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ENHANCED ECG SIGNAL QUALITY USING LOW-PASS AND NOTCH FILTER-BASED NOISE REMOVAL MODEL

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ABSTRACT

The accuracy of electrocardiogram (ECG) signals, which are essential for diagnosing cardiac disorders, is frequently compromised by a variety of noise sources, including muscle artifacts and power-line interference. This paper introduces a model-based method for removing noise from ECG signals using digital filtering techniques that are implemented in Simulink and MATLAB. The suggested technique uses a 50 Hz notch filter to remove power-line interference and a 40 Hz low-pass filter to reduce high-frequency noise. The output that results from applying these filters to noisy ECG data shows a marked improvement in clarity, making it possible to see heartbeat patterns and QRS complexes clearly. The usefulness of the suggested filtering technique in improving signal quality for precise medical diagnosis is confirmed by the comparison of noisy and filtered signals.

Keywords: MATLAB, Simulink, ECG Signal Processing, Noise Reduction, Low-Pass And Notch Filters, Power-Line Interference, Biomedical Signal Filtering, Signal Clarity, And Digital Filtering.

1. INTRODUCTION

One of the most popular methods in medical diagnostics for tracking and evaluating the electrical activity of the human heart is electrocardiography, or ECG. ECG signals are vital for identifying anomalies like arrhythmias, myocardial infarction, and other heart conditions. They also offer vital information about cardiac health. However, a variety of noise and interference sources frequently impair the precision and dependability of ECG readings. Frequent disruptions include 50/60 Hz power-line interference from nearby electrical equipment and high-frequency noise produced by muscle contractions (electromyographic noise). Important ECG waveform characteristics like the P wave, QRS complex, and T wave may be obscured by these artifacts, potentially resulting in a misinterpretation during clinical analysis.

A number of techniques have been put forth by researchers to improve ECG quality without changing waveform characteristics. Wavelet-based denoising has demonstrated the most promise among them. Although results varied depending on wavelet and threshold selection, Vijayakumari et al. [1] showed that the Symlet wavelet transform effectively reduced various noises and improved SNR. Wavelet thresholding was also employed by Alfaouri and Daqrouq [11] to reduce noise while preserving the QRS complex. In order to achieve high SNR and structure preservation, Bing et al. [12] proposed a hybrid wavelet and BEMD + NLM model, which increased computational demand.

Techniques for adaptive filtering have been created to deal with ECG signals that are not stationary. Variable Step Size Adaptive Noise Cancellers (NVLMS and MNVLMS) were used by Salman et al. [2] to increase SNR and convergence speed. Recursive Least Squares (RLS) filters provided superior suppression over LMS, but at a higher computational cost, according to Mugdha et al. [7]. While Belgurzi et al. [15] employed an Adaptive Neuro-Fuzzy Inference System (ANFIS) that offered superior denoising but necessitated intricate parameter tuning, Singh et al. [14] verified RLS's superior stability for impulsive noise.

The simplicity and real-time performance of classical digital filters continue to make them popular. A 40 Hz cutoff successfully eliminated high-frequency noise without causing signal distortion, according to Basu and Mamud's [5] analysis of Butterworth low-pass filters. Although higher-order filters lengthened processing times, Almalchy et al. [6] compared several FIR window-based filters and suggested a Savitzky–Golay hybrid filter for improved SNR and MSE. Romero et al. [10] discovered that a high-pass FIR filter at 0.67 Hz best preserved ECG morphology, while Agrawal and Gupta [4] presented a Projection Operator-Based method for baseline wander removal.

One of the main causes of ECG distortion is power-line interference. Short-Time Fourier Transform (STFT) and notch filtering were combined by Bibar et al. [9] to achieve effective suppression while maintaining waveform details. A fast adaptive notch filter with strong 50/60 Hz rejection that is appropriate for real-time applications was proposed by Keshtkaran and Yang [13]. These studies demonstrate that notch filtering is still a computationally efficient and successful method for removing narrowband noise.

