



# Assignment 1

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## EEG Signal

A piece of electroencephalogram (EEG) signal is provided to you in the file '`sig_EEG.mat`'. This file contains a matrix 'Z', which represents a 32-channel signal over time samples. The characteristics of this signal are specified in the variable 'des', which includes the sampling frequency and channel labels (in the order of channel numbers). This signal belongs to an epileptic patient and has been recorded during the pre-seizure and seizure intervals. Due to the real nature of the signal, muscle artifacts are clearly observable on it.

### Question 1

Plot the signal of the fifth channel over time. Adjust the time axis so that it is displayed in seconds. Manually adjust the height and width of the image so that the signal's shape changes over time are clearly visible. Write the channel label as the vertical axis label or the title of the figure.

```
1 % Extract the sampling frequency and channel labels from the 'des'
2 % variable
3 fs = des.samplingfreq; % Sampling frequency (Hz)
4 channel_labels = des.channelnames; % Channel labels
5
6 % Extract the signal data for the 5th channel (row 5 of matrix Z)
7 eeg_channel_5 = Z(5, :);
8
9 % Generate time vector in seconds
10 time = (0:length(eeg_channel_5)-1) / fs;
11
12 % Plot the signal for the 5th channel
13 figure;
14 plot(time, eeg_channel_5);
15
16 % Set axis labels and title
17 xlabel('Time (s)');
18 ylabel('Amplitude (\muV)');
19 title(['EEG Signal - Channel: ', channel_labels{5}]);
20
21 % Adjust the figure size manually to better show the signal's variation
22 % over time
23 set(gcf, 'Position', [100, 100, 1000, 400]); % Adjust figure size
24
25 % Display the plot
26 grid on;
```

Source Code 1: EEG - Question 1

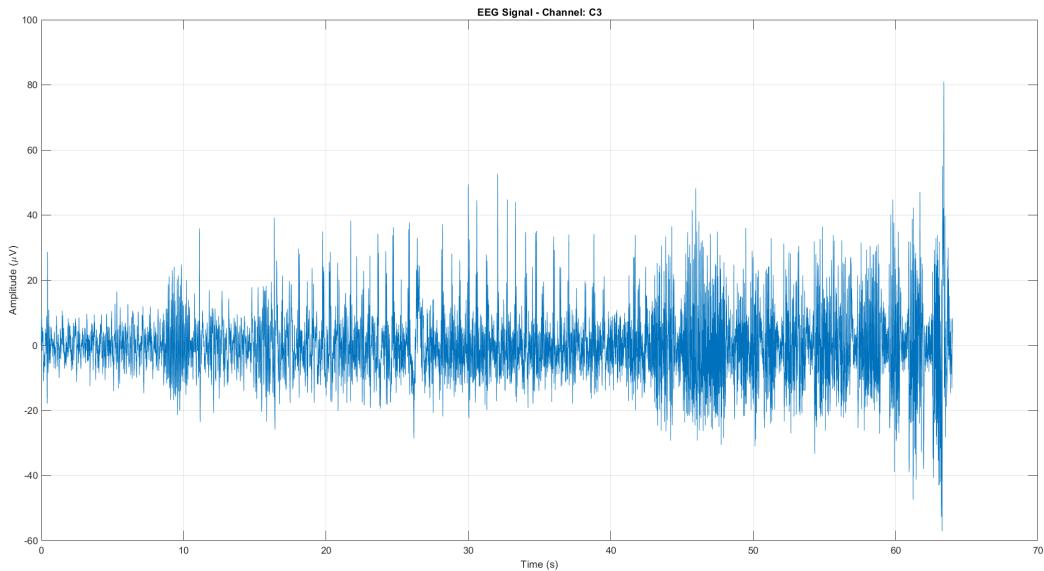


Figure 1: Question 1 - 5th Channel

## — Question 2

Examine the time-domain characteristics of the signal at different times (in the first 15 seconds, approximately between 18 to 40 seconds, approximately between 45 to 50 seconds, and in the final 50 seconds to the end of the signal). What prominent features are observed in the signal?

```

1 % Define time intervals for analysis
2 intervals = {[0 15], [18 40], [45 50], [50 max(time)]}; % Time
3 intervals in seconds
4 interval_labels = {'0-15s', '18-40s', '45-50s', '50s to end'};
5
6 % Plot each time interval
7 figure;
8 for i = 1:length(intervals)
9     % Find the indices corresponding to the time range
10    idx_range = find(time >= intervals{i}(1) & time <= intervals{i}(2))
11 ;
12
13    % Extract the corresponding signal and time
14    time_interval = time(idx_range);
15    signal_interval = eeg_channel_5(idx_range);
16
17    % Plot the signal for the given time interval
18    subplot(length(intervals), 1, i);
19    plot(time_interval, signal_interval);
20    xlabel('Time (s)');
21    ylabel('Amplitude (\muV)');
22    title(['EEG Signal - Channel: ', channel_labels{5}, ', (',
23    interval_labels{i}, ')']);
24
25    % Adjust plot appearance
26    grid on;
end

```

```
27 set(gcf, 'Position', [100, 100, 1000, 800]); % Adjust figure size
```

### Source Code 2: EEG - Question 2

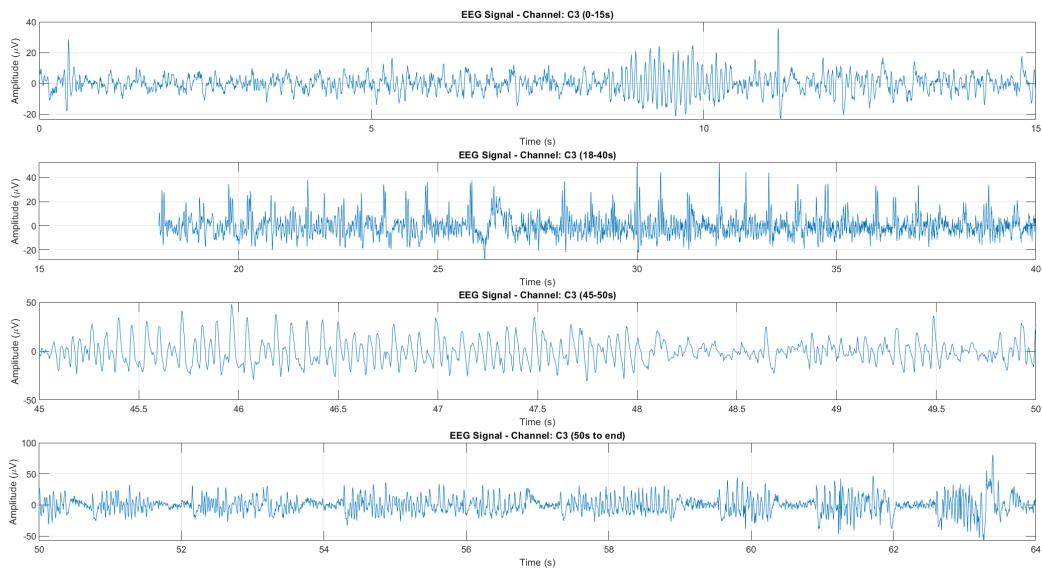


Figure 2: Question 2 - 5th Channel in different intervals

#### Solutouion

In the second interval, we can observe some high amplitude, especially between 30 to 35.

### Question 3

Plot another channel of your choice. Is the signal shape over time the same as in the fifth channel?

```
1 eeg_channel_10 = Z(10, :); % Change 10 to any other channel number if
2
3 % Plot the entire signal for the 5th channel
4 figure;
5 subplot(2, 1, 1); % First plot for 5th channel
6 plot(time, eeg_channel_5);
7 xlabel('Time (s)');
8 ylabel('Amplitude (\muV)');
9 title(['EEG Signal - Channel 5 (', channel_labels{5}, ')']);
10 grid on;
11
12 % Plot the entire signal for the 10th channel
13 subplot(2, 1, 2); % Second plot for 10th channel
14 plot(time, eeg_channel_10);
15 xlabel('Time (s)');
16 ylabel('Amplitude (\muV)');
17 title(['EEG Signal - Channel 10 (', channel_labels{10}, ')']);
18 grid on;
19
20 % Adjust figure size
21 set(gcf, 'Position', [100, 100, 1000, 600]); % Adjust figure size
```

---

### Source Code 3: EEG - Question 3

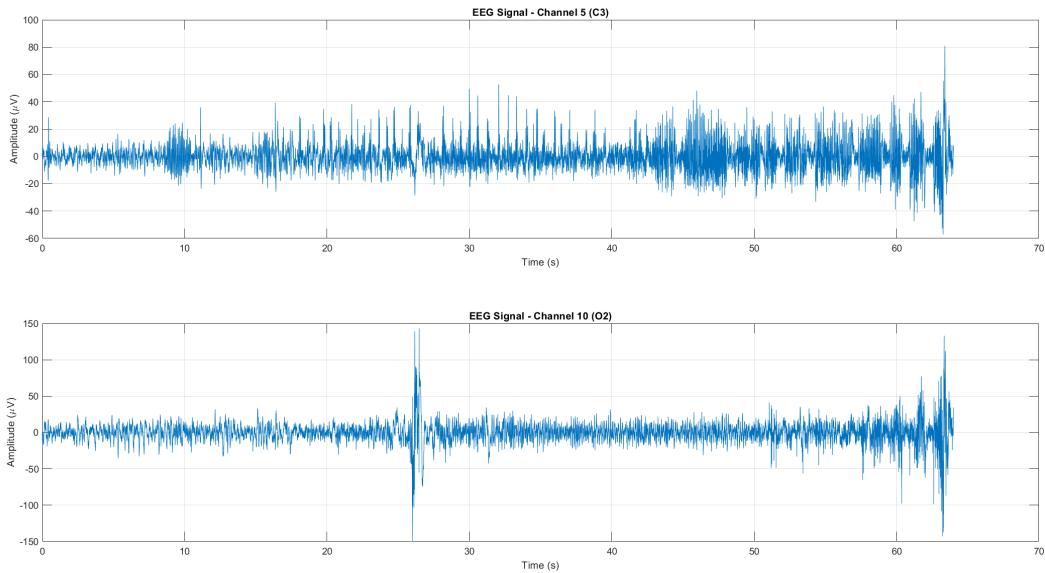


Figure 3: Question 3 - 5th Channel & 10th Channel

#### Solutouion

No. Channel 10 and channel 5 do not have the same shape and none pairs of eeg signals are the same.

