AN OPTIMIZED FIR FILTER DESIGN FOR NOISE REDUCTION IN ECG SIGNAL

A Project Work

Submitted in partial fulfillment of the requirements for the award of the Degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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2024-2025

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CERTIFICATE

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In partial fulfilment for the award of the Degree of Bachelor of Technology in Electronics & Communication Engineering to the Anurag University, Hyderabad is a record of bonafide work carried out under my guidance and supervision. The results embodied in this project report have not been submitted to any other University or Institute for the award of any Degree or Diploma.

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ACKNOWLEDGEMENT

This project is an acknowledgement to the inspiration, drive and technical assistance contributed by many individuals. This project would have never seen light of this day without the help and guidance we have received. We would like to express our gratitude to all the people behind the screen who helped us to transform an idea into a real application.

It’s our privilege and pleasure to express our profound sense of gratitude to **Dr. G.M. Anitha Priyadarshini , Assistant Professor,** Department of ECE for her guidance throughout this dissertation work.

We express our sincere gratitude to **Prof. N. Mangala Gouri, Head of Department,** Electronics and Communication Engineering for her precious suggestions for the successful completion of this project. She is also a great source of inspiration to our work.

We would like to express our deep sense of gratitude to the Dean School of Engineering **Prof. Dr. V. Vijay Kumar** for his tremendous support, encouragement and inspiration. Lastly, we thank almighty, our parents, friends for their constant encouragement without which this assignment would not be possible. We would like to thank all the other staff members, both teaching and non- teaching, which have extended their timely help and eased my work.

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DECLARATION

We hereby declare that the result embodied in this project report entitled **"An Optimized FIR Filter Design for Noise Reduction in ECG Signal"** is carried out by us during the year 2024-2025 for the partial fulfilment of the award of **Bachelor of Technology** in **Electronics and Communication Engineering,** from ANURAG UNIVERSITY. We have not submitted this project report to any other Universities / Institute for the award of any degree.

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ABSTRACT

This project explores the design and implementation of an optimized Finite Impulse Response (FIR) filter aimed at improving the quality of electrocardiogram (ECG) signals by reducing noise. ECG signals, which are critical for monitoring heart activity, are often contaminated by various noise sources such as muscle artifacts, power line interference, and baseline drift. To address this, a band pass FIR filter is designed with tailored passband frequencies to eliminate unwanted noise while retaining the essential components of the ECG signal. The ECG data used in this project is sampled at 125 Hz over a 60-second interval, providing a robust dataset for analysis.

The filtering process, which employs a linear interpolation technique for resampling the signal, ensures that both continuous and discrete representations are effectively handled. After filtering, the signal is evaluated in both the time and frequency domains to verify the successful removal of noise. The primary focus is on achieving a balance between noise suppression and the preservation of critical signal features, resulting in a cleaner and more interpretable ECG waveform.

The results demonstrate that the FIR filter significantly enhances the signal quality, making it suitable for further analysis in medical and clinical environments. This improvement in signal clarity supports more accurate diagnostic assessments and provides a reliable foundation for automated ECG signal processing and interpretation systems. By implementing this optimized filter design, the project contributes to advancements in biomedical signal processing, ultimately enhancing the effectiveness of ECG-based diagnostics.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
ECG	Electrocardiogram
FIR	Finite Impulse Response

CHAPTER - I

INTRODUCTION

Electrocardiography (ECG) is a widely used medical technique for monitoring the heart's electrical activity, providing essential information about cardiac health. The ECG signal consists of several key waveforms that reflect various stages of the cardiac cycle, and these waveforms are vital for diagnosing heart-related conditions. However, the accuracy and reliability of ECG signal analysis can be compromised by the presence of noise. To address this issue, effective noise reduction techniques are crucial for improving signal quality, enabling better diagnosis, and enhancing the performance of automated ECG systems.

1.1 Noise Reduction In ECG Signal

ECG signals are prone to various types of noise that can distort or obscure important cardiac features. Common sources of noise include power line interference, muscle artifacts (electromyography noise), baseline drift caused by patient movement, and environmental factors. These unwanted components can severely impact the ability to detect and analyze important ECG features, such as the P-wave, QRS-complex, and T-wave. In clinical environments, reducing noise is essential to enhance the clarity and precision of the ECG signal. In this project, an optimized band pass Finite Impulse Response (FIR) filter is designed to remove low-frequency baseline wander and high-frequency noise while preserving the signal's integrity.

1.2 Signal Processing in Vibration Analysis

Signal processing techniques are widely applied to ECG signals to improve the detection and analysis of heart activity. Finite Impulse Response (FIR) filters are especially useful in ECG signal processing due to their stability and linear phase response, which ensures that no phase distortion occurs during filtering. FIR filters can be designed to selectively filter out unwanted noise while preserving the ECG's essential components. In this project, a bandpass FIR filter is implemented with a passband frequency range that focuses on removing noise while maintaining the relevant features of the ECG signal. The effectiveness of this approach is demonstrated through time-domain and frequency-domain analysis.

1.3 ECG Signal Processing Using Z – Transform

The Z-transform is a powerful mathematical tool used to analyze discrete signals in the frequency domain, and it plays an essential role in the design and analysis of digital filters. In this project, the ECG signal, initially represented in the time domain, is transformed into the frequency domain using the Z-transform. This allows for more efficient processing and filtering of the ECG signal, enabling the design of the FIR filter for optimal noise reduction. The use of the Z-transform facilitates the conversion of discrete ECG data into a form suitable for digital filtering, ultimately improving the performance of the filtering process. By applying the Z-transform, the project ensures that the ECG signal can be analyzed in both the time and frequency domains for comprehensive noise removal and feature extraction.

1.4 Problem Statement

Designing An Optimized Band pass FIR Filter for Noise Reduction in ECG signal and detecting the P – wave, QRS – Complex and T – wave in the ECG signal which predicts the patient's health condition.

1.5 Objectives

- To design an optimized FIR filter to effectively reduce noise from ECG signals.
- To preserve the essential features of the ECG signal such as P – wave, QRS – complex and T – wave ensuring accurate detection and analysis.
- To evaluate the performance of the filter through time domain and frequency domain analysis and verifying it's effectiveness in enhancing signal clarity for reliable use.

1.6 Organization of Report

- **Chapter I** presents an overview of Noise reduction in ECG signal and effective diagnose techniques.
- **Chapter II** conducts a literature review, examining previous research related to ECG Signal Processing and methodologies.
- **Chapter III** gives an idea on pervious works done on ECG signal and enhancement techniques used and use of Z – Transform in signal processing.
- **Chapter IV** details the proposed methodology for noise reduction in ECG signal and diagnose of patient using suitable algorithm.
- **Chapter V** introduces the software developed for Noise reduction in ECG Signal focusing on MATLAB commands and codes essential for analyzing the patient's condition.
- **Chapter VI** presents the results of the filtered ECG signal, including detection of essential components and analyzing condition of patient.
- **Chapter VII** discusses the applications and advantages of the proposed methodology in various engineering fields, highlighting its effectiveness in ensuring effective analysis of patient using ECG signal.
- **Chapter VIII** concludes the project by summarizing the successful implementation of Z - transformation techniques in Noise reduction in ECG signal and developing a Band pass FIR filter and scope in future research directions.
- **Chapter IX** references the research articles and studies that contributed to the development of this project.

CHAPTER - II

LITERATURE REVIEW

The challenge of noise reduction in electrocardiogram (ECG) signal processing has been widely studied, with numerous techniques proposed to enhance signal quality for accurate diagnosis. ECG signals are prone to various noise sources, including power line interference, baseline wander, and muscle artifacts, which can obscure the signal's diagnostic features.

1. The journal titled "**Design and Implementation of Digital Low Pass FIR and IIR Filters Using VHDL for ECG Denoising**" addresses the removal of noise from ECG signals through digital filters. Accurate ECG interpretation is vital for diagnosing cardiac conditions, but the quality of ECG signals is often compromised by noise, which can affect the reliability of these diagnoses. Common sources of noise in ECG signals include baseline wander—caused by breathing or patient movement—and power line interference, which introduces 50/60 Hz noise from the electrical grid. These types of noise can distort the ECG waveform, masking critical features like the P, QRS, and T waves, which are essential for detecting heart rhythm irregularities and other cardiac anomalies. To mitigate the impact of noise on ECG signals, the study explores the design and implementation of digital filters using VHDL (VHSIC Hardware Description Language). The research focuses on two types of digital filters: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR). Linear phase ensures that all frequency components of the signal are delayed equally, which helps preserve the original waveform shape—an important aspect in medical signal processing where even small distortions could lead to inaccurate diagnoses. FIR filters are stable by design because their impulse response is finite, meaning the filter output eventually settles to zero after a limited number of samples. This characteristic eliminates the risk of instability, as FIR filters do not involve feedback loops, which are often the source of instability in filter designs. In contrast, IIR filters are computationally more efficient than FIR filters, as they can achieve similar filtering performance with fewer coefficients. However, IIR filters use feedback loops, making them potentially unstable if not designed carefully. Additionally, IIR filters do not always provide a linear phase response, which can distort the ECG waveform. Given the need to preserve signal integrity in ECG applications, this non-linear phase characteristic makes IIR filters less desirable for ECG denoising. The study calculates the coefficients of both FIR and IIR filters using MATLAB, a widely-used tool in signal processing. After calculating these coefficients, the filter designs are implemented using VHDL and synthesized using the Xilinx ISE Vivado tool, which allows the researchers to evaluate the filter designs based on criteria such as area, speed, and power consumption. The journal's findings reveal that FIR filters, especially those utilizing Vedic multipliers, outperform IIR filters in terms of filtering accuracy, computational speed, and power efficiency. Vedic multipliers, known for their efficient arithmetic operations, reduce the computational complexity of FIR filters, making them faster and more energy-efficient. This makes FIR filters better suited for real-time ECG signal processing, where timely and accurate analysis is critical for monitoring a patient’s heart health. Moreover, FIR filters demonstrate

superior filtering accuracy due to their precise linear phase response, which prevents distortion of the ECG signal during the filtering process. This is crucial in ECG applications, where signal distortion could lead to incorrect interpretations or missed cardiac abnormalities. While IIR filters offer advantages in terms of reduced memory usage and faster computations, their drawbacks—instability and non-linear phase response—make them less suitable for ECG denoising, especially in real-time medical applications where preserving signal integrity is of utmost importance. In conclusion, the research highlights the superiority of FIR filters, particularly those with Vedic multipliers, over traditional IIR filters for ECG denoising. FIR filters not only offer better filtering accuracy but also provide significant advantages in power efficiency and computational speed. By leveraging tools like MATLAB and VHDL, this study demonstrates how optimized filter designs can enhance the accuracy of ECG-based diagnoses and improve outcomes in medical applications.

2. The journal titled "**Efficient Design of FIR Filter Based Low-Pass Differentiators for Biomedical Signal Processing**" presents an innovative approach to designing low-pass differentiators using Finite Impulse Response (FIR) filters for biomedical applications. Biomedical signal processing, especially in applications like ECG and EEG, requires efficient filters capable of accurately detecting key signal features while minimizing resource usage such as memory and computational power. The authors propose a method that uses a Fourier series to approximate the differentiator's transfer function, which allows for a significant reduction in the filter order. This method addresses one of the main challenges in FIR filter design: balancing performance with efficiency. By reducing the number of filter coefficients, the proposed design minimizes memory usage and decreases the overall filter delay, which is critical for real-time signal processing. At the same time, the design maintains the ability to detect important signal characteristics, such as rapid transient events, which are crucial for diagnosing conditions in biomedical signals. The primary goal of the proposed FIR filters is to optimize the trade-off between effective signal filtering and efficient event detection. The approach aims to ensure that filtering does not distort the original signal while maintaining a high level of accuracy in detecting key events, such as the QRS complex in ECG signals or spike activity in neural recordings. The low-pass differentiators designed using this method effectively reduce noise and isolate critical signal features without introducing significant delays. One of the key findings of the research is the efficiency of the proposed design compared to traditional FIR filter-based differentiators. The study shows that the number of filter coefficients can be reduced by up to 36% without compromising performance. This reduction is significant in real-time biomedical applications, where computational resources and processing speed are often limited, such as in portable or embedded systems. By lowering the number of coefficients, the design not only reduces the computational burden but also enhances the speed of event detection, making it ideal for fast, real-time biomedical signal processing. In conclusion, the journal demonstrates that the proposed FIR filter-based low-pass differentiator design offers a substantial improvement in efficiency for biomedical signal processing. The ability to reduce filter order while maintaining accuracy and real-time performance makes this approach a promising solution for applications requiring rapid detection of transient events in noisy biomedical signals.