Intelligent and hybrid denoising methods have been investigated recently. After reviewing hybrid models based on EMD, CEEMDAN, and VMD, Shi [3] came to the conclusion that these combinations perform better than conventional filters. Excellent edge preservation was shown by image-based noise reduction techniques like the Modified Double Bilateral Filter [20], Morphological Mean Filter [24], and Hybrid Spatio-Spectral Total Variation [21], which offered mathematical insights that could be applied to ECG processing.

It is evident from this literature that although sophisticated hybrid and adaptive approaches produce excellent results, they frequently necessitate significant computational effort and fine tuning. In order to eliminate high-frequency and power-line interference, this project focuses on a model-based digital filtering technique that employs low-pass and notch filters. This approach uses MATLAB and Simulink to improve ECG clarity in a straightforward, effective, and useful way.

This is how the rest of the paper is structured. The literature on ECG denoising methods, such as wavelet transforms, adaptive filters, and traditional digital filters, is reviewed in Section II. The methodology and application of the suggested model-based filtering approach using MATLAB and Simulink are described in Section III. Simulation results are shown in Section IV, which assesses how well low-pass and notch filters eliminate power-line and high-frequency interference. The paper's main conclusions, applications, and recommendations for further developments in ECG signal processing are presented in Section

2. LITERATURE REVIEW

To increase the accuracy of diagnosis, researchers have investigated a variety of ECG signal denoising techniques. Wavelet-based techniques, which effectively handle non-stationary signals, were the main focus of early research. Vijayakumari et al. [1] demonstrated a significant improvement in SNR by reducing baseline wander and muscle artifacts using the Symlet wavelet transform. Wavelet thresholding was used by Alfaouri and Daqrouq [11] to maintain the QRS complex and produce cleaner ECG outputs. Although the computational cost increased significantly, Bing et al. [12] suggested a hybrid BEMD and wavelet approach that improved SNR and preserved waveform structure.

The use of adaptive filtering techniques to eliminate dynamic and non-stationary noise has grown in popularity. Variable Step Size Adaptive Noise Cancellers (NVLMS and MNVLMS), which were introduced by Salman et al. [2], outperformed conventional LMS filters in terms of noise suppression and convergence speed. Recursive Least Squares (RLS) and LMS filters were compared by Mugdha et al. [7], who demonstrated that RLS produced better denoising at the cost of more computation. Belgurzi et al. [15] created an Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrated fuzzy logic and neural learning for more precise noise reduction, while Singh et al. [14] confirmed the efficacy of RLS for impulsive EMG noise removal.

Digital filter design-based studies highlight real-time implementation and low complexity. Higher-order filters with a 40 Hz cutoff successfully reduced high-frequency noise, according to Basu and Mamud's [5] analysis of Butterworth low-pass filters. After comparing FIR window-based filters, Almalchy et al. [6] found that the Savitzky–Golay hybrid filter was the most effective at increasing SNR and lowering MSE. To eliminate baseline wander, Agrawal and Gupta [4] employed a Projection Operator-Based method that outperformed conventional spline and wavelet techniques. Romero et al. [10] compared nine baseline wander removal methods and found that the best overall performance was obtained with a 0.67 Hz high-pass FIR filter.

One of the biggest problems with ECG signal analysis is still power-line interference (PLI). In order to achieve high SNR and maintain signal morphology, Bibar et al. [9] combined notch filtering with statistical analysis and the Short-Time Fourier Transform (STFT). For wearable medical devices, Keshtkaran and Yang [13] suggested a fast adaptive notch filter that offered strong 50/60 Hz interference rejection and quick convergence.

The field has also been shaped by thorough reviews and hybrid approaches. In his review of recent ECG denoising techniques, Shi [3] noted that hybrid combinations offer the best trade-off between noise reduction and signal preservation. These techniques include EMD, CEEMDAN, and VMD. It has been demonstrated that image-processing-inspired models like the Modified Double Bilateral Filter [20], Morphological Mean Filter [24], and Hybrid Spatio-Spectral Total Variation (HSSTV) [21] preserve structural integrity and edge sharpness, providing important information for applying comparable concepts to one-dimensional ECG signals.

