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A Comprehensive Survey of ECG Signal Denoising Techniques, Challenges and Novel Trends

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ABSTRACT
The accurate analysis of electrocardiogram (ECG) signals is crucial for cardiovascular diagnosis, but these signals are frequently corrupted by various forms of noise during collection and preprocessing. This survey presents a comprehensive overview of the primary types of noise that affect ECG signals, such as baseline wander, muscle noise, power line interference, and motion artifacts. These sources of noise significantly impair the effectiveness of ECG diagnosis systems. While conventional filtering methods can address some types of noise, they often fall short when it comes to dealing with non-stationary and complex noise patterns. Recent advancements in denoising techniques, including wavelet transforms, empirical mode decomposition (EMD), and deep learning models, demonstrate enhanced performance in reducing noise and preserving signal quality. This review underscores the increasing significance of hybrid approaches that combine traditional and modern techniques, highlighting their potential for real-time applications and improved diagnostic accuracy.

Keywords: *Electrocardiogram (ECG), Cardiovascular, Power line interference, Denoising, Empirical mode decomposition (EMD), Deep learning.*

1. Introduction

Electrocardiography (ECG) is the process of recording the electrical activity associated with the heart. The records thus obtained are known as ECG (Merdjanovska and Rashkovska 2022). This activity is characterized by a succession of events that coincide with the filling and emptying of the heart chambers (Männer 2024). During each of these sequences, a small amount of electrical potential is generated between the heart and the electrodes that are attached to the surface of the skin (Salinet et al. 2023).

The normal ECG has several waves which are given by a P-wave followed by a QRS complex, ST segment, and T-wave. The P-wave corresponds to atrial depolarization, the QRS complex corresponds to ventricular depolarization, the T-wave represents ventricular repolarization, and the U-wave represents atrial repolarization (Okuyama, Kabutoya, and Kario 2024). These waves are recorded in a typical ECG, and these are identified by the neurologist (Pang et al. 2022). Figure 1 (Saad, Abdullah, and Low 2006). shows the general ECG waveform along with these waves. The P-wave shows a change in the electric potential as impulses travel over the atria, which potentially reflects atrial activity (Varaganti, Manisha, and Muvvala 2024). Then, the PR segment is considered to where the junction or atrial pacemaker environment is desired despite the presence of a straight line, which shows no recording activity (Ehnesh 2022). The PRI interval represents the excitement leaders traveling from the sinus node to the atrium which corresponds to the segment (Al Kury et al. 2022). These P, PR segment, and PR interval give an idea about atrial activation (Vedage and Cronin 2024). The QRS complex shows the ventricular activity (De Marco et al. 2022). The ST segment provides the vectors for ventricular activity (Fernández et al. 2022). The T-wave represents the repolarization of the ventricles.

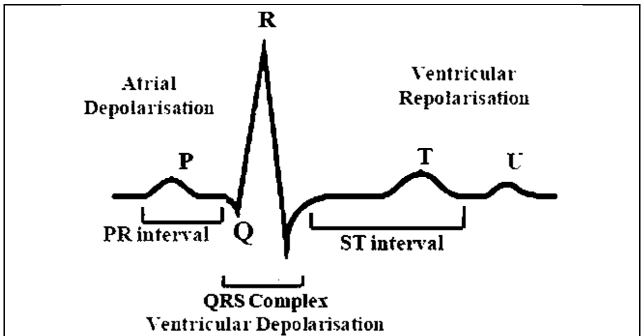

Figure 1: Normal ECG Waveform. (Saad et al. 2006)

The ECG signal suffers from many types of noise. Each type of noise has its own effects on the ECG signal, which influence character recognition, developing of diagnostic systems, etc. (Pereira et al. 2023).

1.1 Predominant noises in ECG Signal

1.1.1 Baseline Wander

Baseline wander in ECG analysis is caused by movement in the setup or other influences (Li et al. 2022). It can originate from muscle signals, power network, or trembling (Deuschl et al. 2022). This disturbance is seen as baseline shift or offset in the signals (Gyurkovics et al. 2022). The error is typically 0.5mm (LI et al. 2022). Electrical interference is a common occurrence (Mulko, Soldera, and Lasagni 2022).

