Al-Khwarizmi Engineering Journal

Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 22, No. 3, September, (2026), pp. 1- 13

A Hybrid-Elliptic-Notch-Savitzky–Golay Filter Approach for Enhanced ECG Signal Denoising

Fatima W. Abdullah[1,2*], Hadeel N. Abdullah[1]

[1] *Electronic Engineering Department, Electrical Engineering College, University of Technology, Baghdad, Iraq*
[2] *Ministry of Electricity, Operation and Control Office, Baghdad, Iraq*
*Email: eee.24.06@grad.uotechnology.edu.iq

(Received 7 April 2025; Revised 11 March 2026; Accepted 31 May 2026; Published 1 September 2026)
https://doi.org/10.22153/kej.2026.05.001

Abstract

One of the most important testing tools for the assessment and diagnosis of cardiovascular diseases is the electrocardiogram (ECG) signal. However, the ECG signal is very sensitive to different types of noise, such as baseline drift, powerline interference and electromyogram (EMG) noise. Therefore, these noises need to be removed from the ECG signals due to their significance in detection and diagnosis of cardiovascular disease. In this paper, a novel method for simultaneously removing these different types of noise from the ECG signals by using a hybrid filtering framework is proposed. This hybrid approach assures efficient noise reduction, and the integrity of the ECG signal is preserved for accurate diagnosis. The proposed method consists of two stages. In the initial stage, the three filters that make up the hybrid filtering are applied: an elliptic high-pass filter to remove the baseline wander, a notch filter to reduce the 50/60 Hz power line interference and a Savitzky–Golay filter to reduce the high-frequency EMG noise. Second, the preprocessed ECG signal is divided into segments of different durations by segmentation to facilitate practical analysis and feature extraction in later stages. The effectiveness of the proposed method is shown by the tests and proven results using MATLAB R2023a. The method is evaluated using a large collection of real ECG signals from the MIT-BIH arrhythmia database. The proposed method outperforms other methods in signal-to-noise ratio (39.10 dB) and mean square error ($0.06014*10^{-3}$); it can remove different types of noise without distorting the ECG signal characteristics. The study's contribution to reliable noise removal of ECG signals for clinical applications is significant.

Keywords: *Baseline wander; distorting; electrocardiogram; electromyogram; power line interference; noise reduction.*

1. Introduction

The electrocardiogram (ECG or EKG) is a physiological signal that reflects the heart's electrical activity and can be readily recorded with surface electrodes placed on the limbs or chest [1, 2]. ECG signals include a wide variety of low- and high-frequency disturbances caused by the acquisition of ECG signals from patients for the interpretation and identification of physiological and pathological phenomena, which are baseline wander (BW) and the frequency of the BW noise below 0.5 Hz. Power line interference (PLI) and the frequency of 50/60 Hz, and electromyogram (EMG) noise in the frequency range from 100 to 500 Hz [1, 3]. PLI is a high-frequency noise of 50 or 60 Hz. Detecting arrhythmias or other heart diseases in the presence of PLI noise is challenging because it affects important components of the ECG signals, especially low-amplitude signals such as the P wave [4-6]. BW is a low-frequency noise typically ranging from 0 to 0.5 Hz. BW refers to the phenomenon in which the base axis (x-axis) of a signal appears to 'wander' vertically rather than remaining linear when displayed on a screen. This phenomenon results in a complete displacement of the signal from its standard baseline. However, BW obscures small changes in the signal and distorts the S-T segment, potentially leading to misinterpretation of critical diagnostic features [4-6]. EMG is high-frequency noise, typically above a frequency of 100 Hz. The muscular contraction generates high-frequency, low-amplitude random noise. EMG noise can obscure small ECG features, such as the P wave, and distort the T wave and other features of the signal. This situation complicates the execution of accurate analyses, particularly in clinical contexts where accurate identification of cardiac anomalies is essential [5, 6]. Therefore, in the field of biomedical engineering, eliminating noise in the ECG signal is a crucial step of great importance before ECG signal analysis via appropriate techniques [2, 7]. As a result, numerous literature studies have examined the answers suggested in this field of research. Researchers have performed multiple experiments to reduce or eliminate noise in ECG signals, employing various methods to enhance signal quality as demonstrated below.

In contrast to traditional techniques such as electromagnetic dynamic modulation (EMD), Fourier transform modulation (FTM) offers distinct advantages in eliminating BW and PLI noise, preserving the essential features of ECG signals and significantly enhancing the signal-to-noise ratio (SNR). However, it may cause slight distortions in complex signals, especially when affected by high-frequency noise [4]. MA, BW and high-frequency noise are taken out of ambulatory ECG signals by the multistage denoising framework. The framework employs noise-adaptive thresholding, Complete Ensemble Empirical Mode Decomposition (CEEMD) and wavelet transforms. Although efficient in artifact elimination, its computing demands and difficulties in severe noise environments could limit real-time application [5]. The hybrid noise reduction technique for ECG signals consists of nonlocal means (NLM) and high-order synchro squeezing transform (FSSTH). This method can effectively reduce the complex noise whilst preserving the important details of the ECG signal. This method improves performance based on SNR, root mean squared error (RMSE) and percent root mean square difference (PRD). However, it is very costly computationally and has difficulty determining the optimal number of intrinsic mode functions (IMFs) [7]. Gaussian, Mittag–Leffler and Savitzky–Golay (SG) filters are tested, and the SG filter is more effective in removing noise from ECG signals. The filter is effective in reducing noise and preserving the details of the signal. The filter performs better in terms of MSE and SNR [8]. The combination of a high-pass and band-stop filter in an IIR filter is an effective method to remove noise from ECG signals. This method removes BW, low-frequency noise and PLI noise, which improves the clarity of the signal for the classification of arrhythmia. However, its main weakness is that it cannot cope with complex artifacts such as motion noise [9]. The hybrid ECG denoising technique is based on S-transform, bidimensional empirical mode decomposition (EMD) and NLM filtering. This technique efficiently removes various types of noise whilst preserving ECG characteristics but may require more computational resources and careful adjustment for high noise levels [10]. The ECG signal denoising, especially in the existence of motion artifacts, is successfully performed by using the combination of stationary wavelet transform (SWT) and interval-dependent thresholds. This approach outperforms DWT and SWT, with improvements of 18% in RMSE and 45% in PRD. This approach is effective at adaptive thresholding and transient noise handling. However, it may perform poorly at very high noise levels, and the need for manually setting intervals could limit its effectiveness [11]. A two-step ECG noise reduction method is based on CEEMDAN for removing Gaussian noise and SDROM-ADF filters for removing ectopic beats. This method is very efficient at preserving the quality of signal with low RMSE values. However, it is computationally intensive and can run into problems with other complex artifacts constrained by its real-time clinical application [12]. EMD, wavelet thresholding and sparse code reduction improve SNR (19.24), MSE (0.005) and PRD (20.38%) compared with the traditional methods. However, it requires careful selection of parameters, and it may lose signal details by removing higher-order IMFs [13]. The method of ECG BW removal using a resting cycle template is more effective in the reduction of BW than high-pass filters and spline interpolation. This method requires the user to insert a period of rest, limiting its use in some circumstances. More research is needed, especially on arrhythmias [14]. The study investigates four methods for removing PLI from ECG: Discrete Wavelet Transform (DWT), EMD, Kalman Filter (KF) and Kalman Filter Smoothing (KFS). KFS > denoising > preserving ECG morphology > KF DWT and EMD are less effective, especially for low SNR. The algorithms KF and KFS are more efficient and therefore more suitable for real-time applications [15]. FIR filters effectively eliminate low-frequency noise, adaptive filtering modifies in response to signal variations, and wavelet transforms manage temporal and spectral components whilst preserving essential characteristics. Excessive filtering might impair the signal, and wavelet transforms may complicate computations, hence reducing the effectiveness of real-time processing [16].

