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ECG SIGNAL DENOISING: AN INTEGRATED FILTERING APPROACH FOR IMPROVED SIGNAL QUALITY

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ABSTRACT

The electrocardiogram is an essential tool in biomedical diagnostics for detecting cardiovascular diseases. However, the non-stationary characteristics of ECG signals frequently result in noise contamination, leading to inaccuracies that prevent diagnosis and analysis. The proposed methodology improves electrocardiogram signal processing by preserving essential diagnostic features, including the ST segment, which exists in the low-frequency region and is susceptible to noise interference. The proposed methodology involves three key steps: first, a bandpass filter is used to separate the electrocardiogram frequency band within 0.5–40 Hz; second, noise reduction techniques like Savitzky-Golay, Butterworth, and Gaussian window filters are used to eliminate of Electromyogram, Baseline Wander, and Power Line Interference noise; and third, segmenting the processed data for further analysis. These steps make the signal stronger and more reliable, which leads to more accurate diagnostic results and easier advanced feature extraction. The performance metrics with MATLAB R2023a and the MIT-BIH database showed a notable increase in the signal-to-noise ratio going up to 44.13 dB and the mean squared error going down to 0.0000.

KEYWORDS

Electrocardiogram, Signal Denoising, Butterworth Filter, Gaussian Window Filter, Baseline Wander, Power Line Interference.

1. INTRODUCTION

Signal processing is essential in biomedical applications, enabling precise health monitoring and correct clinical diagnostics introduction (Rawash et al., 2024). Recording the electrocardiogram (ECG) signal can interfere with some noise artefacts. After all, it is a relatively weak signal because it has amplitude and frequency ranges of 10 μV–5 mV and 0.05–100 Hz, respectively (Waheed, 2023, Azzouz et al., 2024). These noise artefacts create changes in the signal's characteristics, leading to difficulty in diagnosis. So, it is essential to denoise ECG signals before clinical evaluation. Denoising is a crucial pre-processing step for analysing signals and precise diagnosis of diseases (Manju.B.R and Sneha.M.R, 2020, Liu and Li, 2021). ECG signals include a wide variety of low and high-frequency disturbances (N. Hussin et al., 2022, Talib et al., 2021). which is Baseline Wander (BW) and the frequency of the BW noise below 0.5 Hz. However, this noise hinders the detection of peaks in the ECG signal. Due to wander, the T peak exceeds the R peak, leading to peak detection inaccuracies and distorting the ST segment of the ECG signal (Waheed, 2023). Power Line Interference (PLI) is caused by inductive and capacitive couplings of 50/60 Hz power lines during ECG signal acquisition. This leads to P-wave distortions and the wrong diagnosis (Chatterjee et al., 2020). Electromyogram (EMG) noise and the EMG frequency range from 100 to 500 Hz. EMG noise heavily influences the ECG signal due to direct interference with the QRS complex. This noise is primarily caused by contractions of muscles other than the heart muscle, brought on by the patient's movement (Waheed, 2023).

In this section of the paper, several techniques previously proposed in the literature are covered for eliminating these noises before the detection and classification of disease.

The test results showed Gaussian, Mittag-Leffler, and Savitzky-Golay filters showed that the Savitzky-Golay filter is better at getting rid of noise in ECG signals. The filter efficiently reduced noise while preserving the signal's details. Because it did better at Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR). Mittag-Leffler requires careful fine-tuning, and a Gaussian filter removes noise, but it may lose complex details (Rawash et al., 2024). An EMG noise is attenuated (low-pass Butterworth filtering) and a zero-phase shift filtering corrects the baseline drift. This process eliminates ECG noise. It slightly reduces the MSE while improving the SNR to 15.72 dB. This method preserves the ECG signal, but it may become less computationally straightforward and have potential residual baseline drift (Waheed, 2023). Wavelet transform combines the particle swarm optimization (PSO) to reduce noise and improve ECG signals, while the S-G filter combined with DWT is superior to others on denoising, but it needs a lot of processing resources and parameter adjustment (Azzouz et al., 2024, Samann and Schanze, 2019). The Wiener filter preserves the ECG signal better than Kalman in all criteria for measuring SNR, MSE and PRD. Nevertheless, the Kalman filter has problems in practical non-linear systems (Manju.B.R and Sneha.M.R, 2020). An IIR filter that combines high-pass and band-stop filters is an effective way to remove noise from an ECG signal. However, its weakness is that it cannot handle complex artifacts such as motion noise (K and Syed, 2024). Based on the tendency method and WT, the difference approach and WT can efficiently denoise ECG signals by rejecting outliers, reducing noise, maintaining signal characteristics, and dealing with non-stationary signals. However, possible distortion requires careful calibration (Che et al., 2021; Alrubei and Dmitrievich, 2023). The S-transform-based denoising approach has been successfully applied for the elimination of various noise in ECG signals, such as Gaussian noise, muscle artifact, and artifacts due to movement of electrodes (Mishra et al., 2021). The S-transform, BEMD and NLM filtering are elements of the hybrid ECG denoising method. It needs more computational resources and works only under high noise level conditions (Bing et al., 2024). Discrete wavelet transform (DWT) is more effective than the threshold and notch filtering approaches to eliminate PLI on ECG signals without employing any kind of thresholding techniques (Oliveira et al., 2018; Leski, 2021). A four-level cascaded adaptive noise canceller for removing multiple ECG noises. The SNR goes up by 12.73 db. However, although this technique eliminates a lot of different artifacts, it requires fine-tuning and is more difficult to program than single-stage filters (Faiz and Kale, 2022). Different wavelet types of DWT with different signal filter designs (Chieng et al., 2020; Abdulwahab et al., 2021). The proposed approach employs SWT and an IDT for denoising ECG signals. This procedure is superior to DWT and conventional SWT methods because it reduces noise without distorting the ECG morphology. However, its performance might degrade under very high noise levels and the use of a manual interval setting may reduce its effectiveness (Hermawan et al., 2024). CiSSA is used for filtering BW and a four-stage Savitzky-Golay filter is employed to filter out PLI. It yields very good results (SNR 24.48 dB, CC 0.99), preserves the form of the ECG and is able to accommodate diverse types of noise. It is, however, computationally demanding, and its efficacy drops in very noisy conditions (Krishna Chaitanya and Sharma, 2022). Compared to the conventional method EMD, which has an SNR of only 5.43 dB, the hybrid MLPT-EEMD technique achieves a significantly better SNR of 25.93 dB. However, it may also require a greater amount of processing capability (Sinnoor and Janardhan, 2022).

