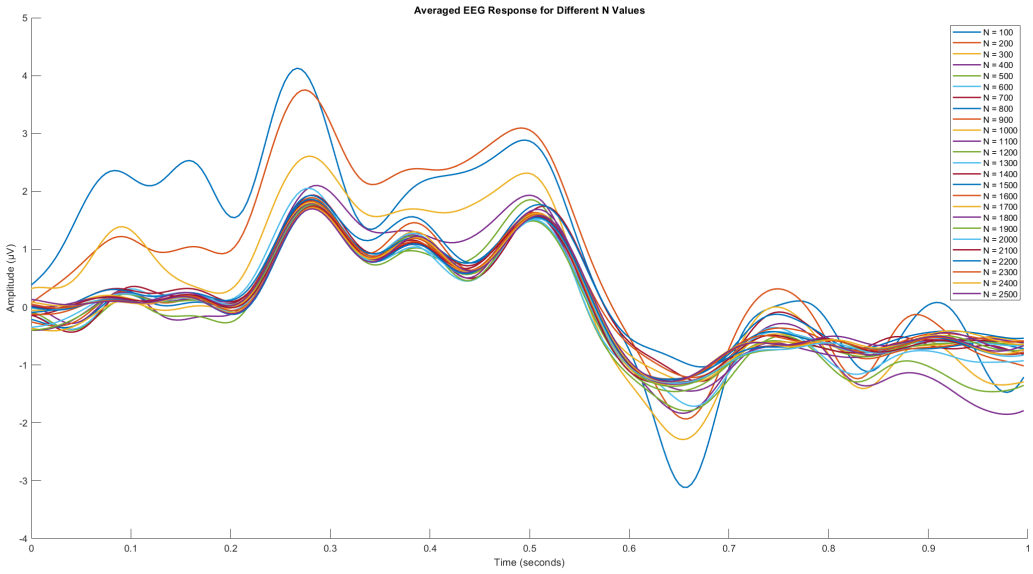

Figure 1

(b) For $N = 2550$: Plot the power spectral density of the signal, averaged across the trials, in a single figure.

```
% Define the range for N values
N_values = 1:2550;

% Preallocate an array to store the maximum absolute amplitude for each N
max_amplitude = zeros(1, length(N_values));

% Loop over different values of N
for N = N_values
    % Randomly select N trials from the 2550 available trials
    selected_trials = ERP_EEG(:, [1:N]);

    % Compute the average response across the N selected trials
    avg_response = mean(selected_trials, 2);

    % Calculate the maximum absolute amplitude of the averaged response
    max_amplitude(N) = max(abs(avg_response));
end

% Plot the maximum absolute amplitude versus N
figure;
plot(N_values, max_amplitude, LineWidth=1.5);
title('Maximum Absolute Amplitude vs. Number of Averaged Trials (N)');
xlabel('Number of Averaged Trials (N)');
ylabel('Maximum Absolute Amplitude (V)');
grid on;
```

Source Code 2: 1-2

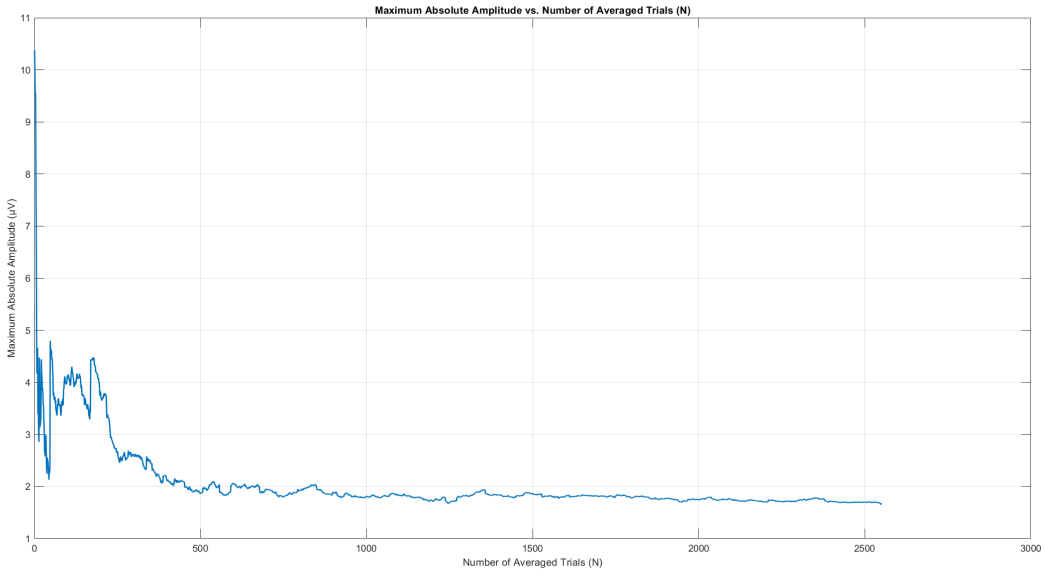

Figure 2

(c) Calculate the root mean square error (RMSE) between the average response patterns N-th and $(N-1)$-th for different numbers of averaged trials up to $N = 2550$. Plot these results in a single figure.

```
% Preallocate an array to store RMSE between N-th and (N-1)-th averaged patterns
rmse_values = zeros(1, length(N_values) - 1);

% Initialize the previous average response for N=1
prev_avg_response = mean(ERP_EEG(:, [1:N]), 2);

% Loop over values of N from 2 to 2550
for N = 2:length(N_values)
    % Randomly select N trials from the 2550 available trials
    selected_trials = ERP_EEG(:, randperm(2550, N));

    % Compute the average response across the N selected trials
    avg_response = mean(selected_trials, 2);

    % Calculate the RMSE between the current and previous averaged response
    rmse_values(N-1) = sqrt(mean((avg_response - prev_avg_response).^2));

    % Update the previous average response
    prev_avg_response = avg_response;
end

% Plot RMSE versus N
figure;
plot(N_values(2:end), rmse_values);
title('RMSE Between Consecutive Averaged Patterns vs. Number of Averaged Trials (N)');
xlabel('Number of Averaged Trials (N)');
ylabel('RMSE (V)');
```

```
28    grid on;
```