Therefore, as summarized from the literature reviewed in this field, some limitations exist for traditional methods such as EMD with empirical wave transform (EWT), Fourier decomposition method (FDM) and wavelet-based methods, such as high processing costs, signal distortion or insufficient noise removal for some types of interference. Significant progress in ECG signal denoising has been made lately with the introduction of hybrid and intelligent filtering methods. In recent years, a combination of conventional filters with adaptive and machine learning techniques has been proposed to improve the denoising efficiency whilst preserving important signal characteristics. Hybrid methods of wavelet transforms and median or Gaussian filtering perform better in terms of accuracy and reliability. Moreover, some recent methods such as adaptive decomposition and data-driven models have been proposed to handle the complex noise patterns in real-world ECG signals [10, 17]. The recent modifications indicate an increasing tendency for hybrid and optimized denoising frameworks. These results motivated the development of the strategy proposed in this study. The proposed method combines three filters (elliptic high pass, notch and SG) for the efficient removal of noise types that compromise signal integrity and make diagnosis difficult, such as PLI, EMG and BW. The proposed method does this whilst maintaining the detail of low-frequency ECG features such as the ST segment, which is close to the noise frequency, and high-frequency features such as the QRS complex. This multistage method is less demanding in computing power compared with traditional approaches and needs fewer adjustments whilst enhancing the signal quality and processing time. This approach is preferable for real-time clinical applications. The purpose of this study is to find the best compromise between reduction of noise and preservation of the characteristics of the original signal by evaluating the effectiveness of various filters and thus demonstrating their effectiveness in reducing noise and improving the quality of ECG signals, thereby improving the reliability of diagnostics in clinical environments.

This multistage filtering method can overcome the limitations of traditional denoising methods such as computational complexity, preservation of critical ECG features including the ST segment and effective removal of noise sources such as PLI, EMG and BW noise, thus enhancing the diagnostic reliability in real-time clinical applications.

The remainder of the paper is organized as follows. Section 2 describes the methodology related to the ECG signal details and filtering techniques utilized in the experiments. Section 3 explains the proposed method in depth. Section 4 presents the results and discussion to illustrate the efficacy of the proposed denoising methods. Section 5 states the conclusions.

2. Methodology

An ECG records the heart's electrical activity and is a routine examination in clinical environments for the prevention and detection of cardiovascular disease [5]. An ECG records the heart's electrical activity and contains several cardiac cycles. A cardiac cycle refers to the sequence of contractions and relaxations of the heart muscles that move blood through the four chambers of the heart, circulating it throughout the body and lungs. Recording allows real-time observation of cardiac activity with a cardiac monitor [18]. The ECG signal's abnormalities are diagnosed by looking at the way these waves behave [1]; it provides helpful details about the structural and functional activities of the heart and other tissues in the body [18]. Furthermore, the ECG data contain valuable information that enables doctors to analyse and diagnose CVD [16]. The amplitude and frequency range of a normal ECG signal are generally 10 μV to 5 mV and 0.05 Hz to 40 Hz, respectively [4]. Therefore, before beginning the analysis, the signal must be appropriately filtered from certain types of noise [16]. Figure 1 illustrates the ECG signal's characteristics.

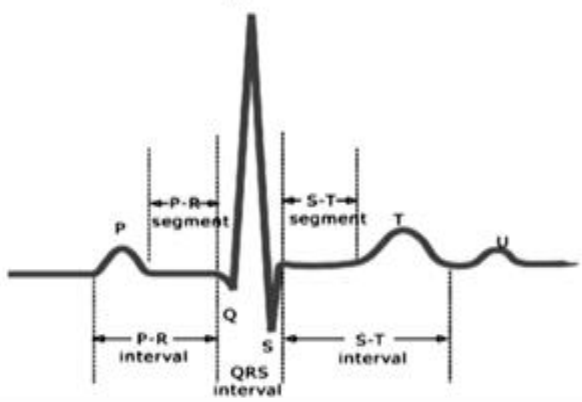


Fig. 1. ECG signal characteristics [19].

Noise, described as any unwanted interference in a signal, can significantly decrease data quality, especially in fields requiring high precision, such as medical diagnostics [8]. Efficient denoising techniques are essential for enhancing the clarity as well as accuracy of signals in essential uses such as ECG [20].

2.1 Elliptic Filter

Elliptic filters, also known as Cauer filters, exhibit ripples in the passband and stopband, enabling a more abrupt transition band and allowing a lower filter order compared with Chebyshev filters for an equivalent cutoff rate. These filters achieve a precise cutoff using notches in the stopband, resulting in the transfer function decreasing at specified frequencies and effectively reducing unwanted noise. A high-pass elliptic filter is often used in ECG signal processing to reduce BW noise. A high-pass elliptic filter can be distinguished from other filters because it has a high cutoff frequency that reduces low-frequency drifts. Figure 2 shows that the filter's response has ripples in the passband and stopband. This feature enables reducing noise very well whilst keeping the original ECG signal intact [21]. The squared magnitude response is expressed by Equation (1).

$$|H)j\omega|^2 = \frac{1}{1+\varepsilon^2 U_n^2(\omega, L)} \quad \dots (1)$$

where ε is the passband parameter, and $U_n^2(\omega, L)$ is the n^{th}-order Jacobian elliptic function. L contains information about relative heights of ripples in the passband and stopband.

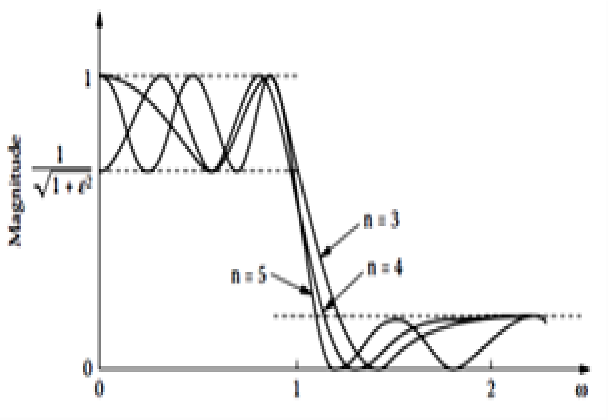


Fig. 2. Elliptic filters [21].