### **Question 4**

Using the ‘eeg\_disp’ function and the following piece of code, plot the EEG signal across all channels.

```

1 offset = max(max(abs(Z)))/5 ;
2 freq = 256 ;
3 ElecName = des.channelnames ;
4 disp_eeg(Z,offset,freq,ElecName) ;

```

### Source Code 4: Displaying EEG

For better visualization, you can adjust the variable ‘offset’ (the distance between the displayed signals of two channels). Compare the behavior of the EEG signal in channel 3C (the fifth channel) with the other channels. Channel 3C is close to the seizure focus and clearly shows the EEG signal changes before and after the onset of the seizure.

```

1 % Define parameters for the display function
2 offset = max(max(abs(Z))) / 5; % Offset to separate the signals for
3 clarity
4 freq = 256; % Frequency for displaying the time axis (if not provided,
5 set it manually)
6
7 % Call the display function to plot all channels with clear labeling
8 disp_eeg(Z, offset, freq, channel_labels);
9 xlim('tight')

```

```

8      % Customize the figure for a more visually appealing output
9      title('EEG Signal Display - All Channels');
10     xlabel('Time (s)');
11     ylabel('Amplitude (\muV) with Offset for Each Channel');
12
13     grid on;
14     set(gca, 'FontSize', 12); % Set font size for better readability
15
16     % Adjust figure size for better presentation
17     set(gcf, 'Position', [100, 100, 1200, 800]); % Make the figure larger
for easier viewing

```

Source Code 5: EEG - Question 4

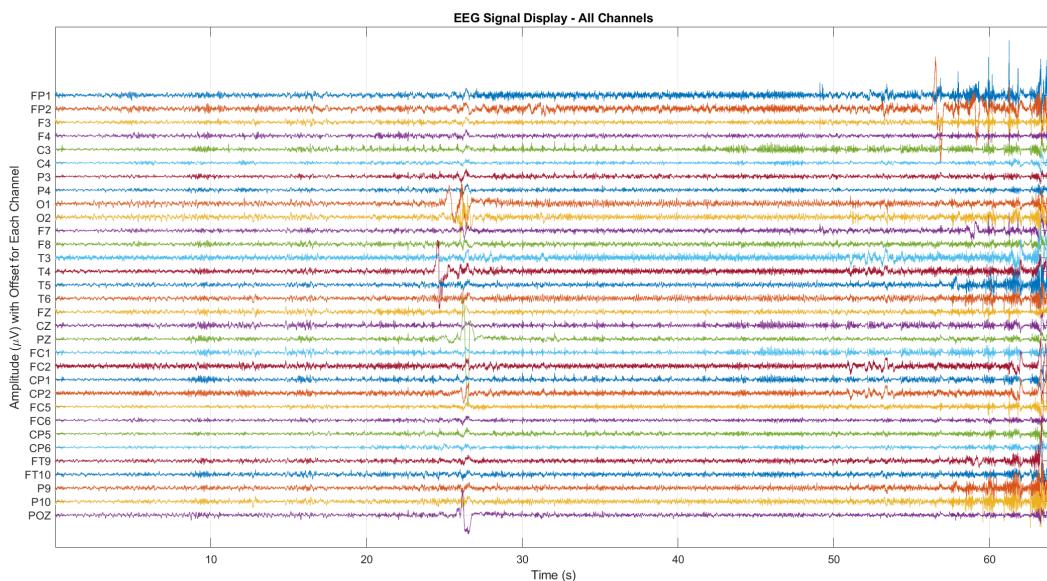


Figure 4: Question 4 - all Channels with Offset = 5

### Solutouion

Comparison has been shown in the class to TA.

### Question 5

Figure 1 shows the EEG signal of the first six channels. Investigate the characteristics of the signal in the three intervals specified in the figure and summarize your findings.

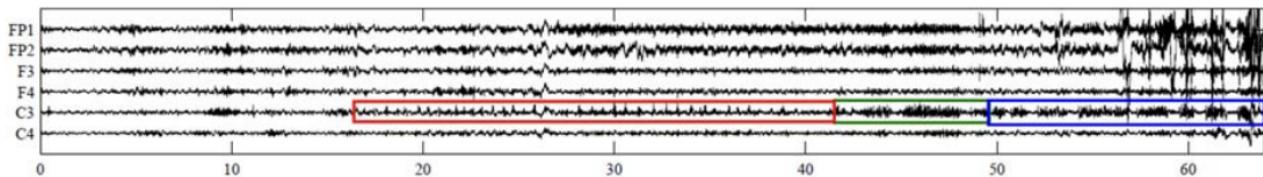


Figure 5: A real EEG signal recorded from an epileptic patient during a seizure period (almost noise-free). Channel C3 shows seizure activity consisting of three sections: 1. rhythmic spikes before the onset of the seizure (red box), 2. fast activity (green box), and 3. slower irregular activity (blue box).

**Solutioun**

This figure shows the EEG signal corresponding to the first six channels. The signal has been recorded from an epileptic patient during a seizure period (almost noise-free). Channel C3 shows seizure activity, which consists of three sections:

1. Rhythmic spikes before the onset of the seizure (red box)
2. Fast activity (green box)
3. Slower irregular activity (blue box)

Investigate the characteristics of the signal in the three intervals marked in the figure and summarize your findings as follows:

- In the first interval (red box), the rhythmic spikes are likely a pre-seizure warning sign. These spikes indicate abnormal neural activity preceding the seizure onset.
- In the second interval (green box), there is a sudden increase in the frequency of the signal, indicating the onset of the seizure, characterized by fast activity.
- In the third interval (blue box), the frequency decreases, and the signal becomes more irregular, reflecting the post-seizure state where the brain activity is starting to normalize but remains disorganized.

**Question 6**

Extract four 5-second intervals from the signal of channel C3 as follows:

- First interval: from 2 to 7 seconds
- Second interval: from 30 to 35 seconds
- Fourth interval: from 50 to 55 seconds
- Third interval: from 42 to 47 seconds

Plot both the time-domain signal and the frequency spectrum (DFT) for each interval, and provide an appropriate title for each figure. Display the time and frequency axes in seconds and Hertz, respectively. Adjust the frequency axes so that the frequency content is clearly visible (i.e., remove high frequencies that do not contain relevant information).

```
1 % Time vector in seconds
2 time = (0:length(eeg_channel_5)-1) / fs;
3
4 % Define the time intervals in seconds (start and end times)
5 intervals = [2 7; 30 35; 42 47; 50 55]; % Four intervals, each 5
seconds long
6
7 % Define the number of FFT points and frequency vector for DFT
8 nfft = 1024; % Number of points for FFT
9 freq = (0:nfft-1)*(fs/nfft); % Frequency vector
10
11 % Plot the time-domain and frequency-domain signals for each interval
12 figure;
13 for i = 1:size(intervals, 1)
    % Find the indices corresponding to the time range
```

```
15     idx_range = find(time >= intervals(i, 1) & time <= intervals(i, 2))
16 ;
17 % Extract the corresponding signal and time for the current
18 % interval
19 time_interval = time(idx_range);
20 signal_interval = eeg_channel_5(idx_range);
21 %
22 % Compute the Discrete Fourier Transform (DFT) of the signal
23 signal_dft = fft(signal_interval, nfft);
24 %
25 % Plot the time-domain signal
26 subplot(4, 2, 2*i-1); % Odd-numbered subplots for time-domain
27 signals
28 plot(time_interval, signal_interval);
29 xlabel('Time (s)');
30 ylabel('Amplitude (\muV)');
31 title(['Time-Domain Signal (C3) - Interval ', num2str(intervals(i,
32 1)), ' to ', num2str(intervals(i, 2)), ' s']);
33 grid on;
34 %
35 % Plot the frequency-domain signal (magnitude of DFT)
36 subplot(4, 2, 2*i); % Even-numbered subplots for frequency-domain
37 signals
38 plot(freq(1:nfft/2), abs(signal_dft(1:nfft/2))); % Plot up to
39 Nyquist frequency (fs/2)
40 xlabel('Frequency (Hz)');
41 ylabel('Magnitude');
42 title(['Frequency-Domain Signal (C3) - Interval ', num2str(
43 intervals(i, 1)), ' to ', num2str(intervals(i, 2)), ' s']);
44 grid on;
45 end
46 %
47 % Adjust figure size for better viewing
48 set(gcf, 'Position', [100, 100, 1200, 800]); % Make the figure larger
```

Source Code 6: EEG - Question 6

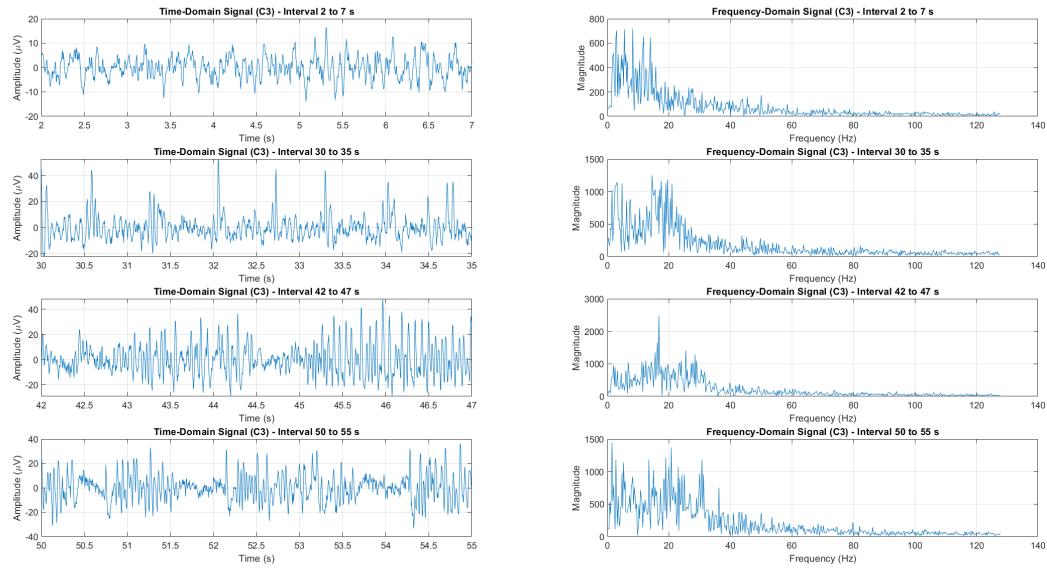


Figure 6: Question 6 - Time Domain and Frequency Domain in all the intervals

## Question 7

Plot the frequency spectrum of the signal for each of the four intervals using the ‘`pwelch.m`’ function. Adjust the input parameters such that the frequency content is clearly displayed. What can be said about the frequency characteristics of each of the four intervals?

```

1 % Define parameters for Welch's method (pwelch)
2 window_size = 256; % Window size for pwelch
3 nooverlap = window_size / 2; % Overlap between segments
4 nfft = 512; % Number of FFT points
5
6 % Plot the frequency-domain signals for each interval using pwelch
7 figure;
8 for i = 1:size(intervals, 1)
9     % Find the indices corresponding to the time range
10    idx_range = find(time >= intervals(i, 1) & time <= intervals(i, 2))
11    ;
12
13    % Extract the corresponding signal for the current interval
14    signal_interval = eeg_channel_5(idx_range);
15
16    % Compute and plot the power spectral density using pwelch
17    subplot(4, 1, i);
18    [pxx, f] = pwelch(signal_interval, window_size, nooverlap, nfft, fs)
19    ;
20
21    % Plot the PSD
22    plot(f, 10*log10(pxx)); % Convert to decibels
23    xlabel('Frequency (Hz)');
24    ylabel('Power/Frequency (dB/Hz)');
25    title(['PSD - Interval ', num2str(intervals(i, 1)), ' to ', num2str
26    (intervals(i, 2)), ' s']);
27    grid on;
28
29    % Set x-axis limit to show useful frequency range (0 to 60 Hz)
30    xlim([0 128]); % Adjust based on the relevant frequency range

```

```
28     end  
29  
30 % Adjust figure size for better viewing  
31 set(gcf, 'Position', [100, 100, 1200, 800]); % Make the figure larger
```

Source Code 7: EEG - Question 7

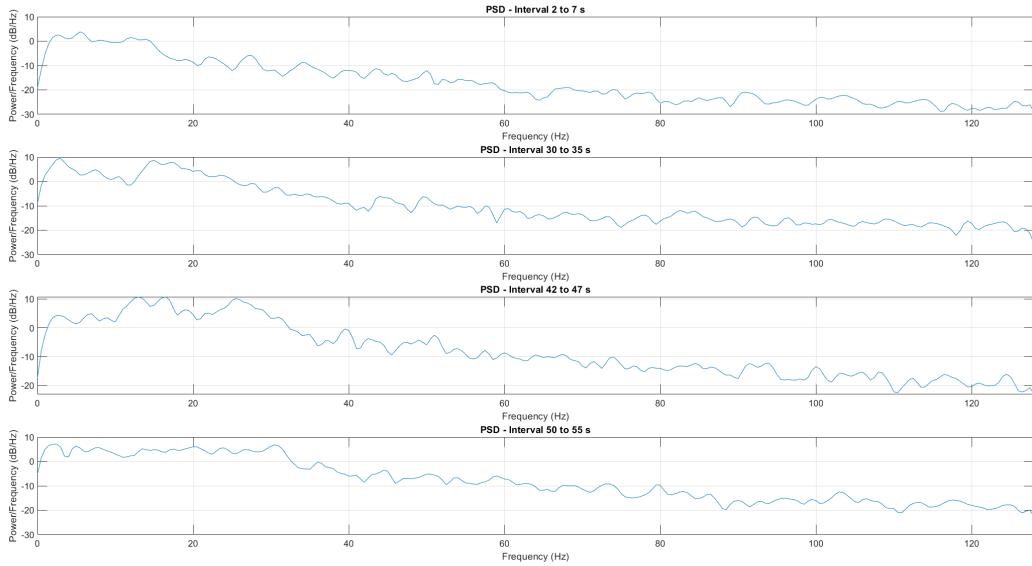


Figure 7: Question 7 - Frequency Spectrum of all the intervals

**Solutoun****1. Interval 2 to 7 seconds:**

- There is a notable peak in the lower frequency range, below 20 Hz. This indicates dominant activity in the lower frequency bands, which could correspond to delta or theta waves, typically associated with slower brain rhythms or rest states.