Source Code 3: 1-3

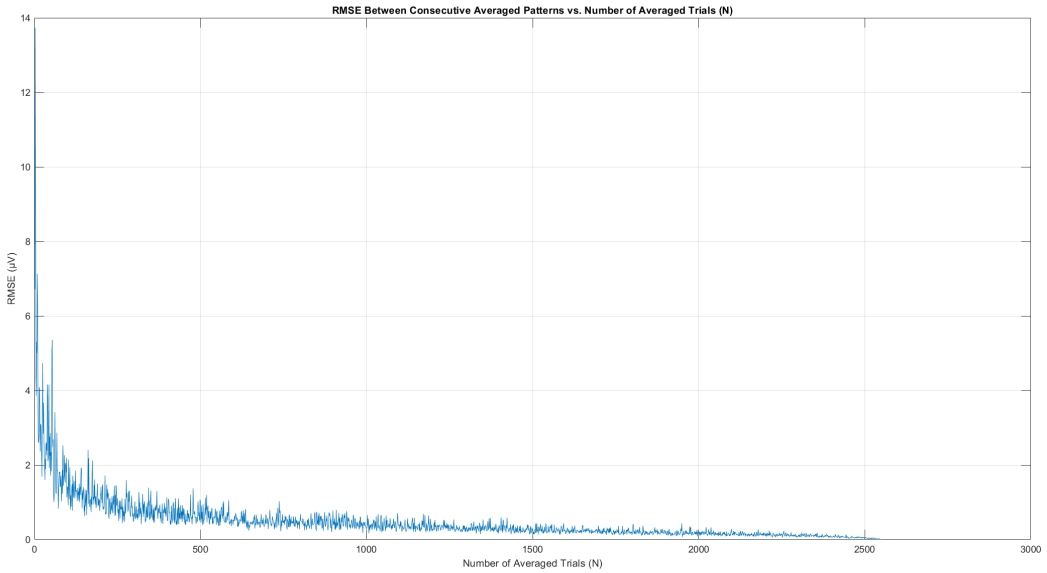

Figure 3

(d) Using the results obtained from parts (a), (b), and (c), determine the number of trials required to reliably extract the P300 response. How many trials are necessary?

Soloution

To identify the minimum N_0 for reliable extraction of the P300 signal, look for the point where the RMSE stabilizes and remains low, as well as where the maximum amplitude plot flattens out. So, we choose $N_0 = 1000$.

(e) Plot and analyze the following results:

- The mean response obtained from part (d) alongside the calculated responses for the following conditions:
- $N = 2550$
- $N = \frac{N_0}{2}$ where N_0 is the required number of trials for reliable P300 extraction
- $N = \frac{N_0}{3}$ with selective trials from responses between trials 1 and 2550.

```
1    % Define the number of trials for each condition
2    N_all = 2550;
3    N0 = 1000;
4    N_third = round(N0 / 3);
5
6    % Calculate the average response for each condition
7
8    % 1. Average response using all trials (N = 2550)
9    avg_response_all = mean(ERP_EEG(:, [1:N_all]), 2);
```

```
10
11      % 2. Average response using N0/3  trials
12      avg_response_N0_third = mean(ERP_EEG(:, [1:N_third]), 2);
13
14      % 3. Average response using N0 trials
15      avg_response_N0 = mean(ERP_EEG(:, randperm(2550, N0)), 2);
16
17      % 4. Average response using N0 / 3 trials
18      avg_response_N0_third_random = mean(ERP_EEG(:, randperm(2550, N_third)),
        2);
19
20      % Plotting the responses
21      figure;
22      plot(t, avg_response_all, 'DisplayName', 'N = 2550', LineWidth=1.5);
23      hold on;
24      plot(t, avg_response_N0_third, 'DisplayName', sprintf('N = 1000/3 not
        Random'), LineWidth=1.5);
25      plot(t, avg_response_N0, 'DisplayName', sprintf('N = 1000  Random'),
        LineWidth=1.5);
26      plot(t, avg_response_N0_third_random, 'DisplayName', sprintf('N = 1000/3
        Random'), LineWidth=1.5);
27      hold off;
28
29      % Customize the plot
30      title('Comparison of Averaged EEG Responses for Different Trial Counts');
31      xlabel('Time (seconds)');
32      ylabel('Amplitude (V)');
33      legend show;
34      grid on;
```

Source Code 4: 1-5

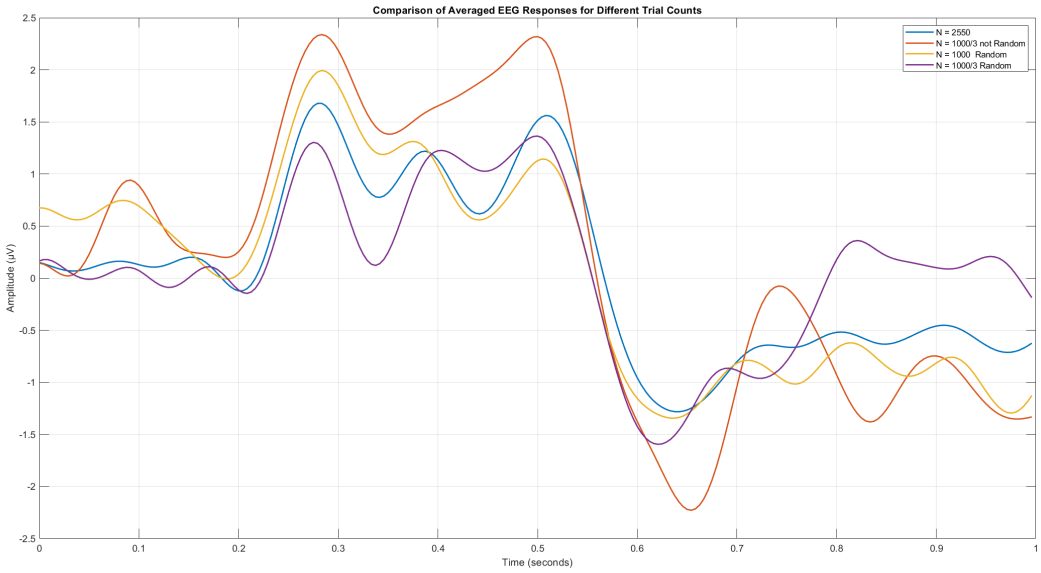

Figure 4

Soloution

Based on the figure, the response obtained from the randomly selected N_0 trials is more consistent than the other selections. We can observe that as the number of selected trials decreases, the signal shows more distortion.

