ECG Signal Processing

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BONAFIDE CERTIFICATE

Certified that this project report entitled "ECG SIGNAL PROCESSING" is a bonafide work of **JOSEPH – 23BVD1009, A SANJAY- 23BVD1012, NOEL JOSE – 23BVD1029 and DRAHVIDAN C – 23BVD1050 who** carried out the Project work under my supervision and guidance for **BEVD203L –Signal Processing.**

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ABSTRACT

This project endeavours to design and implement an advanced signal processing framework for analysing electrocardiogram (ECG) signals. The framework employs techniques such as Discrete Wavelet Transform (DWT) and Biorthogonal Wavelets to preprocess ECG data, effectively removing noise, including baseline wander, high-frequency artifacts, and powerline interference.

Utilizing a 9-level wavelet decomposition with the Biorthogonal 3.7 wavelet, the system successfully isolates and reconstructs the fundamental components of the ECG signal. Furthermore, it facilitates the detection of PQRST complexes, a pivotal step in extracting clinically relevant features such as heart rate and diagnosing cardiac anomalies. The project integrates automated algorithms for R-peak detection and heart rate estimation, thereby providing quantitative insights into cardiac health.

The methodology ensures accurate signal representation by preserving the morphological characteristics of ECG features while effectively eliminating noise. The framework possesses the potential to be applied in real-time monitoring systems, wearable health devices, and telemedicine platforms, thereby facilitating efficient and reliable cardiac diagnostics.

This research underscores the significance of wavelet-based approaches in biomedical signal processing and paves the way for future advancements in automated ECG analysis and predictive healthcare.

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1.INTRODUCTION

1.1 OBJECTIVES AND GOALS

The primary objectives of this project are focused on analysing and interpreting ECG signals to aid in understanding cardiac health and diagnosing potential abnormalities. These objectives are elaborated as follows:

- **Observing ECG Signals from the MIT-BIH Arrhythmia Database**

This project accesses ECG data from the MIT-BIH Arrhythmia Database, which contains ECG recordings of patients with various cardiac conditions. By observing these signals, we study their waveform characteristics, including the PQRST complexes, to assess their relevance to cardiac health. The database provides diverse cardiac data, ensuring our methods are validated on real-world patient signals.

- **Pre-Processing the ECG Signals to Remove Artifacts**

Pre-processing removes artifacts, such as baseline wander, powerline interference, and muscle noise, from the ECG signal. Filtering techniques, including wavelet-based methods and notch filtering, clean the signal while preserving its key features.

- **Detecting PQRST Waves and Determining Heartbeat**

Advanced signal processing techniques, like the Discrete Wavelet Transform (DWT), identify the PQRST complexes with high precision. R-peaks are detected to calculate the patient's heartbeat in beats per minute (BPM). This quantifies cardiac rhythm and enables the identification of irregularities.

- **Cardiac Monitoring**

The ability to accurately detect PQRST waves and calculate heart rate ensures the system's effectiveness in cardiac monitoring.

1.2 APPLICATIONS

Filtering ECG signals is an essential preprocessing step in biomedical signal processing. It ensures the removal of noise and artifacts while preserving clinically significant features of the ECG waveform. The following applications show the importance and relevance of ECG signal filtering in various domains:

- **Noise-Free Signal Acquisition in Clinical Diagnostics**

  Filtering removes unwanted artifacts such as baseline wander, powerline interference, and high-frequency noise (e.g., muscle activity). This ensures the ECG signals are clear and reliable for accurate diagnosis of cardiac conditions like arrhythmias, myocardial infarction, and heart blocks.

- **Enhancing PQRST Wave Detection**

  Accurate identification of PQRST waves depends heavily on clean ECG signals. Filtering techniques ensure the suppression of noise components, allowing precise detection of R-peaks, QRS complexes, and T-wave abnormalities, which are crucial for analysing heart rhythms.

- **Patient Monitoring Systems**

  In hospital ICUs and remote patient monitoring setups, filtering is vital for obtaining artifact-free ECG signals in real time. It prevents false alarms caused by noise or movement artifacts and enables accurate tracking of cardiac health during emergencies.

- **Reducing Artifacts in Wearable ECG Devices**

  Wearable devices like smartwatches and portable ECG monitors often suffer from motion artifacts and muscle noise due to user activities. Incorporating filtering techniques enhances the quality of signals, making these devices more reliable for continuous health monitoring.

1.3 FEATURES

The project integrates advanced techniques to preprocess ECG signals, detect PQRST waves, and determine the heartbeat. Below are some detailed features of the project:

Implements effective filtering methods to remove various types of noise:

Baseline Wander: Eliminated using wavelet decomposition to isolate and reconstruct relevant components.

Powerline Interference: Mitigated using notch filtering (e.g., for 50/60 Hz noise).

High-Frequency Noise: Reduced through biorthogonal wavelet-based filtering.

PQRST Wave Detection:

Accurately detects the PQRST complexes, which represent key phases of the heart's electrical activity.