**2. Interval 30 to 35 seconds:**

- Similar to the first interval, the power is concentrated in the lower frequencies (below 20 Hz), but there are minor fluctuations across higher frequencies, showing a slightly more distributed power spectrum. However, higher frequencies still do not show significant activity.

**3. Interval 42 to 47 seconds:**

- This interval shows a more prominent spread across frequencies, with some power reaching frequencies up to 40 Hz. The presence of higher frequency activity could suggest faster brain rhythms, which might be related to seizure onset or heightened neural activity.

**4. Interval 50 to 55 seconds:**

- The power spectrum here appears more evenly spread, with consistent power across both low and mid-range frequencies (up to 50 Hz). This distribution suggests ongoing complex brain activity, possibly related to the post-seizure phase or continued high-level brain function.

***Question 8***

Using the ‘spectrogram’ command and considering a window length of  $L = 128$ , number of points in the window  $N_{overlap} = 64$ , and number of points for DFT or FFT  $n_{fft} = 128$ , obtain and plot the time-frequency spectrum of the signal for the four intervals using a Hamming window (display the time and frequency axes in seconds and Hertz, respectively). What can be said about the time-frequency characteristics of each of the four intervals?

```

1 % Define parameters for spectrogram
2 window_length = 128; % Window length (L)
3 noverlap = 64; % Number of points in overlap (N_overlap)
4 nfft = 128; % Number of DFT points (nfft)
5 window = hamming(window_length); % Use Hamming window
6
7 % Plot the time-frequency spectrum (spectrogram) for each interval
8 figure;
9 for i = 1:size(intervals, 1)
10    % Find the indices corresponding to the time range
11    idx_range = find(time >= intervals(i, 1) & time <= intervals(i, 2))
12    ;
13    % Extract the corresponding signal for the current interval
14    signal_interval = eeg_channel_5(idx_range);
15
16    % Compute and plot the spectrogram
17    subplot(2, 2, i);
18    spectrogram(signal_interval, window, noverlap, nfft, fs, 'yaxis');
```

```
19
20      % Set axis labels and title
21      xlabel('Time (s)');
22      ylabel('Frequency (Hz)');
23      title(['Spectrogram (Channel 5 - C3) - Interval ', num2str(
24 intervals(i, 1)), ' to ', num2str(intervals(i, 2)), ' s']);
25      colorbar; % Display colorbar to indicate power magnitude
26      ylim([0 60]); % Limit frequency axis to 60 Hz (relevant EEG
27      frequencies)
28
29      % Adjust figure size for better viewing
30      set(gcf, 'Position', [100, 100, 1200, 800]); % Make the figure larger
```

Source Code 8: EEG - Question 8

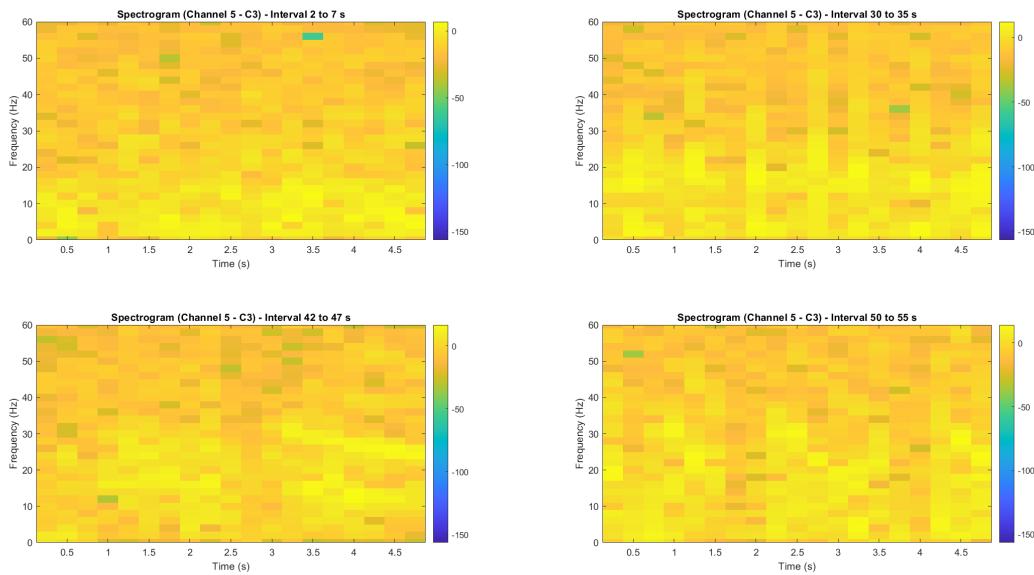


Figure 8: Question 8 - Time-Frequency characteristic of all the intervals

## Solutoun

### 1. Interval 2 to 7 seconds:

- The spectrogram shows some low-frequency activity (below 10 Hz) with relatively stable energy over time. There is minimal high-frequency content, suggesting the brain activity during this period is dominated by slower waves, typical of resting states or early pre-seizure activity.

### 2. Interval 30 to 35 seconds:

- This interval also shows low-frequency activity, but with some small patches of mid-frequency components appearing briefly. The higher frequency activity is still not dominant, but there is slightly more variation in the frequency content, potentially indicating increased neural activity compared to the first interval.

### 3. Interval 42 to 47 seconds:

- The time-frequency spectrum here shows a broader range of frequencies being activated, including mid-range frequencies (around 20–30 Hz) in addition to the low frequencies. This increased frequency spread might indicate heightened brain activity, possibly related to the onset of seizure or other neural events.

### 4. Interval 50 to 55 seconds:

- The spectrogram of this interval exhibits higher activity in the mid-frequency range (around 20–30 Hz) with fewer low-frequency components. This suggests a transition from the earlier stages, possibly representing post-seizure or later neural events where more rapid brain activity occurs.

## Question 9

Consider the second interval of the signal. Given that the sampling frequency is relatively high, we assume that the frequency spectrum obtained is similar to that of a continuous signal. With this assumption, and using the information from parts 6 and 7, reduce the sampling frequency appropriately (down sampling) while preserving the frequency content. Before reducing the sampling rate, use an appropriate low-pass filter. Plot the time-domain signal and the frequency spectrum (both DFT and STFT) of the new signal and compare the results with the previous sections.

```

1 % Define the second interval (30 to 35 seconds)
2 start_idx = round(30 * fs) + 1;
3 end_idx = round(35 * fs);
4 signal_interval = eeg_channel_5(start_idx:end_idx);
5
6 % Design a low-pass Butterworth filter
7 cutoff_freq = 64; % Cutoff frequency in Hz (below Nyquist of the
8 downsampled rate)
9 order = 4; % Filter order
10 [b, a] = butter(order, cutoff_freq/(fs/2)); % Normalize by Nyquist
11 frequency
12
13 % Apply the low-pass filter
14 filtered_signal = filtfilt(b, a, signal_interval);

```

```
14 % Downsample the signal (downsampling factor)
15 downsample_factor = 2; % Change this factor to adjust the downsampling
16 downsampled_signal = downsample(filtered_signal, downsample_factor);
17 fs_downsampled = fs / downsample_factor; % New sampling frequency
18
19 % Time vector for the downsampled signal
20 time_downsampled = (0:length(downscaled_signal)-1) / fs_downsampled;
21
22 % Compute DFT of the downsampled signal
23 nfft = 128; % Number of FFT points
24 dft_signal = fft(downscaled_signal);
25 L = length(dft_signal);
26 f = fs*(-L/2:L/2-1)/L;
27 freq = 128 * (0:(L/2)) / L; % Frequency vector
28
29 % Compute STFT of the downsampled signal
30 window_length = 128; % Window length for STFT
31 nooverlap = 64; % Number of points in overlap
32 window = hamming(window_length); % Use Hamming window
33
34 % Plot results
35 figure;
36
37 % Plot the time-domain signal
38 subplot(3, 1, 1);
39 plot(time_downsampled, downsampled_signal);
40 xlabel('Time (s)');
41 ylabel('Amplitude (\muV)');
42 title('Time-Domain Signal (Downsampled)');
43 grid on;
44
45 % Plot the frequency spectrum (DFT)
46 subplot(3, 1, 2);
47 plot(freq(1:320), abs(dft_signal(1:320))); % Magnitude in dB
48 xlabel('Frequency (Hz)');
49 ylabel('Magnitude (dB)');
50 xlim('tight')
51 title('Frequency Spectrum (DFT)');
52 grid on;
53 xlim([0 60]); % Limit to 60 Hz
54
55 % Plot the STFT
56 subplot(3, 1, 3);
57 spectrogram(downscaled_signal, window, nooverlap, nfft, 128, 'yaxis');
58 xlabel('Time (seconds)', 'Interpreter', 'latex');
59 ylabel('Frequency (Hz)', 'Interpreter', 'latex');
60 title('Spectrogram (STFT) - Downsampled', 'Interpreter', 'latex');
61
62 % Adjust figure size for better viewing
63 set(gcf, 'Position', [100, 100, 1200, 800]); % Make the figure larger
```

Source Code 9: EEG - Question 9

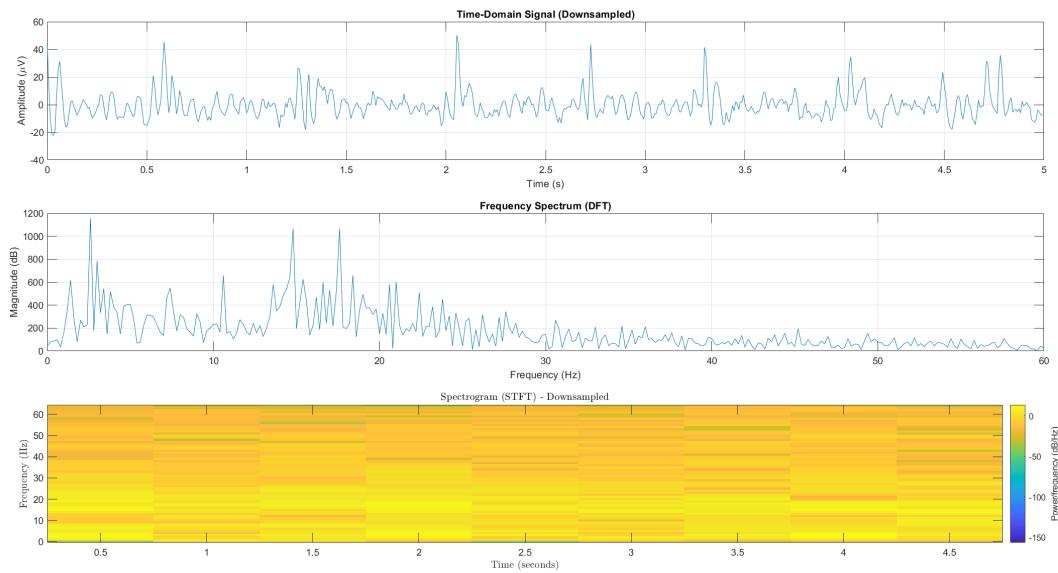


Figure 9: Question 9 - Time-Frequency characteristic of all the intervals

## Soluton

### 1. Time-Domain Signal:

- Before downsampling, the time-domain signal for the second interval (from 30 to 35 seconds) exhibits higher temporal resolution. The amplitude fluctuations are visible, and the overall shape of the signal shows more distinct features, with sharp peaks and troughs that indicate rapid changes in the neural activity.
- After downsampling, the time-domain signal is smoother, and some of the finer details of the signal have been lost. The amplitude variation is still visible, but the temporal resolution is lower, leading to fewer distinct sharp peaks. The signal appears more compressed in time.