3. The journal titled "**Selection of Parameters of Bandpass Filtering of the ECG Signal for Heart Rhythm Monitoring Systems**" explores the critical task of optimizing bandpass filter parameters for accurate ECG signal processing, with a focus on heart rhythm monitoring. The ECG (electrocardiogram) signal is commonly used to assess heart health by monitoring the electrical activity of the heart, particularly by analyzing the R-R intervals—the time between two consecutive R-wave peaks. However, ECG signals are often contaminated by noise from various sources, which can significantly distort the signal and lead to errors in detecting heart rhythm patterns. This study investigates how different noise sources and disturbances affect the accuracy of R-R interval measurements and proposes a systematic approach to selecting the optimal bandpass filter parameters. Specifically, it focuses on minimizing errors in R-R interval measurement, which are essential for diagnosing conditions like arrhythmias. By selecting the right passband and filter type, the accuracy of heart rhythm monitoring systems can be significantly improved, particularly in noisy environments where clear signal detection is difficult. The research evaluates the performance of different types of filters, including Butterworth, Bessel, and Chebyshev type II, and assesses both digital and analog implementations of these filters. Each filter type offers distinct advantages depending on the application. For instance, Butterworth filters are known for their flat frequency response in the passband, which ensures minimal signal distortion. Bessel filters, on the other hand, are valued for their linear phase response, which preserves the waveform shape, while Chebyshev type II filters provide sharp roll-off characteristics, which can be beneficial in isolating the desired signal from noise. One of the key findings of the study is the identification of the optimal passband for filtering ECG signals in heart rhythm monitoring systems. The research suggests that an 8-20 Hz passband is particularly effective when using higher-order filters. This range captures the critical frequency components of the ECG signal necessary for accurate R-R interval measurements while filtering out low-frequency baseline wander and high-frequency noise. The study highlights that Butterworth filters, particularly those with phase correction, offer the best performance in terms of accurate R-R interval detection, even in challenging and noisy conditions. The addition of phase correction to the Butterworth filter is particularly important because it minimizes phase distortion, which can otherwise lead to errors in the timing of R-wave detection. By ensuring that the filtered signal maintains a consistent phase relationship with the original signal, the Butterworth filter provides more accurate timing information, which is crucial for precise R-R interval measurements. In conclusion, the journal demonstrates that optimizing the bandpass filter parameters is essential for improving the accuracy of heart rhythm monitoring systems. The study's results suggest that using an 8-20 Hz passband, especially with higher-order Butterworth filters that incorporate phase correction, significantly reduces errors in R-R interval measurements. This makes the Butterworth filter with phase correction the most reliable choice for heart rhythm monitoring in noisy environments, providing accurate and consistent results for ECG signal processing.
4. The journal titled "**The Use of FIR Filter for Filtering of ECG Signal and Comparison of Some Parameters**" delves into the effectiveness of Finite Impulse Response (FIR) filters in denoising ECG signals. ECG signal processing is crucial for

diagnosing cardiac conditions, and noise can interfere with the accuracy of these signals. Common noise sources include power line interference, muscle activity, and baseline wander, which can obscure the critical features of an ECG, such as the P, QRS, and T waves. This study focuses on how FIR filters can address these challenges and evaluates their performance using key metrics like signal-to-noise ratio (SNR) and power spectral density (PSD). The research primarily investigates the impact of FIR filters designed with various windowing techniques on the filtering of ECG signals. Window functions are mathematical tools used to taper the edges of a filter's frequency response, improving its performance by reducing ripples in the passband and stopband regions. The study compares several commonly used window functions, such as the Hamming, Hanning, and Blackman windows, and assesses their performance in terms of noise reduction and signal preservation. The evaluation metrics, particularly SNR and PSD, are essential in understanding the effectiveness of FIR filters. SNR measures the ratio of the signal power to the noise power, indicating how well the filter can reduce noise relative to the ECG signal. A higher SNR means that more noise has been removed without affecting the signal's key features. PSD, on the other hand, is used to observe how the power of the signal is distributed across different frequencies. This metric helps in determining the filter's ability to suppress noise in specific frequency bands while preserving the essential components of the ECG. The study's findings demonstrate that FIR filters, particularly when designed with optimal window functions, are highly effective at reducing noise without distorting the ECG's critical features. In comparison to traditional filters like Infinite Impulse Response (IIR) filters, FIR filters offer several advantages. One of the most notable benefits is their inherent stability due to their finite impulse response, meaning that they do not rely on feedback loops that can lead to instability. Additionally, FIR filters are capable of maintaining a linear phase response, which ensures that all components of the ECG signal are delayed by the same amount, preserving the shape of the waveform—an essential factor in accurate medical diagnoses. Another key insight from the research is the importance of selecting the right window function in FIR filter design. The study shows that certain windows, such as the Hamming and Blackman windows, provide better noise suppression while maintaining the integrity of the ECG signal. The optimal window function minimizes the trade-off between noise reduction and signal distortion, making FIR filters especially suited for real-time ECG monitoring applications, where precision and accuracy are paramount. In conclusion, the journal highlights the superiority of FIR filters for ECG signal denoising, emphasizing that the careful selection of window functions plays a crucial role in enhancing filtering performance. FIR filters not only outperform other filtering methods in preserving the integrity of ECG signals but also provide effective noise reduction, making them ideal for real-time biomedical signal processing. The research confirms that FIR filters, particularly when optimally designed, are a robust choice for improving the accuracy of ECG monitoring in noisy environments.

CHAPTER - III

METHODOLOGY

3.1 Methodology for Noise Removal in ECG signal

3.1.1 Loading and Preprocessing the ECG signal

The ECG signal is loaded from a dataset in MATLAB, and it undergoes amplitude scaling to bring the signal into a range suitable for processing. A time vector is constructed to represent the continuous time axis over a 60-second interval, ensuring that both the time vector and the ECG signal are of equal length. This step ensures that the signal is ready for subsequent filtering and analysis, and it visualizes the raw ECG signal before any processing occurs.

3.1.2 Discrete Sampling of the ECG signal

The ECG signal is resampled into a discrete form using a sampling frequency of 125 Hz, which is sufficient to capture the critical features of the ECG waveform. By applying linear interpolation, the signal is converted from its continuous form to discrete points, which are essential for digital signal processing. This step adheres to the Nyquist sampling theorem to ensure that the signal's important characteristics are retained without aliasing.

3.1.3 Designing of Bandpass FIR Filter

An optimized bandpass FIR filter is designed to reduce noise while preserving the essential components of the ECG signal. The passband is selected between 0.67 Hz and 50 Hz, which captures the frequency range where the P-wave, QRS-complex, and T-wave are located. By designing a filter with an order of 150, both high-frequency noise (e.g., muscle artifacts) and low-frequency noise (e.g., baseline drift) are removed, enhancing the signal quality for accurate analysis.

3.1.4 Filtering The ECG Signal

After designing the FIR filter, the discrete ECG signal is passed through the filter to remove noise. This step is crucial for improving the clarity of the ECG signal by filtering out unwanted frequencies while retaining the important components of the waveform. The filtered signal is then plotted and compared with the original signal to visually confirm the improvement in signal quality.

3.1.5 Detection of P-wave, QRS-complex, T-wave

The filtered signal is processed to detect critical features such as the P-wave, QRS-complex, and T-wave using peak detection algorithms. Specific amplitude thresholds and minimum peak distances are set to accurately detect each wave. This step ensures that key cardiac features are identified for further analysis, such as heart rate calculation and frequency analysis, which are essential for diagnosing heart health.

3.1.6 Heart Rate and Frequency Calculations

R-R intervals are calculated from the detected QRS complexes to determine the heart rate in beats per minute (BPM). Additionally, the frequencies of the P-wave, QRS-complex, and T-wave are calculated based on the time intervals between successive waveforms. These metrics are vital for assessing the health of the heart and detecting irregularities in the heart rhythm.

3.1.7 Health Assessment Based on Frequency Analysis

The frequencies of the detected waves (P-wave, QRS-complex, and T-wave) are compared with standard healthy ranges. If the frequencies fall within the typical healthy range, the patient is considered healthy; otherwise, abnormalities are flagged. This automated health assessment helps in early diagnosis and monitoring of potential heart conditions based on the ECG signal.

3.2 Block Diagram

The block diagram outlines the flow of the Noise removal in ECG signals visually, from collecting data from datasets to the final output of health diagnose and displaying the results. The key stages of the block diagram are as follow

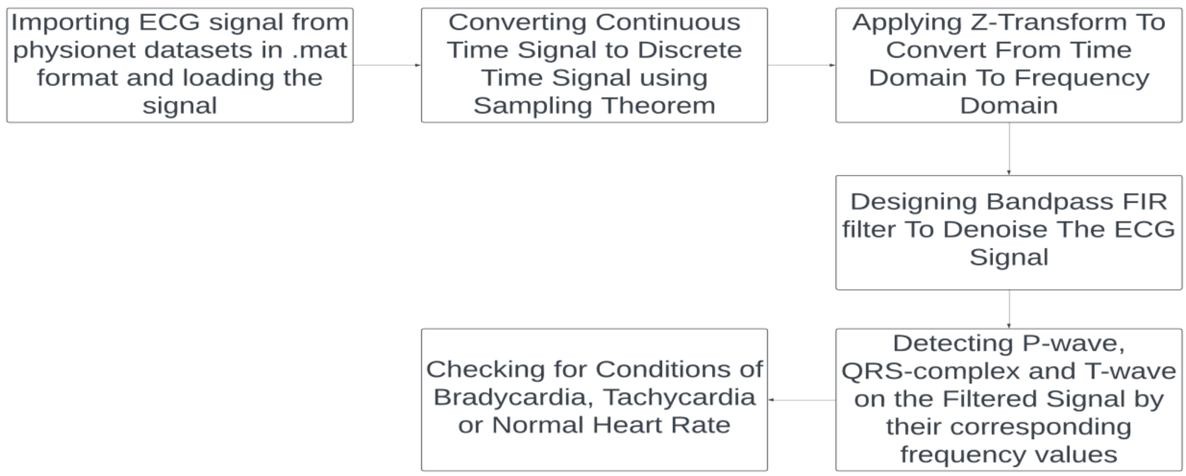

Figure 1 : Block Diagram of the Project

1. **Importing ECG Signal :** The process begins by importing an ECG signal from the Physionet datasets. The signal is typically stored in a .mat format, which is a common file format for MATLAB data.
2. **Converting Continuous Time Signal to Discrete Time Signal :** The imported ECG signal is likely a continuous-time signal, meaning it is measured over a continuous range of time. To process the signal digitally, it needs to be converted into a discrete-time signal. This is done using the Sampling Theorem, which states that if a continuous-time signal is sampled at a rate greater than or equal to twice its highest frequency component, the original signal can be perfectly reconstructed from the samples.
3. **Applying Z-Transform :** The Z-transform is a mathematical tool used to convert a discrete-time signal from the time domain to the frequency domain. [1] This

transformation is useful for analyzing the frequency content of the signal, which is important for identifying different components of the ECG signal, such as the P-wave, QRS complex, and T-wave.

4. **Designing bandpass FIR Filter :** A bandpass filter is designed to pass a specific range of frequencies while attenuating others. In the case of ECG signals, a bandpass filter can be used to remove noise and isolate the frequency components of interest, which are typically within a certain range. An FIR (Finite Impulse Response) filter is a type of digital filter that is commonly used for this purpose due to its stability and ease of implementation.

5. **Denoising the ECG Signal :** The designed bandpass FIR filter is applied to the ECG signal to remove noise and improve the signal quality. This step is crucial for accurate detection of heart conditions.

