Biomedical Engineering

EEC 491

Final Project

Submitted By:

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May 2, 2024

1 Removing signals from muscle movement

1.1 The code

```
clear, clc, close all;

%% Removing signals from muscle movement:

% Load the ECG signal data
load('ecg.mat');

% Extract the ECG signal and adjust for amplification factor
EKG1 =  ecg ./ 500;

% Calculate time vector based on sampling rate
fs = 500; % Sampling frequency (Hz)
t = (0:length(ecg)-1) / fs; % Time vector

% Plot the original EKG signal
figure;
subplot(221)
plot(t, EKG1);
xlabel('Time (seconds)');
ylabel('Voltage (V)');
grid on;
title('Original EKG Signal measured @ leads');
xlim([0, 1]); % Zoom into one period of the signal

% Perform Fourier Transform
N = length(ecg);
f = linspace(-fs/2, fs/2, N); % Frequency axis for FFT

% Compute the FFT of the signal
ecg_fft = fftshift(fft(ecg));

subplot(222)
plot(f, real(ecg_fft));
xlabel('Frequency (Hz)');
ylabel('Voltage (V)');
grid on;
title('ECG Signal in frequency domain');


```

```
% Set frequencies below 0.5 Hz to zero (low-pass filtering)
ecg_fft(f < 0.5) = 0;

subplot(224)
plot(f, real(ecg_fft));
xlabel('Frequency (Hz)');
ylabel('Voltage (V)');
grid on;
title('Removing frequency < 0.5 Hz');

% Inverse FFT to obtain the filtered signal
ecg1 = real(ifft(ifftshift(ecg_fft)));

% Plot the filtered ECG signal
subplot(223)
plot(t, real(ecg1)); % Use real part to avoid complex artifacts
xlabel('Time (seconds)');
ylabel('Voltage (V)');
grid on;
title('ECG Signal with Muscle Signals Removed');
xlim([0, 1]); % Zoom into one period of the signal
```

1.2 The output figures

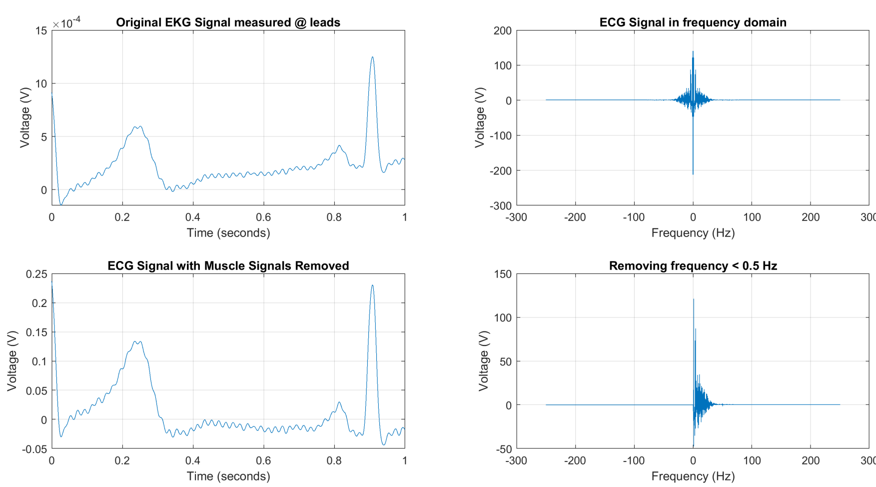

Figure 1: Time and frequency domains of the original and first filtered signals

2 Removing 50 Hz interference

2.1 The code

```
%% Removing 50 Hz interference:

% Design a Notch filter to remove 50 Hz interference
f0 = 50; % Frequency to notch out (Hz)
w0 = f0 / (fs/2); % Normalized frequency
Q = 30; % Quality factor for the Notch filter

% Design the Notch filter using the second-order
   ↪ section (SOS) structure
[b, a] = iirnotch(w0, w0/Q);
figure;
subplot(311)
phasez(b, a, 1024, fs);
title('Response of Notch Filter');
xlabel('Frequency (Hz)');
ylabel('Phase (Radians)');
grid on;

% Apply the Notch filter to the ECG signal
ecg2 = filtfilt(b, a, ecg1); % Zero-phase filtering

% Plot the original ECG signal
subplot(312)
plot(t, ecg);
xlabel('Time (seconds)');
ylabel('Voltage (V)');
grid on;
title('Original EKG Signal measured @ leads');
xlim([0, 1]); % Zoom into one period of the signal

% Plot the filtered ECG signal
subplot(313)
plot(t, ecg2);
grid on;
xlabel('Time (seconds)');
ylabel('Voltage (V)');
title('ECG Signal after 50 Hz Notch Filtering');
xlim([0, 1]); % Zoom into one period of the signal
```