### 2. Frequency-Domain Signal (DFT):

- Before downsampling, the frequency-domain signal (DFT) of the second interval contains higher frequency components extending beyond 100 Hz. The power is more spread out across different frequencies, especially in the higher range, which suggests more complex brain activity during this period.
- After downsampling, the frequency spectrum is more concentrated in the lower frequencies, with fewer high-frequency components. This is expected due to the lower sampling rate, which reduces the ability to capture higher frequency details. Most of the significant energy is now in the lower frequency range, below 30 Hz.

### 3. Spectrogram (STFT):

- Before downsampling, the spectrogram shows a richer distribution of frequency content over time, with visible activity in both low and high frequencies across the 5-second window. The time-frequency representation is more detailed, showing fluctuations across both time and frequency.
- After downsampling, the spectrogram shows reduced high-frequency content. Most of the energy is concentrated in the lower frequencies (below 30 Hz), and the overall resolution of the time-frequency representation has been reduced. The spectrogram appears less detailed compared to the original one before downsampling.

**Conclusion:** Downsampling reduces the temporal resolution of the signal, leading to smoother time-domain representations and a loss of high-frequency components in the frequency domain. This is evident in both the DFT and spectrogram plots, where the higher frequency components are either absent or significantly reduced after downsampling, leaving most of the power concentrated in the lower frequencies.

## ECG Signal

The electrocardiogram (ECG) signal data for two channels, sampled at 360 Hz, is provided in the file ‘ECG\_sig.mat’. The signals represent different states of heart activity recorded from the MIT-BIH Arrhythmia Database, which includes annotations for various heart conditions and arrhythmias. Further information can be found in the [PhysioNet Database](#) and the accompanying [MIT-BIH Arrhythmia\\_Introduction.pdf](#) file.

### Question 1

Plot the ECG signals from the two channels, zoom into different sections of the signal, and compare the features.

```
1 % Loading the Data
2 load('ECG_sig.mat');
3 signal = Sig;
4 fs = sfreq;
5 time = (0:length(signal)-1) / fs;
6
7 % Plotting the signals
8 figure;
9 subplot(2,1,1);
10 plot(time, signal(:,1), 'b', 'DisplayName', 'Lead 1');
11
12 subplot(2,1,2);
13 plot(time, signal(:,2), 'r', 'DisplayName', 'Lead 2');
14 xlabel('Time (seconds)');
15 ylabel('Amplitude');
16 title('ECG Signals for Lead 1 and Lead 2');
17 legend;
18 hold off;
```

Source Code 10: ECG - Question 1

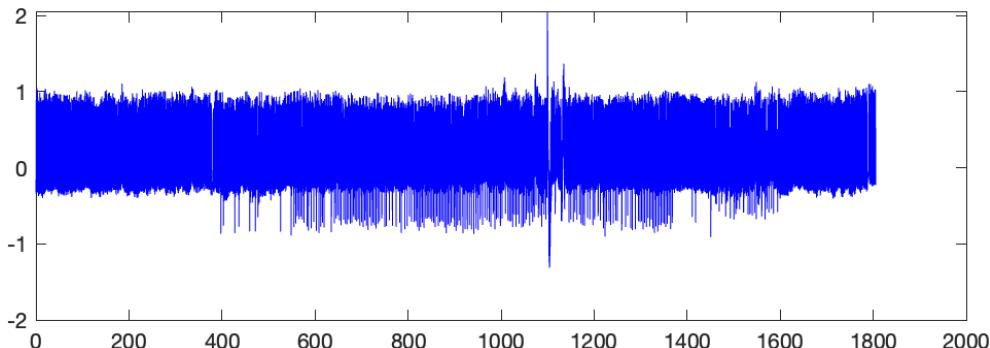


Figure 10: Time-Domain Signal of ECG - Lead 1

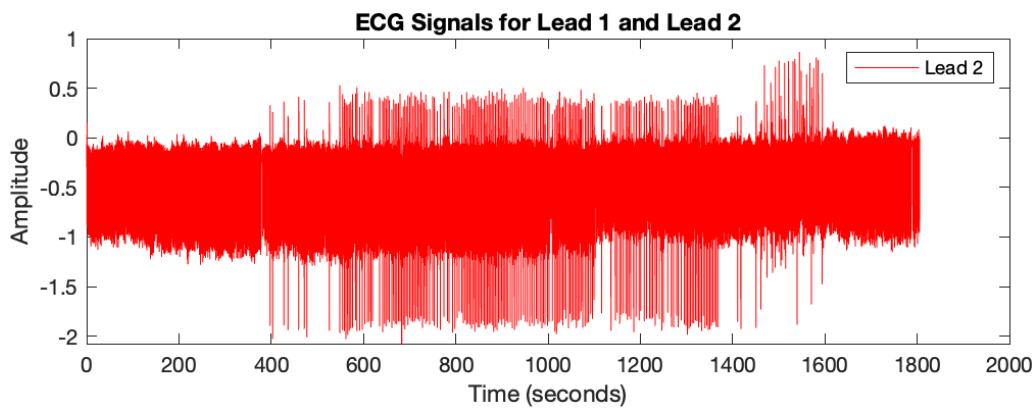


Figure 11: Time-Domain Signal of ECG - Lead 2

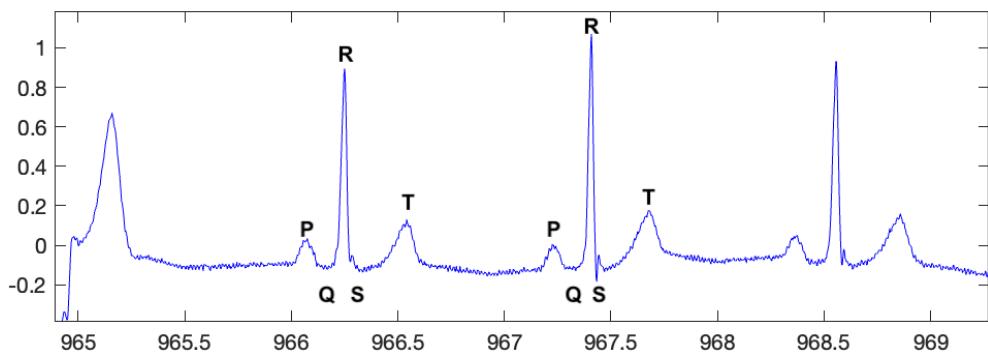


Figure 12: Time-Domain Signal of ECG - Lead 1

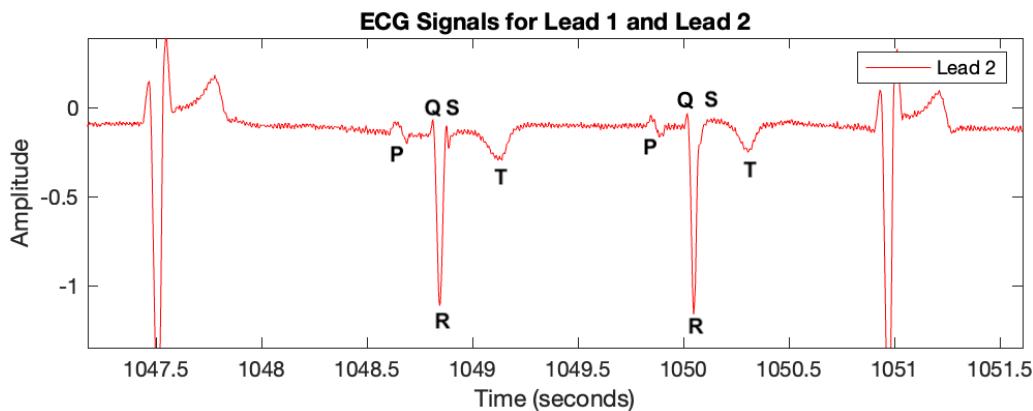


Figure 13: Time-Domain Signal of ECG - Lead 2

### Solutution

- **R-Peak Identification:** The ECG signal shows clear synchronous R-peaks corresponding to each heartbeat.
- **Signal Variability:** There is some variability in the R-R intervals, possibly indicating arrhythmias.
- **Noise:** Minor baseline wandering can be observed in the signal, likely caused by electrode motion artifacts.

## Question 2

Use the annotations provided in the ANNOTATIONS.pdf file to mark the R-peaks and categorize the types of beats (normal/abnormal). Extract the R-wave timing from the annotation data.

```
1 r_peaks = ATRTIMED;
2 annotations = ANNOTD;
3 annotation_labels = {'NOTQRS', 'NORMAL', 'LBBB', 'RBBB', 'ABERR', 'PVC'
4 , ...
5 'FUSION', 'NPC', 'APC', 'SVPB', 'VESCP', 'NESCP', 'PACE', ...
6 'UNKNOWN', 'NOISE', '', 'ARFCT', '', 'STCH', 'TCH', 'SYSTOLE', ...
7 'DIASTOLE', 'NOTE', 'MEASURE', 'PWAVE', 'BBB', 'PACESP', ...
8 'TWAVE', 'RHYTHM', 'UWAVE'};;
9
10 % Plotting the Signals
11 figure;
12 subplot(2,1,1)
13 plot(time, signal(:,1), 'b');
14 hold on;
15
16 for i = 1:length(r_peaks)
17 r_time = r_peaks(i);
18 r_amplitude = signal(round(r_time * fs), 1);
19 plot(r_time, r_amplitude, 'ro', 'DisplayName', 'R-peak');
20
21 anomaly_code = annotations(i);
22 if anomaly_code <= length(annotation_labels)
23     anomaly_label = annotation_labels{anomaly_code + 1};
24     text(r_time, r_amplitude, [ ' ', anomaly_label], 'FontSize', 8, '
25 Color', 'r');
26 end
27
28 subplot(2,1,2)
29 plot(time, signal(:,2), 'b');
30 hold on;
31
32 for i = 1:length(r_peaks)
33 r_time = r_peaks(i);
34 r_amplitude = signal(round(r_time * fs), 2);
35 plot(r_time, r_amplitude, 'ro', 'DisplayName', 'R-peak');
36
37 anomaly_code = annotations(i);
38 if anomaly_code <= length(annotation_labels)
39     anomaly_label = annotation_labels{anomaly_code + 1};
40     text(r_time, r_amplitude, [ ' ', anomaly_label], 'FontSize', 8, '
41 Color', 'r');
42 end
43 xlabel('Time (seconds)');
44 ylabel('Amplitude');
45 title('ECG Signal with R-Peaks and Annotations');
46 legend('ECG Signal', 'R-peaks');
47 hold off;
```