6. **Detecting P-wave, QRS-complex, and T-wave :** The filtered ECG signal is further analyzed to identify the different components of the waveform, including the P-wave, QRS complex, and T-wave. These components correspond to different phases of the cardiac cycle.

7. **Identifying Heart Conditions Based on Frequency Values :** The frequency values of the detected P-wave, QRS complex, and T-wave can be used to identify various heart conditions. For example, abnormal heart rhythms or structural abnormalities can often be detected by analyzing the frequency characteristics of these components.

8. **Checking for Conditions of Bradycardia, Tachycardia, or Normal Heart Rate :** The filtered ECG signal is analyzed to determine the heart rate. If the heart rate is too slow (bradycardia), too fast (tachycardia), or within a normal range, the corresponding condition is identified.

3.3 Flowchart

Start: The process begins.

.mat data sets for ECG signal: The ECG data is loaded from a .mat file (a file format used in MATLAB).

Sampling Theorem ($f_s \geq 2f_m$): The system checks if the ECG signal has been sampled at a rate that is at least twice the maximum frequency in the signal to avoid distortion (aliasing).

Z-Transform: The sampled ECG signal is converted into the Z-domain for further digital processing and filtering.

Band-pass FIR Filter Design: A band-pass FIR filter is applied to allow only the frequencies relevant to heart rate (typically 0.5 Hz to 3 Hz) to pass through, filtering out unwanted noise.

Condition Check: The filtered ECG signal is analyzed:

Yes: If the heart rate is between 60 and 100 BPM, it is classified as normal.
No: If the heart rate is outside this range, it is classified as abnormal.

Stop: The process ends, and the heart rate condition (normal or abnormal) is determined.

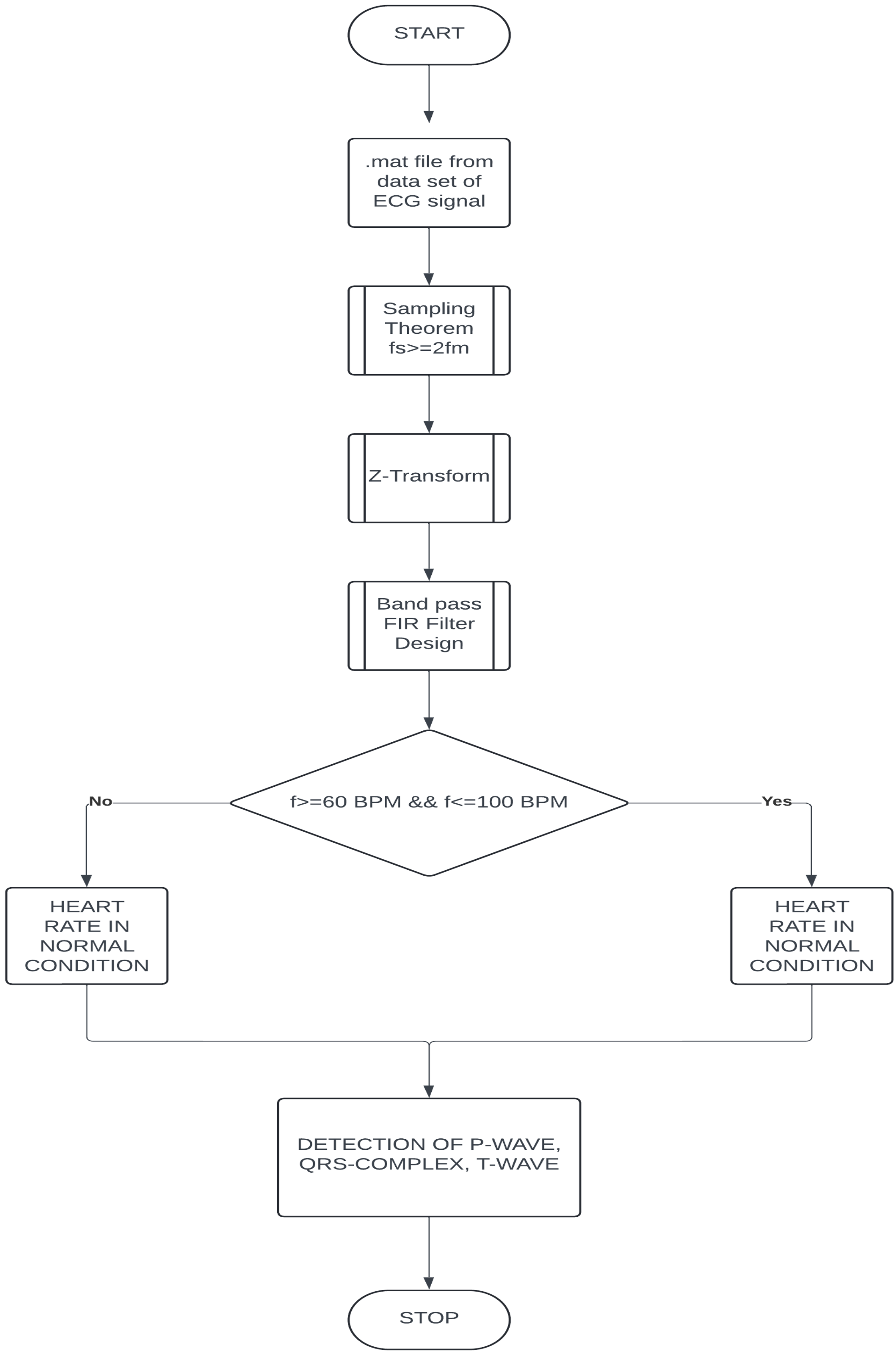

Figure 2 : Flowchart of the Project

3.4 Mathematical Framework

1. Mathematical expression for an FIR filter : $y[n] = \sum_{k=0}^{N-1} h[k]x[n-k]$

   y[n] is the output signal (Filtered ECG signal).
   x[n] is the input signal (Noisy ECG signal).
   h[k] is the FIR filter coefficients.
   N is the filter order.

2. Z – Transform of input signal x[n] is : $\mathrm{X}(z) = \sum_{-\infty}^{\infty} x[n]z^{-n}$

3. Z – Transform of output signal y[n] is : Y(z) = H(z)X(z)

   where H(z) is the transfer function f the FIR filter, given by :

$$H(z) = \sum_{k=0}^{N-1} h[k]z^{-k}$$

4. Normality Conditions of an ECG Signal : 60 BPM to 100 BPM.

5. Sampling Theorem : Fs >= 2*Fm.

6. Equation for P-Wave : $P(t) = \frac{A}{1+e^{-k(t-t0)}}$ where A is the amplitude, k is the steepness factor, t0 is time of peak amplitude. Simplified model equation is $P(t) = 0.15 * \sin(2 * pi * 10 * t) + 0.05 * \sin(2 * pi * 20 * t)$ where t is time in seconds.

7. QRS Complex Equation: : QRS(t) = A * sin(2 * π * 50 * t) + B * sin(2 * π * 100 * t)
   Where : A = amplitude, B = scaling factor

8. T-wave equation : T(t) = A * exp(-((t-t0)/σ)^2) + B * sin(2 * π * 10 * t)

   where: A = amplitude

   t0 = time of peak amplitude

   σ = standard

CHAPTER - IV
SOFTWARE REQUIREMENTS

4.1 Introduction

In this project, use the software MATLAB to execute the required results. MATLAB (matrix laboratory) is a fourth-generation high-level programming language and interactive for numerical, visual and programming.

Matrix laboratory is developed by MathWorks. This MATLAB allows

- Matrix manipulations
- Plotting of functions and data
- Implementing of algorithms
- Creation of user interface

It has built-in commands and math functions which help in mathematical calculations, numerical methods and generating plots. MATLAB has many advantages compared to conventional computer languages (e.g., C, FORTRAN) for solving technical problems. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning.

4.2 Basics of Software

MATLAB (Matrix Laboratory) is a powerful software platform designed for numerical computing, data analysis, algorithm development, and visualization. It is widely used in engineering, scientific research, and academic environments due to its versatility and robust features. The basic building block of MATLAB is MATRIX. The fundamental data type is the array. Vectors, scalars, real matrices and complex matrices are handled as specific classes of this basic data type. The built in functions are optimized for vector operations. No dimension statements are required for vectors or arrays.

4.2.1 MATLAB Interface Overview

- **Command Window**:
  This is the primary area where users can interact with MATLAB. It allows users to type commands, execute functions, and see immediate results. MATLAB operates in a command-driven environment, so any command or script entered here is processed immediately.
- **Editor**:
  The Editor is where users can write, edit, and save MATLAB code or scripts. It supports the development of functions, scripts, and programs, with features like syntax highlighting, code folding, and debugging tools to make coding easier.
- **Workspace**:
  The Workspace provides information on the variables that are currently loaded into memory. It displays variable names, sizes, types, and values, making it easier to keep track of data being used or manipulated during a session.
- **Current Folder**:
  This panel shows the files and folders in the current directory. It is useful for

organizing and managing the scripts, data files, and other resources needed for your MATLAB session.

- **Command History**:
  The Command History keeps a record of previously executed commands. Users can scroll through this history and re-run commands without having to re-type them, improving workflow efficiency.
- **Figure Window**:
  MATLAB's visualization capabilities are robust, and the Figure Window is where graphical outputs like plots, charts, and figures are displayed. Users can interact with the figures, zoom in and out, and customize the appearance of the plots.
- **Toolstrip**:
  The Toolstrip at the top of the MATLAB environment includes several tabs that provide access to different tools and features:
  - **Home Tab**: Contains frequently used functions such as file management, import/export tools, preferences, and access to documentation.
  - **Plots Tab**: This provides quick access to various plotting functions and visualization tools. MATLAB automatically suggests types of plots based on the data selected.
  - **Apps Tab**: MATLAB offers a range of built-in apps for tasks like signal processing, data fitting, machine learning, and more. The Apps tab makes it easy to access these tools without having to write extensive code.
  - **Editor Tab**: Includes tools for writing scripts, running sections of code, and setting breakpoints for debugging.
  - **View Tab**: Customizes the layout of the MATLAB desktop, allowing users to show or hide different windows like the Command Window or Workspace.

4.2.2 Additional Features

- **Simulink :** Simulink is a graphical programming environment integrated with MATLAB for modeling, simulating, and analyzing dynamic systems. It is widely used in control system design, signal processing, and embedded systems.
- **Debugger :** MATLAB includes powerful debugging tools that help identify and resolve errors in code. The debugger allows users to set breakpoints, step through code line-by-line, and inspect variable values during execution.
- **Toolboxes :** MATLAB offers specialized toolboxes for different domains, such as signal processing, image processing, machine learning, optimization, and more. These toolboxes extend MATLAB's functionality and provide domain-specific functions and apps.

4.3 Commands Used

clc: Clears the command window, removing all previous text output and providing a clean interface for new commands and outputs. This command enhances readability and organization, especially in lengthy scripts or during iterative development.

clear all: Removes all variables from the workspace, freeing up system memory and ensuring that previous data does not interfere with the current execution. This command is essential for starting fresh when running scripts, particularly in complex projects where variable names may overlap.

close all: Closes all open figure windows created during the session, ensuring that no previous plots interfere with new visualizations. This command is beneficial for maintaining a clean workspace, especially when generating multiple figures during analysis or when running scripts repeatedly.

load() : This command is used to load data from files into MATLAB's workspace. In this case, the ECG signal is loaded from a .mat file for further processing and analysis.

plot() : This command generates 2D plots, which are crucial for visualizing both the original and processed ECG signals. It helps compare the raw and filtered signals to ensure the effectiveness of the filter.

linspace() : This command creates a vector with evenly spaced values between two endpoints. It is used to create the time vector for the continuous ECG signal over the 60-second duration.

interp1() : A 1D interpolation function used to resample the continuous ECG signal at discrete time points. This is important for converting the signal from a continuous to a discrete format while preserving its key features.

fir1() : This command designs an FIR filter based on the specified order and passband frequencies. It is fundamental to the filtering process, ensuring that unwanted noise is removed from the ECG signal.

filter() : Once the FIR filter is designed, this command applies the filter to the signal, removing noise and preserving important cardiac features like the P-wave, QRS-complex, and T-wave.

findpeaks() : This command detects peaks within a signal, which in this context is used to find the P-wave, QRS-complex, and T-wave in the filtered ECG signal. It helps identify key points for further analysis, such as heart rate calculation.

legend() : Adds a legend to the plot, indicating what each plot represents. It enhances the clarity of the visual comparison between different signals, such as the original and filtered ECG signals.