Although much research has been done on denoising of ECG signals, conventional methods still find it difficult to provide reliable and accurate products, particularly in preserving significant diagnosis features like the ST. The proposed method is unique because it developed a real-time integration of three filter methods (Butterworth high-pass, Savitzky-Golay, and Gaussian window) for handling the major noise types in an ECG signal simultaneously. Unlike traditional methods that apply filters individually, this method combines them into a unified pipeline that optimizes signal quality without distorting low- and high-frequency essential diagnostic features, especially low-frequency features or segments close to the noise frequency, such as the ST segment susceptible to baseline wander noise frequency. In this way, it gets around the problems with current methods, which often lose the ST segment, the QRS complex, and other important diagnostic features. Also, the proposed method includes a unique segmentation step that facilitates a more accurate analysis of individual heartbeats, enhancing the diagnostic accuracy and feature extraction of ECG signals such as heart rate, RR-intervals, PR-intervals, QRS complex, and more after the pre-processing stage so that artificial intelligence to autonomously classify them into cardiovascular diseases.

The subsequent section of the paper is structured into four sections. Section 2 elucidates the methodology. Section 3 presents the proposed method. Section 4 contains the presentation of simulation results and discussion. Conclusions are presented in section 5.

2. METHODOLOGY

ECG signals contain a lot of medical information, which is helpful for doctors to diagnose the physiological characteristics of patients. So, to keep the ECG signal's qualities from noise artifacts, it needs to be processed by removing the noise that was present in the original signal. The P wave, the QRS complex wave, and the T wave make up the ECG signal. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular repolarization, as shown in Fig. 1. Each portion of this wave contains information critical for the treating physician to make an accurate diagnosis. As a result, denoising ECG signals and preventing the loss of medical information is one of the most significant challenges in biological signal processing (Waheed, 2023, Azzouz et al., 2024, Liu and Li, 2021).

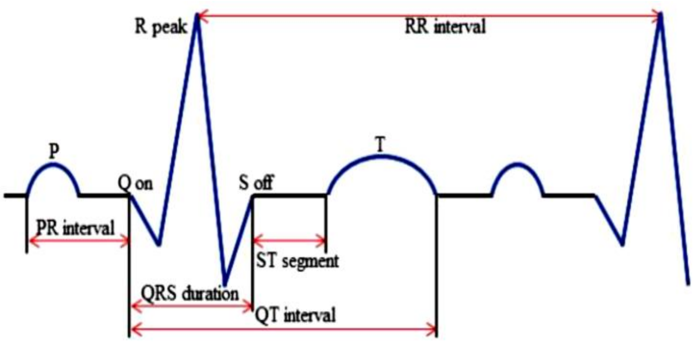


Fig. 1. ECG signal (Waheed, 2023).

After a wide and comprehensive analysis of previous research, the characteristics of the electrical heart signal were examined, and numerous suggested filters were tested. In this context, Savitzky-Golay, Butterworth, and Gaussian window filters emerge as popular choices in signal smoothing and ECG signal noise reduction. These filters, while they offer distinct advantages, also have disadvantages within certain applications. The performance of these filters in noise cancellation is estimated by adding each type of noise to the ECG signal independently and then testing the accuracy of the filter according to the following equation (Oliveira et al., 2018, Mohammed et al., 2022).

$$s(t) = sig + a\cos(2\pi f_r t + \varphi) \quad (1)$$

Where t is the time, s(t) is the noisy ECG signal, sig is the clean ECG signal, the unknown parameter $\varphi \epsilon [0,2\pi]$ and the amplitude $a > 0$.

The following various types of noise are presented:

- Power line interference noise:

$$pli_{noise} = a_{pli}\cos\left(2\pi f_{pli} t\right) \quad (2)$$

$$s(t) = sig + pli_{noise} \quad (3)$$

- Baseline Wander noise:

$$bw_{noise} = a_{bw}\cos\left(2\pi f_{bw} t\right) \quad (4)$$

$$s(t) = sig + bw_{noise} \quad (5)$$

- Electromyogram noise:

$$emg_{noise} = a_{emg}\cos\left(2\pi f_{emg} t\right) \quad (6)$$

$$s(t) = sig + emg_{noise} \quad (7)$$

The three noise sources presented in Eq.2, Eq. 4, and Eq.6 are combined into a singular equation to generate a composite noise signal including these three noises, facilitating a thorough assessment of the proposed filters' efficiency and efficacy in simultaneously eliminating various types of noise.

$$combined_{noise} = pli_{noise} + bw_{noise} + emg_{noise} \quad (8)$$

2.1. Savitzky-Golay Filter

Savitzky and Golay proposed a way of retaining the original signal shape. The Savitzky-Golay (SG) filters are digital FIR low-pass filters that change the least-squares polynomial fit to input data samples that are within a certain range. They are widely used for smoothing and differentiation in many fields, namely ECG, and they are particularly effective for removing high-frequency noise, such as EMG noise, while preserving the shape of the ECG signal without distorting important diagnostic features like the QRS complex, in contrast with traditional filters. However, they exhibit reduced efficacy against baseline wander or low-frequency drift and require precise adjustment of window size and polynomial order to properly reduce noise and preserve a balance between noise reduction and feature preservation. An excessively large window may overly smooth the signal, while too small a window may fail to suppress noise effectively (Krishna Chaitanya and Sharma, 2022, Maduakolam et al., 2022).

$$\acute{y}_i = \sum_{j=-m}^{m} c_j y_{i+j} \quad (9)$$

Where $\acute{y}_i$ the smooth value of the i_{th} points, y_{i+j} the original data value at position $i+j$, c_j the filter coefficients, m window size.