1.1.2 Muscle Noise

Muscle noise is caused by muscle contraction and movement near electrodes (Boyer et al. 2023). It includes electrical noise (EMG) and mechanical vibrations (Kordmiri et al. 2023). Daily activities can introduce rubbing noise, impacts, and other sounds to the ECG leads (Röddiger et al. 2022).

The presence of muscle noise can disrupt the interpretation of ECG signals and affect the reliability of automatic analysis (Xie et al. 2020).

1.1.3 Electromagnetic Interference (EMI)

EMI causes noise in ECG signals. It comes from external electromagnetic fields during transduction from the heart to the body surface and to the sampling device (Roy et al. 2022). Power lines, mobiles, and medical equipment are sources (Sanyal et al. 2021). Biological potential variability also contributes (Fatumo et al. 2022). This review focuses on EMI types in ECG signal processing (Khalili et al. 2024). EMI, or RFI, is man-made noise affecting ECG with 50/60 Hz background noise (Zhuang and Lin 2023).

1.1.4 Power Line Interference (PLI)

Power line interference (PLI) in ECGs is due to frequencies generated by power lines impacting ECG recordings in a powered environment (Anbalagan et al. 2023). PLI prevalence and impact depend on electrical devices and other factors (Kumar et al. 2024). Hospitals may have multiple sources causing PLI (Taghavi et al. 2024). It is typically caused by low frequency electrical networks (50 or 60 Hz) and consists of multiples of that frequency and related artifacts.

1.1.5 Electrode Motion Artifacts

The motion of electrodes can cause noise by changing force on the skin (Zhao et al. 2021). Skin can also move due to physiological processes, affecting the electrode (Wu et al. 2021). Increased motion increases the signal offset (Pollreisz and TaheriNejad 2022). Motion artifacts in an ECG trace shift the baseline, and surgical incisions can produce positive deflections in the QRS complex (Mary and Cann n.d.). Contact between electrodes and electrolyte can also cause noise.

The most important and high-risk form of interference that has a significant impact on the ECG signal is the fourth type of noise, known as power line interference. This interference is the main concern for elimination in the current paper. Subsequent parts will comprehensively examine and address methods for successfully eradicating this power line noise, a difficult task in signal processing.

1.2 Classification of the ECG denoising techniques

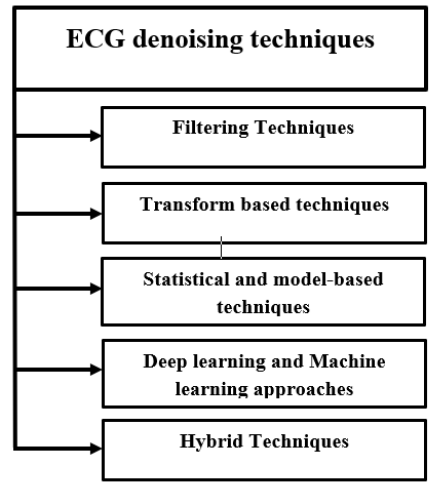

Figure 2: Classification of ECG signal denoising techniques.

This paper is organized as follows. Section 1 introduces the importance of ECG signal processing, the various types of noise that affect ECG recordings, and the significance of denoising techniques. Section 2 outlines the databases used for benchmarking ECG signal denoising methods, highlighting the most widely used datasets in the field. Section 3 presents the different denoising techniques, including traditional filtering, wavelet transforms, empirical mode decomposition, statistical methods, and the emerging role of deep learning models. Section 4 reviews the key challenges in ECG denoising, such as maintaining signal integrity while removing noise, and the complexities of real-time processing. Section 5 discusses future research directions, emphasizing the potential of hybrid techniques and deep learning advancements. Section 6 presents the conclusion of this work.

2. Database

There are several publicly available databases for ECG signals that are commonly used in research and mentioned in many academic papers. Here are some key databases frequently cited:

2.1 MIT-BIH Arrhythmia Database

Description: One of the most popular databases for ECG signals, containing recordings of 48 half-hour excerpts of two-channel ambulatory ECGs.
Use: It's widely used for developing and testing arrhythmia detection algorithms.