Enables precise identification of R-peaks, which are critical for calculating the heart rate.

Detects QRS intervals, P-wave onset, and T-wave morphology for detailed cardiac analysis.

Heart Rate Calculation:

Calculates the patient's heart rate (in beats per minute) by analysing R-peak intervals.

Provides quantitative insights into the patient's cardiac health, detecting conditions like tachycardia or bradycardia.

Wavelet-Based Processing:

Uses **Discrete Wavelet Transform (DWT)** and **Biorthogonal 3.7 wavelets** for multiresolution analysis.

Decomposes the signal into low-frequency (approximation) and high-frequency (detail) components for targeted noise removal.

Artifact Handling:

Addresses common artifacts in ECG signals, including:

Muscle Noise (EMG): High-frequency interference reduced effectively.

Motion Artifacts: Smoothed through filtering and wavelet reconstruction.

Visualization:

Plots the original, filtered, and processed signals to illustrate the effectiveness of the noise removal.

Displays detected PQRST waves and highlights the R-peaks on the ECG waveform.

Adaptability for Real-Time Applications:

The framework can be extended for real-time ECG monitoring systems with appropriate hardware integration.

Suitable for embedding in wearable devices or remote health monitoring systems.

2.PROCESS

2.1 DATABASE:

The MIT-BIH Arrhythmia Database is a benchmark dataset widely used in the field of ECG signal processing and analysis. Developed by the Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (BIH), it is specifically designed to support research on arrhythmias, which are abnormalities in heart rhythm. This database provides high-quality recordings of electrocardiogram (ECG) signals and serves as a standard reference for developing, testing, and validating signal processing algorithms. Since its creation, the database has been instrumental in advancing the understanding of cardiac abnormalities and improving diagnostic tools.

Structure and Content of the Database:

The database consists of 48 recordings from 47 patients, including both men and women, sampled at a frequency of 360 Hz. Each recording is 30 minutes long and contains signals from two leads, typically Lead II and V1, providing complementary views of the heart's electrical activity. The dataset includes over 110,000 annotated heartbeats with labels for normal and abnormal rhythms, including arrhythmias such as premature ventricular contractions and atrial fibrillation. These annotations enable precise identification of PQRST waveforms, arrhythmic events, and other cardiac anomalies, making the database an invaluable resource for medical research and algorithm validation.

Applications in ECG Signal Processing:

The MIT-BIH Arrhythmia Database is widely used for evaluating noise removal, feature extraction, and arrhythmia detection algorithms. It provides a robust foundation for real-time ECG monitoring systems and wearable devices by ensuring algorithm reliability in detecting PQRST complexes and calculating heart rates. Furthermore, the diversity of the dataset allows researchers to validate methods for detecting arrhythmias, such as bradycardia, tachycardia, and fibrillation.

2.2 REMOVAL OF ARTIFACTS:

Removal of Baseline Wander

Baseline wander, a low-frequency artifact typically caused by respiration or patient movement, distorts the ECG signal, affecting the accurate detection of clinically significant features. This noise is primarily in the frequency range of 0.67 Hz and can be effectively removed using **Discrete Wavelet Transform (DWT)**. By decomposing the signal into multiple levels, DWT isolates the low-frequency components responsible for baseline wander. A nine-level decomposition of the original ECG signal using DWT is sufficient to eliminate baseline fluctuations while preserving the higher-frequency cardiac features necessary for further analysis.

Removal of Powerline Interference

Powerline interference is a common high-frequency noise in ECG signals, caused by electromagnetic interference from electrical devices and wiring. This artifact, occurring at 50 Hz (or 60 Hz depending on the region), significantly impacts the signal's clarity, especially in long-term recordings. To remove this noise, a **notch filter** centered at 50 Hz is applied. The filter is designed with a 3-dB bandwidth of 5 Hz, ensuring effective attenuation of powerline interference while minimizing the distortion of nearby frequencies in the ECG signal. This step enhances the signal's quality for accurate feature extraction.

Removal of EMG – High-Frequency Noise

High-frequency noise from electromyographic (EMG) activity, often caused by muscle movements near the electrodes, is another challenge in ECG analysis. Most of the vital information in an ECG signal lies in the frequency range of 0.5–150 Hz, and EMG noise often overlaps with this spectrum. To address this, a two-level decomposition of the ECG signal using **Discrete Wavelet Transform (DWT)** is performed. By isolating and removing high-frequency components, this approach preserves the integrity of the ECG features while eliminating EMG-induced artifacts. This step ensures a clean signal suitable for precise PQRST detection and heart rate analysis.

2.3 DISCRETE WAVELET TRANFORM

Discrete Wavelet Transform (DWT) decomposes a signal into a series of mutually orthogonal wavelet basis functions. Wavelet functions are dilated, translated, and scaled versions of a common function known as the mother wavelet.

DWT possesses the capability to provide both frequency and temporal resolution, enabling the extraction of frequency components and their spatial location within the signal.