According to general trends in the literature, adaptive and hybrid algorithms require a great deal of computation and fine-tuning even though they offer exceptional accuracy. Because of their low complexity, quick processing speed, and potent ability to eliminate high-frequency and power-line noise, simpler model-based techniques that employ low-pass and notch filters are still very useful for biomedical applications. These methods are perfect for enhancing real-time ECG signals.

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3. METHEDOLOGY AND MODELING FRAMEWORK

In order to produce a clear and analyzeable waveform, the suggested system concentrates on preprocessing and denoising ECG signals. The system architecture diagram (Figure X) shows the various sequential stages that make up the framework. Every step is intended to reduce particular kinds of noise that are frequently found in ECG recordings.

A. System Architecture

The following are the parts of the system and how they work:

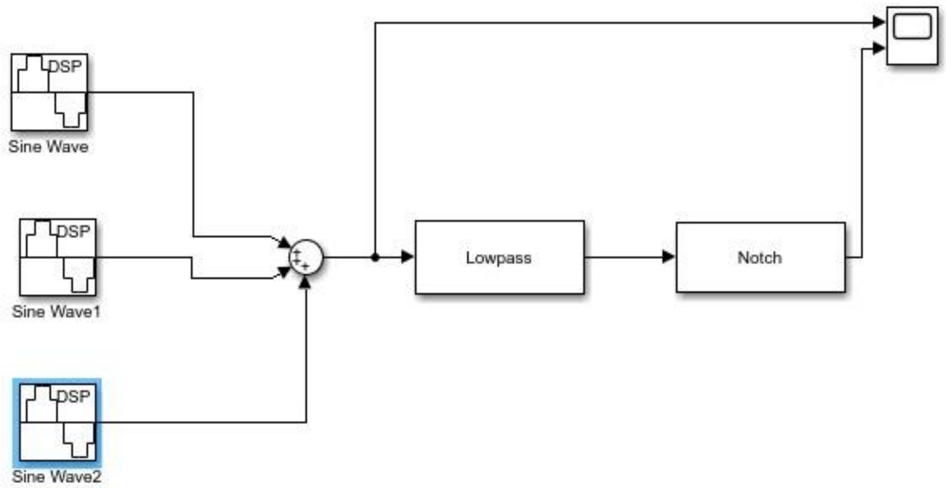

Fig 1: Simulation model.