2.2. Butterworth Filter

Butterworth filter is a high-order filter designed to have a flat response (i.e. no ripples) in the pass band and steep slope immediately after cutoff frequency. This makes it an appropriate option for removing baseline wander noise from the ECG signal, minimizing signal distortion, and preserving clinical signal quality. Butterworth preserves signal integrity while efficiently reducing low-frequency noise (often below 0.5 Hz); it provides an optimal balance between computing efficiency and performance. In contrast to Chebyshev, elliptic, and bessel filters, which create ripples that could affect the shape and characteristics of the underlying ECG signal. Fig. 2 shows the gain or frequency response obtained via the discrete-time Butterworth filter.

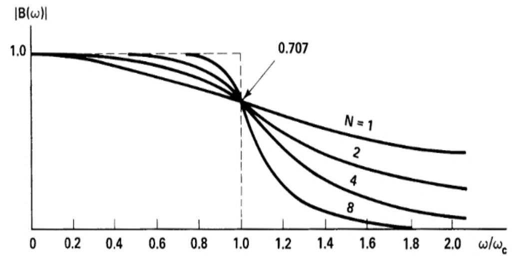


Fig. 2. Butterworth filter frequency response (D.Yusuf et al., 2020).

Hence, the Butterworth high-pass filter removes the baseline wander and restores the ECG signals to the baseline level via its high-pass filtering properties. By setting the cutoff frequency correctly, the DC component (zero frequency) is lowered. This makes a signal with no baseline wander or DC offset (Liu et al., 2017). Frequency response is defined as follows:

$$B(W) = \frac{1}{\sqrt{1 + \epsilon^2 (\frac{W}{W_C})^{2n}}} \quad (10)$$

here: w = Angular frequency, n = Number of poles in the filter, ϵ, Maximum pass band gain, w_c, Cutoff frequency, B, Transfer function.

2.3. Gaussian Window Filter

The Gaussian filter has been widely used in digital signal processing and digital image processing. The Gaussian filter has several favourable properties, such as better insensitivity for noise in comparison with the other window types, such as the rectangular and triangular windows. The rectangular window retains sharp transitions but introduces spectral leakage, whereas the triangle window yields a trade-off between frequency response and smoothness, though achieving noise reduction is potentially less efficient. The Gaussian filter provides a better-sloped signal shape than the other window types. It is a bell-shaped curve, which means that it gives more weight to signals that are close to the canter of the window. The Gaussian function is smooth and robust to outliers as compared to other types of functions (Rawash et al., 2024).

$$W(n) = e^{-\frac{1}{2}(\frac{n-\mu}{\sigma})^2} \quad (11)$$

Where: $W(n)$ the Gaussian window at index n, σ the standard deviation, μ the mean of the Gaussian window.

2.4. Performance Metric

The performance evaluation of the proposed model for ECG signal analysis is an important step in developing it. There are several performance assessment techniques for this concept. Performance comparison of ECG signal processing. In the performance measures adopted are Signal to noise ratio (SNR) as an enhancement measurement, Mean square error (MSE) that measures the difference between actual and filtered signals, Root mean square error (RMSE), and correlation coefficient (CC), which is intended to show RMSE of the signal that should be minimized. They are outlined as follows (Rawash et al., 2024, Liu and Li, 2021, Krishna Chaitanya and Sharma, 2022).

$$SNR_{dB} = 10.\log_{10} \frac{\sum_{n=1}^{N} x[i]^2}{\sum_{n=1}^{N}(x[i]-\tilde{x}[i])^2} \quad (12)$$

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(x[i]-\tilde{x}[i])^2 \quad (13)$$

$$RMSE = \sqrt{MSE} \quad (14)$$

$$CC = \frac{1}{N-1}\sum_{n=1}^{N}(\frac{\tilde{x}[i]-\mu(n)}{\sigma(n)})(\frac{x[i]-\mu(n)}{\sigma(n)}) \quad (15)$$

Where N represent the signal length, x denotes the clean signal, and $\tilde{x}$ signifies the denoised signal.

3. PROPOSED METHODOLOGY

The first and primary step to the proposed method was to compile a data set that accurately represents the problem. The dataset is for ECG signals and is taken from the MIT-BIH Arrhythmia database of PhysioNet, which consists of 45 patients with 17 classes. Data Signals were sampled at 360 Hz according to lead MLII, and 1000 non-overlapping points lasting 10 seconds were picked for analysis (Pławiak, 2018).

The pre-processing of ECG signals comprises three critical processes to improve signal quality and facilitate further analysis. Initially, filtering is conducted to isolate pertinent frequency components and attenuate noise. The encompasses a bandpass filter (31st-order high-pass and low-pass filters) to isolate the frequency range of interest (0.5–40 Hz) together with supplementary denoising techniques, such as the Butterworth HPF, Savitzky-Golay filter, and Gaussian window filter, respectively, to refine and enhance the signal. Secondly, removing the DC component is accomplished by subtracting the mean value of the signal, eliminating baseline offsets, and centring the signal around zero. Third, segmentation is conducted to partition the pre-processed ECG signal into segments of differing durations (e.g., seconds or minutes), facilitating practical analysis and feature extraction in later phases. The proposed method, depicted in Fig. 3, ensures robust signal quality and reliability, facilitating accurate diagnostic and analytical results.