(f) Examine several real samples based on the P300 signal. In real experiments where P300 patterns are used (such as brain-computer interfaces and P300-based applications), how many repetitions of the P300 pattern are used? Does this number correspond to the results obtained in the previous sections? Explain the reason for any differences observed.

Soloution

In real experiments using the P300 signal (such as in brain-computer interfaces or P300-based cognitive research), the number of repetitions of the P300 pattern is often set based on the noise level and the clarity required for the signal. Typically, researchers use a number of trials that is sufficient to get a clear and stable P300 response.
The number of trials used in real experiments may differ from the value we determined in the analysis. This difference is because real experiments are often optimized to balance accuracy with the time and effort required to collect data. In our analysis, we estimated the minimum number of trials needed to achieve a reliable signal based on theoretical calculations. However, in practice, additional factors like environmental noise, subject variability, and task difficulty may require more trials.

Question 2

Question 1

For each channel, apply a bandpass filter to remove frequencies below 1 Hz and above 40 Hz. For each channel, plot the denoised signal along with the original signal.

```
% Design a bandpass filter to keep frequencies between 1 Hz and 40 Hz
filtered_SSVEP = zeros(size(SSVEP_Signal));

for i = 1 : size(SSVEP_Signal,1)
    figure;
    bandpass(SSVEP_Signal(i,:),[1 40],Fs);
    filtered_SSVEP(i,:) = bandpass(SSVEP_Signal(i,:),[1 40],Fs);
end
```