Several families of wavelet transforms are distinguished by their mother wavelet, with the most prevalent being Haar, Shannon, Daubechies, Spline, Biorthogonal, Mexican Hat, and others.

In this project, the Biorthogonal wavelet transform was employed for artifact removal from the ECG signal, while the Daubechies wavelet transform was utilized for the detection of PQRST waves in the ECG signal.

To perform the **Discrete Wavelet Transform (DWT)**, the input signal is passed through a **low-pass filter** to obtain the **approximation coefficients**, which represent the low-frequency components of the signal. Simultaneously, the same input signal is passed through a **high-pass filter** to extract the **detailed coefficients**, which represent the high-frequency components. These two sets of coefficients allow for the separation of different frequency bands within the signal, enabling a detailed analysis of its features.

The **detailed coefficients** are fixed, representing the high-frequency content of the signal, which remains unaltered during further decomposition. However, the **approximation coefficients**, which represent the low-frequency content, are subject to modification. For further decomposition into higher levels or scales, the approximation coefficients are **down sampled by a factor of 2** to reduce the data size while retaining essential low-frequency features. The down sampled approximation coefficients are then passed through another set of high-pass and low-pass filters to obtain the next level of approximation and detailed coefficients. This recursive process continues for the desired number of levels.

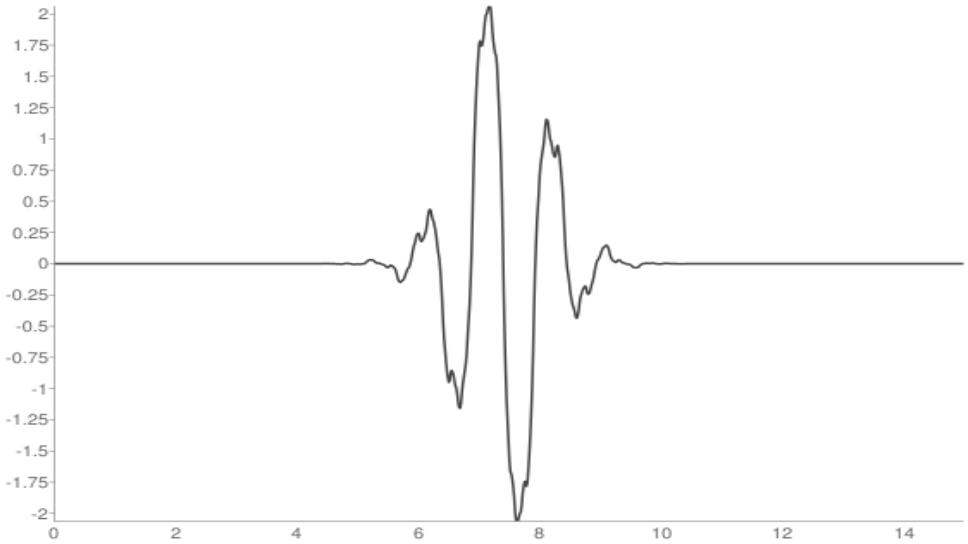
In this project, **nine-level decomposition** is performed using DWT to remove **baseline wander noise**, which predominantly affects the low-frequency range of the ECG signal. The deeper decomposition allows for precise isolation and elimination of baseline fluctuations. In contrast, the removal of **electromyographic (EMG) noise**, which is a high-frequency artifact, requires only a **two-level decomposition**. By targeting specific frequency ranges with appropriate decomposition levels, the project ensures effective noise removal while preserving the clinically significant features of the ECG signal.

BIORTHOGONAL WAVELET

Biorthogonal wavelets, with their compact support and symmetry, are ideal for signal processing where preserving signal morphology is crucial. Unlike orthogonal wavelets, biorthogonal wavelets use two distinct scaling functions for multiresolution analyses, one for decomposition and the other for reconstruction. This duality ensures symmetry while providing efficient and stable signal analysis and reconstruction..

Biorthogonal 3.7 Wavelet (bior3.7)

The Biorthogonal 3.7 (bior3.7) wavelet, with its symmetry and compact support, is commonly used in precise and stable applications like biomedical signal processing. The wavelet filters have three and seven coefficients for decomposition and reconstruction, respectively, ensuring accurate multilevel decomposition and reconstruction. This makes bior3.7 ideal for analyzing signals like ECG, where preserving the waveform's structure is crucial.