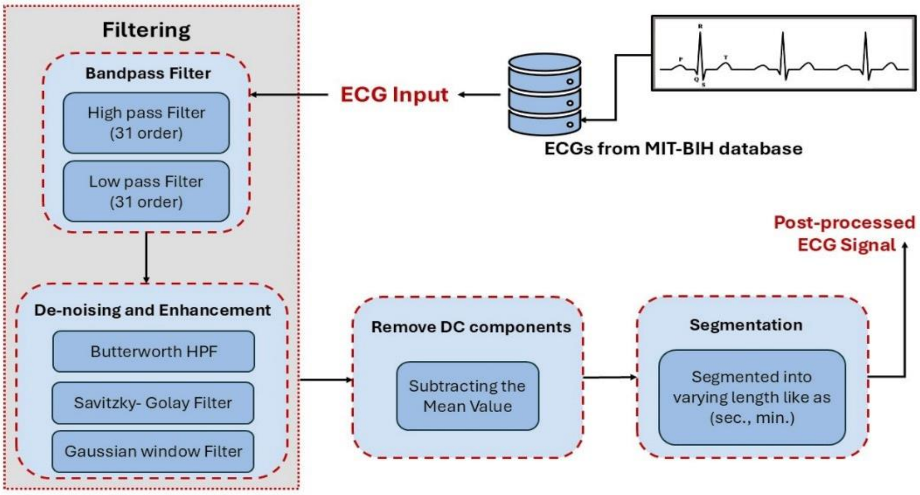


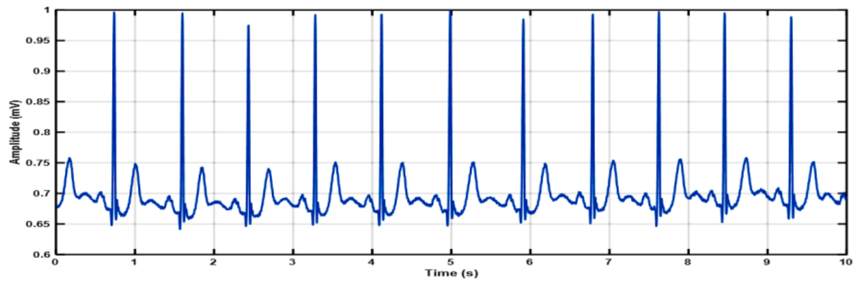
Fig. 3. Proposed methodology workflow.

4. SIMULATION RESULTS AND DISCUSSION

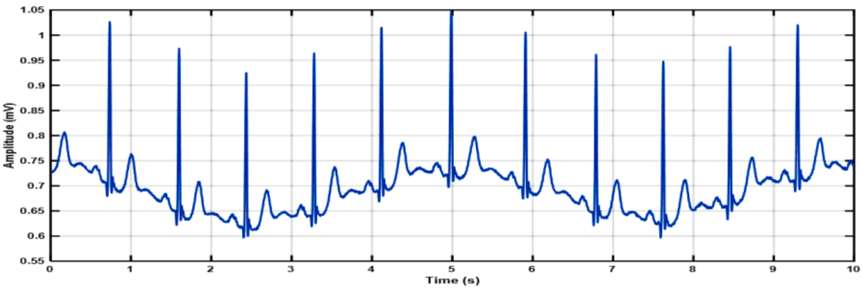
The method proposed in this paper is an overall approach to dealing with common noise components in ECG monitoring. High-pass filtering using a Butterworth high-pass filter to remove baseline wander, a Savitzky-Golay filter for EMG noise removal and a Gaussian window for PLI suppression was adaptive to the proposed method. The noise sources are added to the original ECG signal to produce a noisy equivalent whose behavior would replicate challenges experienced using real-time ECG monitoring. The performance and correctness of testing these filters for noise reduction are measured by noise Eq.1 and simulation analysis by the MATLAB R2023a program (Gaber et al., 2025). The performance of the methods is compared with that obtained using the MIT-BIH Normal Sinus Rhythm Database (MIT-BIH NSR) (Records: 100, 104, 105, 108).

4.1. Case 1: Elimination of Baseline Wander Noise

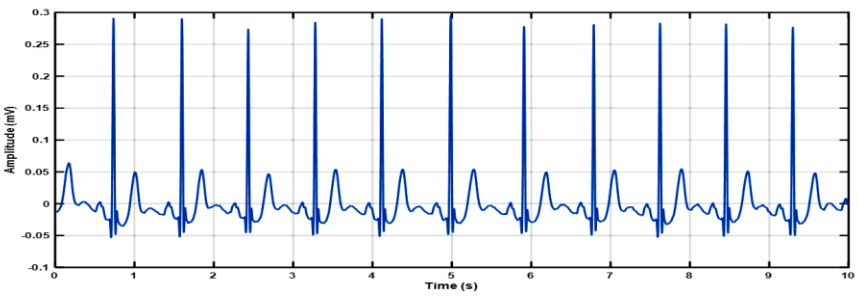
Baseline wander (BW) removal was a major stage in the early process of ECG analysis, as it corrupts certain parts of extracted information, such as the ST segment from the ECG signal, which is one vital feature containing various kinds of medical information. The filter employed in this experiment is a 6th-order high-pass Butterworth filter with a cutoff frequency of 0.5 Hz. The ECG signals were corrupted by a baseline wander frequency of 0.2 Hz with an amplitude of 0.05 that was added through Eq.4, as shown in Fig. 4.



(a)



(b)



(c)

Fig. 4. (a) The original signal from MIT-BIH; (b) the noisy ECG signal with BW noise; and (c) the filtered signal with no BW and without a DC component that is centred around zero.

Fig. 4 illustrates the removal of the baseline wander in the ECG signal. Fig. 4(a) shows the original signal without noise. It is usually recorded to contain a direct current and not cantered on the zero line, as it includes all parts of the signal and its components in an organized and straightforward manner, while in Fig. 4(b), the noise was added to the original signal at several different frequencies ranging from 0.1 to 0.5 Hz to test the noise change on the original signal. As for Fig. 4(c), the filtered signal is without baseline deviation and no direct current component and centres the signal on the zero line thanks to the high-frequency Butterworth filter, and the preservation of important diagnostic features, especially the low-frequency parts close to the noise frequency, such as the ST segment, makes it clearer and better for analysis.

4.2. Case 2: Elimination of Power Line Interference Noise

Noise from power lines, called power line interference (PLI), can also show up in ECG signals. It looks like 50 Hz or 60 Hz sinusoidal interference. It distorts the raw ECG signal by adding 50 Hz and an amplitude of 0.02 to these signals, as shown in Eq. 2. A Gaussian window filter, set to a standard deviation of 10 and a window size of 51, will be utilized to eliminate PLI noise and evaluate the respective performances of the filter, as shown in Fig. 5.