Source Code 5: EEG - Question 2

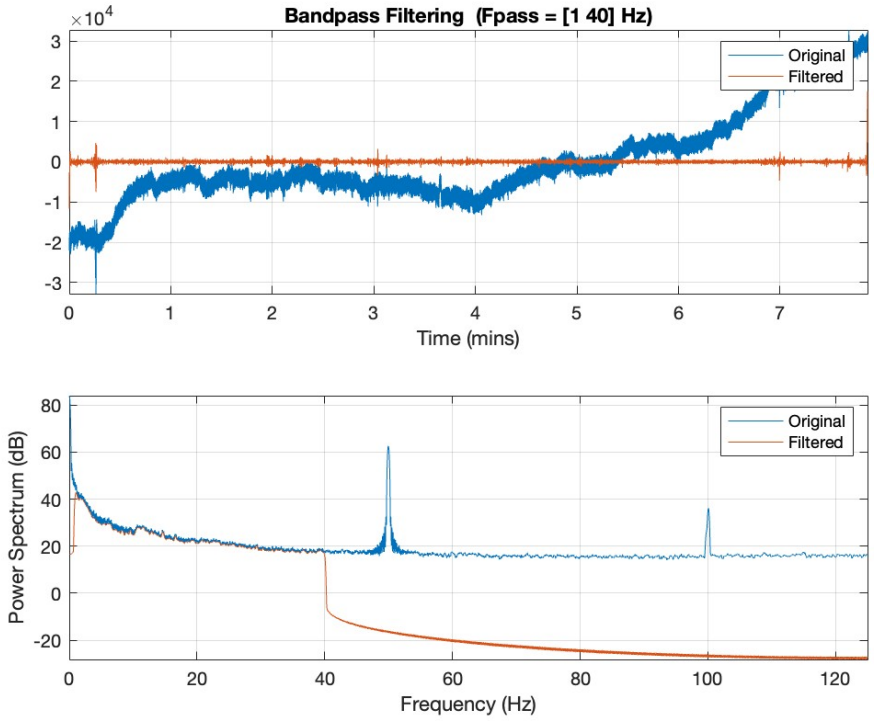

Figure 5: Question 2 - Filtered and Original Signals for Channel 1

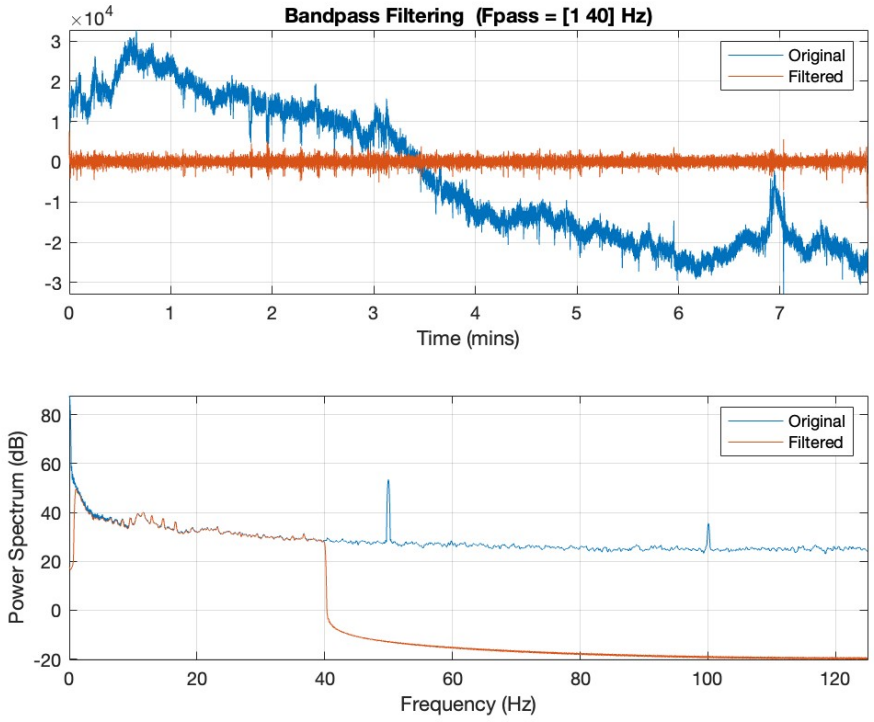

Figure 6: Question 2 - Filtered and Original Signals for Channel 2

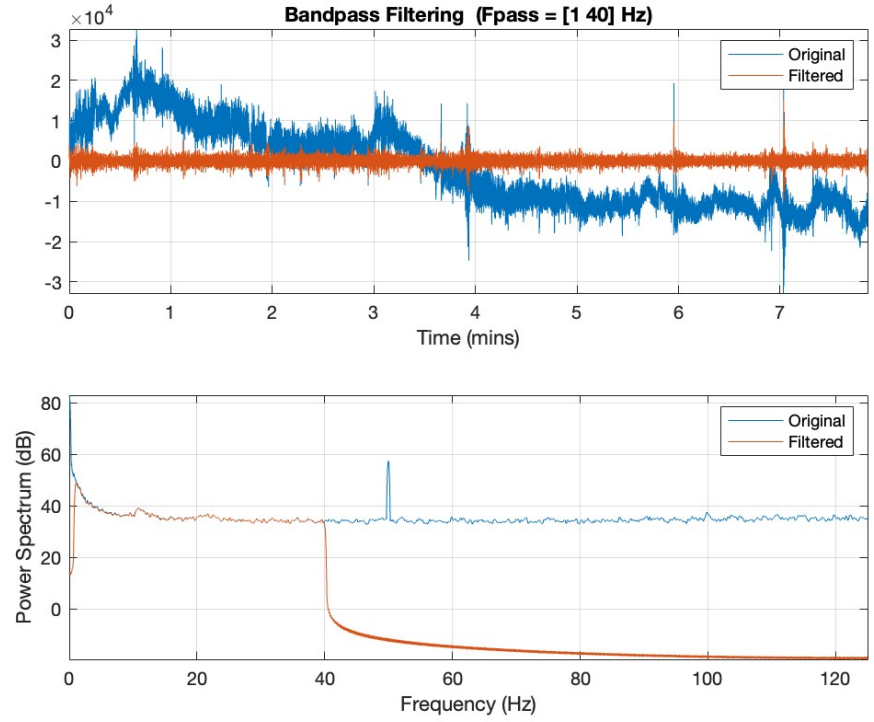

Figure 7: Question 2 - Filtered and Original Signals for Channel 3

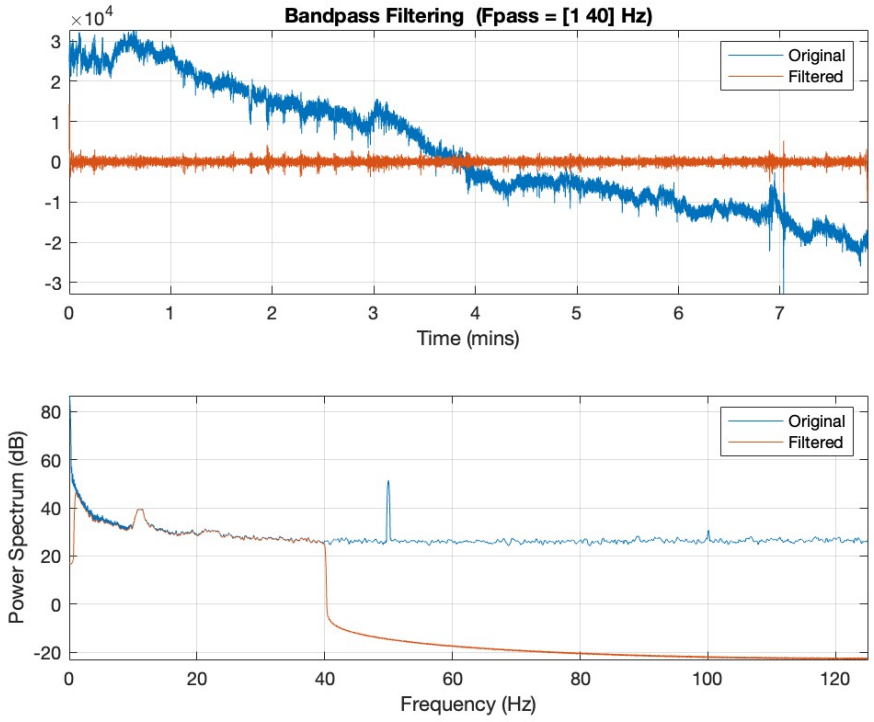

Figure 8: Question 2 - Filtered and Original Signals for Channel 4

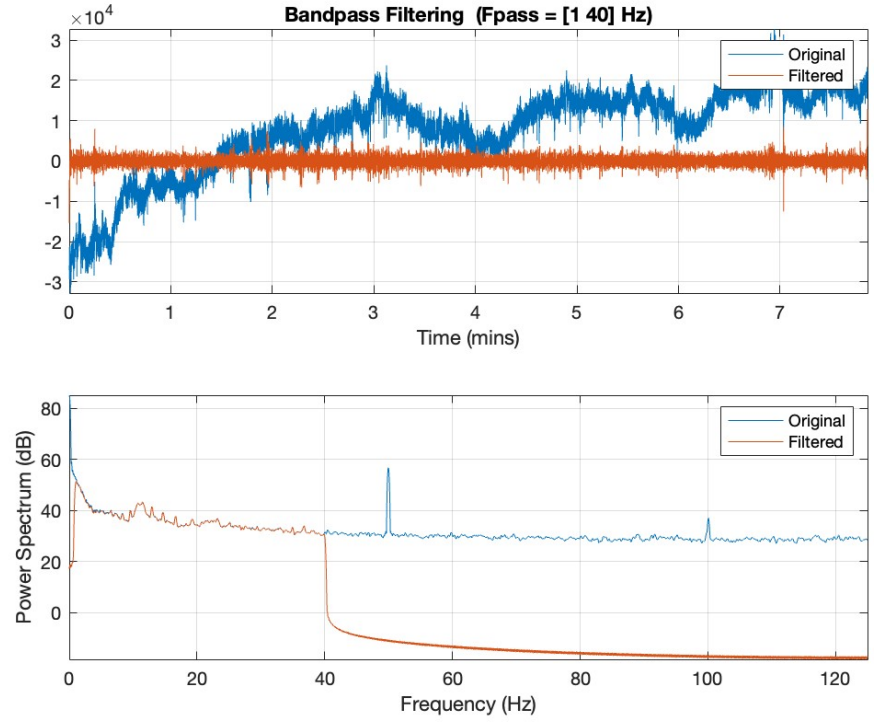

Figure 9: Question 2 - Filtered and Original Signals for Channel 5

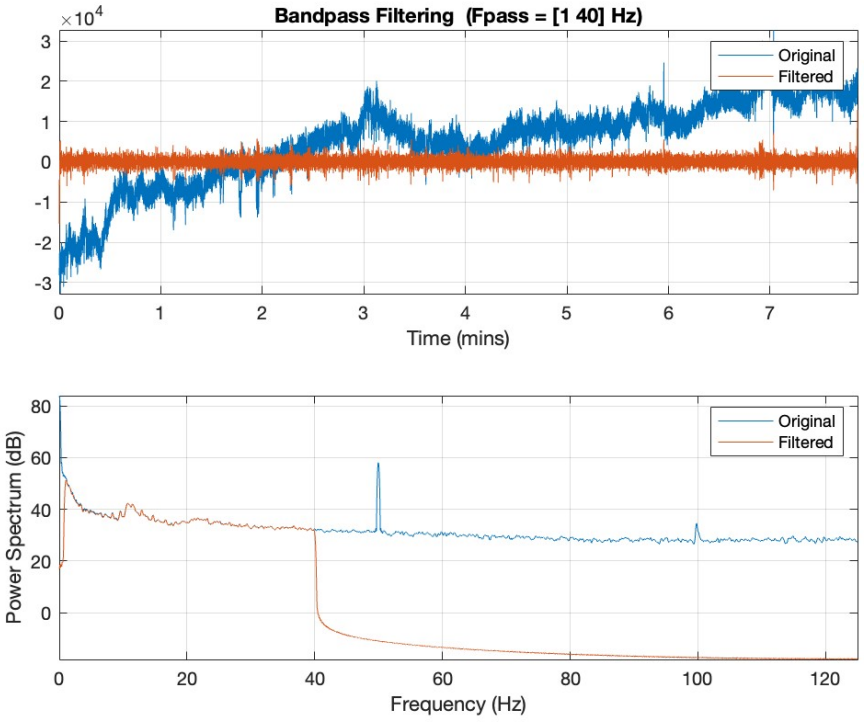

Figure 10: Question 2 - Filtered and Original Signals for Channel 6

Question 2

Separate 15 trials corresponding to 15 stimuli, each with a 5-second window.

```
T = 5;
epochs = zeros([size(filtered_signal, 1), T * Fs, 15]);

for i = 1:15
    ind_s = events(i);
    ind_f = ind_s + T * Fs;
    epochs(:, :, i) = filtered_signal(:, ind_s:ind_f-1); % Store the segmented epoch
end
```

Source Code 6: Extracting 5-second Epochs for Each Trial

Question 3