2.2 European ST-T Database

Description: Contains ECG signals used to detect ischemia and assess ST and T wave abnormalities.
Use: Evaluating ischemia detection algorithms.

2.3 PTB Diagnostic ECG Database

Description: Includes 549 recordings from 290 subjects, with multiple lead ECG recordings.
Use: Diagnostic algorithm development for heart disease.

2.4 Physikalisch-Technische Bundesanstalt (PTB) ECG Database

Description: Contains 549 high-quality ECG recordings, which can be used for noise analysis and feature extraction algorithms.
Use: Evaluating noise reduction methods in ECG signals.

2.5 Fantasia Database

Description: A collection of long-term ECG recordings from both elderly and young individuals in steady-state conditions.
Use: Studies of heart rate variability and ECG signal processing.

2.6 Long-Term AF Database

Description: Includes long-term ECG recordings from patients with atrial fibrillation (AF).

Use: Developing algorithms for AF detection and studying AF-related ECG characteristics.

2.7 The China Physiological Signal Challenge Database

Description: Provides ECG recordings used in various ECG-based competitions and challenges.
Use: Commonly used for developing machine learning and AI-based ECG processing algorithms.

2.8 AHA Database

Description: The American Heart Association (AHA) database contains a wide variety of ECG signals.
Use: Detection of arrhythmias and ECG abnormalities.

These databases offer standardized benchmarks for the assessment and validation of ECG signal processing methods, including noise reduction, arrhythmia detection, and various other diagnostic applications. Their utilization is prevalent in academic research as well as in the advancement of healthcare technology.

Table 1: ECG databases for various application areas.

Work	Database	Frequency	Length of Recordings	No. of Recordings (people)	Applications
(Li et al. 2020), (Mousavi and Afghah 2019)	MIT-BIH Normal Sinus Rhythm	360 Hz	Up to 24 h	18	Biometric identification
(An and Stylios 2020), (Zhai, Zhou, and Tin 2020)	MIT-BIH Arrhythmia	360 Hz	30 min	48	Arrhythmia detection, Signal denoising
(Li et al. 2020)	MIT-BIH Atrial Fibrillation (AF)	250 Hz	10 h	25	Rhythmic arrhythmia detection, Biometric identification
(Li et al. 2020)	MIT-BIH ST Change	360 Hz	30 min	28	Biometric identification
(Huang, Hu, and Sun 2019)	MIH-BIH Noise Stress Test (NST)	360 Hz	30 min	12 ECG + 3 noises	Signal denoising
(Mousavi et al. n.d.) ,2019	Long Term Atrial Fibrillation (AF)	128 Hz	24 h	84	Rhythmic arrhythmia detection
-	European ST-T	250 Hz	2 h	90 (79)	-
(Fotiadou et al. 2020)	PTB Diagnostic ECG	1 kHz	10 s–2 min	549 (290)	Biometric identification
(Fotiadou et al. 2020)	QT	250 Hz	15 min	100	Signal denoising
(Fotiadou et al. 2020)	St. Petersburg Institute of CardiologicalTechnics12-lead Arrhythmia (INCART)	257 Hz	30 min	75	Arrhythmia detection
(Hamilton and Limited n.d.) ,2002	American Heart Association (AHA)	250 Hz	3h (30 min annotated)	155	(ventricular) arrhythmia detection
(Yao et al. 2020)	The China Physiological Signal Challenge 2018	500 Hz	6 s–60 s	6,877	arrhythmia detection

(Da Poian, Bernardini, and Rinaldo 2016), (Fotiadou et al. 2020)	Abdominal and Direct Fetal ECG (ADFE)	1 kHz	10 min	5	Fetal ECG extraction
(Da Poian et al. 2016), (Fotiadou et al. 2020)	Fetal Electrocardiograms B1_Pregnancy_dataset	500 Hz	20 min	10	Fetal ECG extraction
(Da Poian et al. 2016), (Fotiadou et al. 2020)	Fetal Electrocardiograms B2_Labour_dataset	500 Hz–1 kHz	5 min	12	Fetal ECG extraction
(Da Poian et al. 2016)	Noninvasive Fetal ECG PhysioNet/CinC Challenge2013	1 kHz	1 min	75 train+100 test	Fetal ECG extraction
(Charlton, Villarroel, and Salguiero 2016)	MIMIC	1 kHz	-	67,830 (30,000)	Respiration extraction
(Li et al. 2020), (Varon et al. 2020)	Fantasia	250 Hz	2 h	40	Respiration extraction, Biometric identification
(Bassiouni, Ali, and El-Dahshan 2018)	ECG-ID	500 Hz	20 s	310 (90)	Biometric identification