2.2 Notch Filter

A band-reject filter is an electrical circuit that reduces a specific frequency range whilst allowing the passage of all other frequencies. A band-reject filter is categorized into two: broadband and narrowband, commonly referred to as notch filters. A notch filter is a high-quality filter characterized by an extraordinarily narrow stopband. Notch filters are created by combining high- and low-pass filters in parallel, producing a stopband centred at fc, defined by lower (FL) and upper (FH) cutoff frequencies, as demonstrated in Equation 2.

$$f_c = \sqrt{F_H * F_L} \quad \dots (2)$$

These filters are employed for eliminating unwanted noise or interference, including PLI at 50/60 Hz. The essential block diagrams of notch filtering are depicted in Fig. 3, where d(n) indicates the input signal affected by noise, X(n) represents the pristine signal, and N(n) defines the noise [22].

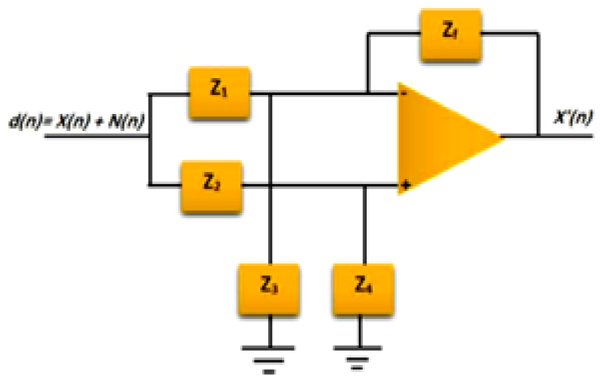


Fig. 3. Notch filter block diagram [22].

2.3 Savitzky–Golay Filter

In 1964, Savitzky and Golay proposed a way of retaining the original signal shape [23]. The SG filter is a digital filter utilized to smooth a collection of digital data points, enhancing data precision without changing the signal's fundamental trend. This method is done with a method called convolution, which involves using the linear least squares method to fit a low-degree polynomial. Polynomial smoothing and differentiation techniques are used in various fields. They are particularly discovered in the processing of ECG and magnetocardiogram signals and in absorption spectroscopy. Small details in a signal are more easily preserved with a higher polynomial order and shorter length of SG filters. Less noise is thrown away [24], as shown in Equation (3).

$$\acute{y}_i = \sum_{j=-m}^{m} c_j y_{i+j} \qquad \text{... (3)}$$

where $\acute{y}_i$ denotes the smoothed value of the i_{th} point, y_{i+j} represents the original data value at position $i+j$, cj signifies the filter coefficients, and m indicates the window size.

The filter parameters (e.g. the cutoff frequencies and the polynomial degree) are carefully selected based on the ECG signal characteristics and the results of previous studies. The cut-off frequencies are picked to preserve the significant features of ECG, such as the P wave, QRS complex and T wave, and efficiently remove BW, PLI and EMG noise. In the SG filter, the polynomial degree was chosen to achieve an optimal compromise between smoothing and preservation of the signal. The parameters were further optimized by empirical evaluation to obtain optimal denoising performance without significant modification of the signal morphology.

2.4 Performance Metrics

The performance of the proposed methodology is evaluated using three evaluation parameters for the proposed filtering techniques in our paper.

SNR is the ratio of the useful signal power to the noise power [3]. Thus, SNR is defined as follows:

$$SNR = 10Log\left(\frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N} n^2(n)}\right) \qquad \text{... (4)}$$

where *s(n)* represents the raw ECG signal, whereas *n(n)* is the noise integrated within the signal. Their relationships are as follows:

$$x(n) = s(n) + n(n) \qquad \text{... (5)}$$

$$n(n) = a\,cos(2\pi f_n t + \varphi) \qquad \text{... (6)}$$

where *x(n)* represents the noisy signal, φ an unknown parameter within the interval [0, 2π], a denotes the amplitude where $a > 0$, and f_n represents the noise frequency.

MSE is the average of the squares of the errors. MSE is the average squared difference between the estimated value and the actual value. MSE is calculated using the equation below [23].

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(x[i] - \tilde{x}[i])^2 \qquad \text{... (7)}$$

The power spectral density (PSD) of an ECG signal represents the power distribution as an expression of frequency. In the PSD figure, the frequency contents of the ECG signal are investigated, and its fundamental characteristics, such as low-frequency components, high-frequency components and notable spikes, are described. To evaluate the effectiveness of a particular filter in terms of noise elimination and preservation of the main characteristics of the ECG signal, the PSD is evaluated before and after filtering [25].

3. Proposed Method

The proposed method is a systematic approach for the analysis of ECG signals obtained from the MIT-BIH database. The proposed method is based on a basic, important step. The proposed method uses signals derived from the raw ECG data of the MIT-BIH arrhythmia database on PhysioNet. The dataset comprises 45 patients (19 girls and 26 men) aged from 23 years to 89 years. The signals are acquired from the MLII lead in 10-second segments with a sampling frequency of 360 Hz and a gain of 200 Adu/mV. Due to its historical importance and comprehensive annotation system, the MIT-BIH database is a benchmark and is cited in 60%–70% of current research on arrhythmia identification and ECG algorithm validation [1, 26].

Firstly, many types of noise, for instance, BW due to patient movement or respiration, PLI from electrical grid signals and EMG noise from muscle contractions, may contaminate raw ECG signals. Real-world scenarios where various types of noise frequently affect ECG signals are simulated in this step to evaluate the efficacy of the proposed method in eliminating integrated noise to address the issues encountered when recording ECG signals from patients in the clinical environment. The signal improvement step employs an elliptic high-pass filter to remove low-frequency noise, including BW and direct current (DC) components, therefore preserving the higher-frequency elements essential for the accurate analysis of the ECG. Additionally, a notch filter is employed to eliminate the 50/60 Hz PLI noise accurately. Subsequently, an SG filter is employed to smooth the signal and remove EMG noise. Then, the postprocessed ECG signal is enhanced and prepared for subsequent analysis.

Finally, the ECG signals are segmented into different lengths for accurate diagnostics, including arrhythmia identification and heart rate variability assessment. Figure 4 presents the general structure of the proposed methodology. The proposed method is effective for noise removal and signal quality improvement and thus appropriate for accurate medical analysis. This outcome is not the case with traditional multistage filtering approaches. The novelty of this method lies in the strategy of filter selection and arrangement. Each stage is designed to remove specific types of noise that generally occur in ECG signals. The design is improved by combining several filtering parameters into a single efficient framework. The design helps enhance, reduce noise and improve signal clarity in ECG analysis.