Source Code 11: ECG - Question 2

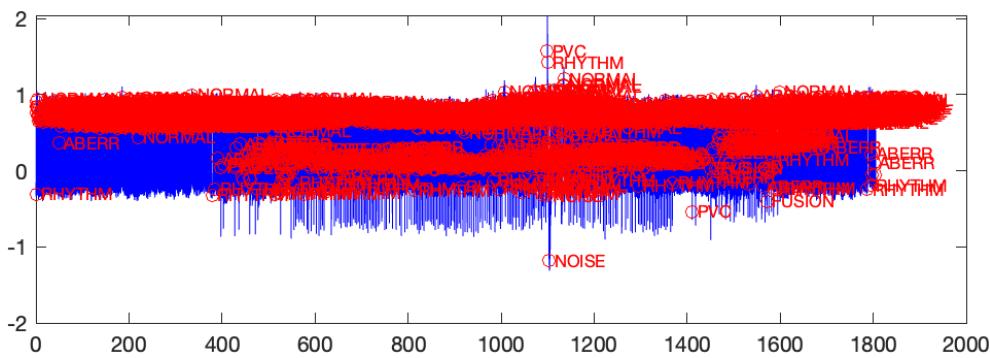


Figure 14: ECG Signal with Annotated R-Peaks - Lead 1

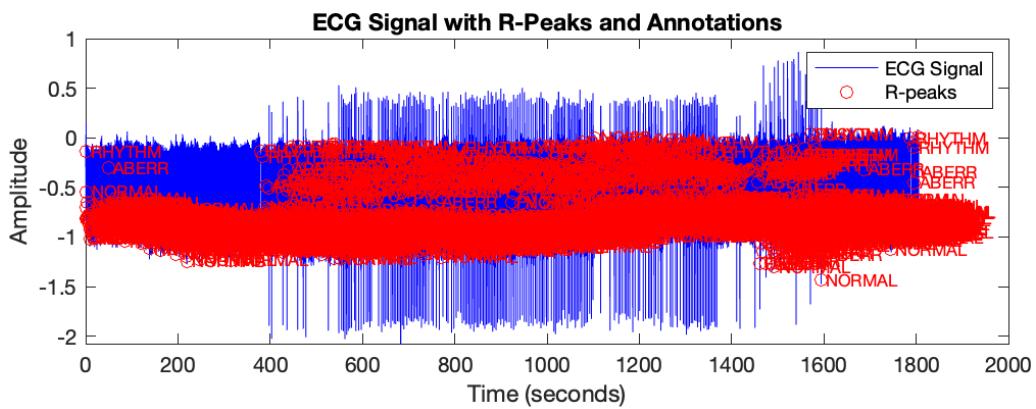


Figure 15: ECG Signal with Annotated R-Peaks - Lead 2

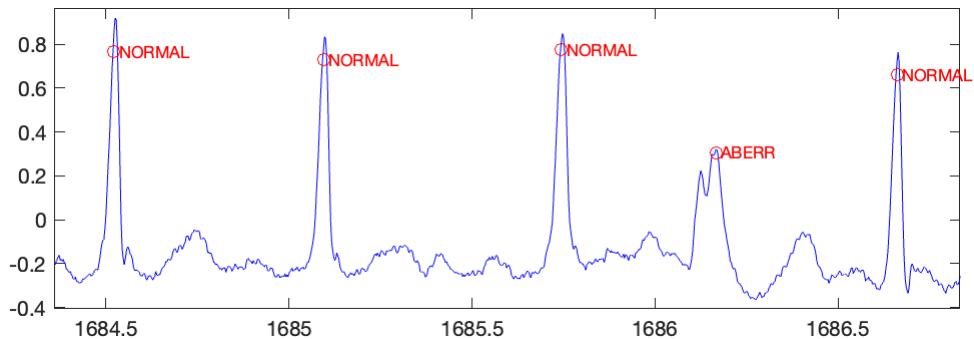


Figure 16: ECG Signal with Annotated R-Peaks - Lead 1

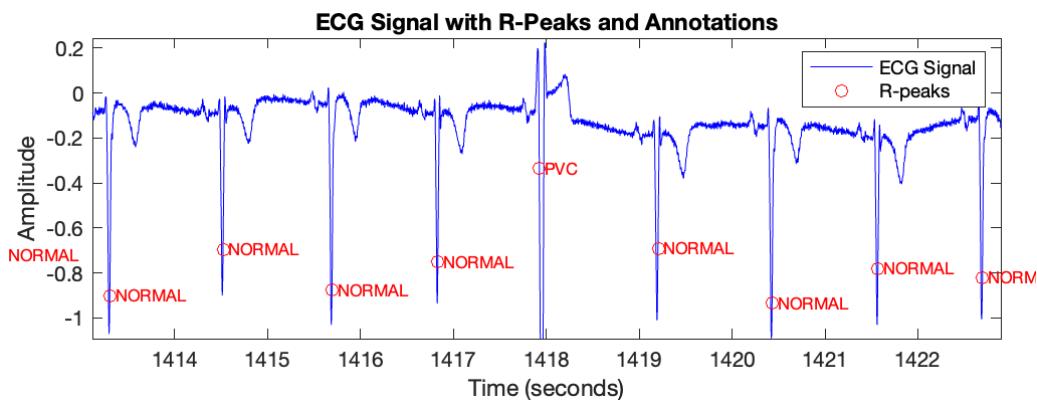


Figure 17: ECG Signal with Annotated R-Peaks - Lead 2

### Solutouion

- The R-peak annotations clearly indicate normal beats with consistent intervals. Abnormal beats are marked with irregular timing.
- The extracted R-wave times help to identify potential arrhythmias and can be further used to analyze beat intervals and variability.

### Question 3

Describe the morphological differences between normal and abnormal beats, and explain how these anomalies occur and their significance.

```

1 window = 0.5;
2
3 % Anomaly Types to Plot
4 anomalies_to_plot = [1, 4, 5, 8, 11, 28];
5
6 % Plotting Anomalies
7 figure;
8 for i = 1:length(anomalies_to_plot)
9     anomaly_code = anomalies_to_plot(i);
10    anomaly_label = annotation_labels{anomaly_code + 1};
11
12    anomaly_indices = find(annotations == anomaly_code);
13    num_beats_to_plot = min(3, length(anomaly_indices));
14
15    for j = 1:num_beats_to_plot
16        r_peak = r_peaks(anomaly_indices(j));
17        beat_start = max(1, round((r_peak - window) * fs));
18        beat_end = min(length(time), round((r_peak + window) * fs));
19        beat_time = time(beat_start:beat_end);
20        beat_signal = signal(beat_start:beat_end, 1); % Lead 1
21
22        subplot(length(anomalies_to_plot), num_beats_to_plot, (i-1)*
23        num_beats_to_plot + j);
24        plot(beat_time, beat_signal, 'b');
25        title([anomaly_label ' (Beat ' num2str(j) ')']);
26        xlabel('Time (s)');
27        ylabel('Amplitude');
28    end
29 end

```

```
30 sgttitle('ECG Beats for Selected Anomalies (NORMAL, ABERR, PVC, APC, NESC, RHYTHM)');
```

Source Code 12: ECG - Question 3

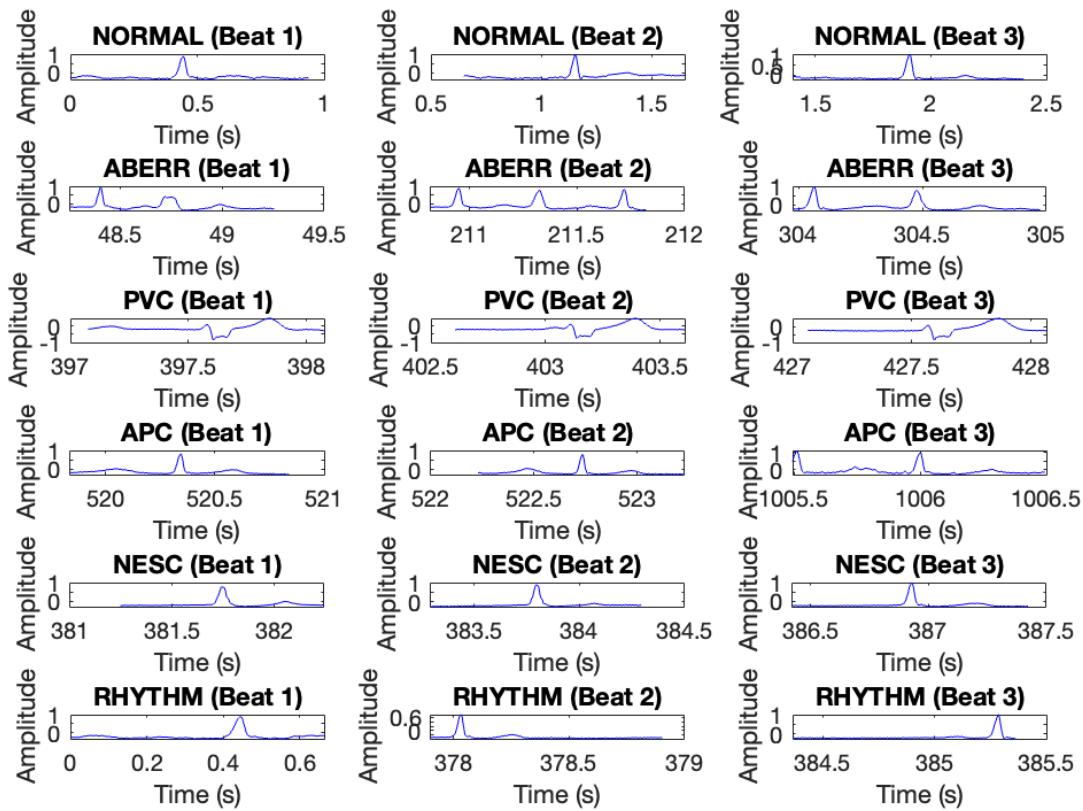
**ECG Beats for Selected Anomalies (NORMAL, ABERR, PVC, APC, NESC, RHYTHM)**

Figure 18: ECG Signal with Annotated R-Peaks

## Solutoun

The following are explanations for the five types of arrhythmias shown in the plots:

### 1. Aberrated Atrial Premature Beat (ABERR):

- **Cause:** Aberrated atrial premature beats occur when a premature atrial impulse travels through the ventricles in an abnormal pathway, often due to a delay in one of the bundle branches.
- **Characteristics:** In the ECG, the QRS complex is wider than normal because the ventricles depolarize through an aberrant pathway. This can look similar to a bundle branch block.

### 2. Premature Ventricular Contraction (PVC):

- **Cause:** PVCs are caused by ectopic impulses originating in the ventricles, which cause the heart to beat earlier than expected.
- **Characteristics:** The QRS complex is wide and irregular, and no P-wave is present. The R-R interval following the PVC is longer due to a compensatory pause.

### 3. Atrial Premature Contraction (APC):

- **Cause:** APCs are premature beats originating in the atria, which are often triggered by stress or fatigue.
- **Characteristics:** APCs are characterized by a premature P-wave, followed by a normal QRS complex. The P-wave may have a different morphology compared to the normal P-wave.

### 4. Nodal (Junctional) Escape Beat (NESC):

- **Cause:** Nodal escape beats occur when the SA node fails to generate an impulse, and the AV node takes over as the pacemaker.
- **Characteristics:** The P-wave is either absent or inverted, and the QRS complex appears normal but follows a longer R-R interval due to the delayed escape beat.

### 5. Rhythm Change (RHYTHM):

- **Cause:** A rhythm change can occur for several reasons, such as shifts in autonomic tone, ischemia, or the onset of arrhythmias like atrial fibrillation or ventricular tachycardia.
- **Characteristics:** The beat shown in the plot could indicate the transition to a new rhythm, with changes in R-R intervals or other waveform abnormalities depending on the underlying cause.

These arrhythmias have distinct characteristics in the ECG signal and can provide important insights into the functioning of the heart.