3. Related work

The ECG denoising methods have been classified into different categories, as mentioned in Figure 2. The first category belongs to ECG denoising using filtering techniques which aims to remove unwanted information from a signal by modifying specific frequencies. It can eliminate variations in a signal and reduce noise.

The proposed approach relies on incorporating a notch filter to diminish the noise present in ECG signals. This involves using various adder topologies. The assessment of different adders is carried out considering their area, delay, and power consumption. Additionally, the efficiency of the notch filter in eliminating noise from ECG signals is evaluated. However, the area of the C-select adder is greater in comparison to other adders. A comparison is made between RCA, C-Skip, and C-Select adders for performance parameters. The design of the notch filter utilizes adders for the analysis of ECG noise removal as presented in (S et al. 2023). A novel real-time filter has been created to effectively eliminate ECG noise with minimal complexity. This method successfully decreases the spikes resulting from power line interference (PLI) while maintaining ECG spikes and identifying the power line frequency. Nevertheless, there are constraints related to the signal-to-noise ratio (SNR) for signals with intricate structures. Additionally, it is challenging to determine the amplitude of noise as the frequency increases. The approach includes canceling single-frequency noise and suppressing PLI interference. Experiments have demonstrated the production of clear ECG readings with minimal computational complexity also presented in (Slimane and Zaid 2021).

Another method depends on adaptive filter for processing in real time. This pioneering method has been tested with simulated signals within the MATLAB software. The adaptation algorithms employed in this study included LMS, NLMS, and Leaky LMS. Despite this, current methods are impractical for real-time processing due to time limitations. Adaptive filters necessitate a reference noise to effectively remove noise. A new method utilizing LMS, NLMS, and Leaky LMS algorithms has been evaluated. This proposed approach is well-suited for real-time application without the need for a reference noise signal. as proposed in (Al-Safi 2021). Another approach utilizing an adaptive filter was tested within the LabVIEW environment, specifically on the MIT-BIH ECG database. This involved comparing the results with those obtained using the LMS and NLMS algorithms, using the Signal to Noise metric as the benchmark. Although, it was found that the LMS and NLMS algorithms were not effective in dealing with high power line noise amplitudes. As a result, the filtered signal still contained noise at certain levels. To address this issue, the algorithm established a threshold for noise magnitude and filtered out the power line noise. The efficiency of this approach was then compared with that of the LMS and NLMS adaptive filter algorithms. also proposed in (Trong Luong, Duc Thuan, and Huy Hoang 2015).

Another research depends on FIR filter employs a Distributed Arithmetic design to successfully remove noise. The evaluation of its effectiveness is based on Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE) using the MIT-BIH database. However, the complexity of the FIR filter increases as the filter order rises, leading to greater memory requirements due to the increase in filter coefficients. The proposal is to implement a Distributed Arithmetic low pass FIR filter on an FPGA for noise reduction. The performance of ECG signal processing will be measured by evaluating SNR and MSE. Xilinx System Generator software will be utilized for FPGA implementation. presented in (Bhaskar and Uplane 2016). While the second depends also reliant on the implementation of a FIR filter to effectively eliminate noise for precise analysis of the ECG signal. The effectiveness is evaluated through comparison with current methods using a range of parameters. Nonetheless, the quality of the ECG signal can be compromised by powerline interference and EMG noise. A sharp cut-off FIR filter with linear phase is employed for noise reduction, and the filtered ECG signal is then compared to the original signal (Roy, Chandra, and In 2018).

Table 2: Comparison of different filtering techniques for PLI Reduction.