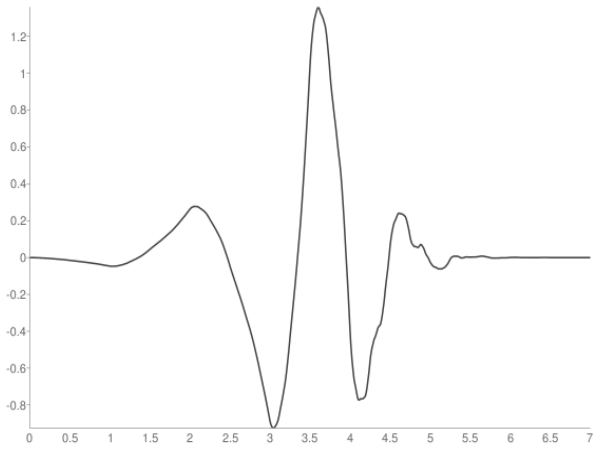
DAUBECHIES WAVELET

Daubechies Wavelet and Its Relevance

The Daubechies 4 (db4) wavelet, known for its excellent frequency response and ability to capture transient and oscillatory features, was chosen for this project due to its similarity to an ECG waveform. This similarity ensures efficient capture of essential ECG features like PQRST complexes while effectively separating noise and artifacts. The db4 wavelet's mathematical structure makes it well-suited for analysing and processing non-stationary signals like ECG, where localized time-frequency analysis is crucial.

Features of the Daubechies 4 Wavelet

The **Daubechies 4 (db4)** wavelet belongs to a family of **asymmetric, orthogonal, biorthogonal, and compactly supported wavelets**, making it versatile for signal processing tasks. Its orthogonality ensures that the original signal can be perfectly reconstructed without redundancy, while its compact support allows for efficient computation and minimal data overlap. The asymmetry of db4 is well-suited for analysing signals with sharp transitions, such as the QRS complex in ECG signals. These properties make the db4 wavelet a powerful tool for multilevel decomposition and noise removal, ensuring the retention of clinically significant ECG features during processing.



GENERATION OF PQRST WAVES

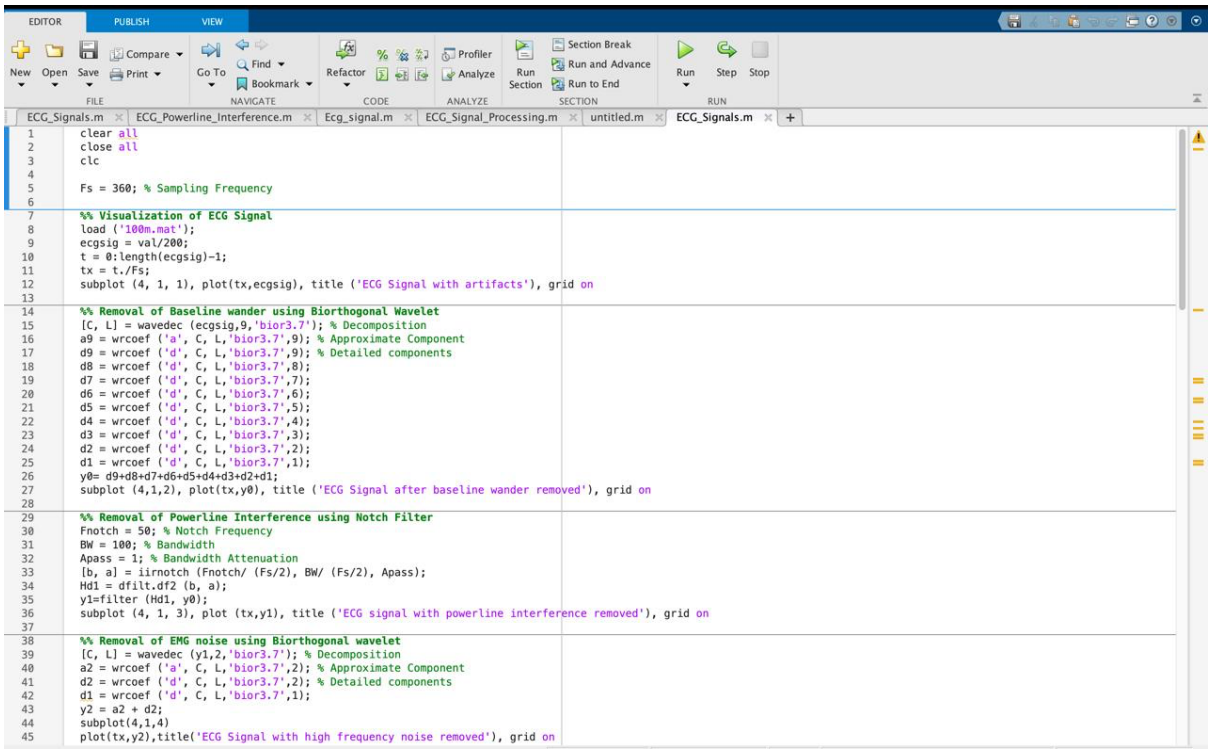
The generation of PQRST waves in an ECG signal represents the electrical activity of the heart as it progresses through a complete cardiac cycle. These waves correspond to distinct physiological events in the heart. The P-wave reflects atrial depolarization, which initiates the contraction of the atria. Following this, the QRS complex, a sharp and high-amplitude waveform, represents ventricular depolarization, marking the contraction of the ventricles, which is the primary pumping action of the heart. Finally, the T-wave corresponds to ventricular repolarization, a recovery phase preparing the heart for the next cycle. Each of these waves is vital for understanding the heart's electrical activity and detecting abnormalities. The accurate detection and analysis of PQRST waves are essential for diagnosing conditions like arrhythmias, ischemia, or conduction abnormalities, making them a central focus in ECG signal processing.