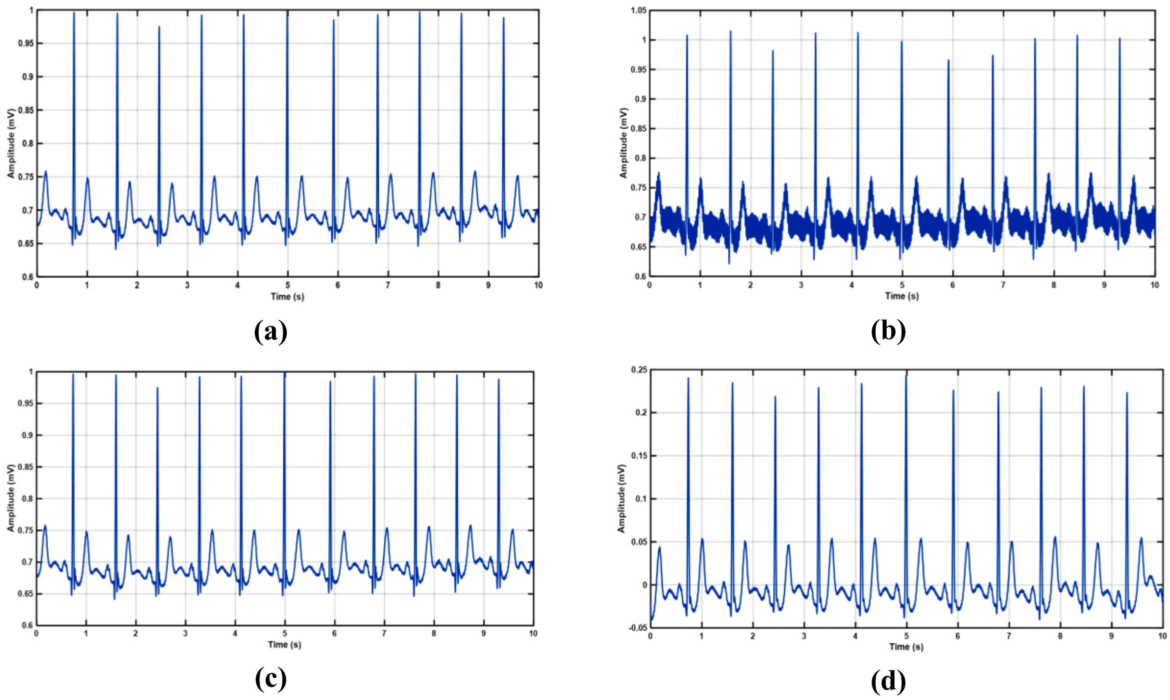


Fig. 5. (a) The original signal from MIT-BIH; (b) the noisy ECG signal with PLI noise; and (c) the filtered signal with no PLI; and (d) the filtered signal without a DC component that is centred around zero.

Fig. 5 illustrates a flow diagram for the processing of ECG signals to eliminate power line interference (PLI) by the use of various filters. Fig. 5(a) displays a pure ECG signal absent of noise, exhibiting distinct R-peaks; conversely, Fig. 5(b) illustrates an ECG compromised by PLI noise, resulting in intermittent disturbances that render the waveform cumbersome to delineate. Fig. 5(c) illustrates the outcome of the Gaussian filter, demonstrating the removal of noise and the resultant smoothing effect. This difference clearly demonstrates the enhanced efficacy of the Gaussian filter in preserving the morphology of the ECG. Fig. 5(d) eliminates the DC offset in the filtered ECG signal, cantering it on the zero line for enhanced filtering.

4.3. Case 3: Elimination of Electromyogram Noise

The electrical activity of muscles during contraction contributes to EMG noise. The frequency of EMG noise ranges from 100 to 150 Hz. A low-pass filter can remove EMG noise with a high frequency above 100 Hz. A Savitzky-Golay filter with a polynomial order of 9 and a frame length of 21 was used to eliminate EMG noise. An electromyogram frequency of 150 Hz and an amplitude of 0.01 was added to the ECG signals to test the performance and accuracy of this filter by Eq.6, as shown in Fig. 6.