Work	Method	Result
(S et al. 2023)	Notch filter	The C-Skip and C-Select adders performed better than the R-Carry adder in delay and power. C-Select had the lowest delay, while C-Skip had the lowest power.
(Slimane and Zaid 2021)	Notch filter	The proposed filter offers clean ECGs, suppresses PLI spikes, and preserves signal. SNR of filtered signal is 217.0 dB, shows accurate selectivity. Filter method compared to Butterworth and wavelet notch filters.
(Al-Safi 2021)	Adaptive filter	The proposed method cleaned ECG signal under different noise scenarios effectively. No need for external signal source for ECG denoising.
(Trong Luong et al. 2015)	Adaptive filter	The proposed algorithm filters power line noise in ECG signals, with higher SNR value than LMS and NLMS. Used MIT-BIH ECG signals database with LabVIEW software.
(Bhaskar and Uplane 2016)	FIR filter	Kaiser window method has superior SNR in FIR filter design. DA FIR filter minimizes hardware resource for noise removal. Spartan FPGA kit has minimum resource for Kaiser window.
(Roy et al. 2018)	FIR filter	Implemented digital FIR filter for ECG noise reduction. Detected QRS complexes, heart rate, and abnormalities. Showed power spectral density of filtered ECG signal.

The second category includes transform-based techniques, which though revealing a distinct heartbeat activity pattern, face significant challenges from power-line interference (PLI) and baseline wandering, leading to considerable noise in the ECG data. These methods utilize a variety of transform approaches such as wavelet transform (WT), Empirical Mode Decomposition (EMD), etc., to reduce the noise.

A proposed a method based on Wavelet transform procedure to efficiently eliminate electrical interference caused by power lines from electrocardiogram readings, thereby ensuring the accurate characterization of f-waves in AF cases. This method has been validated with 48 recordings and has shown improved ECG diagnosis. Despite this, existing PLI reduction methods may not effectively address non-stationary interferences, and there is insufficient information on threshold selection for sinusoidal interference. To address these limitations, a new algorithm has been developed to remove PLI using Stationary Wavelet Transform. The versatile thresholding function of this algorithm ensures optimal performance in various scenarios (García et al. 2018). Wavelet decomposition, without the use of thresholding, proves to be effective in denoising ECG signals. This method outperforms both thresholding and notch filter techniques, with Symlet 8 being identified as the optimal wavelet function. The improvement of ECG is achieved through the process of inverse discrete wavelet transform. Wavelet decomposition effectively smooths the signal while capturing noises. Although, it is important to note the potential energy leakage in the overlap band during the decomposition process (Br et al. 2018). Different families of wavelets and the normalized least mean square (NLMS) algorithm were compared for the purpose of denoising electrocardiogram (ECG) signals, with evaluation based on factors such as mean square error (MSC), power spectral density (PSD), signal-to-noise ratio (SNR), and others. Nevertheless, the sensitivity of the amplitude and duration of ECG signals to noise is a significant concern, as noisy signals can lead to misdiagnosis due to interference. The wavelet transform was found to be more effective than the adaptive NLMS algorithm for denoising ECG signals, particularly in reducing 50 Hz interference, as demonstrated by the superior MSC values (Uzzal Biswas* 2015). The proposed algorithm effectively eliminates powerline interference from ECG signals, enhancing signal quality by 10-72% compared to adaptive filtering. It maintains ECG morphology while minimizing noise. However, adaptive filtering performance deteriorates in the presence of noise, and notch filtering is ineffective for moderate and high levels of noise. The algorithm employs Wavelet Transform for ECG denoising, with a criteria-based approach that balances noise reduction and ECG preservation. Adaptive thresholding is essential for suppressing powerline interference and maintaining signal integrity as presented in (Rodenas et al. 2018). ECG signal denoising with DWT and threshold filters. Metrics: SNR, RMSE, PRD, L2N for noise assessment. An algorithm is being developed for the optimal selection of thresholds using SNR, but it is also necessary to devise an algorithm for selecting the best threshold combinations for various types of ECG noise. This involves applying DWT to effectively denoise ECG signals using specific threshold values, filtering coefficients below a certain value, and selecting suitable SNR and error thresholds. Finally, an analysis of noisy ECG signals from the MITDB is also being conducted. as also presented in (Gualsaquí et al. 2018).