## Question 4

For two segments of ECG signals, plot the frequency spectrum of normal beats and a segment containing abnormal beats. Compare the frequency characteristics.

```
1  normal_times = ATRTIMED(61:63);
2  abnormal_times = ATRTIMED(640:642);
3  beat_window = 0.5;
4
5  normal_start_idx = max(1, round((normal_times(1) - beat_window) * sfreq));
6  normal_end_idx = min(length(signal), round((normal_times(end) + beat_window) * sfreq));
7  normal_segment = signal(normal_start_idx:normal_end_idx, :);
8  normal_time_segment = time(normal_start_idx:normal_end_idx);
9
10 abnormal_start_idx = max(1, round((abnormal_times(1) - beat_window) * sfreq));
11 abnormal_end_idx = min(length(signal), round((abnormal_times(end) + beat_window) * sfreq));
12 abnormal_segment = signal(abnormal_start_idx:abnormal_end_idx, :);
13 abnormal_time_segment = time(abnormal_start_idx:abnormal_end_idx);
14
15 % Plots
16 figure;
17 sgttitle('Normal Beats (Time, FFT, and Spectrogram)');
18
19 % Lead 1 - Time Domain
20 subplot(3, 2, 1);
21 plot(normal_time_segment, normal_segment(:, 1), 'b');
22 title('Time Domain - Normal (Lead 1)');
23 xlabel('Time (s)');
24 ylabel('Amplitude');
25
26
27 % Lead 1 - FFT
28 subplot(3, 2, 3);
29 n = length(normal_segment(:, 1));
30 f = (0:n-1)*(sfreq/n); % Frequency vector
31 fft_signal = abs(fft(normal_segment(:, 1)));
32 plot(f, fft_signal);
33 title('Frequency Domain (FFT) - Normal (Lead 1)');
34 xlabel('Frequency (Hz)');
35 ylabel('Amplitude');
36 xlim([0, sfreq/2]);
37
38 % Lead 1 - Spectrogram
39 subplot(3, 2, 5);
40 spectrogram(normal_segment(:, 1), 128, 120, 128, sfreq, 'yaxis');
41 title('Spectrogram - Normal (Lead 1)');
42
43 % Lead 2 - Time Domain
44 subplot(3, 2, 2);
45 plot(normal_time_segment, normal_segment(:, 2), 'r');
46 title('Time Domain - Normal (Lead 2)');
47 xlabel('Time (s)');
48 ylabel('Amplitude');
49
50 % Lead 2 - FFT
```

```
51 subplot(3, 2, 4);
52 n = length(normal_segment(:, 2));
53 f = (0:n-1)*(sfreq/n); % Frequency vector
54 fft_signal = abs(fft(normal_segment(:, 2)));
55 plot(f, fft_signal);
56 title('Frequency Domain (FFT) - Normal (Lead 2)');
57 xlabel('Frequency (Hz)');
58 ylabel('Amplitude');
59 xlim([0, sfreq/2]);
60
61 % Lead 2 - Spectrogram
62 subplot(3, 2, 6);
63 spectrogram(normal_segment(:, 2), 128, 120, 128, sfreq, 'yaxis');
64 title('Spectrogram - Normal (Lead 2)');
65
66 % Plot abnormal beats for both leads
67 figure;
68 sgttitle('Abnormal Beats (Time, FFT, and Spectrogram)');
69
70 % Lead 1 - Time Domain
71 subplot(3, 2, 1);
72 plot(abnormal_time_segment, abnormal_segment(:, 1), 'b');
73 title('Time Domain - Abnormal (Lead 1)');
74 xlabel('Time (s)');
75 ylabel('Amplitude');
76
77 % Lead 1 - FFT
78 subplot(3, 2, 3);
79 n = length(abnormal_segment(:, 1));
80 f = (0:n-1)*(sfreq/n);
81 fft_signal = abs(fft(abnormal_segment(:, 1)));
82 plot(f, fft_signal);
83 title('Frequency Domain (FFT) - Abnormal (Lead 1)');
84 xlabel('Frequency (Hz)');
85 ylabel('Amplitude');
86 xlim([0, sfreq/2]);
87
88 % Lead 1 - Spectrogram
89 subplot(3, 2, 5);
90 spectrogram(abnormal_segment(:, 1), 128, 120, 128, sfreq, 'yaxis');
91 title('Spectrogram - Abnormal (Lead 1)');
92
93 % Lead 2 - Time Domain
94 subplot(3, 2, 2);
95 plot(abnormal_time_segment, abnormal_segment(:, 2), 'r');
96 title('Time Domain - Abnormal (Lead 2)');
97 xlabel('Time (s)');
98 ylabel('Amplitude');
99
100 % Lead 2 - FFT
101 subplot(3, 2, 4);
102 n = length(abnormal_segment(:, 2));
103 f = (0:n-1)*(sfreq/n); % Frequency vector
104 fft_signal = abs(fft(abnormal_segment(:, 2)));
105 plot(f, fft_signal);
106 title('Frequency Domain (FFT) - Abnormal (Lead 2)');
107 xlabel('Frequency (Hz)');
108 ylabel('Amplitude');
```

```
109     xlim([0, sfreq/2]);
110
111 % Lead 2 - Spectrogram
112 subplot(3, 2, 6);
113 spectrogram(abnormal_segment(:, 2), 128, 120, 128, sfreq, 'yaxis');
114 title('Spectrogram - Abnormal (Lead 2)');
```

Source Code 13: ECG - Question 4

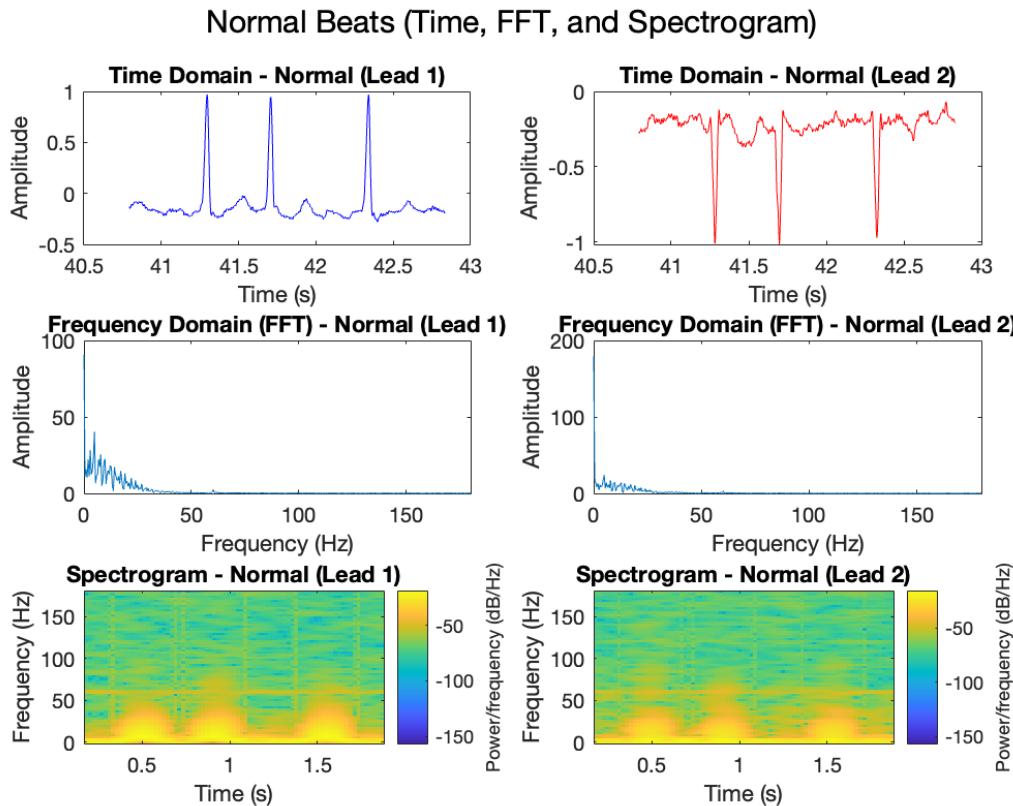


Figure 19: Normal Beats

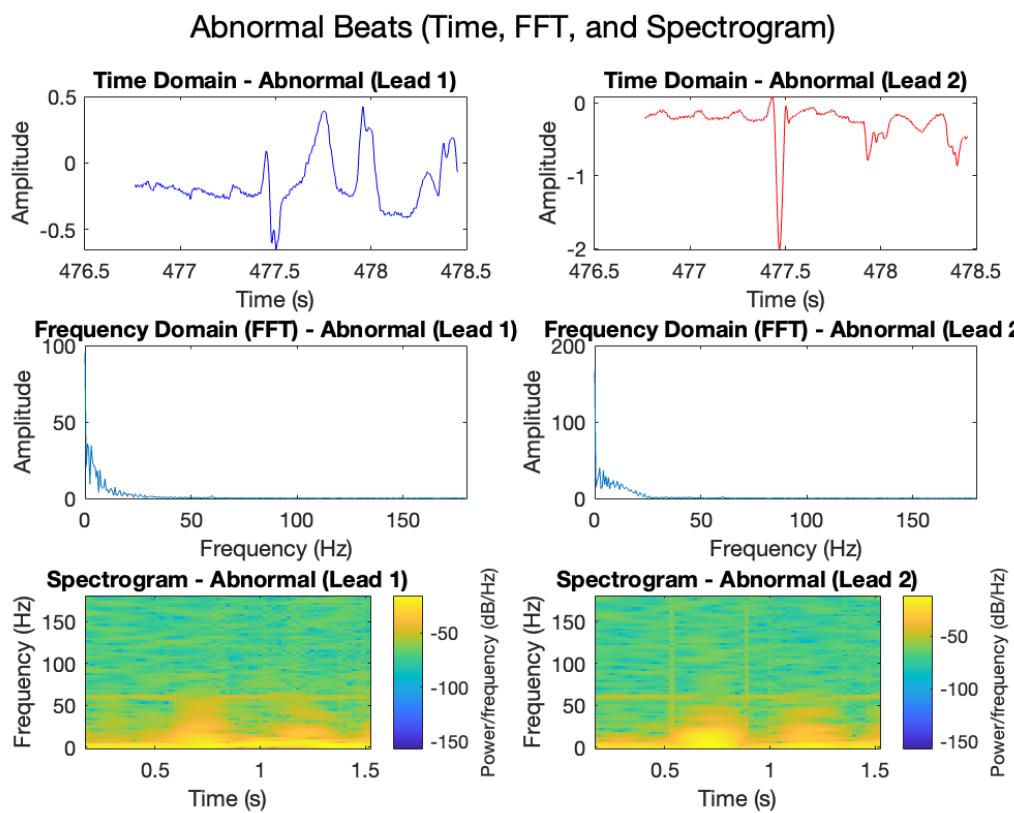


Figure 20: Abnormal Beats

## Soluton

**1. Time Domain (Lead 1 and Lead 2):** In the time domain, the signal's amplitude is plotted against time for both Lead 1 and Lead 2:

- **Normal Beats:** The normal beats exhibit a consistent, regular pattern with well-defined peaks that repeat over time. The signal is regular, with a clear pattern of repeating amplitudes.
- **Abnormal Beats:** The abnormal beats show irregularities in the waveform, with higher fluctuations and distorted signals. The signal's amplitude deviates from the regular beat pattern, indicating abnormalities in the ECG signals.

**2. Frequency Domain (FFT) - Lead 1 and Lead 2:** The frequency domain is represented using a Fast Fourier Transform (FFT) that shows how the power of the signal is distributed across different frequencies:

- **Normal Beats:** Most of the energy is concentrated at lower frequencies (below 50 Hz), indicating a regular periodicity in the beats.
- **Abnormal Beats:** The energy in abnormal beats also concentrates at lower frequencies but has a broader spread, reflecting the irregular nature of the signal.

**3. Spectrogram (Time-Frequency Domain):** The time-frequency representation (spectrogram) reveals how the frequency content of the signal evolves over time:

- **Normal Beats:** The spectrogram shows a regular pattern, with energy concentrated below 50 Hz. The periodicity is clearly visible, with consistent bands of energy appearing over time.
- **Abnormal Beats:** In contrast, the abnormal beats show a more scattered and less organized energy distribution across time and frequencies. There is more variability in the spectrogram, which reflects the irregular and complex nature of the abnormal signal.

## Conclusion

The comparison between normal and abnormal beats in the time domain, frequency domain, and spectrogram reveals that the abnormal beats have greater complexity and irregularities compared to normal beats. In the time domain, the abnormal beats are less regular, while in the frequency domain, they exhibit a broader spread in frequency components. The spectrogram further highlights the irregular nature of abnormal beats, with more scattered frequency content over time.

## EOG Signal

The electrooculogram (EOG) signal data, recorded from two channels (left eye and right eye), is provided in the file ‘`EOG_sig.mat`’. This data records eye movement signals, which can be used to analyze visual tracking and gaze patterns.