The **PQRST waves** form the foundation of the electrocardiogram (ECG) signal, representing the electrical activity of the heart as it goes through a complete cardiac cycle. Each wave corresponds to a specific physiological event occurring in the heart. The **P-wave** is the first wave in the cycle and reflects the **depolarization of the atria**, which is the electrical stimulus that triggers atrial contraction. This phase ensures blood flows from the atria into the ventricles, preparing the heart for effective pumping. The **PR segment** that follows represents the delay at the atrioventricular (AV) node, allowing the ventricles to fill completely before contraction.

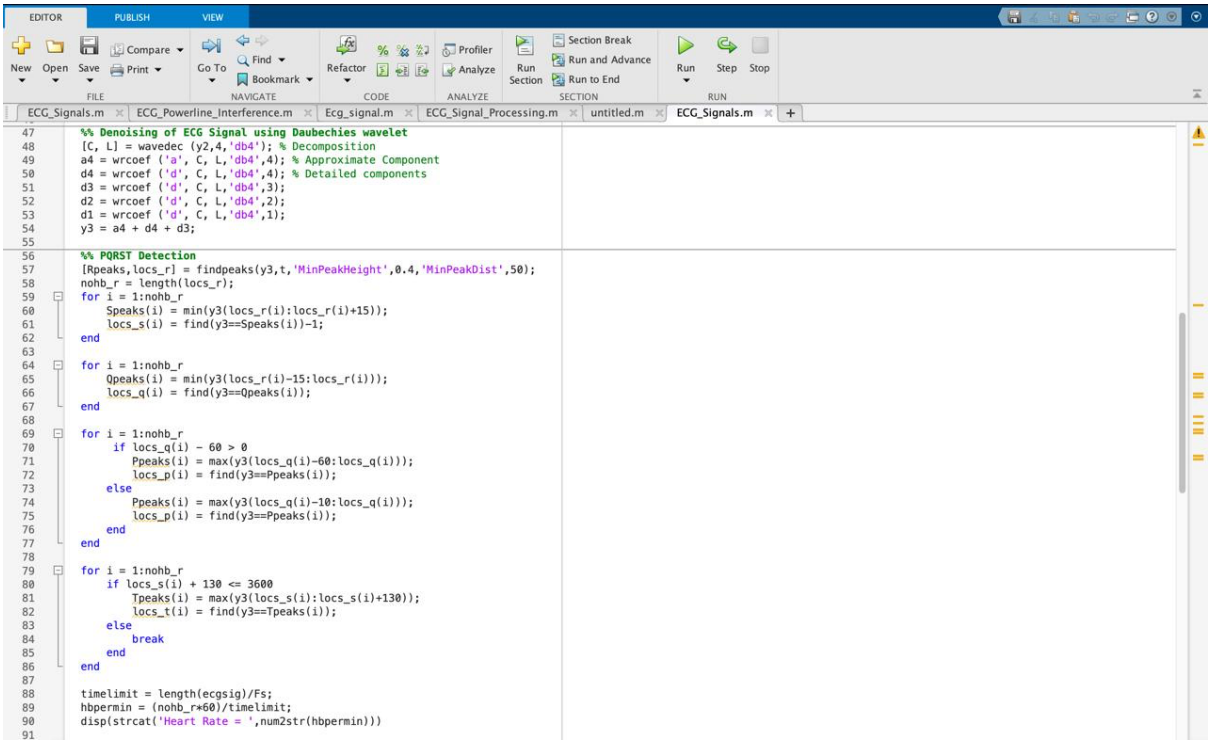
The **QRS complex** is the most prominent feature of the ECG and represents **ventricular depolarization**, where electrical impulses spread rapidly through the ventricles, causing them to contract and pump blood to the lungs and the rest of the body. The sharpness and amplitude of the QRS complex reflect the robust electrical activity of the ventricles. At the same time, atrial repolarization occurs, although it is not visible on the ECG due to being masked by the larger QRS complex. After the QRS complex, the **ST segment** marks the beginning of the ventricular repolarization phase.

Finally, the **T-wave** represents **ventricular repolarization**, where the ventricles recover and prepare for the next cycle. This phase is critical for ensuring that the heart's electrical system resets properly. Together, these waves form the PQRST complex, which is essential for assessing the heart's electrical and mechanical function. Abnormalities in these waves, such as deviations in amplitude, duration, or timing, can indicate a variety of cardiac conditions, including arrhythmias, ischemia, myocardial infarction, or conduction blockages. Analysing PQRST waves is, therefore, a cornerstone of cardiac diagnostics and monitoring.