Other approaches used EMD, which is a local and adaptive method in frequency–time analysis. EMD-based adaptive ECG noise removal enhances diagnostic functions, reduces noise with minimal distortion. The proposed technique is more efficient than current methods in terms of signal-to-noise ratio and signal recovery. However, EMD may result in loss of data, FIR methods are not effective in retaining low-frequency components of ECG, and Neural networks require training and are not real-time. On the contrary, EMD technique may lead to loss of data, FIR methods are ineffective in retaining low-frequency ECG components, and Neural network systems require training and are not real-time. The EMD technique improves signal quality by eliminating noise with minimal distortion, breaking down the signal into intrinsic mode functions for filtering, thus enhancing traditional ECG noise removal as presented in (Hussein et al. 2022). In (Bingze Dai 2021) paper proposes EMD and adaptive filter techniques to eliminate BW, PLI, EM, and MA noise from ECG signals, resulting in the best improvement in SNR on the MIT-BIH arrhythmia database. EMD and adaptive filters are employed to refine ECG signals by modifying the transfer functions according to the characteristics of the input signal and breaking down the signals into IMFs. In (Zhang et al. 2020) ECG denoising method using EMD, sample entropy, and an improved threshold function has been developed. This method has been found to be resilient to different types of noise, resulting in improved SNR and reduced MSE. It should be noted, Nonetheless, that the traditional EMD method discards first-order IMF and leaves noise behind, which then requires additional signal smoothing. This can result in the retention of noise even after denoising, necessitating further signal smoothing. The ECG signal denoising process involves EMD, sample entropy, and improved threshold techniques for addressing these challenges by applying EMD decomposition for IMF denoising and utilizing an improved threshold for IMFs. In (Nguyen and Kim 2016) a new adaptive technique for ECG denoising has demonstrated superior performance in enhancing signal-to-noise ratio, minimizing error metrics, and delivering precise and reliable results for healthcare practitioners. This method also effectively maintains the fidelity and quality of ECG recordings, enabling accurate diagnosis of cardiac irregularities. Despite its advantages, Empirical Mode Decomposition (EMD) has limitations such as mode-mixing and challenges in identifying Intrinsic Mode Functions (IMFs) in time-frequency distribution. To address these issues, Enhanced EMD (EEMD) and Genetic Algorithm-based thresholding have been proposed for adaptive denoising, effectively separating noise-dominant IMFs.

Table 3: Comparison of different transform-based techniques for PLI Reduction.

Work	Method	Result
(García et al. 2018)	Wavelet Transform	Algorithm superior in PLI reduction for ECGs. Sixth-order Daubechies wavelet best for PLI. Algorithm preserves waveform integrity in ECGs with AF.
(Br et al. 2018)	Wavelet Transform	Proposed method better than thresholding & notch filter in denoising ECG. Best wavelet: Symlet 8. Superior results for 75% synthetic & 100% real ECG signals.
(Uzzal Biswas* 2015)	Wavelet Transform	Wavelet transform outperformed NLMS and notch filter for denoising ECG. 'bior5.5' had the highest SNR improvement for 50 Hz interference. All three techniques reduced 50 Hz interference.
(Rodenas et al. 2018)	Wavelet Transform	The proposed method enhances ASCI by 10-72% compared to adaptive filtering. Adaptive filtering performs poorly at moderate to high noise levels.

(Gualsaquí et al. 2018)	Discrete Wavelet Transform (DWT)	The algorithm selects optimal threshold for maximum SNR and minimum error, addressing various ECG noise types.
(Hussein et al. 2022)	Empirical Mode Decomposition (EMD)	Proposed ECG noise removal outperforms existing methods in SNR with effective signal recovery.
(Bingze Dai 2021)	Empirical Mode Decomposition (EMD)	Proposed methods remove BW, PLI, MA, and EM from ECG, PEAF has best SNR improvement. EMD reduces PLI and BW effectively.
(Zhang et al. 2020)	Empirical Mode Decomposition (EMD)	Proposed method has higher SNR and lower MSE than previous techniques, superior denoising effect on MIT-BIH arrhythmia database.
(Nguyen and Kim 2016)	Ensemble empirical mode decomposition (EEMD)	The proposed method outperforms others in SNR, MSE, and percent RMSE. Tested on MIT-BIH arrhythmia database with white Gaussian noise.