Xlabel() and ylabel() : These commands label the x-axis and y-axis of a plot, respectively. For this project, they define the time (seconds) and amplitude (signal strength) axes, improving the readability of the ECG signal plots.

title() : Titles each plot, providing context such as "Filtered ECG Signal" or "Original ECG vs Filtered ECG." This is crucial for understanding the content of the visualized data at a glance.

hold on : Allows multiple plots to be overlaid in the same figure window. In this project, it's used to overlay the discrete and continuous ECG signals for direct comparison.

stem() : This command is used to create a discrete plot, where data points are shown as vertical lines, ideal for displaying sampled discrete signals alongside continuous signals.

grid on : Adds a grid to the plot, making it easier to view and compare data points. It is especially useful for examining the time intervals and amplitudes in the ECG signal.

disp() : Displays messages in the MATLAB console. In this project, it reports diagnostic information such as heart rate or whether the patient's health is normal based on ECG analysis.

diff() : Calculates the difference between consecutive elements in a vector. This is applied to compute the R-R intervals (time between successive QRS complexes), which are key to determining heart rate.

assert() : Ensures that a condition is met before proceeding. Here, it checks that the time vector and ECG signal are of equal length, ensuring they can be processed correctly.

4.4 Implementation

The implementation of the ECG signal processing code begins with loading the ECG data from a .mat file and preprocessing it for analysis. The ECG signal is scaled to adjust its amplitude and ensure it falls within a manageable range. A continuous time vector is created to represent the time duration of the ECG signal, allowing for proper alignment during analysis. The continuous signal is then converted to a discrete format using linear interpolation, facilitating further processing steps that require discrete data points. This conversion is crucial to prepare the signal for filtering, as many digital signal processing techniques operate on discrete datasets.

Once the ECG signal is prepared, the next step involves designing an optimized Finite Impulse Response (FIR) bandpass filter to remove unwanted noise while preserving the key features of the signal. The filter is designed with specified passband frequencies, typically ranging from 0.67 Hz to 50 Hz, ensuring that both low-frequency baseline wander and high-frequency noise are adequately addressed. The filter coefficients are calculated, and the designed filter is applied to the discrete ECG signal. This filtering process significantly enhances the quality of the ECG signal, making it suitable for subsequent analysis.

After filtering, the code employs peak detection algorithms to identify critical components of the ECG signal, including the P-wave, QRS-complex, and T-wave. This step is essential for further analysis, such as calculating heart rate and evaluating the overall health of the patient. The R-R intervals, derived from the detected QRS complexes, are used to calculate the heart rate in beats per minute. Additionally, the frequencies of the P-wave, QRS-complex, and T-wave are compared to standard healthy ranges to assess the patient's cardiac health. The implementation concludes with diagnostic messages that indicate whether the patient is healthy based on the analyzed frequency characteristics of the ECG signal. Overall, the code integrates various signal processing techniques to achieve effective noise reduction and accurate cardiac feature detection, providing a robust framework for ECG analysis.

CHAPTER - V

ANALYSIS OF RESULTS

The outputs from the MATLAB code provide both visual and numerical insights into the ECG signal processing workflow, showcasing the effectiveness of the FIR filter in noise reduction and feature detection.

The first figure displays the raw ECG signal over the entire 60-second duration. This signal is plotted against a continuous time vector and represents the unfiltered ECG data directly loaded from the dataset. In this plot, we can observe the presence of typical noise components such as baseline wander and high-frequency interference. These noise elements obscure key features of the ECG, like the P-wave, QRS-complex, and T-wave, making it difficult to analyze the signal for diagnostic purposes.

The second figure compares the original continuous ECG signal with its resampled discrete version. The discrete signal is generated by applying the sampling theorem, which converts the continuous-time signal into a series of samples at regular intervals, based on a sampling frequency of 125 Hz. This comparison is useful to show how the signal looks when digitized and confirms that the sampling frequency is sufficient to capture the essential details of the ECG without introducing aliasing artifacts. The discrete plot (stem plot) overlays the original continuous signal, demonstrating how closely the resampled signal follows the original, even in the presence of noise.

In the next output, the filtered ECG signal is shown, after the optimized FIR filter is applied. This plot highlights the efficiency of the FIR filter in reducing both high-frequency noise and baseline drift, while preserving the key cardiac features. The filtered signal is smoother and clearer, allowing for more accurate identification of the P-wave, QRS-complex, and T-wave. In the subsequent figure, the original noisy signal and the filtered version are overlaid for direct comparison. This visual comparison highlights the filter's success in removing unwanted noise, with the filtered signal retaining the crucial waveforms while eliminating much of the interference present in the original signal.

Finally, another figure displays the detected P-wave, QRS-complex, and T-wave on the filtered ECG signal. These features are marked on the signal, allowing for clear visualization of key cardiac events. The peaks corresponding to each waveform are identified using peak detection algorithms, making the ECG signal ready for further analysis, such as heart rate variability studies or rhythm analysis.

In the command window, the computed heart rate and frequencies of the P-wave, QRS-complex, and T-wave are displayed. Based on these values, the system assesses the patient's health by comparing the frequencies to standard healthy ranges. If the computed values fall within normal limits, the output indicates that the patient is healthy; otherwise, a potential abnormality is flagged. This command window output provides a concise summary of the diagnostic results derived from the processed ECG signal, contributing to a quick health assessment.

DATASET_1 :

Output wave forms in figure window :