2.2 The output figures

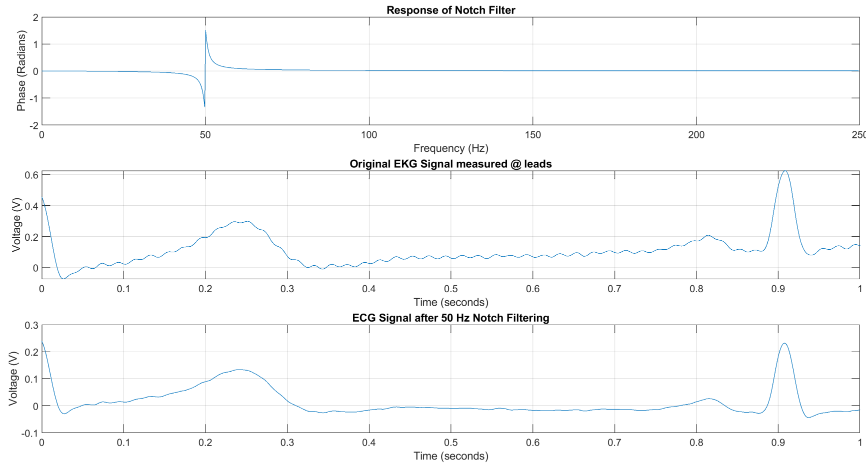

Figure 2:

3 Increasing the signal-to-noise ratio

3.1 The code

```
%% Increasing the signal-to-noise ratio:

% Define different cutoff frequencies for the low-pass filter
cutoff_freqs = [20, 30, 40, 50]; % Hz

figure;
% Plot the original ECG signal
subplot(321)
plot(t, ecg);
xlabel('Time (seconds)');
ylabel('Voltage (V)');
grid on;
title('Original ECG Signal');
xlim([0, 1]); % Zoom into one period of the signal

% Apply low-pass filtering with different cutoff frequencies
for i = 1:length(cutoff_freqs)
```

```
    % Design a Butterworth low-pass filter
    cutoff = cutoff_freqs(i);
    [b, a] = butter(4, cutoff / (fs/2), 'low'); % 4th-order Butterworth filter

    % Apply the low-pass filter to the ECG signal
    filtered_signal = filtfilt(b, a, ecg2);

    % Plot the filtered ECG signal with specific color
        subplot(3,2,i+2)
    plot(t, filtered_signal);
        xlabel('Time (seconds)');
        ylabel('Voltage (V)');
        grid on;
        title(['Cutoff = ', num2str(cutoff), 'Hz']);
        xlim([0, 1]); % Zoom into one period of the signal
        hold on;
end
hold off; % Disable hold on

cutoff = 30;
[b, a] = butter(4, cutoff / (fs/2), 'low'); % 4th-order Butterworth filter

% Apply the low-pass filter to the ECG signal
ecg3 = filtfilt(b, a, ecg2);

% Plot the filtered ECG signal with specific color
subplot(322)
plot(t, ecg3);
xlabel('Time (seconds)');
ylabel('Voltage (V)');
grid on;
title('A compromise on the cut-off frequency, we found = 30 Hz');
xlim([0, 1]); % Zoom into one period of the signal
```

3.2 The output figures

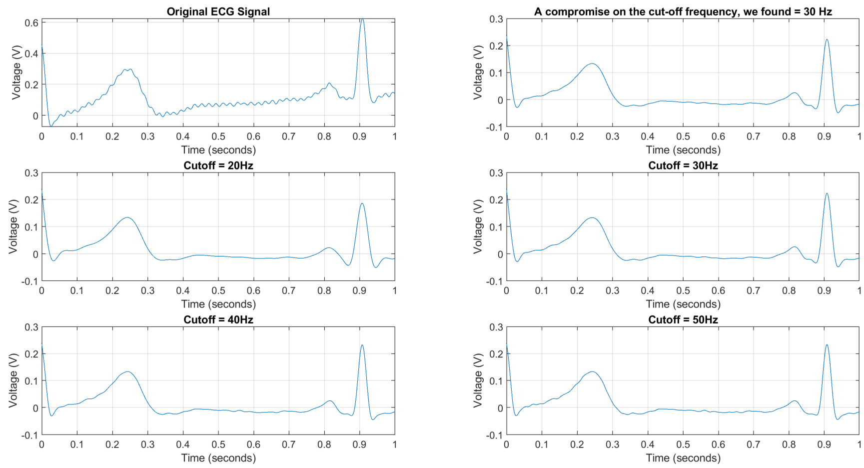

Figure 3: The original signal and that with different cutoffs showing that the optimal cutoff is 30 Hz. It provides suitable details and less noise in the ECG