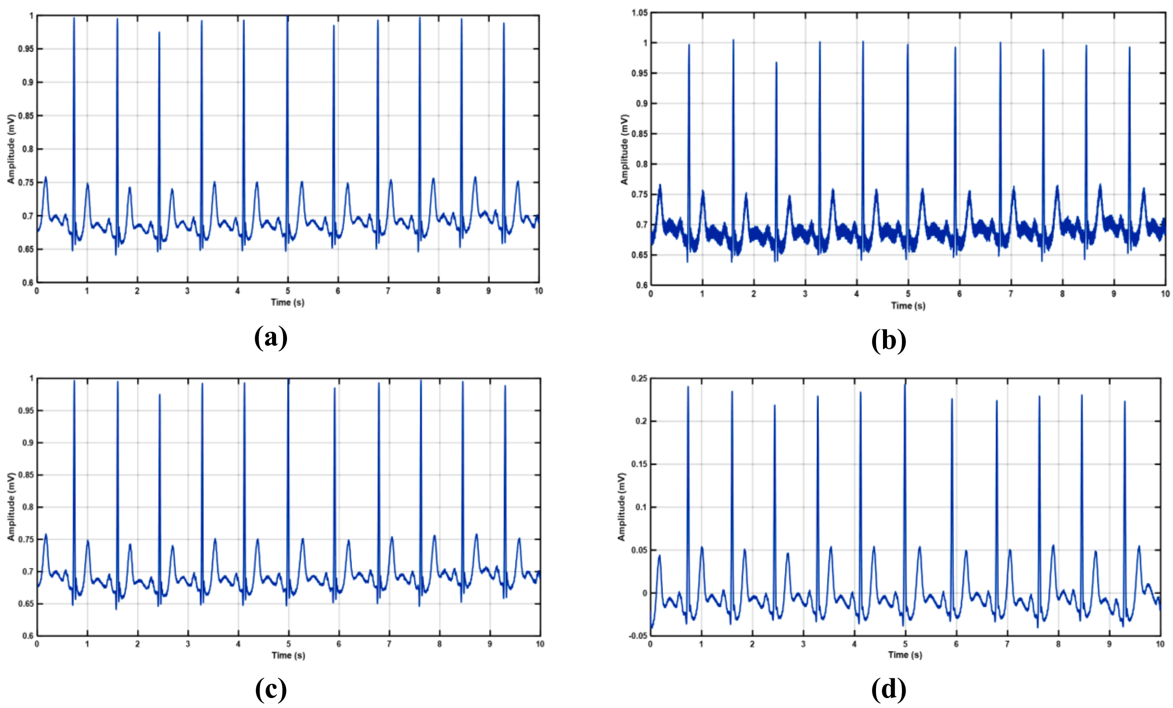
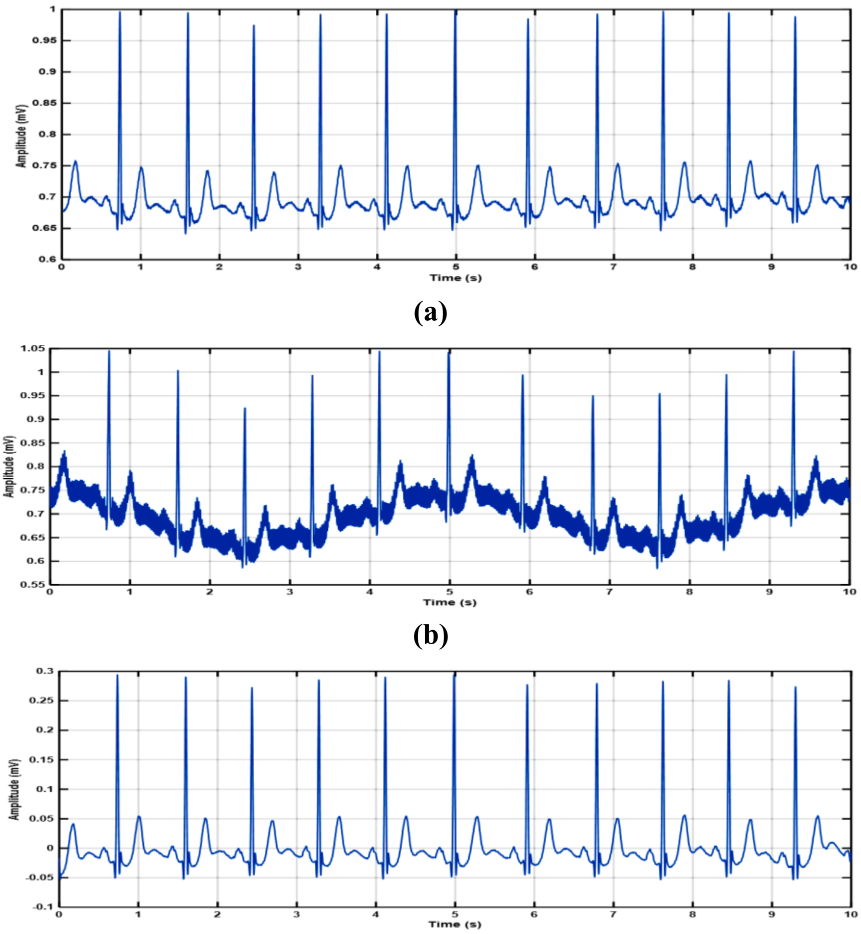


Fig. 6. (a) The original signal from MIT-BIH; (b) the noisy ECG signal with EMG noise; and (c) the filtered signal with no EMG; and (d) the filtered signal without a DC component that is centred around zero.

Fig.6 shows the steps that are used to process an ECG signal from EMG noise: Fig.6(a) is the original ECG signal with a baseline offset; Fig.6(b) is an ECG signal that is noisy due to EMG noise, which introduces high-frequency interference; and Fig.6(c) is the filtered signal after a Savitzky-Golay filter is applied, which skillfully smooths out the noise while keeping essential features like the QRS complexes, making the signal clear and suitable for precise analysis. Fig.6(d) is the signal without the DC component, centered at the zero line for better analysis.

4.4. Case 4: Eliminate multiple sources of noise

A combined noise signal was constructed by combining three noise sources from cases (1, 2, and 3) to simulate real-world conditions impacting ECG signal accuracy. These filters effectively eliminated multiple noise sources. This maintained the integrity of the ECG signal for precise analysis. Fig. 7 illustrates this.



(c)

Fig. 7. (a) Original ECG signal; (b) Added BW, PLI, and EMG noise; and (c) Filtered ECG signal without noise and DC component and is centred around the zero line.

Fig. 7 illustrates denoising an ECG signal using several filter designs. Fig. 7(a) represents the original waveform having distinct PQRST complexes. Fig. 7(b) shows the corrupted ECG signal, which contains BW, EMG and PLI noise, where the BW caused baseline drifts, the high-frequency jitter was due to EMG and the high level of periodic noise was responsible for PLI. When the filter is set in Fig. 7(c), the implemented filters are utilized to purify a filtered signal finally. The last result maintains the physiologic character of the ECG, indicating that the filters are effective in reducing noise.

4.5. Segmentation

The processed ECG is subjected to a segmentation process, which plays a crucial role in the detection of some cardiac events like QRS complexes, P-waves, and T-waves. Segmentation is a fundamental requirement for applications such as heartbeat classification, arrhythmia detection, and feature extraction in machine learning algorithms. The corresponding result is shown in Fig. 8.