3. SOFTWARE



```
clear all
close all
clc

Fs = 360; % Sampling Frequency

%% Visualization of ECG Signal
load ('100m.mat');
ecgsig = val/200;
t = 0:length(ecgsig)-1;
tx = t./Fs;
subplot (4, 1, 1), plot(tx,ecgsig), title ('ECG Signal with artifacts'), grid on

%% Removal of Baseline wander using Biorthogonal Wavelet
[C, L] = wavedec (ecgsig,9,'bior3.7'); % Decomposition
a9 = wrcoef ('a', C, L,'bior3.7',9); % Approximate Component
d9 = wrcoef ('d', C, L,'bior3.7',9); % Detailed components
d8 = wrcoef ('d', C, L,'bior3.7',8);
d7 = wrcoef ('d', C, L,'bior3.7',7);
d6 = wrcoef ('d', C, L,'bior3.7',6);
d5 = wrcoef ('d', C, L,'bior3.7',5);
d4 = wrcoef ('d', C, L,'bior3.7',4);
d3 = wrcoef ('d', C, L,'bior3.7',3);
d2 = wrcoef ('d', C, L,'bior3.7',2);
d1 = wrcoef ('d', C, L,'bior3.7',1);
y0= d9+d8+d7+d6+d5+d4+d3+d2+d1;
subplot (4,1,2), plot(tx,y0), title ('ECG Signal after baseline wander removed'), grid on

%% Removal of Powerline Interference using Notch Filter
Fnotch = 50; % Notch Frequency
BW = 100; % Bandwidth
Apass = 1; % Bandwidth Attenuation
[b, a] = iirnotch (Fnotch/ (Fs/2), BW/ (Fs/2), Apass);
Hd1 = dfilt.df2 (b, a);
y1=filter (Hd1, y0);
subplot (4, 1, 3), plot (tx,y1), title ('ECG signal with powerline interference removed'), grid on

%% Removal of EMG noise using Biorthogonal wavelet
[C, L] = wavedec (y1,2,'bior3.7'); % Decomposition
a2 = wrcoef ('a', C, L,'bior3.7',2); % Approximate Component
d2 = wrcoef ('d', C, L,'bior3.7',2); % Detailed components
d1 = wrcoef ('d', C, L,'bior3.7',1);
y2 = a2 + d2;
subplot(4,1,4)
plot(tx,y2),title('ECG Signal with high frequency noise removed'), grid on
```



```
%% Denoising of ECG Signal using Daubechies wavelet
[C, L] = wavedec (y2,4,'db4'); % Decomposition
a4 = wrcoef ('a', C, L,'db4',4); % Approximate Component
d4 = wrcoef ('d', C, L,'db4',4); % Detailed components
d3 = wrcoef ('d', C, L,'db4',3);
d2 = wrcoef ('d', C, L,'db4',2);
d1 = wrcoef ('d', C, L,'db4',1);
y3 = a4 + d4 + d3;

%% PQRST Detection
[Rpeaks,locs_r] = findpeaks(y3,t,'MinPeakHeight',0.4,'MinPeakDist',50);
nohb_r = length(locs_r);
for i = 1:nohb_r
    Speaks(i) = min(y3(locs_r(i):locs_r(i)+15));
    locs_s(i) = find(y3==Speaks(i))-1;
end

for i = 1:nohb_r
    Qpeaks(i) = min(y3(locs_r(i)-15:locs_r(i)));
    locs_q(i) = find(y3==Qpeaks(i));
end

for i = 1:nohb_r
     if locs_q(i) - 60 > 0
        Ppeaks(i) = max(y3(locs_q(i)-60:locs_q(i)));
        locs_p(i) = find(y3==Ppeaks(i));
    else
        Ppeaks(i) = max(y3(locs_q(i)-10:locs_q(i)));
        locs_p(i) = find(y3==Ppeaks(i));
    end
end

for i = 1:nohb_r
    if locs_s(i) + 130 <= 3600
        Tpeaks(i) = max(y3(locs_s(i):locs_s(i)+130));
        locs_t(i) = find(y3==Tpeaks(i));
    else
        break
    end
end

timelimit = length(ecgsig)/Fs;
hbpermin = (nohb_r*60)/timelimit;
disp(strcat('Heart Rate = ',num2str(hbpermin)))
```

EDITOR PUBLISH VIEW

New Open Save Compare Print Go To Find Bookmark Refactor Profiler Analyze Run Section Section Break Run and Advance Run to End Run Step Stop