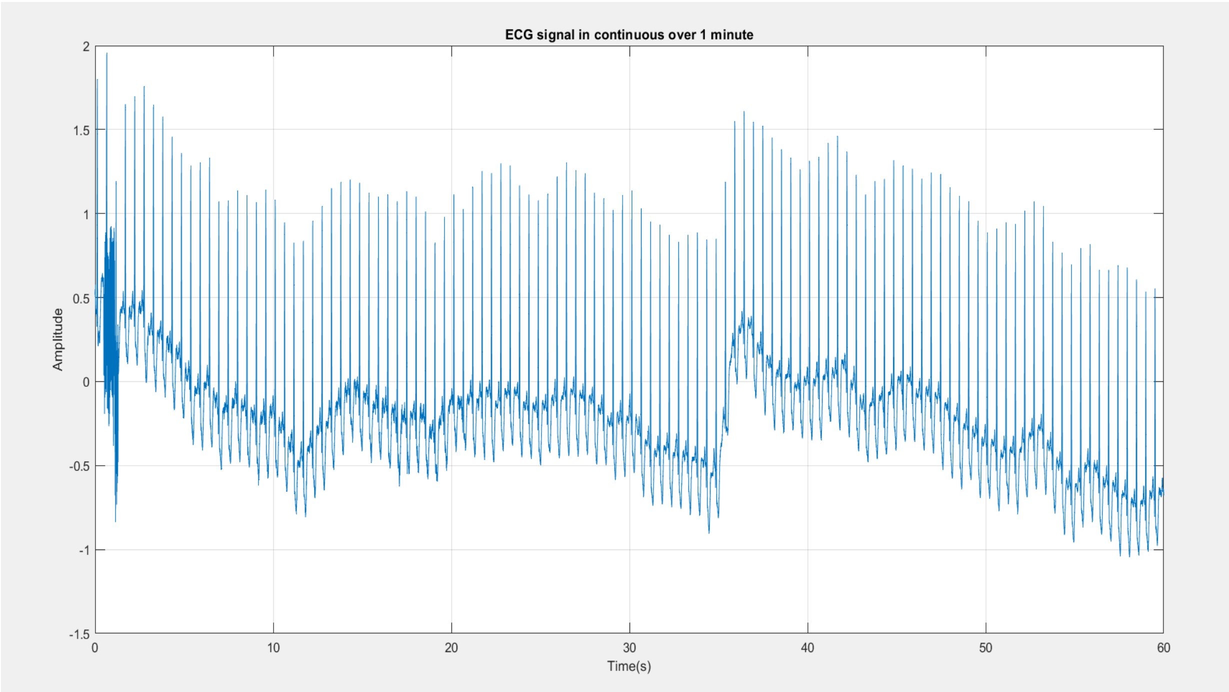

Figure : 3.i.a

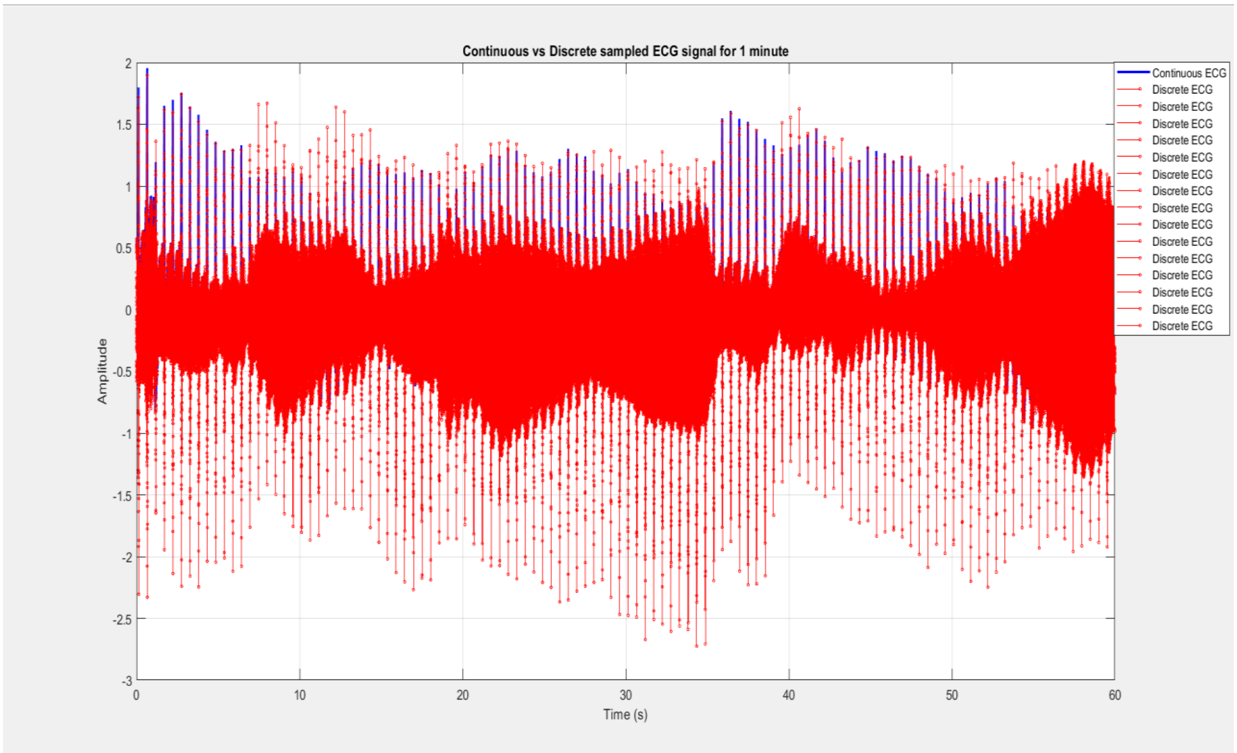

Figure : 3.i.b

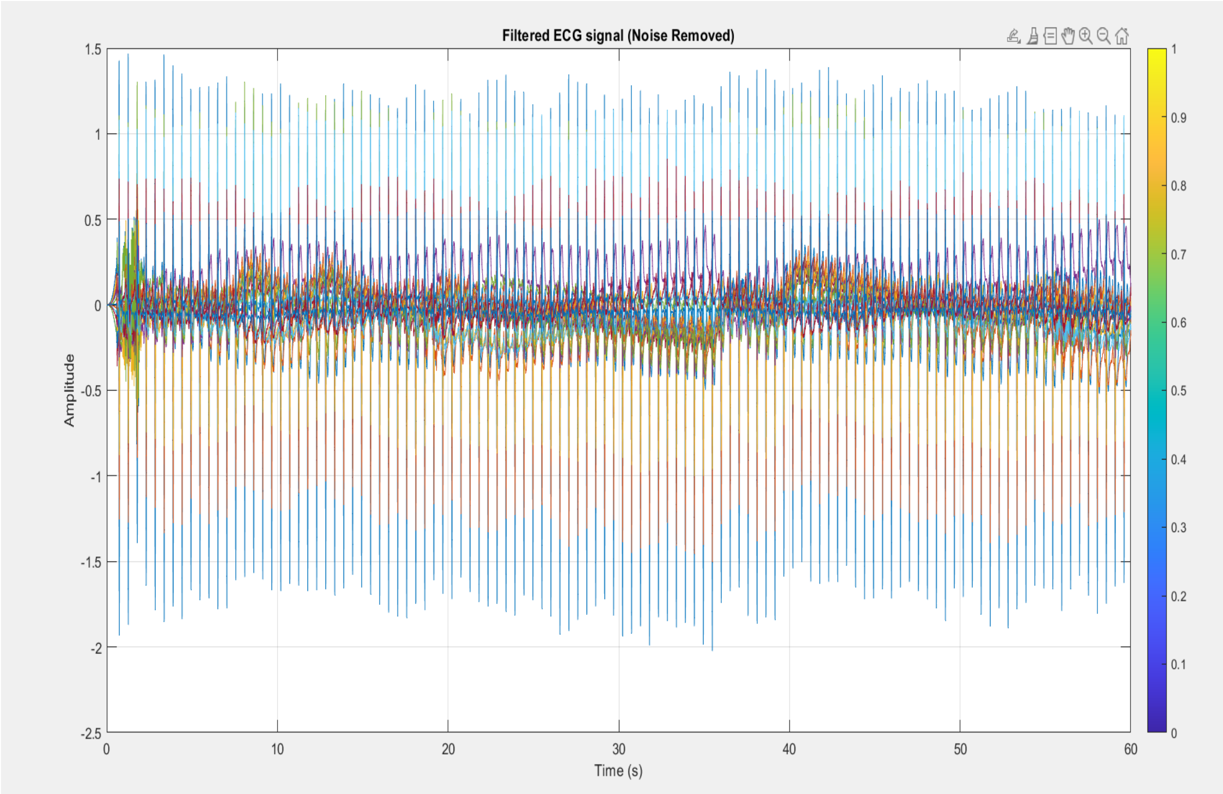

Figure : 3.i.c

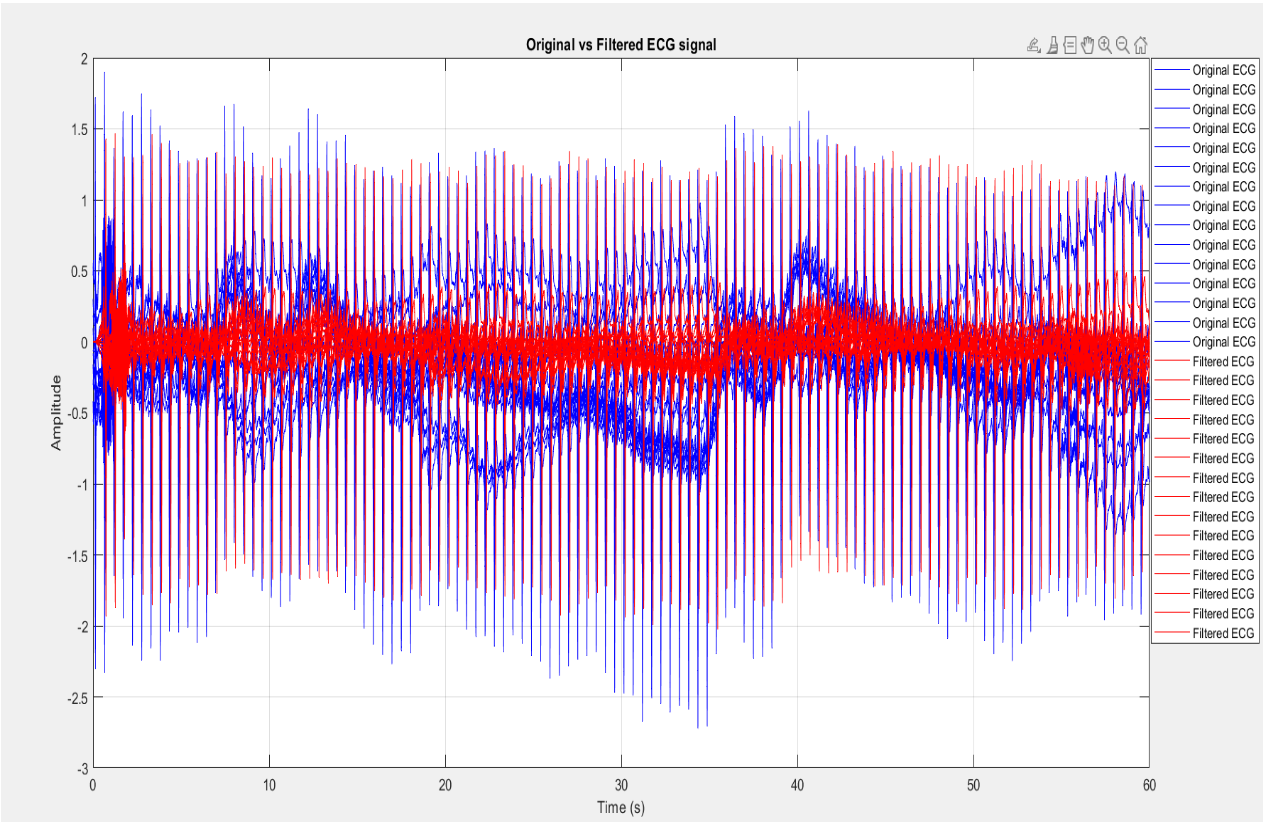

Figure : 3.i.d

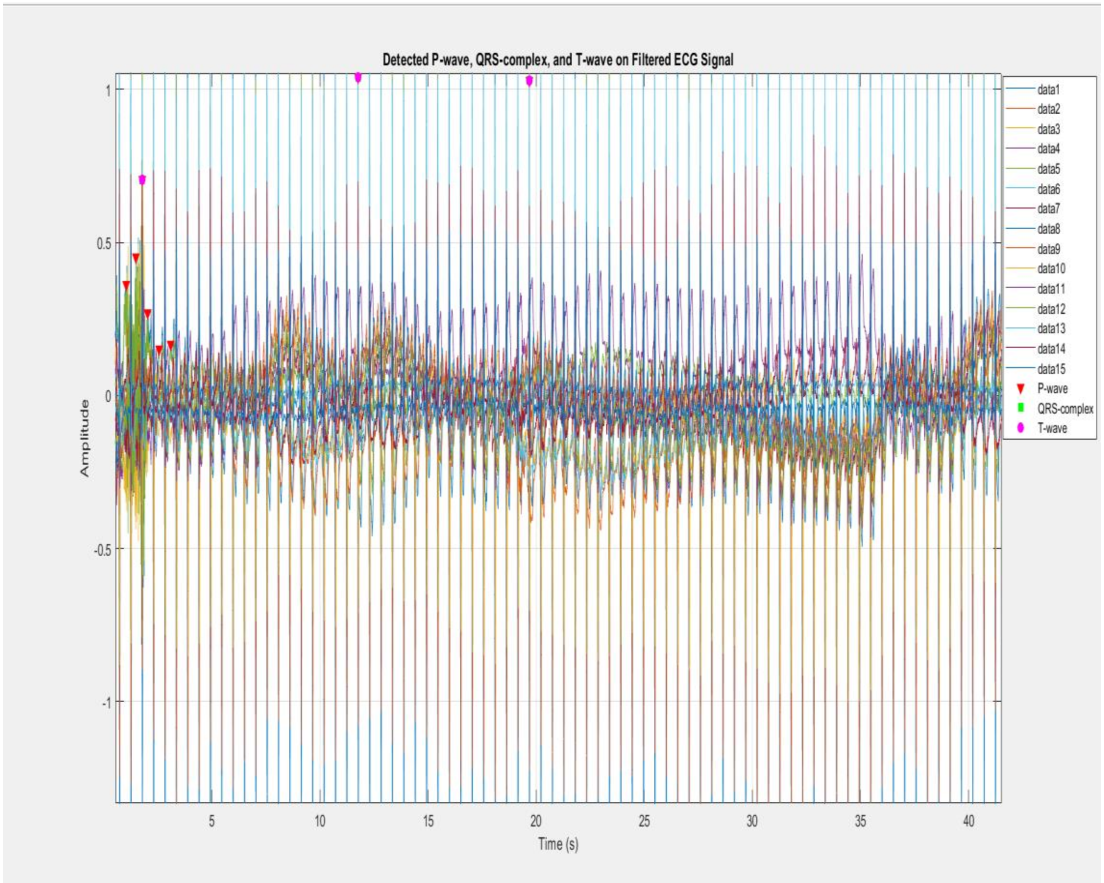

Figure : 3.i.e

Output in command window :

```
Command Window
Tachycardia : Heart rate is too fast
frequency of p-wave is :
    1.9876

frequency of qrs-complex is :
    1.9027

frequency of t-wave is :
    1.9027

The patient is not healthy.
fx >>
```

DATASET_2 :

Output wave forms in figure window :