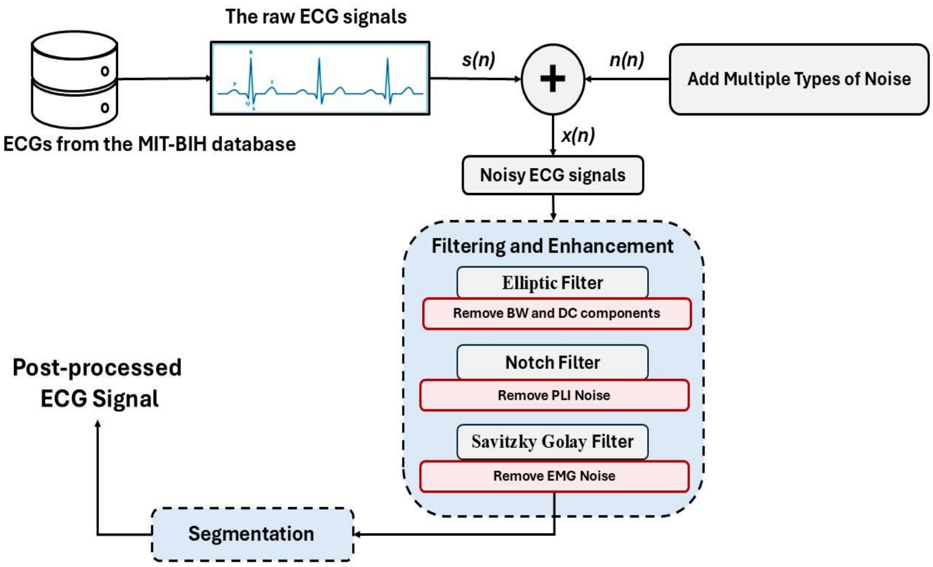


Fig. 4. Proposed Method.

4. Simulation Results and Discussion

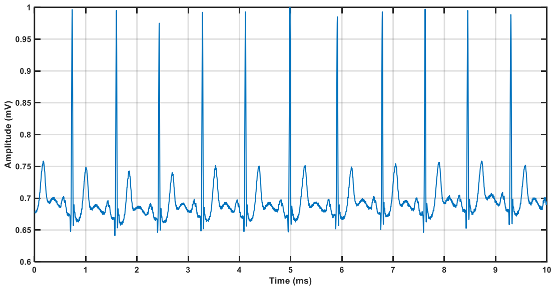
This section presents the results of the proposed methodology for ECG denoising and enhancement. Initially a noisy ECG signal is generated by adding a noise component to the raw ECG signal. In Equation 5, a noise component is added to the original ECG signal to generate a noisy signal, which simulates the challenges of real ECG monitoring. The different types of noise can be removed simultaneously by using an elliptic high-pass filter and a notch filter, and the SG filter. The proposed method attempts to minimize noise significantly whilst preserving the integrity of important ECG signal features such as the ST segment and QRS complex.

4.1 First Case: Filtering Baseline Wander and Power Line Interference

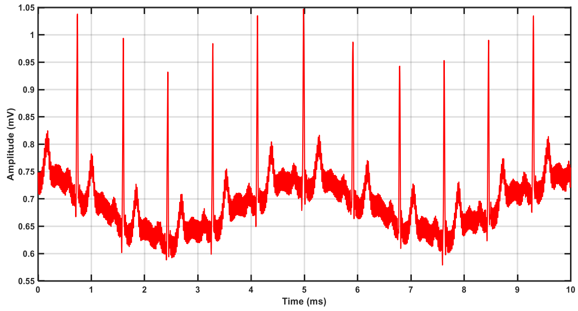
BW is a low-frequency noise artifact that can significantly distort the ECG signal, especially the important signal components such as the ST segment. To simulate the noise, the ECG signal is contaminated with BW noise with frequency 0.2 Hz and amplitude 0.05 mV, in addition to PLI with frequency 50 Hz and amplitude 0.02 mV. Mathematically, this noisy signal is expressed by Equation 8:

$$x(n) = s(n) + (BW_{noise} + PLI_{noise}) \qquad \dots (8)$$

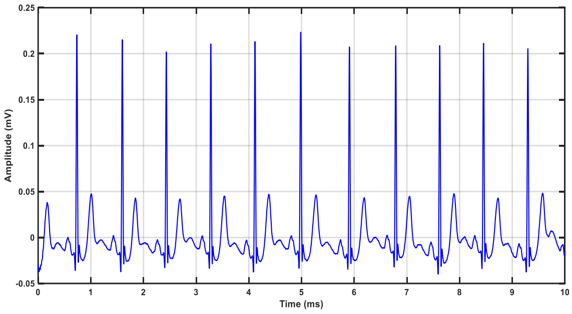
To reduce the effect of BW and PLI, the following filtering techniques are used: BW noise is removed with a sixth-order elliptic high-pass filter with a cutoff frequency of 0.5 Hz. The filter is designed to have a passband ripple of 1 dB and a stopband attenuation of 40 dB, permitting it to reduce the low-frequency components effectively without distorting the signal. The 50 Hz PLI is suppressed by a notch filter with a normalized notch frequency of 0.2778 Hz and a bandwidth of 0.00794 Hz. The notch filter successfully removes the PLI and preserves the ECG signal fidelity. Figure 5 demonstrates the results after applying these filtering techniques. The filtered ECG data depict the efficacy of BW and PLI removal.



(a)



(b)



(c)

Fig. 5. (a) Original ECG signal; (b) Added BW, PLI noise; and (c) Filtered ECG signal without BW, PLI noise and DC component and is centred around the zero line.

Figures 5 illustrates the processing of the ECG signal. Figure 5(a) shows the original, pure ECG shows a smooth, noise-free waveform with clearly recognizable heartbeats. Figure 5(b) reveals that noise PLI and BW introduce distortion to the pure ECG signals. Understanding is now complicated by noise effects and fluctuations that compromise the pure structure of the original signal. Figure 5(c) shows the final filtered signal. The signal is passed through a notch filter and an elliptical high-pass filter to reduce noise and the DC component, respectively. This approach results in a significantly clearer ECG, where the heartbeats are more easily distinguished, thus demonstrating the effectiveness of filtering methods in enhancing the quality of the signal without removing the significant characteristics of the ECG signals.

4.2 Second Case: Filtering Baseline Wander, Power Line Interference and Electromyogram

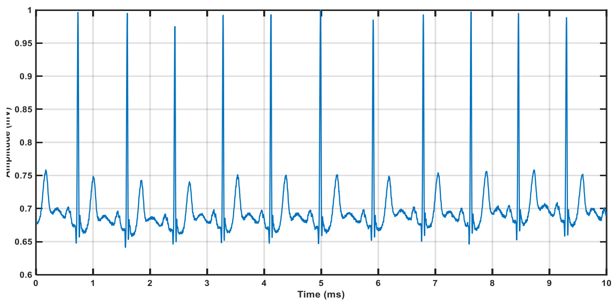
The ECG signal is integrated with BW, PLI and EMG noise. The following noise components contaminate the initial ECG signal:

- BW: Frequency of 0.2 Hz and amplitude of 0.05 mV.
- PLI: Frequency of 50 Hz and amplitude of 0.02 mV.
- EMG noise: frequency of 150 Hz and amplitude of 0.01 mV.