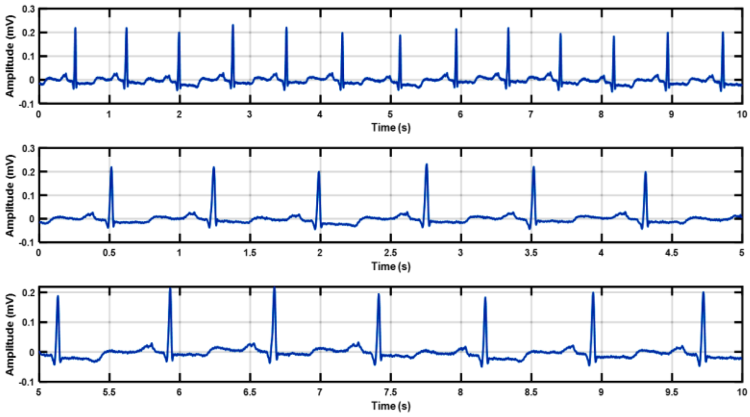


Fig. 8. A segmented ECG signal.

Fig. 8 is the segmented ECG signal. The high figure shows the 10 second filtered signal in its entirety and the two lower figures contain various information about segment 1 (0–5 seconds) and segment 2 (5–10 seconds). The segmentation provides a better visualization of different heartbeats, notably the more dominant R-wave peaks. The magnified views aid in identifying minor alterations that would be overlooked in the complete signal. This approach aids in ECG interpretation for both automatic evaluation and manual diagnosis of cardiac diseases.

4.6. Performance Metrics Results

The performance of the filters in terms of a denoised effective filter was subsequently statistically compared using signal-to-noise ratio (SNR), mean square error (MSE), root-mean-square error (RMSE), and correlation coefficient (CC). These criteria quantitatively determine the performance for each of the filtering techniques in signal reconstruction via comparing the filtered signals with the real clean ones. The results are shown in Table 1 and Table 2.

Table 1. Performance metrics analysis (SNR, MSE) for digital filters.

Case No.	Filter Type	Filter order	ECG signal (100m)		ECG signal (104m)	
			Before filtering		Before filtering	
			SNR (dB)	MSEx10^{-3}	SNR (dB)	MSEx10^{-3}
			26.75	1.25	25.92	1.31476
			After filtering		After filtering	
			SNR (dB)	MSEx10^{-3}	SNR (dB)	MSEx10^{-3}
Case 1	Butterworth HPF	6	44.13	1.19555	43.33	1.25
Case 2	Gaussian Window Filter	51	35.49	0.16720	34.15	0.18786
Case 3	Savizky-Golay Filter	9	42.28	0.03503	41.54	0.03433
Case 4	Integrated Filters	---	39.50	0.06642	39.65	0.05295

Table 2. Performance metrics analysis (RMSE, CC) for digital filters.

Case No.	Filter Type	Filter order	ECG signal (100m)		ECG signal (104m)	
			Before filtering		Before filtering	
			RMSEx10^{-3}	CC	RMSEx10^{-3}	CC
			0.03873	0.6002	0.03873	0.7575
			After filtering		After filtering	
			RMSEx10^{-3}	CC	RMSEx10^{-3}	CC
Case 1	Butterworth HPF	6	0.01129	0.9373	0.01102	0.9701
Case 2	Gaussian Window Filter	51	0.01300	0.9266	0.01377	0.9596
Case 3	Savizky-Golay Filter	9	0.00663	0.9819	0.00658	0.9902
Case 4	Integrated Filters	---	0.00569	0.9633	0.00559	0.9863

Table 1 and Table 2 demonstrate the performance of different filters on ECG signals. It shows clear improvements in signal quality, as shown by the higher SNR, lower MSE, lower RMSE, and higher CC. Before filtration, the unprocessed ECG signals display moderate noise levels, with SNR values of about 25–26 dB, MSE of 1.25x10^{-3}, 1.31476x10^{-3}, RMSE of 0.03873x10^{-3}, 0.03873x10^{-3}, and CC of 0.6002, 0.7575.

Table 3 displays the performance metrics of the proposed method compared to other methods in terms of SNR and MSE. As can be seen, the proposed method outperforms other methods in terms of SNR.

Table 3. A comparative analysis of the proposed techniques against different techniques for SNR and MSE.

Reference	Technique	SNR (dB)	MSE
(Rawash et al., 2024)	Gaussian	8.0443	---
(Rawash et al., 2024)	Mittag-Leffler	8.0443	---
(Rawash et al., 2024)	Savitzky-Golay	40.1950	---
(Waheed, 2023)	Low pass filter [2]	12.32	0.049
(Waheed, 2023)	Zero phase shift [2]	15.72	0.006
(Sinnoor and Janardhan, 2022)	MLPT [20]	16.26	0.0350
(Sinnoor and Janardhan, 2022)	EMD [20]	9.250	0.1297
(Sinnoor and Janardhan, 2022)	HYBRID MLPT-EEMD	22.84	0.0140
Proposed Technique		39.65	0.052x10-3

5. CONCLUSIONS

The proposed method in this study is a new standard ECG noise reduction procedure using three high-performance filters (Butterworth high-pass filter, Savitzky-Golay, and Gaussian window filter). This novel multistage filtering scheme successfully eliminates the BW, PLI, and EMG noises, resulting in a substantial enhancement in the quality of the collected signal. The approach is successful in providing significant signal quality improvement with an increase of SNR from 25 dB to the value of 39.65 dB and decrease of MSE from 0.0015 to 0.05295x10^{-3}, while not affecting important diagnostic components such as ST segment and QRS complex. Additionally, the segmentation also enhances the accuracy of ECG analysis in arrhythmia detection. This method provides a significant improvement in ECG signal processing, indicating that it has the potential to serve as an efficient tool for clinical diagnosis and real-time monitoring. Further development will involve extending the current approach to incorporate machine learning with integrated filtering and developing a real-time database, which makes it more clinically applicable.

6. REFERENCES

ABDULWAHAB, S. S., K.KHLEAF, H. & H.JASSIM, M. 2021. EEG Motor-Imagery BCI System Based on Maximum Overlap Discrete Wavelet Transform (MODWT) and cubic SVM. Journal of Physics: Conference Series.

ALRUBEI, M. A. T. & DMITRIEVICH, P. A. 2023. An Approach for Single-Tone Frequency Estimation Using Dft Interpolation with Parzen Windowing. Kufa Journal of Engineering, 14, 93-104.