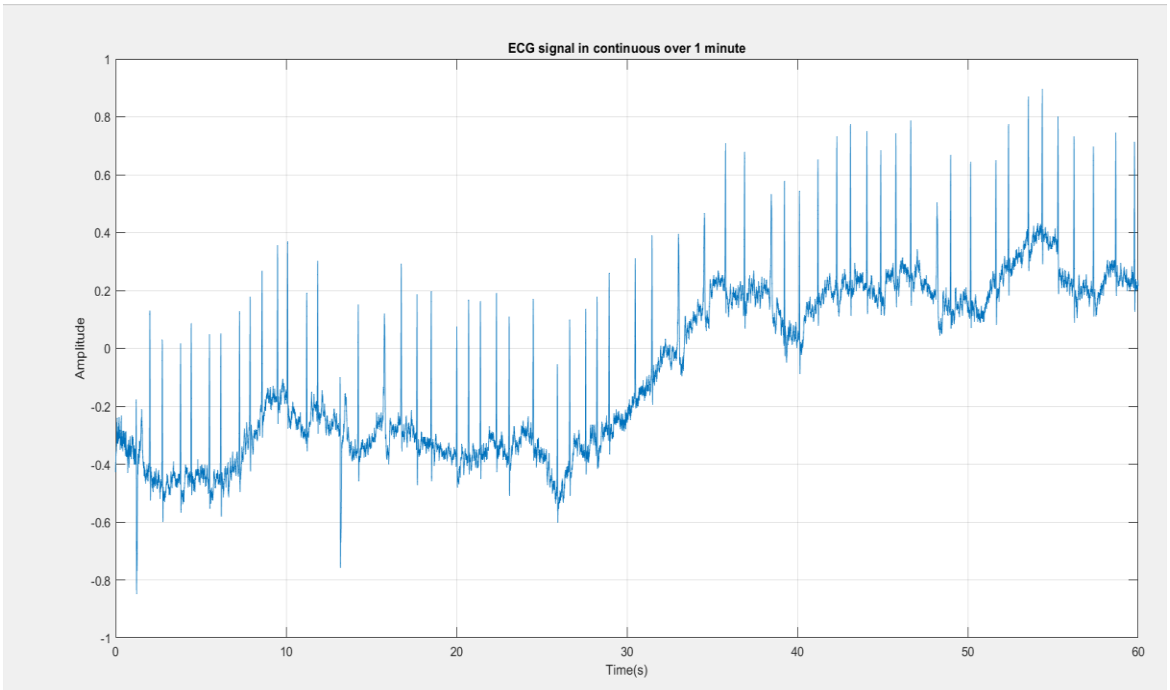

Figure : 3.ii.a

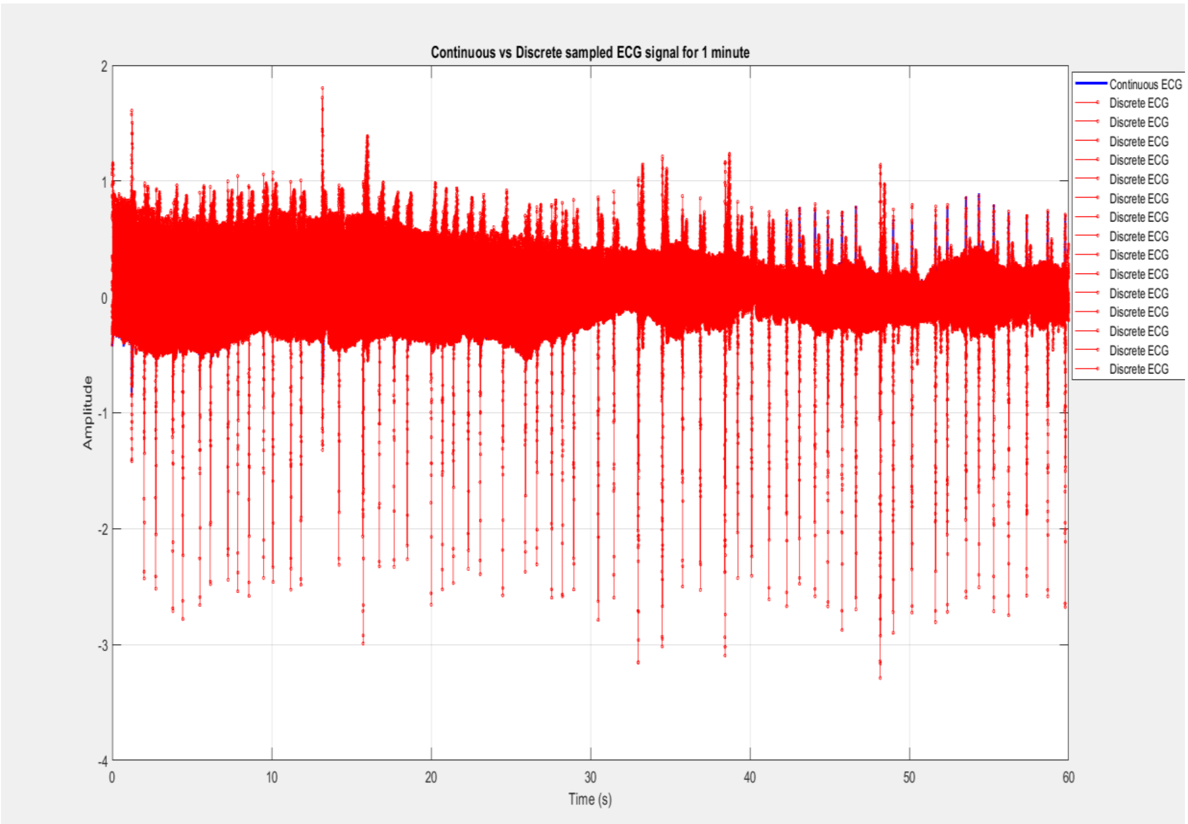

Figure : 3.ii.b

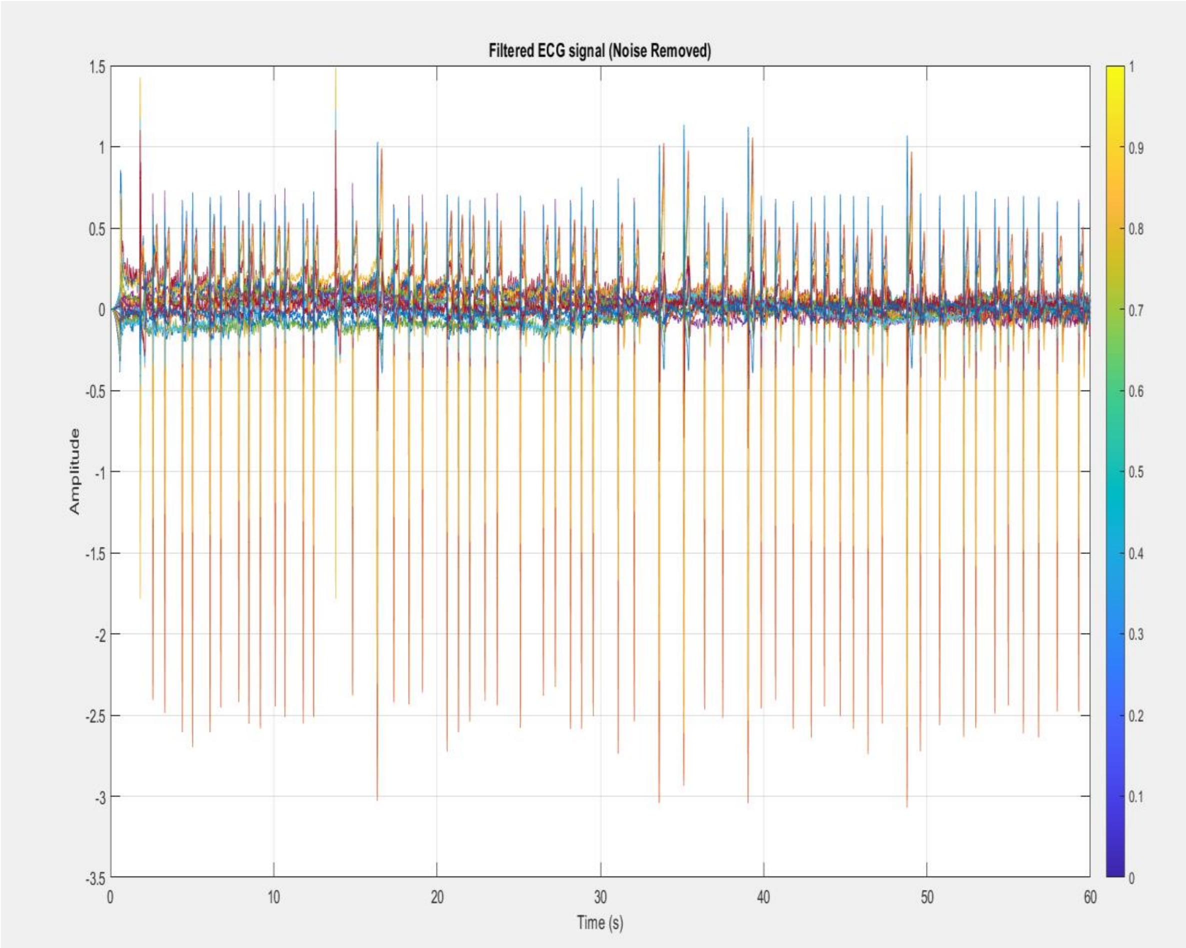

Figure : 3.ii.c

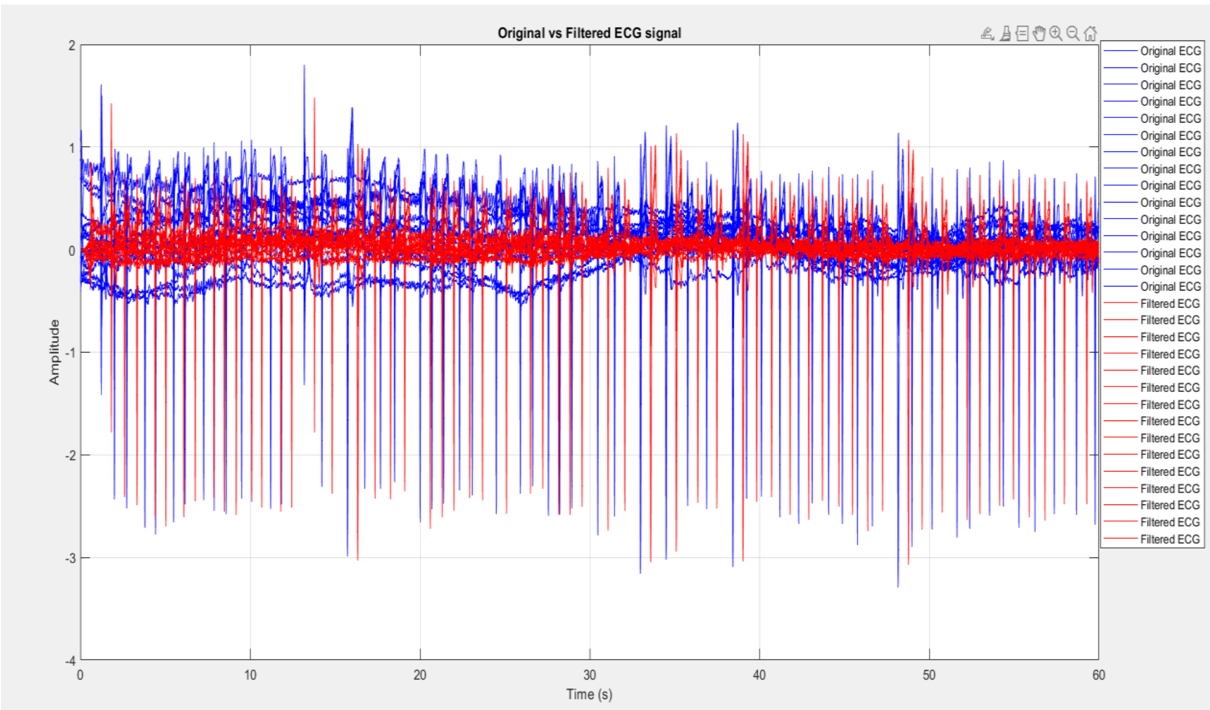

Figure : 3.ii.d

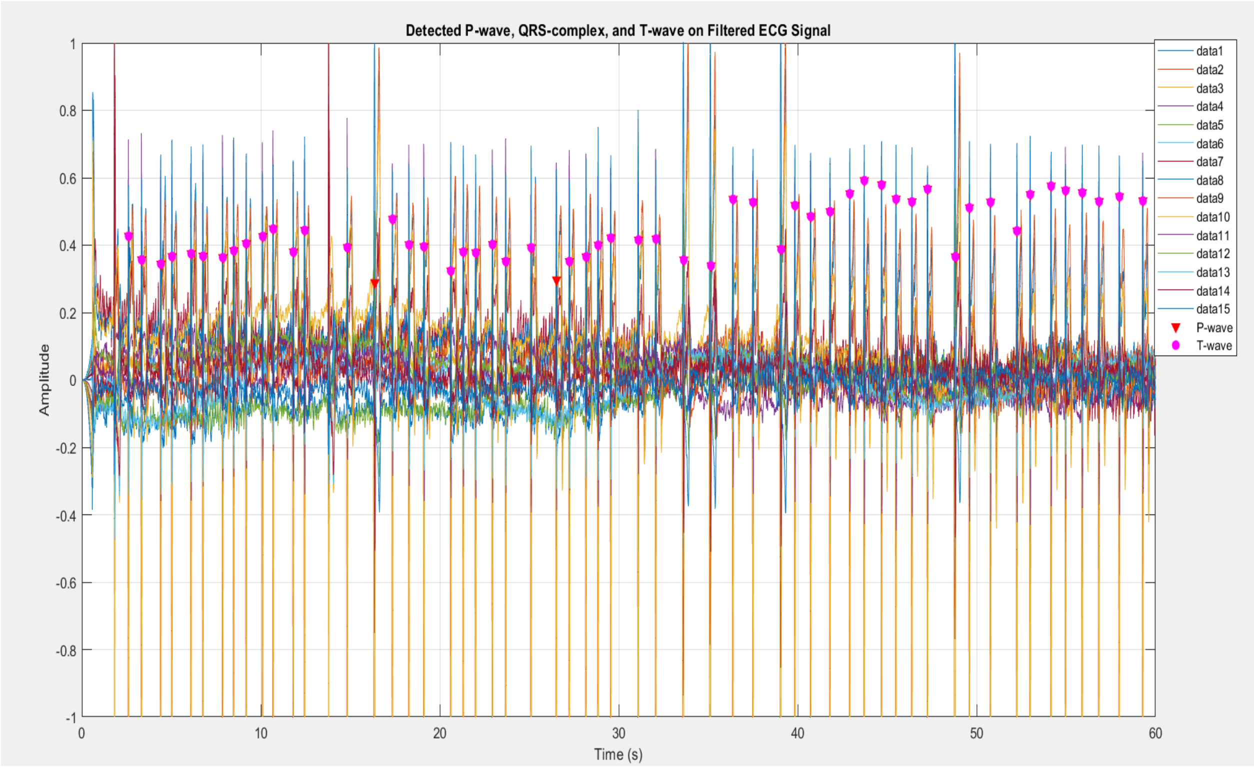

Figure : 3.ii.e

Output in command window :

```
Command Window
Warning: Invalid MinPeakHeight. There are no data points greater than MinPeakHeight.
> In findpeaks>removePeaksBelowMinPeakHeight (line 535)
In findpeaks (line 162)
In project_ecg (line 72)
Normal Heart rate
frequency of p-wave is :
    0.9704

frequency of qrs-complex is :
   NaN

frequency of t-wave is :
    0.9351

The patient is not healthy.
fx >>
```