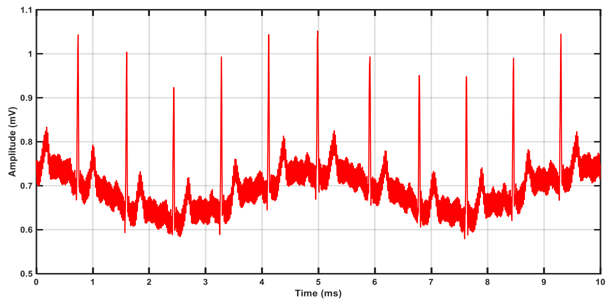
The ECG signal, characterized by combined noise, is expressed in Equation 9.

$$x(n) = s(n) + BW_{noise} + PLI_{noise} + EMG_{noise} \quad \text{... (9)}$$

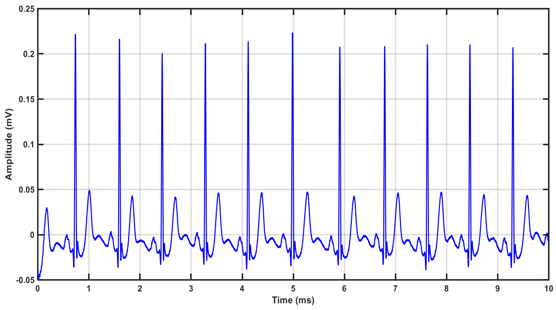
To reduce these noise sources, the subsequent filters are used: An elliptic high-pass filter and a notch filter: SG Filter: As described in Case 1, an SG filter is used to remove high-frequency (EMG) noise. The filter has a window size of 15 and a polynomial degree of 3. The SG filter attenuates the high-frequency noise of the signal and preserves the significant features of the ECG waveform. The SG filter is especially effective in reducing EMG noise whilst preserving the original ECG signal. Figure 6 shows the results of using these filtering techniques in combination. The combined technique is effective for removing the noise of BW, PLI and EMG from the ECG signal.



(a)



(b)



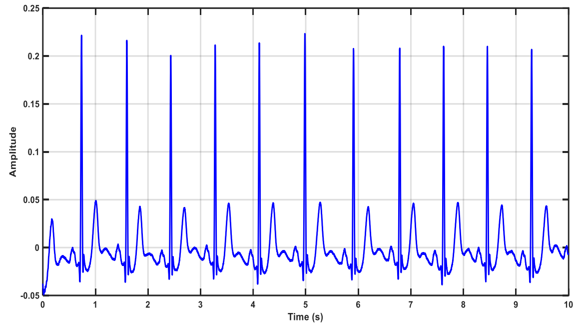
(c)

Fig. 6. (a) Original ECG signal; (b) Added BW, PLI and EMG noise; and (c) Filtered ECG signal without BW, PLI, EMG noise and DC component and is centred around the zero line.

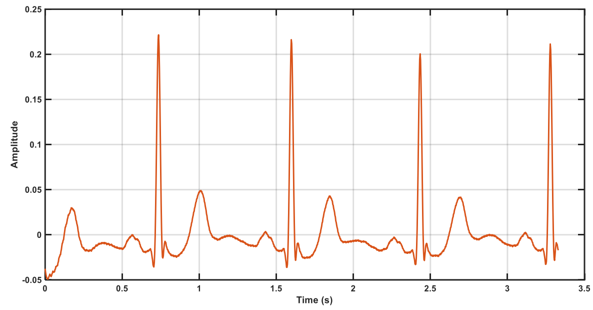
Figure 6 demonstrates the process of ECG signals starting from Figure 6(a) where the clean original ECG shows clear heartbeats with prominent R-wave peaks. Figure 6(b) shows many noise sources such as PLI, BW and EMG, which significantly distort the signal and hinder identifying heartbeats. Figure 6(c) shows the ECG after applying a mixture of notch and elliptical high-pass filters and an SG filter. This approach effectively filters out noise and the DC component, thus providing the signal cleaner and the heartbeats easier to identify. This outcome shows that advanced filtering techniques can improve the quality of ECG signals whilst preserving the properties of the original signal.

4.3 Segmentation

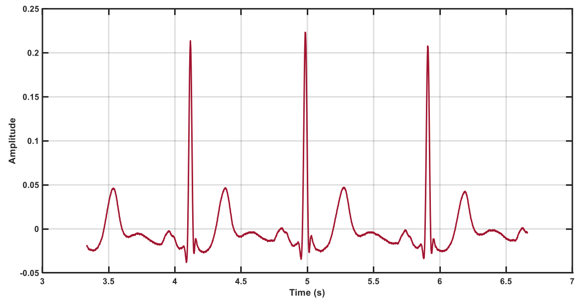
ECG segmentation has several advantages, such as specific evaluation where researchers can focus on some parts of the signal, such as the P wave, QRS complex and T wave, for detailed research. Making these patterns visible in some parts of the signal facilitates finding problems such as cardiac arrhythmias and premature beats. Segmentation enhances signal processing by filtering and analysing each segment separately, which reduces noise and isolates important characteristics. The segmentation of ECG in the present work is performed using MATLAB code. Figure 7 demonstrates the results of ECG signal segmentation.



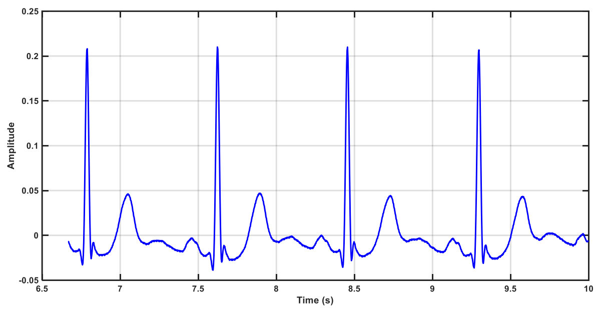
(a)



(b)



(c)



(d)

Fig. 7. (a) Original ECG signal, (b) segment1, (c) segment 2 and (d) segment 3.

Figure 7 shows the segmented analysis of an ECG signal, which is broken down into three sections, each dealing with a different part of the signal. Figure 7(a) shows the final filtered signal. Figure 7(b) demonstrates the initial segment of the ECG, which is important for the evaluation of early cardiac activity. Figure 7(c) presents that the second segment emphasizes the middle part, which contains important components such as the R wave and T wave, which are valuable for the study of ventricular activity. Figure 7 shows that the final segment is on the ending phases (d), which facilitates analysing repolarization. The segmentation of the signal allows a detailed look at some cardiac processes by isolating important components of the ECG signal for accurate evaluation. This method enables identifying issues and improves diagnostics.