4 Finding the heart rate using auto-correlation

4.1 The code

```
%% Finding the heart rate using autocorrelation:

% Compute the cross-correlation and lags for the original ECG signal
[ECG_autoc_original, lags] = xcorr(ecg);

% Plot the autocorrelation of the original ECG signal
figure
subplot(2,1,1)
plot(lags/fs, ECG_autoc_original);
grid on;
title('Autocorrelation of Original ECG Signal');
xlabel('Lag');
ylabel('Autocorrelation');

% Compute the cross-correlation and lags for ECG3 signal
[ECG_autoc3, lags] = xcorr(ecg3);

% Plot the autocorrelation of ECG3 signal
subplot(2,1,2)
plot(lags/fs, ECG_autoc3);
```

```
grid on;
title('Autocorrelation of ECG3 Signal');
xlabel('Lag');
ylabel('Autocorrelation');

% Find the global maximum of autocorrelation for the original ECG signal
[ECG_autoc_original_gmax, ECG_original_gmax_loc] = max(ECG_autoc_original);

% Find local peaks after the global maximum for the original EKG1 signal
[peaks, locations] = findpeaks(ECG_autoc_original((ECG_original_gmax_loc+1):end));
local_max_original_indices = find(ECG_autoc_original == max(peaks));
local_max_original_index = max(local_max_original_indices) - ECG_original_gmax_loc;

% Compute heart rate (in bpm) based on the local max index and sampling frequency (Fs) for the original ECG signal
heart_rate_original = (60 * fs) / local_max_original_index;

% Find the global maximum of autocorrelation for ECG3 signal
[ECG3_gmax, ECG3_gmax_loc] = max(ECG_autoc3);

% Find local peaks after the global maximum for ECG3 signal
[peaks3, locations3] = findpeaks(ECG_autoc3((ECG3_gmax_loc+1):end));
local_max3_indices = find(ECG_autoc3 == max(peaks3));
local_max3_index = max(local_max3_indices) - ECG3_gmax_loc;

% Compute heart rate (in bpm) based on the local max index and sampling frequency (Fs) for ECG3 signal
heart_rate3 = (60 * fs) / local_max3_index;

% Display the estimated heart rate
```

```
disp(['Estimated Heart Rate of original ECG: '
    ↪ num2str(heart_rate_original) ' bpm ,While the
    ↪ Estimated Heart Rate of ECG3: ' num2str(
    ↪ heart_rate3) ' bpm']);
```

4.2 The output figures

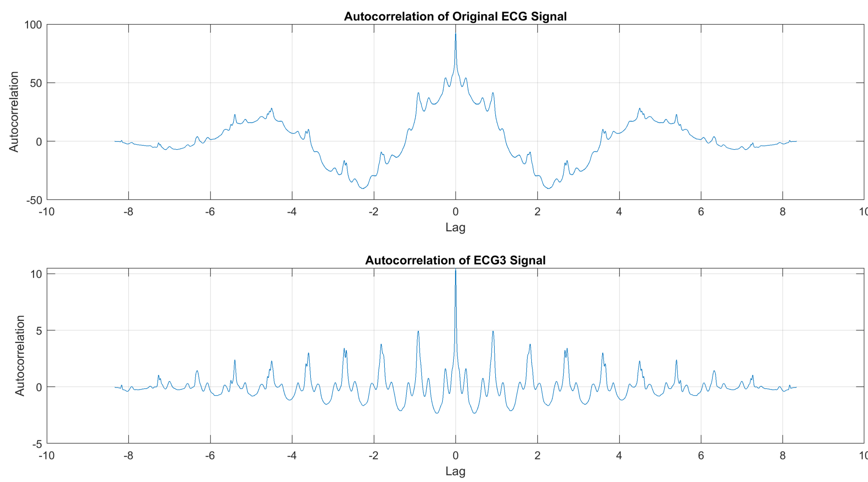

Figure 4: Autocorrelation of original and filtered signal

4.3 Command Window

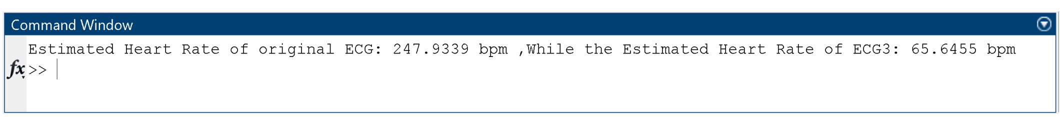

Figure 5: The output from the above code in the command window

4.4 Comment

Our program has found a right pulse rate which is approximately = 65 bpm. This rate is within the normal limits of heart rate for the human.