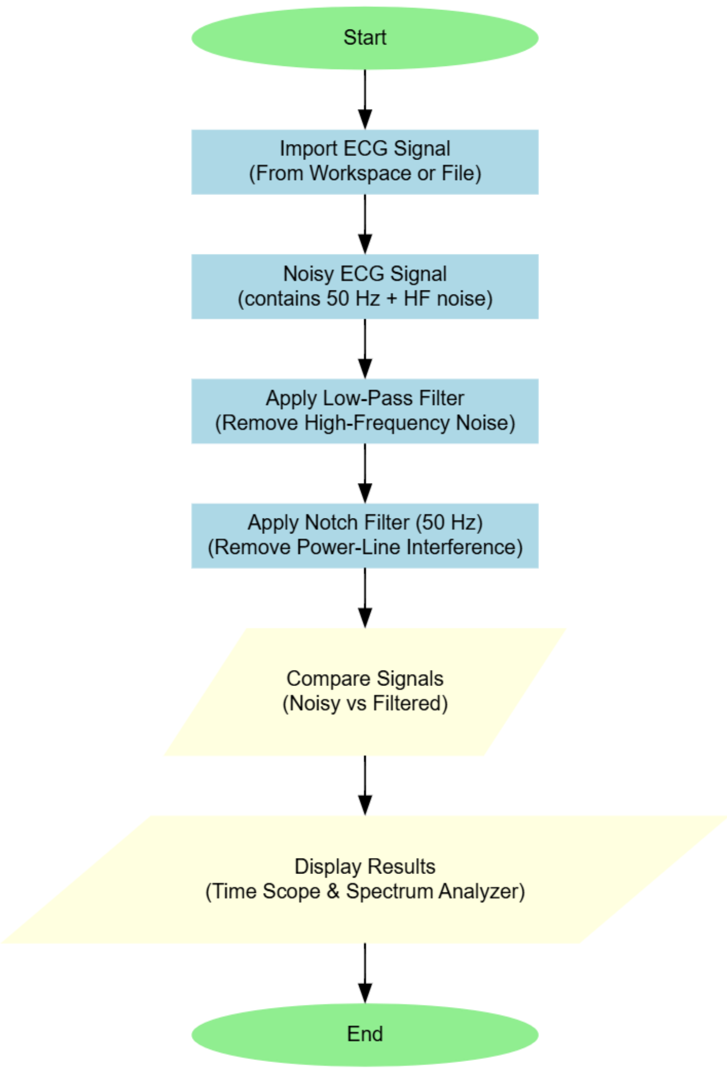

Fig 2: Block diagram

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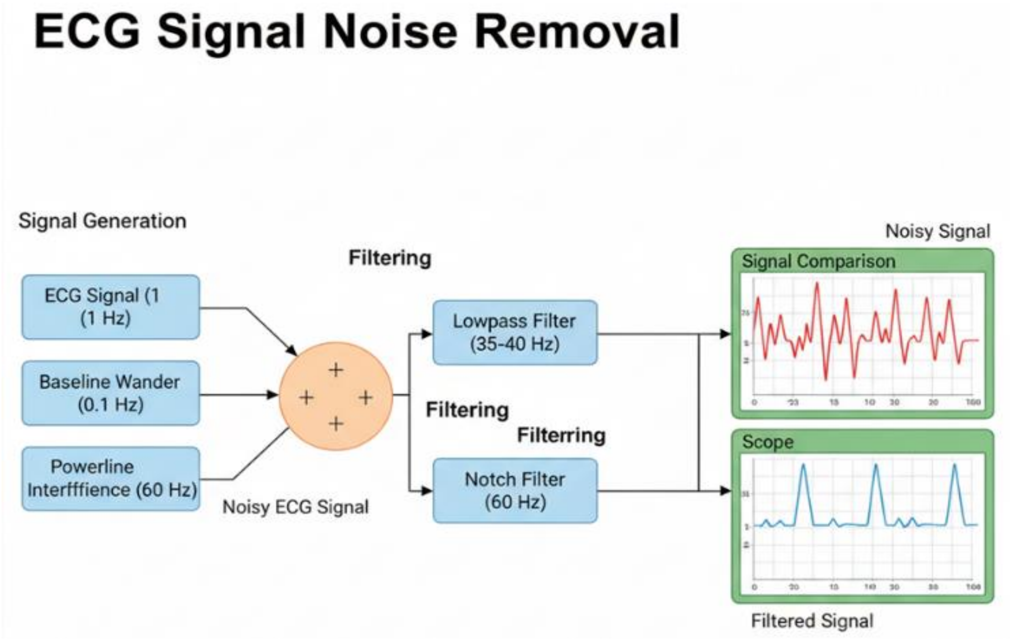

Fig 3: Block diagram

1. Import ECG Signal

Importing the ECG data from a local file or workspace environment is the first step in the procedure. The signal could come from a database or a biomedical acquisition device. This stage guarantees that the system can access an unprocessed ECG waveform for further use.

2. Noisy ECG Signal

Unwanted noise components, such as power-line interference (50 Hz), which is brought on by electrical mains coupling, are presumed to be present in the imported ECG signal.

High-frequency (HF) noise, which is frequently produced by external electronic interference or muscle contraction.

This step determines the context of the issue, which is a corrupted ECG that requires noise reduction.