FILE NAVIGATE CODE ANALYZE SECTION RUN

ECG_Signals.m | ECG_Powerline_Interference.m | Ecg_signal.m | ECG_Signal_Processing.m | untitled.m | ECG_Signals.m

```
for i = 1:nohb_r
    Qpeaks(i) = min(y3(locs_r(i)-15:locs_r(i)));
    locs_q(i) = find(y3==Qpeaks(i));
end

for i = 1:nohb_r
     if locs_q(i) - 60 > 0
        Ppeaks(i) = max(y3(locs_q(i)-60:locs_q(i)));
        locs_p(i) = find(y3==Ppeaks(i));
    else
        Ppeaks(i) = max(y3(locs_q(i)-10:locs_q(i)));
        locs_p(i) = find(y3==Ppeaks(i));
    end
end

for i = 1:nohb_r
    if locs_s(i) + 130 <= 3600
        Tpeaks(i) = max(y3(locs_s(i):locs_s(i)+130));
        locs_t(i) = find(y3==Tpeaks(i));
    else
        break
    end
end

timelimit = length(ecgsig)/Fs;
hbpermin = (nohb_r*60)/timelimit;
disp(strcat('Heart Rate = ',num2str(hbpermin)))

figure
plot(t,y3)
grid on
xlim([0,length(ecgsig)])
hold on

plot(locs_r,Rpeaks,'^r');
plot(locs_s,Speaks,'xm')
plot(locs_q,Qpeaks,'*g')
plot(locs_p,Ppeaks,'om')
plot(locs_t,Tpeaks,'pk')

xlabel('samples')
legend('','Rpeaks','Speaks','Qpeaks','Ppeaks','Tpeaks')
title(strcat('PQRST Detection and Heart Rate : ',num2str(hbpermin)))
```

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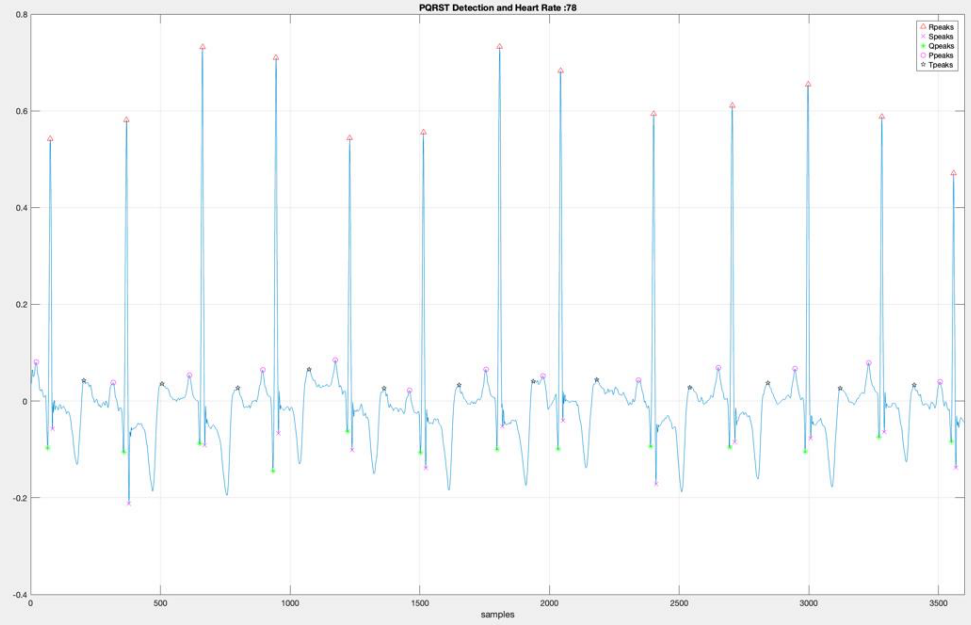