4.4 Performance Metrics Analysis

Table 1 demonstrates the filters are applied in sequence to improve the quality of the signal gradually. Firstly, the signal is filtered by an elliptic high-pass filter to eliminate the BW noise, which enhances the SNR and reduces the MSE, especially for Case 1. Then, a notch filter addresses 50/60 Hz frequencies to remove PLI noise, thereby improving the SNR and further decreasing the MSE in both scenarios. The SG filter, recognized for its smoothing properties, offers superior improvement by effectively eliminating high-frequency EMG noise, significantly enhancing SNR and reducing MSE in both scenarios. When these filters are used one after the other, the signal becomes stronger because each one targets a different type of noise. After the whole process, the signal is precisely and clearly filtered.

Table 1,
Performance Metrics Analysis.

Filter types	**Case 1**		**Case 2**	
	Before filtering		**Before filtering**	
	SNR (dB)	**MSE *10^{-3}**	**SNR (dB)**	**MSE *10^{-3}**
	25.28	1.45	25.13	1.5
	After filtering		**After filtering**	
	SNR (dB)	**MSE *10^{-3}**	**SNR (dB)**	**MSE *10^{-3}**
Elliptic HPF	33.33	0.22712	32.64	0.26649
Notch Filter	35.98	0.12352	35.98	0.12336
Savitzky–Golay Filter	43.21	0.02337	39.10	0.06014
Final Filtered Signal	43.21	0.02337	39.10	0.06014

The flow chart illustrates the variations in SNR and MSE for Cases 1 and 2, as depicted in Figs. 8 and 9, respectively.

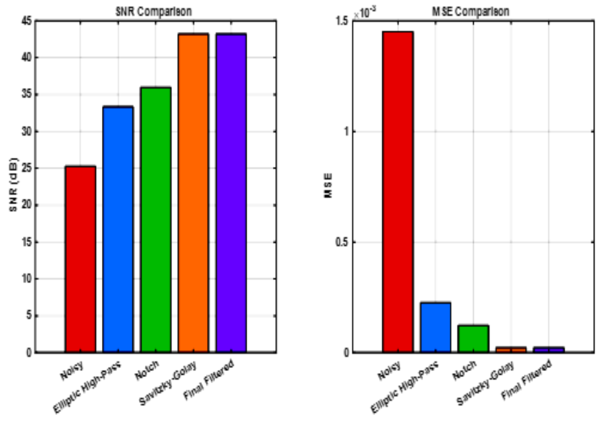


Fig. 8. Comparison of SNR and MSE in Case 1.

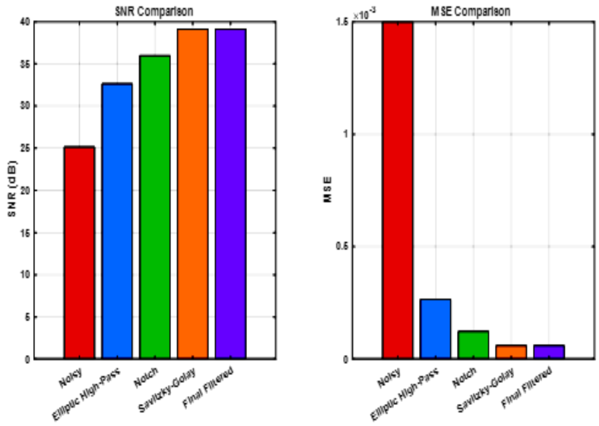
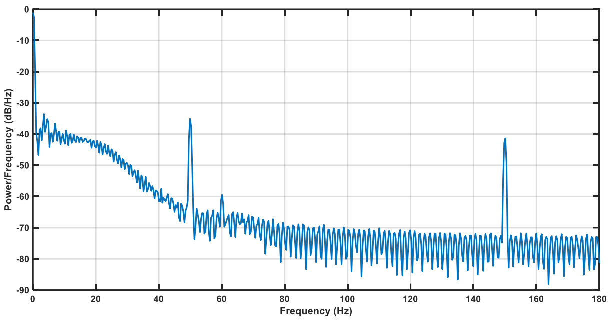
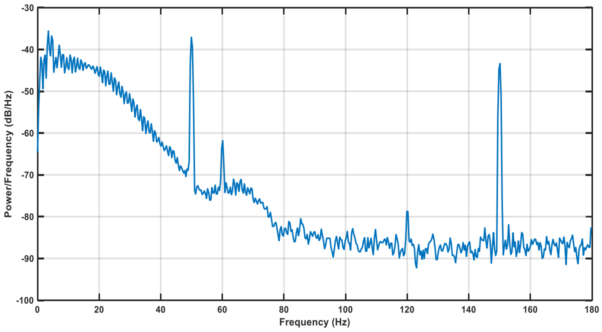


Fig. 9. Comparison of SNR and MSE in Case 2.

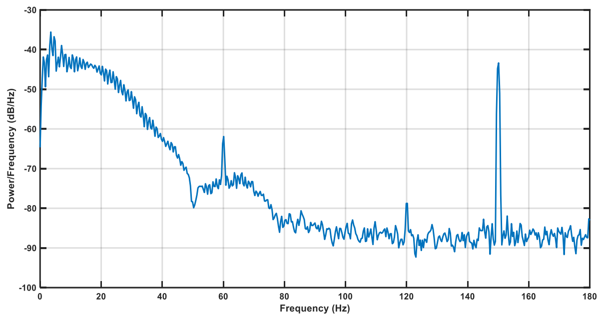
Figure 10 compares the PSDs of an ECG signal before and after different filtering methods are used. Figure 10(a) shows the noisy ECG signal with high-frequency spikes, especially at 60 Hz, which show electrical interference. Figure 10 (b) presents that after using high-pass filtering in the second plot, low-frequency noise is eliminated; however, residual high-frequency noise remains. Figure 10(c) shows the efficient elimination of 60 Hz interference following notch filtering, significantly reducing that specific noise. Finally, Figure 10(d) shows that the SG filtering in the fourth plot attenuates high-frequency noise whilst preserving the overall trend of the signal, producing a cleaner ECG.



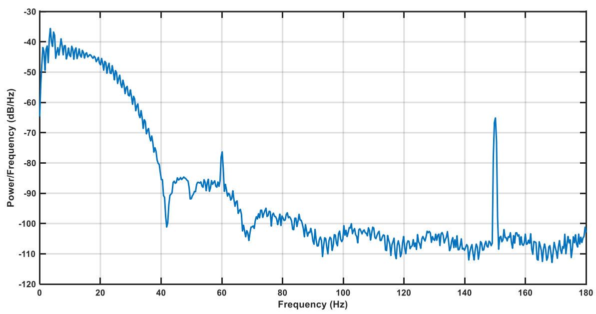
(a)



(b)



(c)



(d)

Fig. 10. (a) PSD noisy ECG signal, (b) PSD after elliptic HPF, (c) PSD after notch filter and (d) PSD after Savitzky Golay filter.