DATASET_3 :

Output wave forms in figure window :

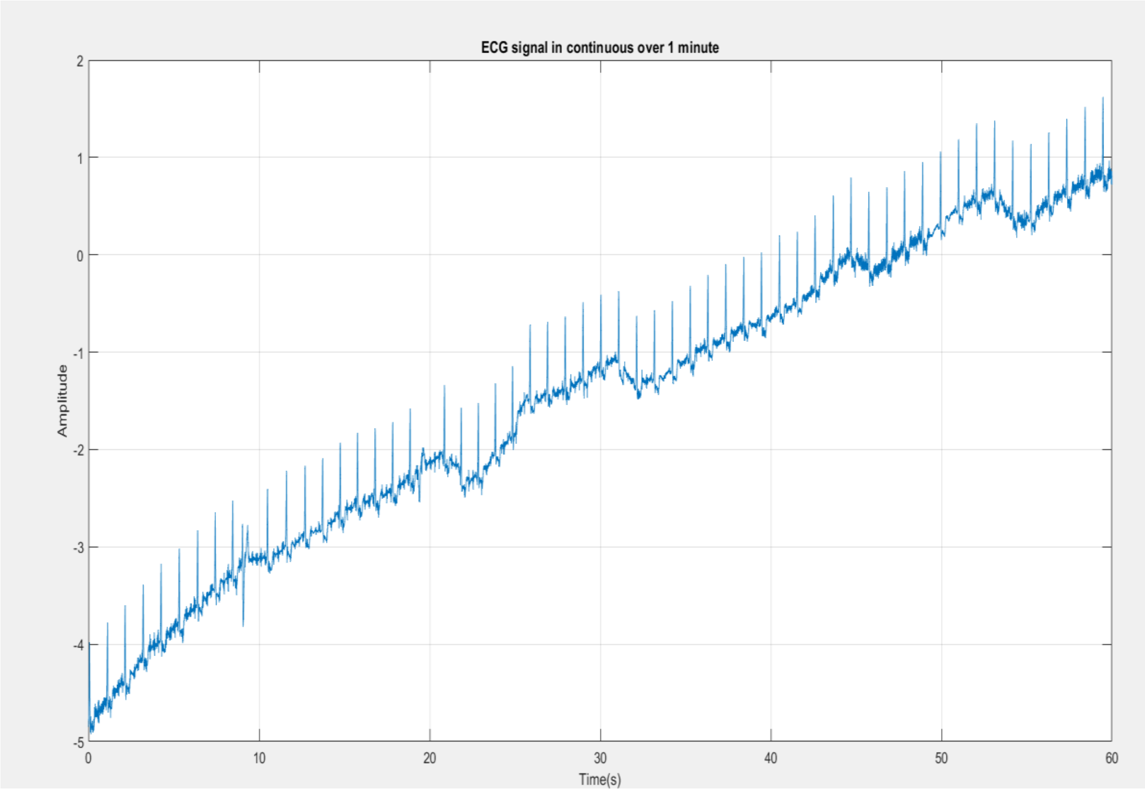

Figure : 3.iii.a

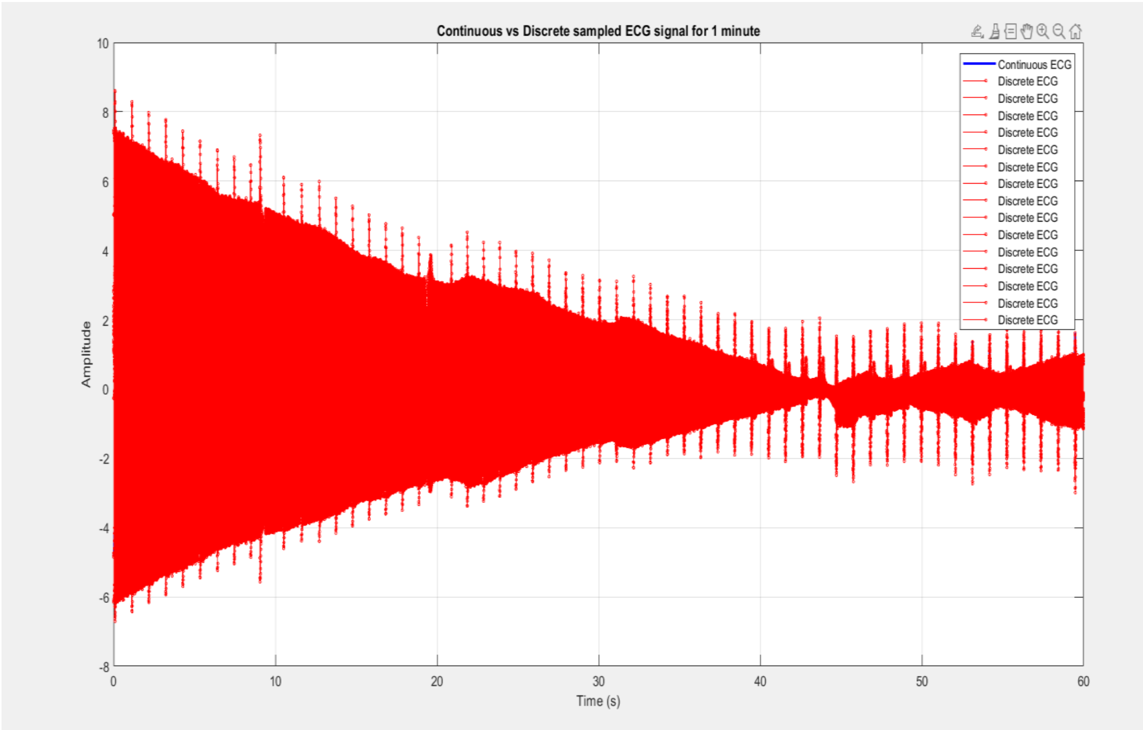

Figure : 3.iii.b

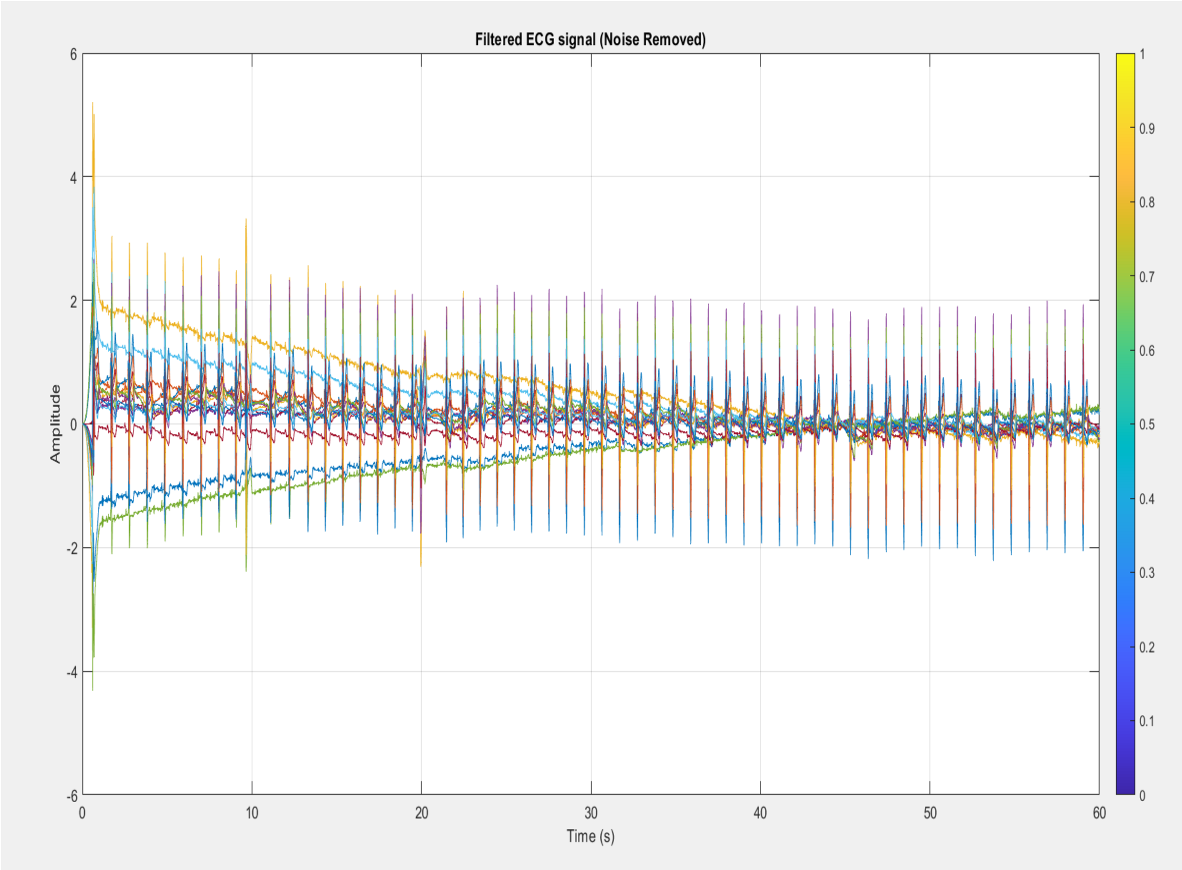

Figure : 3.iii.c

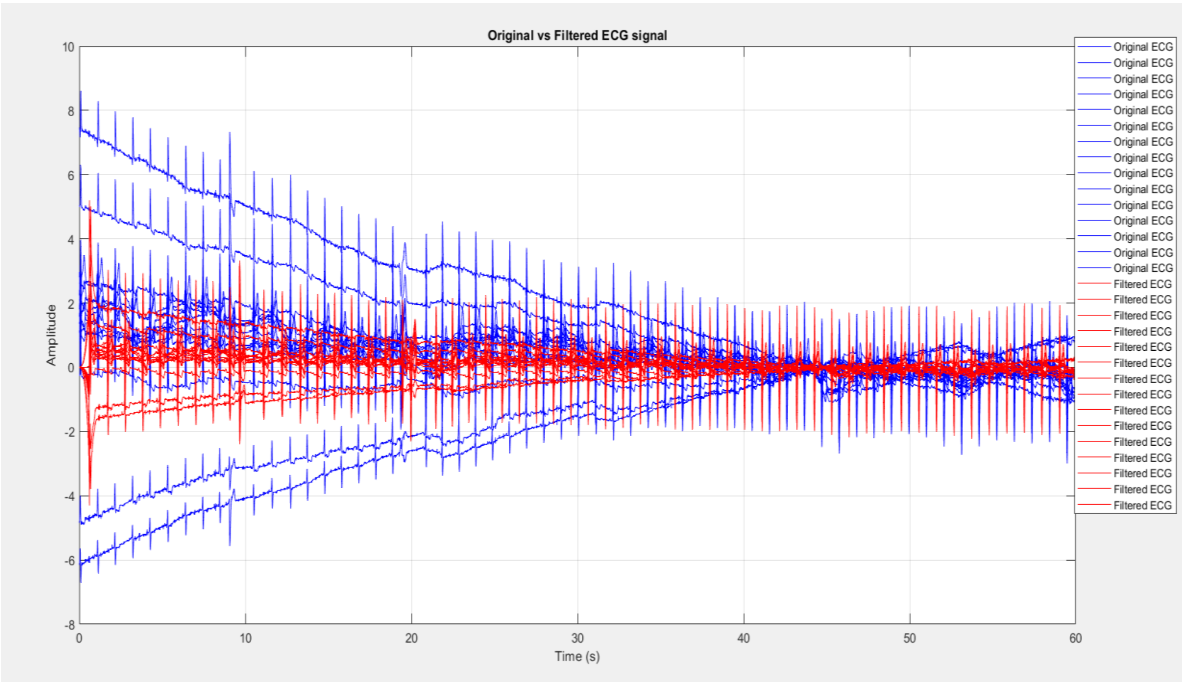

Figure : 3.iii.d

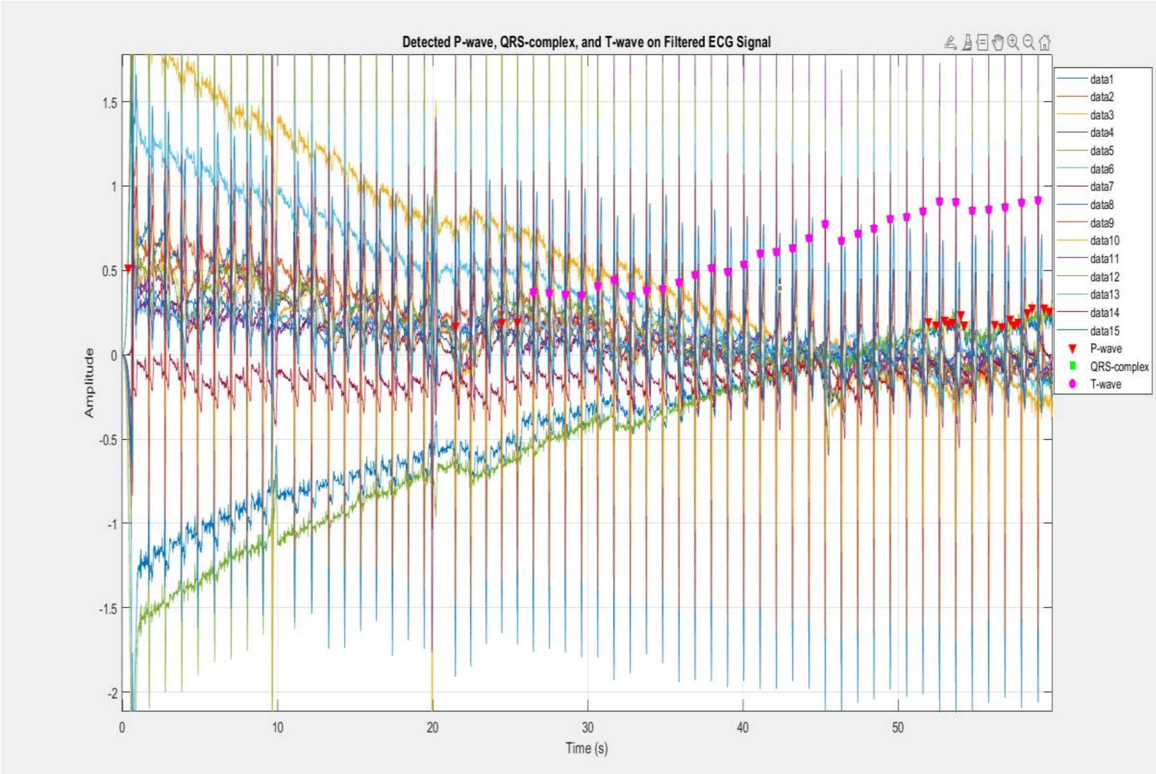

Figure : 3.iii.e

Outputs in command window :

```
Command Window
Bradycardia : Heart rate is too slow
frequency of p-wave is :
    0.8890

frequency of qrs-complex is :
    0.2909

frequency of t-wave is :
    0.5476

The patient is not healthy.
fx >>
```

CHAPTER - VI

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This project demonstrates the effectiveness of an optimized FIR filter in enhancing the quality of ECG signals by significantly reducing noise while preserving essential cardiac features. By employing this filtering technique, the analysis of ECG data becomes more accurate, facilitating the reliable detection of key waveforms such as the P-wave, QRS-complex, and T-wave. The results illustrate the filter's capability to operate efficiently in real-time applications, which is crucial for effective patient monitoring and diagnostics. Furthermore, the methodology provides a solid foundation for future advancements in biomedical signal processing. Overall, this work highlights the importance of advanced filtering techniques in improving cardiac health assessment and clinical decision-making.

6.2 Future Scope

The future scope of this project includes expanding the application of the optimized FIR filter to accommodate more complex and diverse biomedical signals beyond ECG, such as electroencephalograms (EEG) and electromyograms (EMG). By refining the filter design and incorporating adaptive filtering techniques, the methodology can be adapted to various physiological signals that also require noise reduction and feature preservation. This enhancement will enable the development of more versatile and robust medical devices capable of providing comprehensive health monitoring across different physiological parameters.

Additionally, the integration of machine learning algorithms with the FIR filtering process presents an exciting avenue for future research. By utilizing machine learning models, the system can learn to adaptively adjust filtering parameters based on the characteristics of the incoming signal, thus improving performance in dynamic and noisy environments. This combination of advanced filtering and artificial intelligence could lead to the development of intelligent diagnostic systems that provide real-time analysis and decision support, ultimately enhancing patient care and outcomes in clinical settings. These advancements will contribute significantly to the growing field of telemedicine and personalized healthcare, paving the way for innovative solutions in medical technology.

CHAPTER - VII

REFERENCES

[1] Kumar, Manoj. (2024). Design and Implementation of Digital Low Pass FIR and IIR Filters Using VHDL for ECG Denoising. 71. 252-265. 10.14445/22315381/IJETT-V72I1P125.

[2] Wulf, Michael & Staude, Gerhard & Knopp, A. & Felderhoff, Thomas. (2016). Efficient design of FIR filter based low-pass differentiators for biomedical signal processing. Current Directions in Biomedical Engineering. 2. 10.1515/cdbme-2016-0048.

[3] Fedotov, Aleksandr. (2016). Selection of Parameters of Bandpass Filtering of the ECG Signal for Heart Rhythm Monitoring Systems. Biomedical Engineering. 50. 10.1007/s10527-016-9600-8.

[4] Behera, S., Samal, M., & Layak, R. (2017). The Use of FIR Filter for Filtering of ECG Signal and Comparison of Some Parameters. *International Journal of Engineering Science Invention*, 6(4), 71-79. ISSN (Online): 2319–6734, ISSN (Print): 2319–6726.

CHAPTER - VIII

APPENDIX

```
clc;
clear;
close all;
% AN OPTIMIZED FIR FILTER DESIGN FOR NOISE REMOVAL IN ECG SIGNAL
fs = 125; % Sampling frequency (in Hz)
Ts = 1/fs; % Sampling period (in seconds)
duration = 60; % Signal duration (in seconds)
% Loading the ECG signal from Datasets
x = load("data_3.mat");
y = x.val/2000; % Scaling the signal
y = y'; % Transpose the signal to ensure the correct format
% Number of samples in the signal