For each trial, calculate the frequency content for each of the six channels and plot them in a single figure. Use the ‘pwelch‘ function and add a legend to indicate which plot corresponds to each channel.

```
% Channel labels
strs = ["Pz","Oz","P7","P8","O2","O1"];

figure("units","normalized","OuterPosition",[0 0 1 1]);

for i = 1 : 15
    subplot(5,3,i);
    hold on
    for j = 1 : 6
        [pxx,f] = pwelch(epochs(j,:,i),[],[],[],Fs);
```

```
            plot(f,pxx,'LineWidth',1.5);
            title("Welch PSD Estimate for Event"+ num2str(i));
            xlabel("f[Hz]");ylabel("Power/frequency(dB/Hz)");
        end
        xlim([0 40]);
    end
    legend(strs);
```

Source Code 7: Welch PSD Estimate for Each Trial

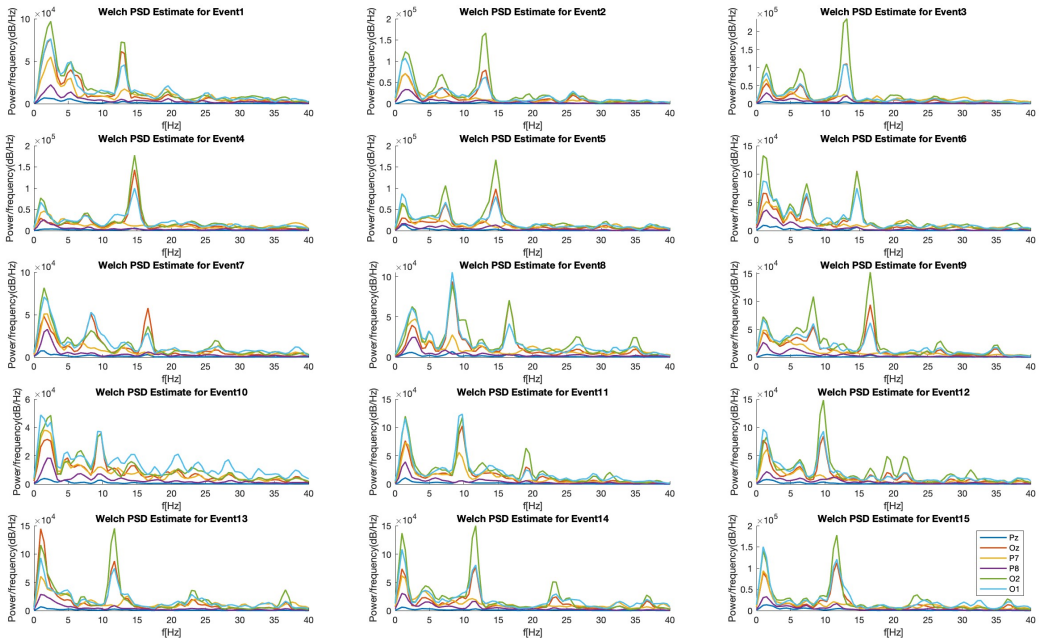

Figure 11: Welch PSD Estimate for all Events

Soloution

As we can see, in each row of three trials, we observe that the frequency bands align with the expected stimulation frequencies. The PSD demonstrates that these target frequencies, along with some of their harmonic components, exhibit higher power levels.