AZZOUZ, A., BENGHERBIA, B., WIRA, P., ALAOUI, N., SOUAHLIA, A., MAAZOUZ, M. & HENTABELI, H. 2024. An efficient ECG signals denoising technique based on the combination of particle swarm optimisation and wavelet transform. Heliyon, 10, e26171.

BING, P., LIU, W., ZHAI, Z., LI, J., GUO, Z., XIANG, Y., HE, B. & ZHU, L. 2024. A novel approach for denoising electrocardiogram signals to detect cardiovascular diseases using an efficient hybrid scheme. Front Cardiovasc Med, 11, 1277123.

CHATTERJEE, S., THAKUR, R. S., YADAV, R. N., GUPTA, L. & RAGHUVANSHI, D. K. 2020. Review of noise removal techniques in ECG signals. IET Signal Processing, 14, 569-590.

CHE, C., ZHANG, P., ZHU, M., QU, Y. & JIN, B. 2021. Constrained transformer network for ECG signal processing and arrhythmia classification. BMC Med Inform Decis Mak, 21, 184.

CHIENG, T. M., HAU, Y. W., BIN OMAR, Z. & LIM, C. W. 2020. Qualitative and Quantitative Performance Comparison of ECG Noise Reduction and Signal Enhancement Method based on Various Digital Filter Designs and Discrete Wavelet Transform. International Journal of Computing and Digital Systems, 9, 553-565.

D.YUSUF, S., MADUAKOLAM, F. C., UMAR, I. & Z.LOKO, A. 2020. Analysis of Butterworth Filter For Electrocardiogram De-Noising Using Daubechies Wavelets. International Journal of Electronics and Communication Engineering, 7, 8-13.

FAIZ, M. M. U. & KALE, I. 2022. Removal of multiple artifacts from ECG signal using cascaded multistage adaptive noise cancellers. Array, 14.

GABER, R. K., SALIH, R. S. & JIAAD, S. M. 2025. Artificial Neural Network (ANN) based Proportional Integral Derivative (PID) for Arm Rehabilitation Device. Kufa Journal of Engineering, 16.

HERMAWAN, I., SEVANI, N., ABKA, A. F. & JATMIKO, W. 2024. Denoising Ambulatory Electrocardiogram Signal Using Interval-Dependent Thresholds-based Stationary Wavelet Transform. International Journal on Informatics Visualization.

K, M. & SYED, K. 2024. Arrhythmia classification for non-experts using infinite impulse response (IIR)-filter-based machine learning and deep learning models of the electrocardiogram. PeerJ Comput Sci, 10, e1774.

KRISHNA CHAITANYA, M. & SHARMA, L. D. 2022. Electrocardiogram signal filtering using circulant singular spectrum analysis and cascaded Savitzky-Golay filter. Biomedical Signal Processing and Control, 75.

LESKI, J. M. 2021. Robust nonlinear aggregation operator for ECG powerline interference reduction. Biomedical Signal Processing and Control, 69.

LIU, B. & LI, Y. 2021. ECG signal denoising based on similar segments cooperative filtering. Biomedical Signal Processing and Control, 68.

LIU, M., HAO, H., XIONG, P., LIN, F., HOU, Z. & LIU, X. 2017. Constructing a Guided Filter by Exploiting the Butterworth Filter for ECG Signal Enhancement. Journal of Medical and Biological Engineering, 38, 980-992.

MADUAKOLAM, F. C., YUSUF, S. D. & UMAR, I. 2022. Analysis of Savitzky-Golay Filter for Electrocardiogram De-Noising Using Daubechies Wavelets. EDUCATUM Journal of Science, Mathematics and Technology, 1.

MANJU.B.R & SNEHA.M.R 2020. ECG denoising using Wiener filter and Kalman filter. Procedia Computer Science,171.

MISHRA, A., SAHU, S. S., SHARMA, R. & MISHRA, S. K. 2021. Denoising of Electrocardiogram Signal Using S-Transform Based Time–Frequency Filtering Approach. Arabian Journal for Science and Engineering, 46, 9515-9525.

MOHAMMED, H. A., KAREEM, S. W. & MOHAMMED, A. S. 2022. A Comparative Evaluation of Deep Learning Methods in Digital Image Classification. Kufa Journal of Engineering, 13, 53-69.

N. HUSSIN, K., K. NAHAR, A. & KAREEM KHLEAF, H. 2022. A hybrid bat-genetic algorithm for improving the visual quality of medical images. Indonesian Journal of Electrical Engineering and Computer Science, 28.

OLIVEIRA, B. R. D., DUARTE, M. A. Q., ABREU, C. C. E. D. & VIEIRA FILHO, J. 2018. A wavelet-based method for power-line interference removal in ECG signals. Research on Biomedical Engineering, 34, 73-86.

PŁAWIAK, P. 2018. Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system. Expert Systems with Applications, 92, 334-349.

RAWASH, Y. Z., AL-NAAMI, B., ALFRAIHAT, A. & OWIDA, H. A. 2024. Advanced Low-Pass Filters for Signal Processing: A Comparative Study on Gaussian, Mittag-Leffler, and Savitzky-Golay Filters. Mathematical Modelling of Engineering Problems, 11, 1841-1850.

SAMANN, F. & SCHANZE, T. 2019. An efficient ECG Denoising method using Discrete Wavelet with Savitzky-Golay filter. Current Directions in Biomedical Engineering, 5, 385-387.

SINNOOR, M. & JANARDHAN, S. K. 2022. An ECG Denoising Method Based on Hybrid MLTP-EEMD Model. International Journal of Intelligent Engineering and Systems, 15.

TALIB, M., ABDULLAH, A., ABDULLAH, A. & HAMZAH, B. 2021. Twin Fetus Ecg Signal Extraction Based on Temporal Predictability. Kufa Journal of Engineering, 11, 35-51.

WAHEED, M. 2023. Pre-processing of ECG signal based on multistage filters. Journal of Integrated Circuits and Systems, 18, 1-6.