Table 2 shows that the proposed hybrid method achieves an SNR of 39.10 dB and an MSE of 0.06014×10^{-3}, demonstrating superior noise suppression compared with methods such as Gaussian, Mittag–Leffler, CEEMD with WT and EMD. The SG filter by itself has a slightly higher SNR (40.195 dB), but it cannot handle more than one type of noise at a time. The strength of the proposed hybrid approach is that it can reduce BW, PLI and EMG noise simultaneously without changing important parts of the ECG. This feature makes it stronger and more useful for real-world diagnostic purposes.

Table 2,
Comparison between the proposed technique and other techniques.

Techniques	SNR (dB)	MSE
Gaussian [8]	8.0443	---
Mittag–Leffler [8]	8.0443	---
Savitzky–Golay [8]	40.1950	---
CEEMD with WT [5]	25	---
EMD with wavelet domain sparse code shrinking [13]	19.24	0.005
Proposed Techniques	39.10	$0.06014*10^{-3}$

5. Conclusion

Noise needs to be efficiently eliminated from ECG signals. This paper presents a hybrid filtering method that combines elliptical high-pass filters, notch filters and SG filters to eliminate various types of noise whilst preserving the integrity of the useful ECG signal. The proposed method can improve the SNR to 39.10 dB and decrease the MSE to 0.06014×10^{-3}. The results obtained on the MIT-BIH database show that the proposed method is an excellent alternative. Moreover, the proposed method is more effective in removing EMG, PLI and BW noise, thus enhancing signal quality without affecting the essential diagnostic features such as P wave, QRS complex, T wave and ST segment compared with other methods. This paper highlights the efficiency of this hybrid approach as a dependable approach. This method is accurate and robust and is an excellent choice for real-time clinical implementation and integration in wearable health-monitoring devices. Further studies could involve optimizing the algorithm for low-power devices so that it can be used more widely for continuous patient monitoring and telemedicine. The proposed denoising method can improve diagnosis accuracy and patient monitoring in a clinical setting. The proposed method is effective but has some limitations. Performance is sensitive to the selection of parameters that may need to be changed for different data sets. The multistage filtering can improve the computational complexity, which can affect real-time applications, especially when quick decision-making is crucial, as in autonomous systems or live data processing. Improper tuning can also lead to slight distortion of the signal. Future work will focus primarily on the optimization of adaptive parameters for improving performance and reducing computational complexity in real-time applications. These limitations are particularly relevant in real-time, wearable applications, where computational efficiency, power consumption and robustness to noisy environments are important parameters.

Notation

a	Amplitude
fc	Cutoff frequency
F_H	Upper cutoff frequency
F_L	Lower cutoff frequency
w_c	Cutoff frequency
φ	Friction angle

Acknowledgment

The authors express their gratitude and appreciation for the help, support and academic advice provided by their supervisor in completing this scientific research.

Conflict of Interest

The authors declare that they have no conflicts of interest.

References

[1] S. Boda, M. Mahadevappa, and P. K. Dutta, "A hybrid method for removal of power line interference and baseline wander in ECG signals using EMD and EWT," Biomedical Signal Processing and Control, vol. 67, 2021, https://doi.org/10.1016/j.bspc.2021.102466.

[2] X. An, Y. Liu, Y. Zhao, S. Lu, G. K. Stylios, and Q. Liu, "Adaptive Motion Artifact Reduction in Wearable ECG Measurements Using Impedance Pneumography Signal," Sensors (Basel), vol. 22, no. 15, Jul 23 2022, https://doi.org/10.3390/s22155493.

[3] M. Zhang and G. Wei, "An integrated EMD adaptive threshold denoising method for reduction of noise in ECG," PLoS One, vol. 15, no. 7, p. e0235330, 2020, https://doi.org/10.1371/journal.pone.0235330 .

[4] P. Singh, I. Srivastava, A. Singhal, and A. Gupta, "Baseline Wander and Power-Line Interference Removal from ECG Signals Using Fourier Decomposition Method," in Machine Intelligence and Signal Analysis, (Advances in Intelligent Systems and Computing, 2019, ch. Chapter 3, pp. 25-36, https://doi.org/10.1007/978-981-13-0923-6_3?utm_source=chatgpt.com.

[5] X. Xie et al., "A multi-stage denoising framework for ambulatory ECG signal based on domain knowledge and motion artifact detection," Future Generation Computer Systems, vol. 116, pp. 103-116, 2021, https://doi.org/10.1016/j.future.2020.10.024.

[6] S. Chatterjee, R. S. Thakur, R. N. Yadav, L. Gupta, and D. K. Raghuvanshi, "Review of noise removal techniques in ECG signals," IET Signal Processing, vol. 14, no. 9, pp. 569-590, 2020, https://doi.org/10.1049/iet-spr.2020.0104

[7] P. Bing, W. Liu, Z. Wang, and Z. Zhang, "Noise Reduction in ECG Signal Using an Effective Hybrid Scheme," IEEE Access, vol. 8, pp. 160790-160801, 2020, DOI: 10.1109/access.2020.3021068.

[8] Y. Z. Rawash, B. Al-Naami, A. Alfraihat, and H. A. Owida, "Advanced Low-Pass Filters for Signal Processing: A Comparative Study on Gaussian, Mittag-Leffler, and Savitzky-Golay Filters," Mathematical Modelling of Engineering Problems, vol. 11, no. 7, pp. 1841-1850, 2024, DOI: 10.18280/mmep.110713.

[9] M. K and K. Syed, "Arrhythmia classification for non-experts using infinite impulse response (IIR)-filter-based machine learning and deep learning models of the electrocardiogram," PeerJ Comput Sci, vol. 10, p. e1774, 2024, https://doi.org/10.7717/peerj-cs.1774.

[10] P. Bing et al., "A novel approach for denoising electrocardiogram signals to detect cardiovascular diseases using an efficient hybrid scheme," Front Cardiovasc Med, vol. 11, p. 1277123, 2024, https://doi.org/10.3389/fcvm.2024.1277123.