5 Finding the QRS complex

5.1 The code

```
%% Finding the QRS complex:
figure;
 [qrs_amp_raw,qrs_i_raw,delay,mean_RR] = pan_tompkin(
   ↪ ecg3,fs,1);
```

5.2 The output figures

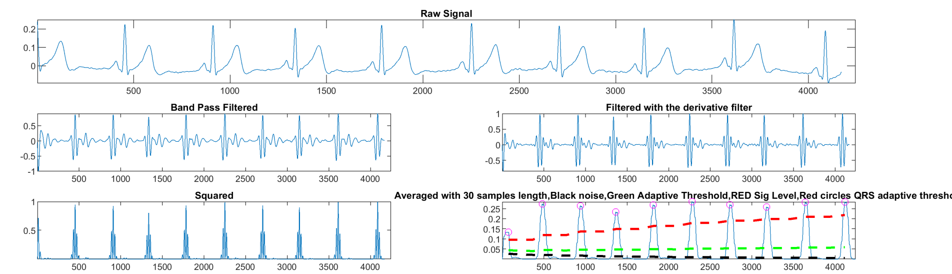

Figure 6:

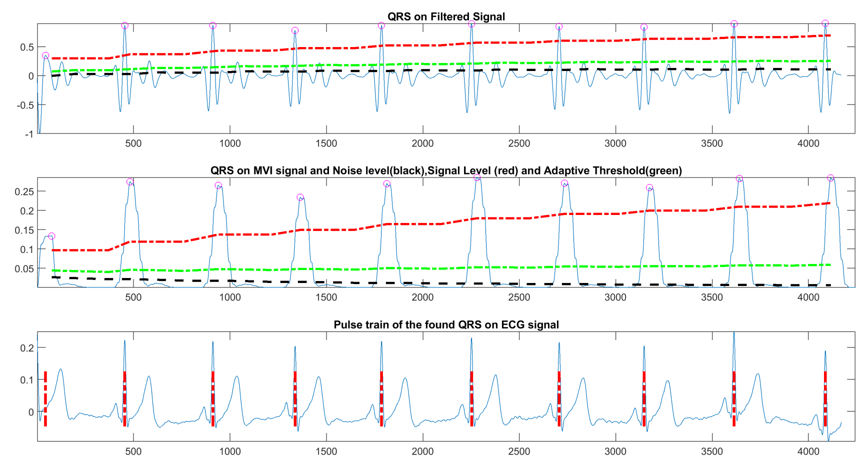

Figure 7:

6 Survey about various heart diseases diagnosed from the waves of ECG signals

Heart Disease Diagnosis: Unveiling the Secrets in ECG Waves Electrocardiograms (ECGs) are a cornerstone of diagnosing heart disease. By analyzing the electrical impulses of the heart captured as waves on the ECG, healthcare professionals can identify various abnormalities and underlying heart conditions. This report explores some of the key heart diseases diagnosed through ECG analysis.

6.1 Decodng the ECG Waves:

An ECG tracing comprises distinct waves, each representing a specific electrical stage in the heart's beat:

- P wave: Reflects atrial depolarization (contraction).
- QRS complex: Represents ventricular depolarization (contraction).
- ST segment: Indicates the period between ventricular depolarization and repolarization.
- T wave: Represents ventricular repolarization (relaxation).

6.2 Diseases Revealed by ECG Patterns:

1. Arrhythmias: Irregular heartbeats can manifest as abnormal patterns in ECG waves. For instance, premature beats might show extra P waves or QRS complexes, while atrial fibrillation appears as chaotic baseline variations.