Question 4

Are all channels frequency content identical for a single trial? Is there a difference in frequency content across channels, and what might be the reasons for these differences?

Soloution

As shown in the figure above, for a single trial, all channels do not have identical frequency content. Some channels exhibit higher power at certain frequencies, while others show lower responses or lack prominent peaks at those frequencies. For instance, in most trials, we observe that channels O1, O2, and Oz generally display higher power at target stimulation frequencies. This finding indicates that these channels are more responsive to the stimulus. These channels are associated with the occipital lobe, which contains the visual cortex that processes visual stimuli, making them more sensitive to SSVEP (Steady-State Visual Evoked Potential) responses. The electrodes closest to the occipital lobe (channels Pz, O1, O2, and Oz) exhibit the strongest responses, while channels like P7 and P8, which are farther from the visual cortex, show relatively lower responses.
The differences in frequency content across channels can stem from various factors, such as electrode placement and individual electrode sensitivity. Each electrode's positioning on the scalp corresponds to different brain regions, and these regions have distinct resonance frequencies based on their functions and neural activity. Noise in certain channels may also contribute to the observed variations in the PSD plots. If a channel is noisy, it can lead to a reduced power representation in the PSD plot, affecting the channel's power levels. To address these variations, averaging the signals across trials or using additional preprocessing methods can help reduce noise and highlight the true response patterns across channels.

Question 5

Analyze the frequency content observed in each trial and identify the stimulation frequencies and their harmonics. Highlight any significant peaks in the Power Spectral Density (PSD) for each trial.

Soloution

In trials 4 to 6, the stimulation frequency is approximately 6.5 Hz, with a peak at around 7.25 Hz and a second harmonic at 14.7 Hz. We observe that the power at these frequencies is high. Additionally, trials 7 to 9 show a stimulation frequency around 8.3 Hz, with a harmonic at about 10 Hz and another at approximately 9.6 Hz, both of which show strong power responses.
Moving to trials 13 to 15, we observe a stimulation frequency of approximately 13 Hz, with harmonics present at 16 Hz. In some trials, higher harmonics appear at even multiples of the fundamental frequency. Although these harmonics do not always show prominent peaks, they are generally present across trials and are aligned with the expected stimulation frequencies in the dataset. The results indicate that the harmonics in each trial are largely consistent with the primary response frequencies.
Overall, the initial peak close to DC in the PSD of all trials represents DC offset and baseline drift. This is an easily removable component, followed by the subsequent peaks resulting from the stimulation frequencies and their harmonics.
Figure 12 below shows the Power Spectral Density (PSD) plots for selected trials, highlighting the primary and harmonic frequencies observed. The data are consistent with the expected response patterns based on the known stimulation frequencies.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	6.5000	6.5000	6.5000	7.3500	7.3500	7.3500	8.3000	8.3000	8.3000	9.6000	9.6000	9.6000	11.6100	11.6100	11.6100

Figure 12: PSD Analysis for Selected Trials - Identified Stimulation Frequencies and Harmonics

Question 6

Discuss effective methods for determining dominant frequencies in SSVEP signals and provide an overview of Canonical Correlation Analysis (CCA) and Dominant Frequency Analysis techniques.

Soloution

One of the most effective methods for analyzing SSVEP signals is Canonical Correlation Analysis (CCA). This method involves finding correlation coefficients that maximize the correlation between two multivariate sets. In this context, we set the input variables, X, as our EEG channels, and define Y with multiple reference signals, each corresponding to the stimulus frequency and its harmonics (using sine and cosine functions). By optimizing the weights, we aim to maximize the correlation at each frequency, which helps in identifying the dominant response frequencies.

Another commonly used approach for identifying the dominant frequency in SSVEP signals is to use individual frequency content from each channel. This approach may provide better results compared to using the collective frequency content from all channels. By exploring related research articles and online resources, one can learn more about other methods suitable for processing SSVEP signals and identifying the main frequency components.

Additionally, the Dominant Frequency Analysis technique can be applied by leveraging models such as autoregressive (AR) models. This technique allows us to detect peaks in the EEG frequency spectrum by modeling the signal, making it effective in pinpointing frequencies that recur consistently in the data.

Event Related synchronization/desynchronization

The file `FiveClass_EEG.mat` contains EEG signals recorded at a frequency of 256 Hz from a single user while performing various mental tasks. The EEG signal is recorded from 20 channels according to the international 10-20 system. The channels are:

`AFz, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO3, PO4, O1, and O2`.

The user performed five mental tasks as follows:

1. **Letter Composition in Mind:** The user imagines letters or words that are shown on a screen (e.g., starting a word in their mind).
2. **Simple Arithmetic Task in Mind:** The user mentally calculates a number shown on a screen. For instance, subtracting seven repeatedly from 113 is shown as follows on the screen: $113 \rightarrow 106 \rightarrow 99 \rightarrow 92 \rightarrow 85 \rightarrow 78 \rightarrow 71 \rightarrow \ldots$
3. **Navigation (Navigation in Imagery):** The user imagines navigating from a specific location to another, such as from home to a particular room (e.g., imagining home to the office room).
4. **Right Arm Movement:** Imagining the movement of the right arm.
5. **Left Arm Movement:** Imagining the movement of the left arm.