### Question 1

Plot the two-channel signals over time and compare them. Based on the shapes of the signals, determine the approximate location of the electrodes and plot the eye movements in a single visual representation. What temporal information can be obtained from the signals?

```

1 % loading the Signals
2 load('EOG_sig.mat');
3 signal = Sig;
4 fs = fs;
5 time = (0:length(signal)-1) / fs;
6
7 % Plotting the Signals
8 figure;
9 plot(time, signal(1,:), 'b', 'DisplayName', 'Left Eye');
10 hold on;
11 plot(time, signal(2,:), 'r', 'DisplayName', 'Right Eye');
12 xlabel('Time (seconds)');
13 ylabel('Amplitude');
14 title('EOG Signals for Left and Right Eye');
15 legend;
16 hold off;
```

Source Code 14: EOG - Question 1

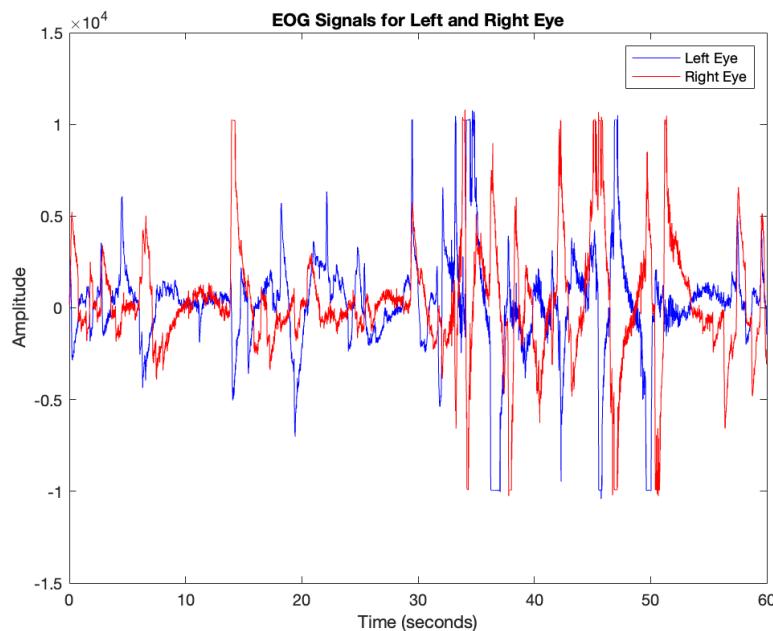


Figure 21: EOG Signal for Left and Right Eye Channels

### Solutioun

By analyzing the two-channel EOG signals, we can make the following observations:

- The left and right eye signals appear to be mirrored around the baseline, indicating that the electrodes were likely placed symmetrically around each eye. The positive deflection in one channel corresponds to a negative deflection in the other.
- Temporal information such as blinks and saccades (rapid eye movements) can be identified as sharp spikes in both channels.
- The relative positions of the eye can be inferred based on the polarity and amplitude of the signals. For example, when the eyes move to the left, the left eye signal shows a positive deflection, and the right eye signal shows a negative deflection.

**Electrodes Placements:** The EOG signal reflects the relative eye positions. When one eye exhibits a positive signal, the other eye often shows a negative signal, which indicates that both eyes are moving symmetrically.

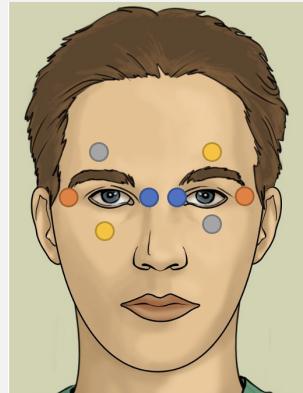


Figure 22: Possible Electrode placements for EOG recording (Based on Colors)

**Blink Detection:** Blinks are also visible in the EOG signal as sharp, high-amplitude spikes. The following image shows the pattern of a blink in the EOG signal:

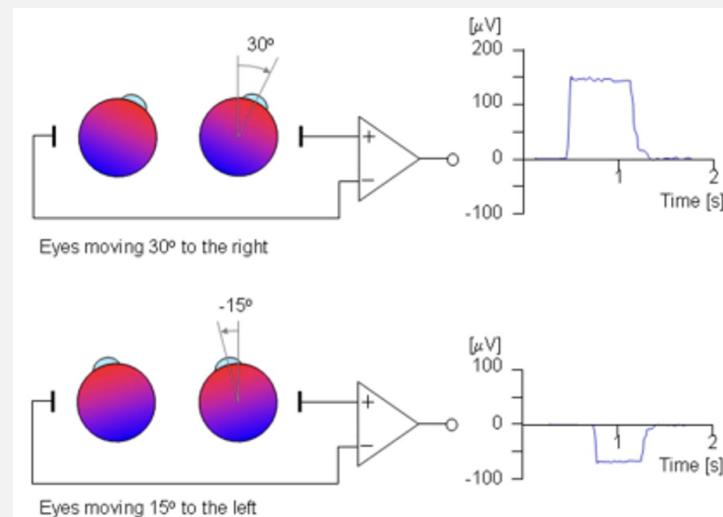


Figure 23: EOG Signal Pattern for Blink Detection

## Question 2

Plot the Fourier transform and frequency spectrum for each channel and explain the frequency characteristics of the EOG signal.

```
1 % Fourier Transform of the Signals
2 n = length(signal);
3 frequencies = (0:n-1)*(fs/n);
4
5 % Performing FFT
6 fft_left_eye = abs(fft(signal(1,:)));
7 fft_right_eye = abs(fft(signal(2,:)));
8
9 % Plotting the Frequency Spectrum
10 figure;
11 subplot(2, 1, 1);
12 plot(frequencies, fft_left_eye);
13 xlim([0 30])
14 xlabel('Frequency (Hz)');
15 ylabel('Amplitude');
16 title('DFT of Left Eye Signal');
17
18 subplot(2, 1, 2);
19 plot(frequencies, fft_right_eye, 'r');
20 xlim([0 30])
21 xlabel('Frequency (Hz)');
22 ylabel('Amplitude');
23 title('DFT of Right Eye Signal');
24
25 % Spectrogram for Left Eye
26 figure;
27 subplot(2,1,1);
28 spectrogram(signal(1,:), 256, 128, 256, fs, 'yaxis');
29 title('Spectrogram of Left Eye EOG Signal');
30 colorbar;
31
32 % Spectrogram for Right Eye
33 subplot(2,1,2);
34 spectrogram(signal(2,:), 256, 128, 256, fs, 'yaxis');
35 title('Spectrogram of Right Eye EOG Signal');
36 colorbar;
37
38 xlabel('Time (s)');
39 ylabel('Frequency (Hz)');
```

Source Code 15: EOG - Question 2

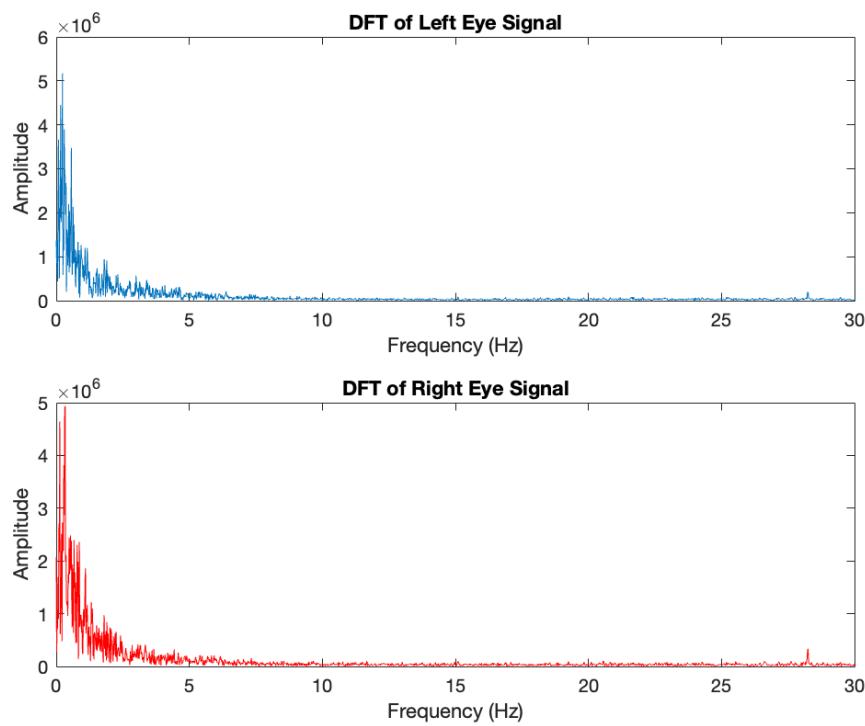


Figure 24: Fourier Transform of EOG Signal for Left and Right Eye

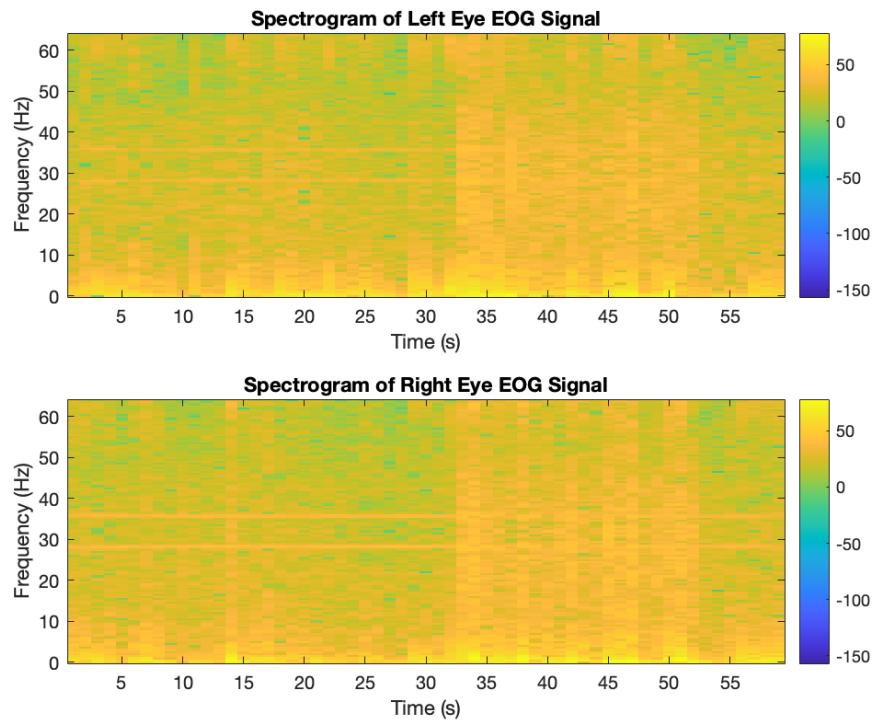


Figure 25: Frequency Spectrum of EOG Signal for Left and Right Eye

### Solutioun

The EOG signal primarily contains low-frequency components, as expected for eye movement signals. The following key points can be derived from the frequency spectrum:

- **Low-Frequency Dominance:** Most of the signal energy is concentrated at frequencies below 10 Hz, which is typical for slow eye movements such as saccades.
- **DC Components:** The presence of a strong DC component reflects the steady positioning of the eye between movements. Variations in the DC component correspond to changes in eye position.
- **Blink Artifacts:** Blinks introduce high-frequency noise into the EOG signal, which can be seen as small peaks at higher frequencies in the spectrum.

Overall, the EOG signal shows characteristic features in the lower frequency range, with occasional higher-frequency components corresponding to blinks or noise from muscle contractions.

## EMG Signal

Three electromyogram (EMG) signal segments, recorded from three individuals using needle electrodes, are provided in the file ‘`sig_EMG.mat`’. The signals were sampled at a frequency of 50 kHz and then the sampling frequency was reduced to 4 kHz. One segment corresponds to a healthy individual, and the other two segments correspond to patients with Neuropathy and Myopathy, respectively. You can find more details about the data at this [link](#).