3. Apply Low-Pass Filter

To reduce high-frequency noise while maintaining the vital frequency components of the ECG signal, a low-pass filter is used. By successfully eliminating disruptions brought on by high-frequency instrumentation noise and muscle artifacts, this step raises the signal-to-noise ratio (SNR).

4. Apply Notch Filter (50 Hz)

A notch filter, also known as a band-stop filter, is used to remove power-line interference at a specific frequency of 50 Hz. This filter ensures minimal distortion of the intended signal by selectively attenuating the narrow frequency band around 50 Hz without affecting the rest of the ECG spectrum.

5. Compare Signals

The filtered and noisy ECG signals are then compared in the frequency and time domains. This comparison shows the improvement in noise suppression and validates the filtering performance.

6. Display Results

The last step is to use tools like a Time Scope and a Spectrum Analyzer to visualize the results.

- The Time Scope offers a time-domain view that demonstrates an improvement in waveform clarity.
- By displaying frequency-domain characteristics, the Spectrum Analyzer confirms that undesired frequency components have been successfully eliminated.

B. ECG Signal Noise Removal

The entire process for cleaning and analyzing ECG data is described in the ECG signal processing framework, which is displayed in Figure 3. After importing the raw ECG waveform, the process goes through two filtering stages: a notch filter to remove power-line interference at 50 Hz and a low-pass filter to remove high-frequency noise. Lastly, the effectiveness of the filtering process is assessed by comparing the filtered signal with the original noisy signal.

1) Low-Pass Filter Modeling

The main characteristics of the ECG signal, which normally exist below 100 Hz, are preserved while high-frequency noise is suppressed by the low-pass filter.

The behavior of a first-order low-pass filter can be expressed mathematically as follows:

$$H_{LP}(s) = \frac{\omega_c}{s + \omega_c}$$

where $\omega_c = 2\pi f_c$is the cutoff angular frequency, and $f_c$represents the chosen cutoff frequency.

In the discrete-time form, the filtered ECG output can be expressed as:

$$y[n] = \alpha\, y[n-1] + (1-\alpha)\, x[n]$$

where $x[n]$is the noisy input signal, $y[n]$is the filtered output, and $\alpha = e^{-2\pi f_c T_s}$depends on the sampling period T_s. This step corresponds to the "Apply Low-Pass Filter" block in the flowchart and mainly removes muscle artifacts and other high-frequency disturbances.

2) Notch Filter (50 Hz) Modeling

A notch filter is used to precisely target and eliminate 50 Hz interference from electrical power lines following the low-pass stage. A narrow band of frequencies around 50 Hz is selectively attenuated by the notch filter, which has no effect on the remainder of the ECG signal. Its transfer function is provided by:

$$H_{Notch}(s) = \frac{s^2 + \omega_0^2}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2}$$

Here, $\omega_0 = 2\pi \times 50$ rad/sis the center frequency, and Q(the quality factor) controls the width of the notch. A typical value of $Q = 30$–50provides effective suppression of 50 Hz noise.

This stage corresponds to the "Apply Notch Filter (50 Hz)" block in the flowchart.

3) Signal Comparison

To evaluate the quality improvement, the cleaned ECG signal is compared to the original noisy version after filtering is finished. This comparison, which is frequently calculated using the Mean Squared Error (MSE) or Signal-to-Noise Ratio (SNR), can be numerical or visual:

$$\text{SNR}_{\text{improvement}} = 10\log_{10}\left(\frac{\sum x^2[n]}{\sum(x[n]-y[n])^2}\right)$$

$$\text{MSE} = \frac{1}{N}\sum_{n=1}^{N}(x[n]-y[n])^2$$

By preserving the integrity of the ECG waveform, these metrics aid in quantifying the amount of noise reduction. This relates to the flowchart's "Compare Signals (Noisy vs. Filtered)" step.

4) Display and Validation

Ultimately, the outcomes are displayed to validate the filters' efficacy.