In performing each mental task, the following procedure was used: Initially, a cross (+) is shown on the screen for a specific duration (rest time) to allow the user to focus on the center of the screen. This is followed by a mental task sign ($*$), which signals the user to start the specific task. Each task was performed for 7 seconds, followed by a rest time of 3 seconds (a total of 10 seconds). This procedure was repeated 4 times, so the duration of each task in one session is $4 \times 10 = 40$ seconds.

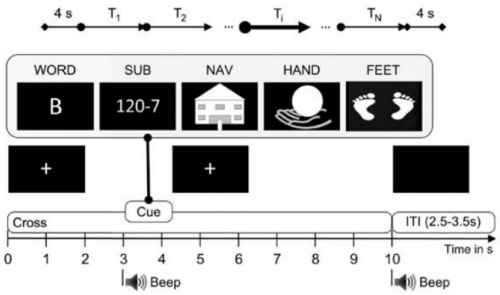

Figure 13

The dataset includes several matrices as described below:

- **X:** EEG signals recorded with dimensions *time samples* $\times$ *channels* (20 trials per session).
- **y:** Class labels ranging from 1 to 3.
- **t0:** The starting time of each trial (representing the moment when the user begins the task).

In this experiment, we want to filter the EEG signal for each class of trials using a bandpass filter, with a passband frequency range of 8-13 Hz, and analyze the results.

(a) Filter the signal for each channel using a bandpass filter with a frequency range of 8 to 13 Hz, as shown below:

```
% Bandpass filter between 8 - 13
fs = 256;             % Sampling Frequency
N = 4;                % Order
Fpass1 = 8;           % First Passband Frequency
Fpass2 = 13;          % Second Passband Frequency
Apass = 1;            % Passband Ripple (dB)

% Construct an FDESIGN object and call its CHEBY1 method.
h = fdesign.bandpass('N,Fp1,Fp2,Ap', N, Fpass1, Fpass2, Apass, fs);
Hd = design(h, 'cheby1');
for c = 1:30
    Alpha_X(:,c) = filter(Hd, X(:,c));
end
```

To ensure filter performance, apply the filter to the initial signal for each channel and plot the results for different frequency bands.

```
    % Load EEG signal data
    load('FiveClass_EEG.mat', 'X', 'trial', 'y'); % EEG data with variables X, trial, and y

    % Filter parameters
    N = 4; % Filter order
    Apass = 1; % Passband Ripple (dB)
    fs = 250; % Sampling frequency (update if different)
    channels = 30;
    bands = {'delta', 'theta', 'alpha', 'beta'};
    freq_ranges = [1, 4; 4, 8; 8, 13; 13, 30];

    % Filter EEG data for each frequency band
    filtered_X = struct();
    for b = 1:length(bands)
        Fpass1 = freq_ranges(b, 1);
        Fpass2 = freq_ranges(b, 2);
        h = fdesign.bandpass('N,Fp1,Fp2,Ap', N, Fpass1, Fpass2, Apass, fs);
        Hd = design(h, 'cheby1');
        filtered_X.(bands{b}) = zeros(size(X,1), channels);
        for c = 1:channels
            filtered_X.(bands{b})(:, c) = filter(Hd, X(:, c));
        end
    end

    % Plot filtered signals
    t = 0:1/fs:5 - 1/fs;
    figure;
    titles = {'Original', 'Delta', 'Theta', 'Alpha', 'Beta'};
    plot_signals = [{X}, filtered_X.delta, filtered_X.theta, filtered_X.alpha, filtered_X.beta];
    for i = 1:length(plot_signals)
        subplot(length(plot_signals), 1, i);
        plot(t, plot_signals{i}(1:5*fs, 1));
        title(titles{i});
        grid minor;
    end
```

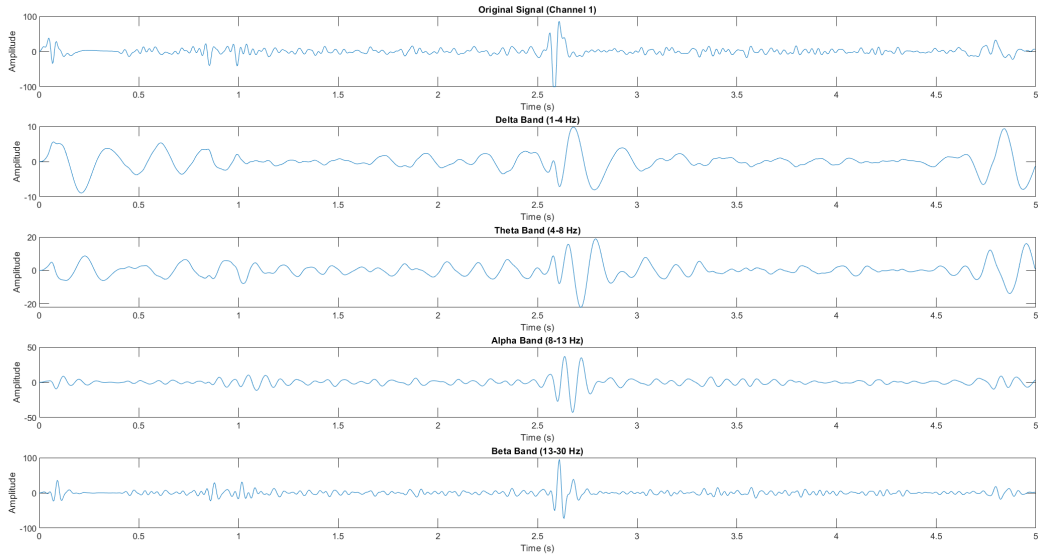

Figure 14

(b) Segregate trials from 1 to 10, and reorganize the signals into different matrices based on trial information.

```
for i = 1:200
    Alpha_Trials(:,:,i) = Alpha_X(trial(i):trial(i)+256*10, :);
end
```

```
    trial_duration = 10 * fs + 1;
    num_trials = 200;
    trial_data = struct();
    for b = 1:length(bands)
        trial_data.(bands{b}) = zeros(trial_duration, channels, num_trials);
        for i = 1:num_trials
            trial_data.(bands{b})(:, :, i) = filtered_X.(bands{b})(trial(i):
   trial(i) + trial_duration - 1, :);
        end
    end
```