### Question 1

Plot the time-domain signal for each of the three individuals. Zoom into different sections of the signal along the horizontal axis, analyze the features of each signal, and compare them with each other.

```
1 % Load the EMG signals from the .mat file
2 load('Lab 1_data/EMG_sig.mat'); % Replace with actual filename if
3 % different
4 % Assuming the file contains variables 'EMG1', 'EMG2', and 'EMG3' for
5 % the three subjects
6 % EMG1: Healthy subject
7 % EMG2: Neuropathy patient
8 % EMG3: Myopathy patient
9 % If the variables are in a different format, adjust the following
10 assignments
11 EMG1 = emg_healthy(1, :); % Healthy subject
12 EMG2 = emg_myopathy(1, :); % Neuropathy
13 EMG3 = emg_neuropathy(1, :); % Myopathy
14 % Sampling frequency and time vector
15 Fs = 4000; % Sampling rate after downsampling to 4 kHz
16 t1 = (0:length(EMG1)-1) / Fs;
17 t2 = (0:length(EMG2)-1) / Fs;
18 t3 = (0:length(EMG3)-1) / Fs;
19 % Plot the EMG signals
20 figure;
21 subplot(3,1,1);
22 plot(t1, EMG1);
23 xlim('tight');
24 title('EMG Signal - Healthy Subject');
25 xlabel('Time (s)');
26 ylabel('Amplitude');
27
28 subplot(3,1,2);
29 plot(t2, EMG2);
30 xlim('tight');
31 title('EMG Signal - Neuropathy Patient');
32 xlabel('Time (s)');
33 ylabel('Amplitude');
34
35 subplot(3,1,3);
36 plot(t3, EMG3);
37 xlim('tight');
38 title('EMG Signal - Myopathy Patient');
39 xlabel('Time (s)');
40 ylabel('Amplitude');
```

```

43 % Zoom into specific regions for analysis
44 disp('Use the zoom tool in the figure to analyze specific parts of the
45 signal.');
    zoom on;

```

Source Code 16: EMG - Question 1

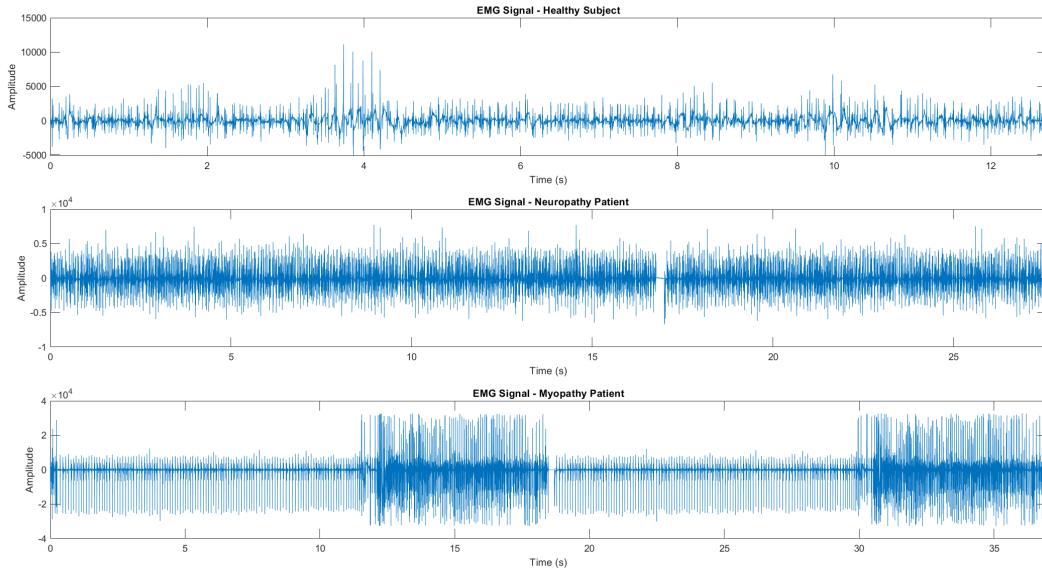


Figure 26: Question 1 - Time-Domain signals

**Soloution**

- Amplitude:** The myopathy signal has the largest amplitude, followed by the neuropathy signal. The healthy signal has the smallest amplitude, indicating more controlled muscle activity.
- Regularity:** The healthy subject has the most regular and consistent signal, while both neuropathy and myopathy exhibit irregular bursts. Neuropathy presents with high-frequency bursts, whereas myopathy shows strong, inconsistent bursts due to impaired muscle control.
- Noise:** Both neuropathy and myopathy signals appear "noisy" due to erratic muscle activity. Neuropathy exhibits rapid bursts, while myopathy has prolonged, chaotic fluctuations indicative of muscle weakness and dysfunction.

**Question 2**

Plot the frequency spectrum and time-frequency representation of each individual's signal, and compare them with each other.

```

1 % Frequency spectrum (using FFT)
2 N = length(EMG1); % Assuming all signals have the same length
3
4 % Frequency axis
5 f = (0:N-1)*(Fs/N);
6

```

```
7      % FFT for each signal
8      EMG1_fft = abs(fft(EMG1)/N);
9      EMG2_fft = abs(fft(EMG2)/N);
10     EMG3_fft = abs(fft(EMG3)/N);
11
12     % Plot frequency spectrum
13     figure;
14     subplot(3,1,1);
15     plot(f(1:N/2), EMG1_fft(1:N/2)); % Plotting up to Nyquist frequency
16     title('Frequency Spectrum - Healthy Subject');
17     xlabel('Frequency (Hz)');
18     ylabel('Amplitude');
19
20     subplot(3,1,2);
21     plot(f(1:N/2), EMG2_fft(1:N/2));
22     title('Frequency Spectrum - Neuropathy Patient');
23     xlabel('Frequency (Hz)');
24     ylabel('Amplitude');
25
26     subplot(3,1,3);
27     plot(f(1:N/2), EMG3_fft(1:N/2));
28     title('Frequency Spectrum - Myopathy Patient');
29     xlabel('Frequency (Hz)');
30     ylabel('Amplitude');
31
32     % Time-frequency analysis (STFT)
33     win = hamming(256); % Window size for STFT
34     nooverlap = 128; % Overlap between windows
35     nfft = 512; % Number of FFT points
36
37     figure;
38
39     % STFT for Healthy subject
40     subplot(3,1,1);
41     spectrogram(EMG1, win, nooverlap, nfft, Fs, 'yaxis');
42     title('Time-Frequency Representation - Healthy Subject');
43
44     % STFT for Neuropathy patient
45     subplot(3,1,2);
46     spectrogram(EMG2, win, nooverlap, nfft, Fs, 'yaxis');
47     title('Time-Frequency Representation - Neuropathy Patient');
48
49     % STFT for Myopathy patient
50     subplot(3,1,3);
51     spectrogram(EMG3, win, nooverlap, nfft, Fs, 'yaxis');
52     title('Time-Frequency Representation - Myopathy Patient');
```

Source Code 17: EMG - Question 2

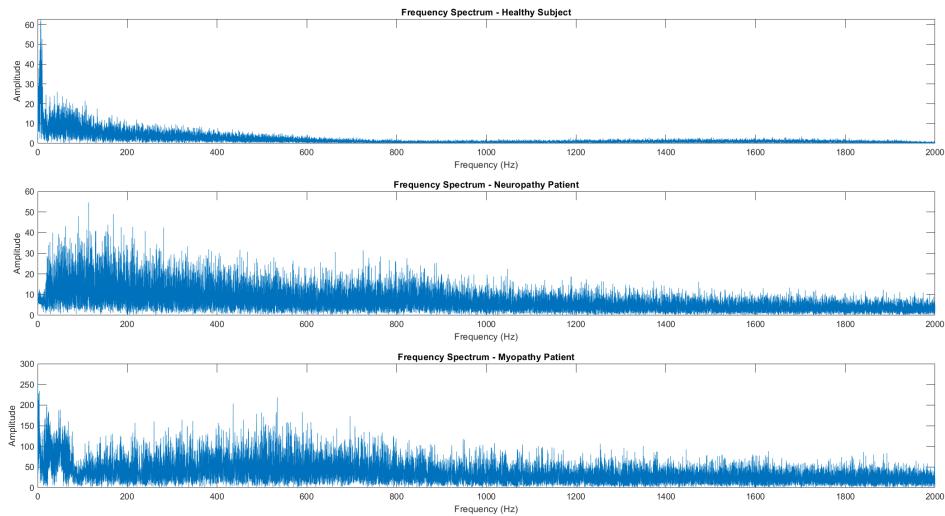


Figure 27: Question 2 - Frequency Spectrum

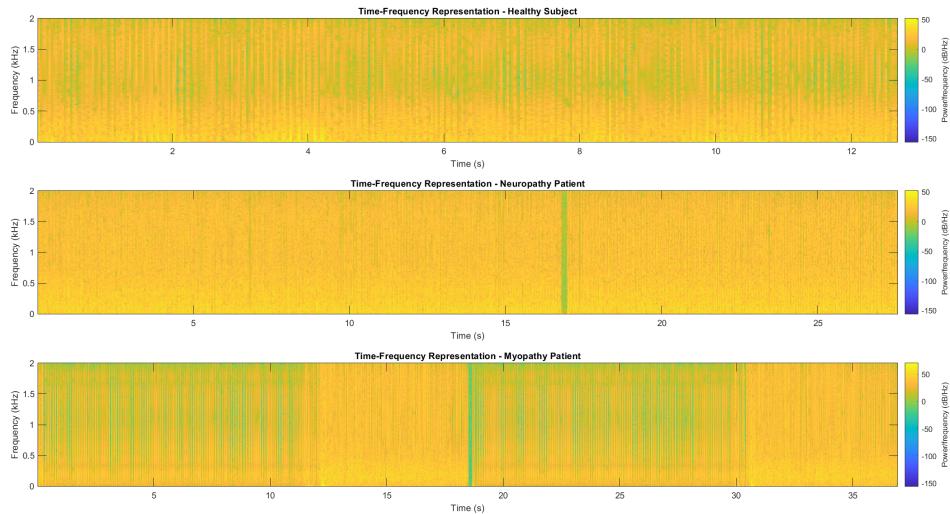


Figure 28: Question 2 - Time-Frequency characteristic

### Soloution

- Frequency Distribution:** The healthy subject has the narrowest and most stable frequency distribution, with most energy concentrated at lower frequencies. In contrast, both the neuropathy and myopathy patients exhibit higher-frequency components, with the myopathy signal showing particularly broad frequency spread.
- Time-Frequency Variability:** The healthy subject's time-frequency plot is the most stable, showing consistent muscle activity. Both neuropathy and myopathy exhibit more time-varying high-frequency activity, indicating irregular muscle firing and dysfunction. Myopathy, in particular, shows greater variability in both frequency and time.

### Question 3

By studying the two diseases, Neuropathy and Myopathy, explain the results obtained from sections 1 and 2.

#### Solutioun

**1. Neuropathy** Neuropathy is a condition that affects the peripheral nerves, leading to impaired nerve signal transmission. In the frequency spectrum and time-frequency analysis, the key features of the neuropathy EMG signal were:

- **Frequency Spectrum:** The signal exhibited a broader spread of energy across higher frequencies compared to the healthy subject. This is consistent with the erratic and irregular firing of motor units that occurs when nerves cannot transmit signals properly.
- **Time-Frequency Representation:** The neuropathy signal demonstrated bursts of high-frequency activity, reflecting irregular muscle contractions. These bursts are characteristic of nerve dysfunction, where muscles receive inconsistent or abnormal signals, resulting in jerky or erratic contractions.

**2. Myopathy** Myopathy refers to diseases that affect the muscles themselves, leading to muscle weakness or dysfunction. The results from the frequency spectrum and time-frequency analysis for the myopathy patient showed:

- **Frequency Spectrum:** The myopathy signal had a higher amplitude across a broader frequency range, particularly at lower frequencies. This reflects the weakened state of the muscles, as they generate abnormal electrical activity when trying to contract.
- **Time-Frequency Representation:** There were visible bursts of high-frequency activity, particularly in the middle and later parts of the signal. These bursts reflect the muscles' difficulty in sustaining contractions and the irregularity of muscle activity, which is typical of myopathic conditions.

#### Comparison of Neuropathy and Myopathy Results

- **Neuropathy:** The results show more irregular high-frequency bursts, indicating abnormal nerve firing and poor control over muscle contractions. The signal is less smooth and more variable in both frequency and time.
- **Myopathy:** The results reflect weakened muscle contractions, with broader energy distribution in the frequency spectrum and more sustained bursts of irregular activity over time. The muscles attempt to contract but struggle, leading to bursts of high-frequency activity that gradually weaken.