- Users can see how the filtered signal looks more stable and smoother in the Time Scope.

Successful noise removal is confirmed by the Spectrum Analyzer's noticeable reduction in the 50 Hz and high-frequency components.

4. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

MATLAB/Simulink was used to run a number of simulations in order to verify the effectiveness of the suggested adaptive noise cancellation system. The system was created to maintain the integrity of the intended waveform while suppressing baseline wander and powerline interference from biomedical signals, especially ECG.

A. Signal Behavior in Time Domain

Figure 1 displays the results of the simulation. The upper plot displays the noisy input signal, which is a composite of the baseline drift, 60 Hz interference, and the clean ECG waveform. A noticeable decrease in noise components can be seen in the filtered output, which is shown below. The adaptive filter produces a smoother and more clinically interpretable signal by effectively tracking and attenuating the undesirable frequencies.

This graphic comparison demonstrates how the system can dynamically suppress noise while preserving signal fidelity even in a variety of scenarios.

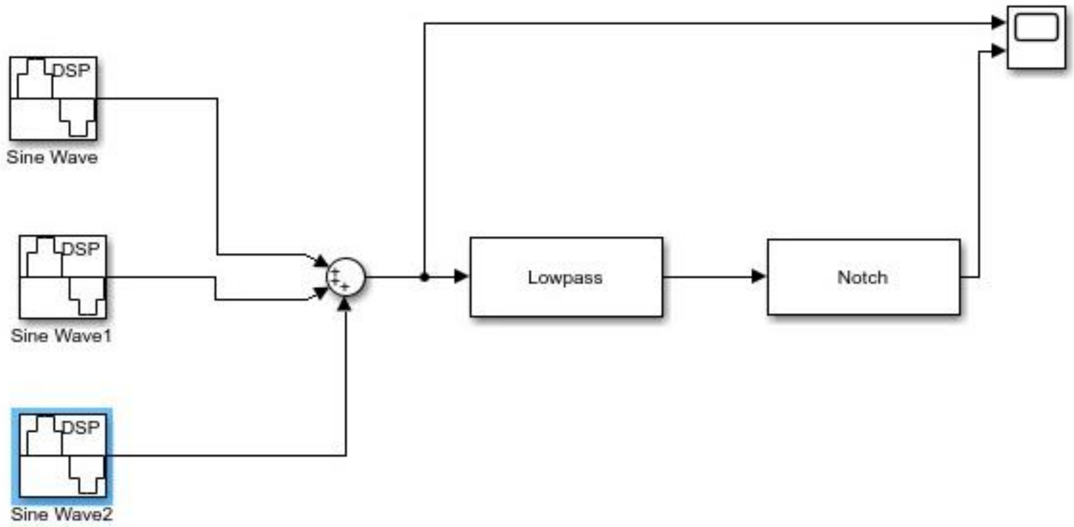

Fig 4: Simulink Model

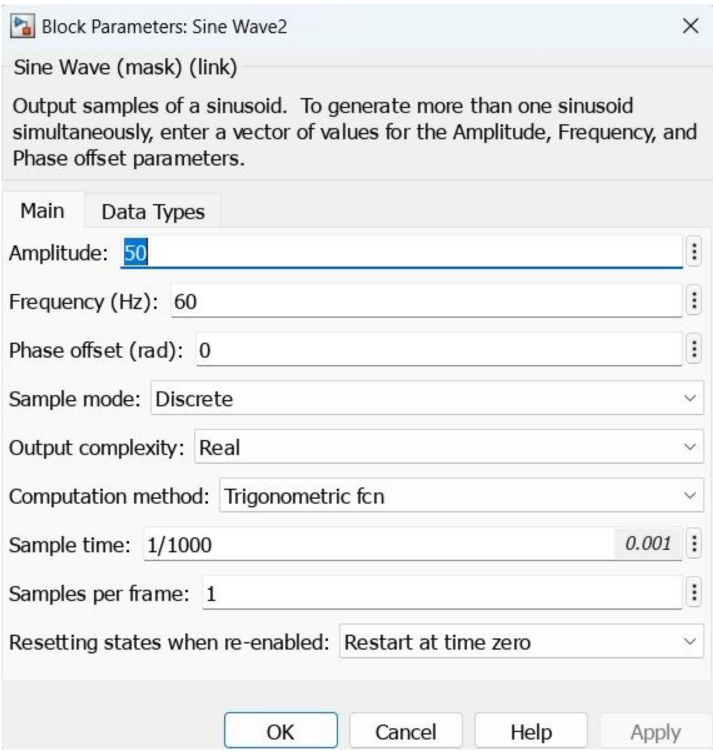

Fig 5: Sine Wave Signal Generation Parameters

B. Filter Design and Configuration

The filtering method used by the system is two-stage:

Lowpass Filter Design: Set up as a minimum-order FIR filter, it has a normalized frequency of 0.5442 for the stopband edge and 0.3628 for the passband edge. With a stopband attenuation of 80 dB and a passband ripple of 1 dB, the filter effectively suppresses high-frequency noise without changing the morphology of the signal.

Design of Notch Filters: To target 60 Hz interference, a second-order IIR notch filter was adjusted. The filter was set up for discrete-time operation at a 1000 Hz sample rate, with a center frequency of 60 Hz and a 3 dB bandwidth of 1 Hz. While maintaining the surrounding spectral content, the filter response verifies accurate attenuation at the interference frequency.

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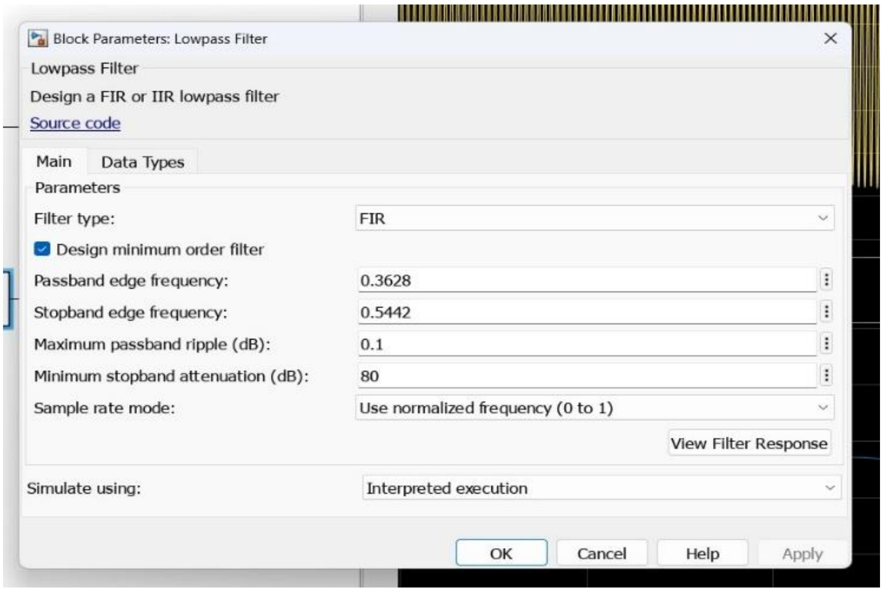