c. To calculate the power of each point, compute the squared amplitude of all time points for each trial in each band and for each channel.

```
    squared_data = struct();
    for b = 1:length(bands)
        squared_data.(bands{b}) = trial_data.(bands{b}).^2;
    end
```

d. Based on the label y (in vector y), separate the data related to the 5 different classes and, for each band, calculate the average for each channel across the trials of that class (results from part c). The output of this step will be four tensors with the following dimensions:

$$\text{Delta\_X\_avg} \in \mathbb{R}^{2560\times 30\times 5}$$

$$\text{Theta\_X\_avg} \in \mathbb{R}^{2560\times30\times5}$$

$$\text{Alpha\_X\_avg} \in \mathbb{R}^{2560\times30\times5}$$

$$\text{Beta\_X\_avg} \in \mathbb{R}^{2560\times30\times5}$$

where 30 is the number of channels, and 5 is the number of classes.

```
class_count = 5;
summed_data = struct();
avg_data = struct();
sizes = zeros(1, class_count);
for b = 1:length(bands)
    summed_data.(bands{b}) = zeros(trial_duration, channels, class_count);
    avg_data.(bands{b}) = zeros(trial_duration, channels, class_count);
end

for i = 1:num_trials
    class = y(i);
    for b = 1:length(bands)
        summed_data.(bands{b})(:, :, class) = summed_data.(bands{b})(:, :, class) + squared_data.(bands{b})(:, :, i);
    end
    sizes(class) = sizes(class) + 1;
end

for b = 1:length(bands)
    for i = 1:class_count
        avg_data.(bands{b})(:, :, i) = summed_data.(bands{b})(:, :, i) / sizes(i);
    end
end
```

e. To smooth the variations in the average signals from part (d), use a rectangular window as follows:

$$\text{newWin} = \text{ones}(1, 200)/\sqrt{200}$$

and apply the `conv` function to filter the signal of each channel in each band for each experiment.

```
window = ones(1, 200) / sqrt(200);
filtered_avg = struct();
for b = 1:length(bands)
    % Adjust filtered_avg to match the length of 'valid' convolution output
    filtered_avg.(bands{b}) = zeros(trial_duration - length(window) + 1, channels, class_count);
    for i = 1:class_count
        for j = 1:channels
            % Use 'valid' to avoid size mismatch errors
            filtered_avg.(bands{b})(:, j, i) = conv(avg_data.(bands{b})(:, j, i), window, 'valid');
        end
    end
end
```

f. Select a channel (preferably a central channel on the scalp, like CPz), and plot the results from part (e) as follows: For each band, plot the smoothed time-frequency signal (duration: 10 seconds) for each of the 5 classes in a single figure (resulting in a total of 4 figures, each with 5 plots).

```
t_adjusted = 0:1/fs:(size(filtered_avg.delta, 1) - 1) / fs;

figure;
for b = 1:length(bands)
    subplot(2, 2, b);
    for i = 1:class_count
        plot(t_adjusted, filtered_avg.(bands{b})(:, 13, i)); hold on;
        grid minor;
    end
    title(bands{b});
    legend(arrayfun(@(x) ['class ' num2str(x)], 1:class_count, '
UniformOutput', false));
 end
```

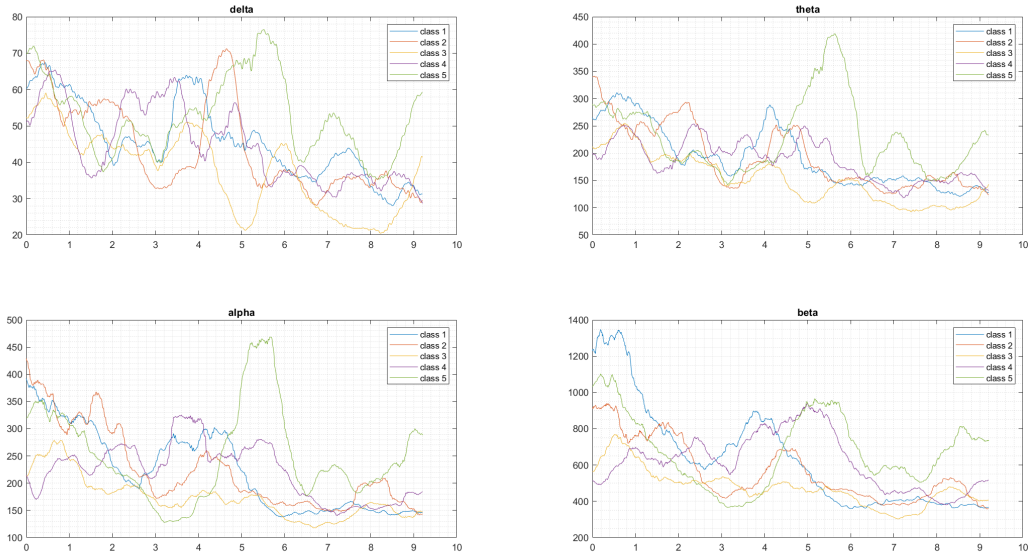

Figure 15

g. Considering the mental task, starting from the third second, what conclusions can be drawn by comparing the frequency information for each of the five classes?

Soloution

1. Class 1: It can be said that, in the delta frequency band, the power has increased more compared to before the movement. Of course, there has been an increase in other bands as well, but in the delta band, this increase has been sharper.

2. Class 2: In this class, the power decreases in all frequency bands after the movement and then gradually increases, with the highest increase observed in the delta frequency band.

3. Class 3: In all bands, there is a general trend of reduced power after movement, but the variation in the delta band is greater than in other bands. In some parts of the delta band, a more noticeable peak can be seen.

4. Class 4: The power decreases in all bands immediately after the movement. The decrease is similar across different bands but is slightly less in the delta band compared to the others.

5. Class 5: In all bands, exactly after the movement, there is a sharper peak in the alpha band compared to other bands, indicating a higher power in this class compared to others.