N = length(y); % Length of the ECG signal from the dataset
% Construct the continuous time vector for 1 minute
t_continuous = linspace(0,duration,N); % Continuous time vector corresponding to the signal
% Ensure that both t_continuous and y have the same length
assert(length(t_continuous) == length(y),"Time vector and ECG signal must have same
length");
% Plot the ECG signal with its continuous time vector for entire 1 minute
figure;
plot(t_continuous,y(:,1));
title("ECG signal in continuous over 1 minute");
xlabel("Time(s)");
ylabel("Amplitude");
grid on;
% Applying sampling theorem to convert continuous time signal to discrete time signal
t_discrete = 0:Ts:max(t_continuous); % Time vector for discrete time signal
% Sample the discrete time ECG signal using interpolation
ecg_signal_discrete = interp1(t_continuous,y,t_discrete,"linear");
% Plot the original continuous and discrete sampled ECG signal for entire 1 minute
figure;
plot(t_continuous,y(:,1),"b","LineWidth",2,"DisplayName","Continuous ECG");
hold on;
stem(t_discrete,ecg_signal_discrete,"r","MarkerSize",2,"DisplayName","Discrete ECG");
title("Continuous vs Discrete sampled ECG signal for 1 minute");
xlabel("Time (s)");
ylabel("Amplitude");
legend;
grid on;
xlim([0,60]);
% Applying Z-transform to convert from time domain to frequency domain
syms z n;
ecg_z_transform = sum(ecg_signal_discrete.*z.^(-n));
% Designing a bandpass FIR filter for noise removal
f_pass = [0.67 50]; % Passband frequencies in Hz
```

```
f_nyquist = fs/2;
f_pass_norm = f_pass/f_nyquist; % Normalized passband
order = 150; % Filter order
b = fir1(order,f_pass_norm,"bandpass"); % Design of bandpass filter
% Filtering the ECG signal
filtered_ecg_signal = filter(b,1,ecg_signal_discrete);
% Plotting the filtered ECG signal
figure;
plot(t_discrete,filtered_ecg_signal);
title("Filtered ECG signal (Noise Removed)");
xlabel("Time (s)");
ylabel("Amplitude");
grid on;
% Overlaying original and filtered signals for comparison
figure;
plot(t_discrete,ecg_signal_discrete,"b","DisplayName","Original ECG");
hold on;
plot(t_discrete,filtered_ecg_signal,"r","DisplayName","Filtered ECG");
title("Original vs Filtered ECG signal");
xlabel("Time (s)");
ylabel("Amplitude");
legend;
grid on;
% Detecting P-wave, QRS-complex, T-wave Mathematically
% P-wave detection
[p_wave_peaks,p_wave_locs] =
findpeaks(filtered_ecg_signal(:,1),"MinPeakHeight",0.15,"MinPeakDistance",0.2*fs);
% QRS complex detection
[qrs_peaks,qrs_locs] =
findpeaks(filtered_ecg_signal(:,1),"MinPeakHeight",0.6,"MinPeakDistance",0.2*fs);
% T-wave detection
[t_wave_peaks,t_wave_locs] =
findpeaks(filtered_ecg_signal(:,1),"MinPeakHeight",0.3,"MinPeakDistance",0.4*fs);
% Plotting detected features on the filtered ECG signal
figure;
plot(t_discrete,filtered_ecg_signal);
hold on;
plot(p_wave_locs/fs,p_wave_peaks,"rv","MarkerFaceColor","r","DisplayName","P-wave");
plot(qrs_locs/fs,qrs_peaks,"gs","MarkerFaceColor","g","DisplayName","QRS-complex");
plot(t_wave_locs/fs,t_wave_peaks,"mo","MarkerFaceColor","m","DisplayName","T-wave");
title("Detected P-wave, QRS-complex, and T-wave on Filtered ECG Signal");
xlabel("Time (s)");
ylabel("Amplitude");
legend;
grid on;
% Adjusting plot parameters for clarity
xlim([0,60]);
ylim([-1,1]);
rr_intervals = diff(qrs_locs)/fs; % R-R intervals (in seconds)
heart_rate = 60./rr_intervals; % Heart rate in BPM
```

```
if mean(heart_rate) < 60
   disp("Bradycardia : Heart rate is too slow");
elseif mean(heart_rate) > 100
   disp("Tachycardia : Heart rate is too fast");
else
   disp("Normal Heart rate");
end
% Calcualting the frequenies of p-wave, qrs-complex and t-wave
p_wave_freq = 1 ./ mean(diff(p_wave_locs) / fs);
disp("frequency of p-wave is :");disp(p_wave_freq);
qrs_freq = 1 ./ mean(diff(qrs_locs) / fs);
disp("frequency of qrs-complex is :");disp(qrs_freq);
t_wave_freq = 1 ./ mean(diff(t_wave_locs) / fs);
disp("frequency of t-wave is :");disp(t_wave_freq);
%FOR HEALTHY PERSON THE FREQUENCY VALUES ARE GIVEN AS :
% P-WAVE : 0.5 TO 10 Hz
% QRS-COMPLEX : 10 TO 100 Hz
% T-WAVE : 0.5 TO 10 Hz
if (p_wave_freq > 0.5 && p_wave_freq < 10) && (qrs_freq > 10 && qrs_freq < 100) &&
(t_wave_freq > 0.5 && t_wave_freq < 10)
   disp("The patient is healthy.");
else
   disp("The patient is not healthy.");
end
```