[11] I. Hermawan, N. Sevani, A. F. Abka, and W. Jatmiko, "Denoising Ambulatory Electrocardiogram Signal Using Interval Dependent Thresholds-based Stationary Wavelet Transform," International Journal on

Informatics Visualization, 2024, https://dx.doi.org/10.62527/joiv.8.2.2428.
[12] S. Saleem, A. H. Khandoker, M. Alkhodari, L. J. Hadjileontiadis, and H. F. Jelinek, "A two-step pre-processing tool to remove Gaussian and ectopic noise for heart rate variability analysis," Sci Rep, vol. 12, no. 1, p. 18396, Nov 1 2022, DOI: 10.1038/s41598-022-21776-2.
[13] V. Tiwari et al., "An efficient sparse code shrinkage technique for ECG denoising using empirical mode decomposition," Technol Health Care, p. 9287329241302749, Feb 2 2025, https://doi.org/10.1177/09287329241302749
[14] E. Altamira-Colado, M. Bravo-Zanoguera, D. Cuevas-González, M. Reyna-Carranza, and R. López-Avitia, "Removal of ECG Baseline Wander Using a Resting Cycle Template," presented at the The 8th International Electronic Conference on Sensors and Applications, 2021, https://doi.org/10.3390/ecsa-8-11289
[15] R. M. Bodile and V. K. H. R. Talari, "Removal of Power-Line Interference from ECG Using Decomposition Methodologies and Kalman Filter Framework: A Comparative Study," Traitement du Signal, vol. 38, no. 3, pp. 875-881, 2021, https://doi.org/10.18280/ts.380334.
[16] A. Kattan, S. R. Marwa, and M. A. Shakir, "Improving ECG signals classification by using deep learning techniques: A review," ITM Web of Conferences, vol. 64, 2024, https://doi.org/10.1051/itmconf/2024640102
[17] A. Pal, H. M. Rai, S. Agarwal, and N. Agarwal, "Advanced Noise-Resistant Electrocardiography Classification Using Hybrid Wavelet-Median Denoising and a Convolutional Neural Network," Sensors (Basel), vol. 24, no. 21, Oct 31 2024, https://doi.org/10.3390/s24217033
[18] M. F. Safdar, R. M. Nowak, and P. Pałka, "Pre-Processing techniques and artificial intelligence algorithms for electrocardiogram (ECG) signals analysis: A comprehensive review," Computers in Biology and Medicine, vol. 170, 2024, https://doi.org/10.1016/j.compbiomed.2023.107908
[19] H. Shi, R. Liu, C. Chen, M. Shu, and Y. Wang, "ECG Baseline Estimation and Denoising With Group Sparse Regularization," IEEE Access, vol. 9, pp. 23595-23607, 2021, DOI: 10.1109/access.2021.3056459
[20] A. Mishra et al., "ECG Data Analysis with Denoising Approach and Customized CNNs," Sensors (Basel), vol. 22, no. 5, Mar 1 2022, https://doi.org/10.3390/s22051928
[21] S. A. PACTITIS, ACTIVE FILTERS Theory and Design. 2007.
[22] T. A. SALIH, "New Approach to Eliminate Noise Attendants ECG Signal Corrupted," Journal of Theoretical and Applied Information Technology, vol. 99, 2021.
[23] F. C. Maduakolam, S. D. Yusuf, and I. Umar, "Analysis of Savitzky-Golay Filter for Electrocardiogram De-Noising Using Daubechies Wavelets," EDUCATUM Journal of Science, Mathematics and Technology, vol. 1, 2022, DOI: 10.53797/aseana.v1i2.3.2021.
[24] M. Krishna Chaitanya and L. D. Sharma, "Electrocardiogram signal filtering using circulant singular spectrum analysis and cascaded Savitzky-Golay filter," Biomedical Signal Processing and Control, vol. 75, 2022, https://doi.org/10.1016/j.bspc.2022.103583
[25] B. Babusiak, S. Borik, and M. Smondrk, "Two-Electrode ECG for Ambulatory Monitoring with Minimal Hardware Complexity," Sensors (Basel), vol. 20, no. 8, Apr 22 2020, https://doi.org/10.3390/s20082386
[26] P. Pławiak, "Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system," Expert Systems with Applications, vol. 92, pp. 334-349, 2018, https://doi.org/10.1016/j.eswa.2017.09.022
[27] S. Kumar and M. Singh, “Big data analytics for healthcare industry: Impact, applications, and tools,” Big Data Min. Anal., vol. 2, no. 1, pp. 48–57, 2019, https://doi.org/10.26599/BDMA.2018.9020031

تحسين إزالة الضوضاء من إشارة تخطيط القلب الكهربائية باستخدام تقنية مرشح غولاي الإهليلجي-الشق- سافيتزكي الهجينة

فاطمة وحيد عبدالله[1,2]* , هديل نصرت عبدالله[1]
[1]قسم الهندسة الالكترونية، كلية الهندسة، الجامعة التكنولوجية، بغداد، العراق
[2] وزارة الكهرباء، دائرة التشغيل والتحكم، بغداد، العراق
*البريد الالكتروني : eee.24.06@grad.uotechnology.edu.iq

المستخلص

تُعد إشارة تخطيط القلب من أهم أدوات الاختبار المستخدمة لتقييم وتشخيص أمراض القلب والأوعية الدموية. ومع ذلك، فإنّها تتأثر بشدة بمختلف أنواع الضوضاء، مثل إنحراف خط الأساس، وتداخل خطوط الطاقة، وضوضاء مخطط كهربية العضلات. وبالتالي، يجب إزالة هذه الضوضاء من إشارات تخطيط كهربية القلب نظرًا لدورها الحاسم في الكشف عن أمراض القلب والأوعية الدموية وتشخيصها. تقدم هذه الورقة تقنية جديدة باستخدام إطار عمل ترشيح هجين لمعالجة هذه الأنواع المختلفة من الضوضاء والقضاء عليها في الوقت نفسه من إشارات تخطيط كهربية القلب. يضمن هذا النهج الهجين تقليل الضوضاء بكفاءة مع الحفاظ على سلامة إشارة تخطيط كهربية القلب من أجل تشخيص دقيق. تتكون الطريقة المقترحة من مرحلتين: في البداية، المرشحات الثلاث المنفصلة التي تشكل الترشيح الهجين: مرشح تمرير عالي بيضاوي لإزالة انحراف خط الأساس، ومرشح شق لتقليل تداخل خطوط الطاقة ٦٠/٥٠ هرتز، ومرشح سافيتسكي-جولاي لتقليل ضوضاء مخطط كهربية العضلات عالية التردد. ثانيًا، تُجرى عملية التجزئة لتقسيم إشارة تخطيط القلب المُعالجة مسبقًا إلى مقاطع ذات فترات زمنية مختلفة، مما يُسهّل التحليل العملي واستخلاص الخصائص في المراحل اللاحقة. تُثبت الاختبارات والنتائج المُثبتة باستخدام MATLAB R2023a فعالية الطريقة المُقترحة، والتي جُرّبت باستخدام مجموعة كبيرة من إشارات تخطيط القلب الحقيقية من قاعدة بيانات MIT-BIH لاضطرابات النظم. تفوقت الطريقة المُقترحة على الطرق الأخرى في نسبة الإشارة إلى الضوضاء (٣٩,١٠ ديسيبل) ومتوسط مربع الخطأ (٠,٠٦٠١٤*١٠$^{-3}$)؛ إذ يُمكنها إزالة أنواع مُختلفة من الضوضاء دون تشويه خصائص إشارة تخطيط القلب. تُعدّ مساهمة هذه الدراسة في إزالة الضوضاء من إشارات تخطيط القلب بشكل موثوق للتطبيقات السريرية كبيرة.