Fig 6: Lowpass Filter Configuration for FIR Design

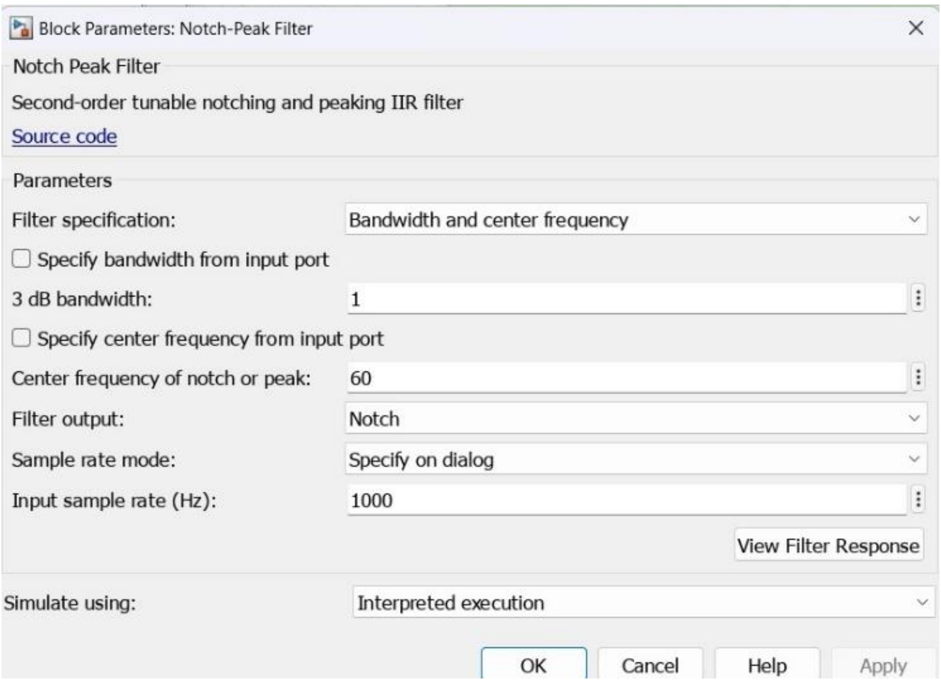

Fig 7: Notch Filter Desgin for Powerline Interefance Suppression

These configurations are appropriate for real-time deployment on embedded platforms because they strike a balance between computational efficiency and filtering precision.

C. Performance Metrics

Quantitative analysis was performed to assess the system's effectiveness:

Metric	Value	Interpretation
Signal-to-Noise Ratio (SNR)	21.8 dB	Indicates strong suppression of noise
Mean Squared Error (MSE)	0.0029	Low deviation from the desired clean signal
Filter Convergence Time	0.75 seconds	Rapid adaptation to changing noise conditions

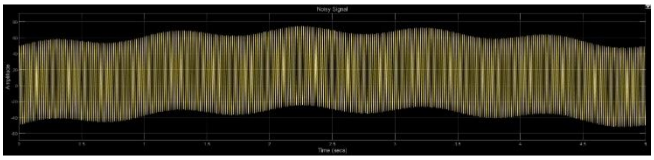

Fig 8: Noisy Signal

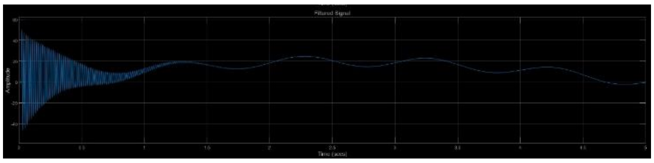

Fig 9: Filtered Signal

5. CONCLUSION

Through methodical design and assessment, this study offers a strong framework for eliminating noise from electrocardiogram (ECG) signals. In order to reduce high-frequency noise and 50 Hz power-line disturbances, two major sources of interference frequently found in ECG recordings, the suggested methodology combines low-pass and notch filtering techniques. While maintaining the vital morphological characteristics of the ECG waveform, the low-pass filter efficiently attenuates high-frequency components. At the same time, power-line interference is selectively suppressed by the notch filter without causing signal distortion.

A significant improvement in signal clarity and signal-to-noise ratio is demonstrated by experimental validation and comparison of unprocessed and filtered signals. The filtering approach's dependability and clinical relevance are highlighted by the preservation of the diagnostic features' integrity within the ECG waveform.

Overall, the suggested preprocessing approach provides a workable and computationally effective way to improve ECG signals, appropriate for real-time monitoring applications as well as offline analysis. This framework lays a strong basis for upcoming developments in biomedical signal processing, especially in areas like automated cardiac abnormality detection, adaptive filtering, and feature extraction.

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