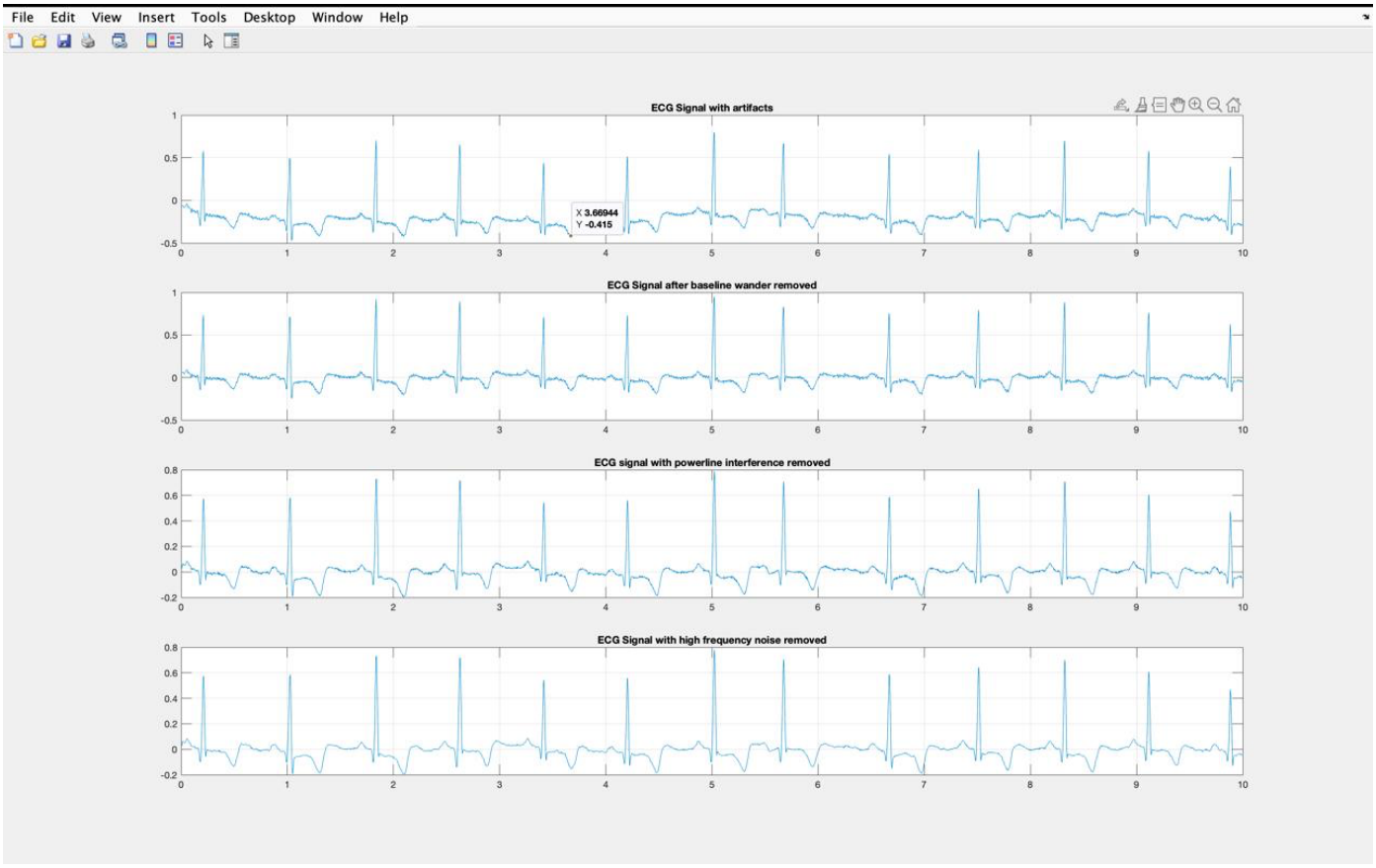
File Edit View Insert Tools Desktop Window Help
ECG Signal with artifacts
X 3.66944
Y -0.415
ECG Signal after baseline wander removed
ECG signal with powerline interference removed
ECG Signal with high frequency noise removed

4.Conclusion

This project demonstrates the effectiveness of advanced signal processing techniques in analysing ECG signals for reliable cardiac monitoring. By employing methods such as Discrete Wavelet Transform (DWT) and notch filtering, the project successfully removes baseline wander, powerline interference, and high-frequency noise, ensuring the extraction of clean and clinically significant ECG signals. The detection of PQRST waves and accurate calculation of heart rate further emphasize the system's capability to identify key cardiac features critical for diagnosing conditions like arrhythmias and myocardial infarction.

The use of standard datasets, such as the MIT-BIH Arrhythmia Database, ensures that the algorithms are validated on real-world patient data, enhancing the system's robustness and applicability in medical scenarios. The modularity of the framework allows for future scalability, such as the integration of additional features like arrhythmia classification, heart rate variability analysis, or real-time ECG monitoring in wearable devices.

In conclusion, this project highlights the vital role of noise-free signal preprocessing in enabling accurate cardiac diagnostics. It serves as a foundation for future developments in healthcare technology, contributing to the design of reliable, efficient, and accessible systems for cardiac health monitoring and early disease detection.

4.2 FUTURE WORK

Enhancing Real-Time Capabilities

One of the key directions for future work is the integration of real-time ECG signal processing. The current framework can be adapted for real-time applications by optimizing algorithms to process streaming ECG data directly from sensors. This would involve developing efficient implementations of noise removal and PQRST detection methods suitable for deployment on low-power microcontrollers or edge computing devices. Real-time monitoring systems can significantly benefit critical care scenarios, such as ICUs or ambulatory settings, where timely detection of arrhythmias or other cardiac abnormalities is essential. Integrating real-time feedback mechanisms into wearable devices or telemedicine platforms could further extend the project's impact.

Advanced Feature Extraction and Classification

Another promising avenue for future work is expanding the system to extract additional cardiac features, such as heart rate variability (HRV), QT intervals, and abnormal waveforms. These features can serve as inputs to machine learning or deep learning models for automated classification of cardiac conditions, such as atrial fibrillation, ventricular tachycardia, or ischemia. Using advanced algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), could enhance the accuracy of arrhythmia detection and prediction. Additionally, incorporating multi-lead ECG data into the framework would provide a more comprehensive view of cardiac activity, further improving diagnostic precision.

Integration with IoT and Wearable Technology

The project can be extended to Internet of Things (IoT) applications by integrating the framework into wearable health devices, such as smartwatches or portable ECG monitors. These devices can continuously collect and process ECG signals, transmit data to cloud-based platforms, and alert users or healthcare providers in case of abnormalities. IoT-enabled systems can facilitate large-scale cardiac health monitoring, enabling predictive analytics and personalized health interventions. Moreover, combining ECG data with other physiological signals,

such as blood pressure or oxygen saturation, could create a holistic health monitoring system capable of early detection of cardiovascular and systemic health issues.

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