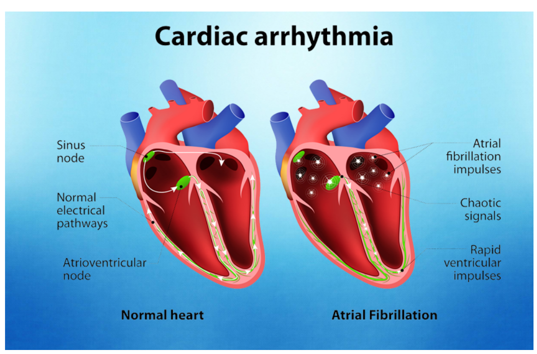

Figure 8: cardiac arrhythmia

2. Myocardial Ischemia: Reduced blood flow to the heart muscle due to narrowed arteries (coronary artery disease) can cause ST segment depression. In a heart attack (acute myocardial infarction), ST segment elevation and abnormal QRS complexes are often observed.

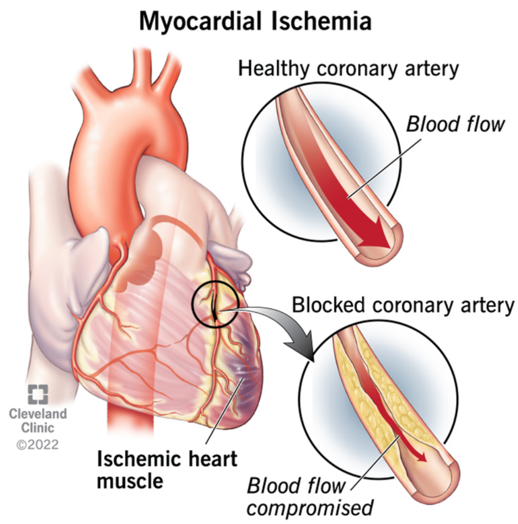

Figure 9: myocardial ischemia

3. Ventricular Hypertrophy: Thickening of the heart muscle, often due to high blood pressure, can be indicated by increased voltage of ECG waves, particularly in the QRS complex.

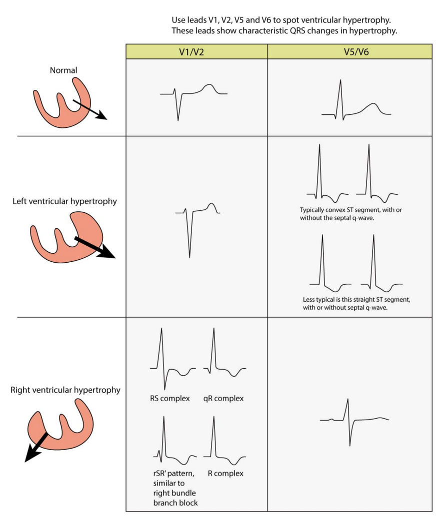

Figure 10: Ventricular Hypertrophy

4. Electrolyte Imbalances: Abnormal levels of electrolytes like potassium and calcium can affect the electrical activity of the heart, reflected in changes like prolonged PR intervals (time between P wave and QRS complex) or QT intervals (time from QRS complex to the end of the T wave).

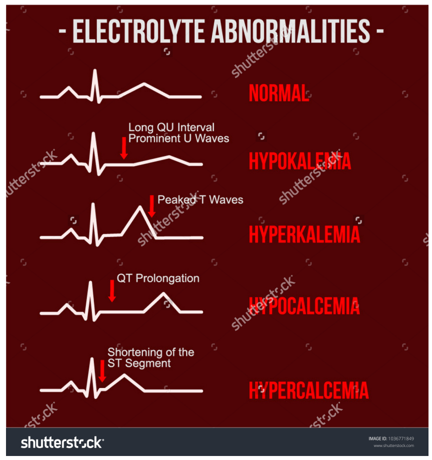

Figure 11: Electrolyte Imbalances

6.3 Limitations of ECG Diagnosis:

While ECG is a valuable tool, it has limitations. Certain heart conditions may not cause significant ECG changes, and sometimes, ECG findings can be inconclusive. Additional tests like echocardiograms or cardiac stress tests might be needed for a definitive diagnosis.

6.4 The Future of ECG Analysis:

Advancements in technology, particularly machine learning, hold promise for automated ECG analysis. This could improve accuracy, efficiency, and early detection of heart disease, allowing for timely intervention and better patient outcomes.

6.5 Conclusion:

ECG analysis plays a crucial role in diagnosing various heart diseases. By understanding the language of ECG waves, healthcare professionals can gain valuable insights into the heart's health. However, ECG is a piece of the puzzle, and a comprehensive evaluation is often necessary for an accurate diagnosis. As technology evolves, ECG analysis is poised to become even more powerful in the fight against heart disease.