The Statistical and Model-based Techniques fall into the third category and offer model-based and linear transformations for minimizing power line interference in ECG signals. These techniques utilize 12-lead ECGs and a novel multi-lead interference canceller, which effectively eliminates both overlapping and non-overlapping power-line interference during normal and irregular heartbeats. The canceller is designed to be simple, with minimal computational complexity, and an effective output filter.

The proposed method depends on Kalman filter which is a flexible method for optimizing digital linear filters to achieve optimal tolerances. It learns from data, updates filter characteristics in real-time, and cancels out noise effectively in diagnostic ECG categories. It outperforms other methods for power-line noise interference in ECG signal filtering. (Bodile and Talari 2021) proposed the comparison of techniques for reducing noise in ECG signals, such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), Kalman Filter (KF), and Kalman Filter with Smoother (KFS), focusing specifically on eliminating power line interference (PLI), indicates that the KFS method exhibits superior denoising capabilities when compared to KF, DWT, and EMD. However, it does not effectively address the harmonic frequencies of 50 or 60Hz power line interference in electrocardiograms and only targets power line interference, neglecting other sources of noise. The study evaluates ECG denoising using KFS, DWT, EMD, and Kalman filter techniques, comparing denoising performance based on reconstructed ECG and computational cost. The removal of PLI enhances the clinical interpretation of ECG recordings. (Tahir et al. 2022) proposed that ECG artifacts, specifically addressing PLI interference, and various filtering techniques for noise reduction have been explored. The proposed EKF-based ANC system has shown superior performance compared to the SSRLS-based ANC in removing PLI. Nevertheless, it should be noted that this method is limited to addressing interference in ECG signals and does not extend to other types of artifacts. It is also important to consider that the evaluation of these methods has been based on simulation rather than real-time clinical data. It has been observed that the Extended Kalman Filter-based ANC surpasses the SSRLS-based ANC in eliminating PLI, with the system state matrix being utilized to calculate the state transition matrix. (Manju and Sneha 2020) proposed that ECG signal denoising can be effectively achieved using Wiener and Kalman filters. The comparison was based on performance parameters such as SNR, MSE, and PSD. It was found that the Wiener filter outperforms the Kalman filter in denoising ECG signals. The Kalman filter was observed to be limited by non-linear systems, making the Wiener filter superior in this context. The Kalman filter was deemed to be inefficient due to its restricted application to non-linear systems. In contrast, the Wiener filter utilizes spectral properties for the separation of signal and noise. On the other hand, the Kalman filter corrects predictions using previous outputs for enhanced performance and initial conditions must be introduced for the Kalman filter algorithm.

Another research depends on Independent Component Analysis (ICA) maximizes independence among signals, eliminating interference based on statistical properties. It is more efficient than other methods, removing multiple interferences without removing normal ECG waves. ICA avoids predicted templates, fulfilling second and higher-order statistical independence. Different algorithms do not greatly impact results. Sparse noise is not fully removed, but other noises can also be eliminated. (He, Clifford, and Tarassenko 2006) proposed that the use of ICA (independent component analysis) has proven to be effective in removing noise from ECG (electrocardiogram) recordings. A new technique for determining the order of ICA has been proposed for online processing. The study is focused specifically on the removal of noise and artifacts from ECGs by utilizing ICA. However, one limitation of ICA is the lack of prior signal information, which makes it challenging to determine the order of independent components. Despite this limitation, ICA has been successful in detecting and eliminating noise and artifacts from ECG recordings. The application of ICA to 3-channel ECG data using a new technique has demonstrated promise. The JADE algorithm is employed for the joint diagonalization of cumulant matrices. The use of ICA in biomedical signal analysis is expanding and has been shown to enhance signal quality.

Another method depends on Bayesian filtering for efficient denoising techniques. Discovering properties of signals and noise distribution is important. Each wavelet coefficient follows a mixture of two Gaussian distributions. Noise flexibility allows method to outperform standard thresholding. (Sameni et al. 2007) proposed that a nonlinear Bayesian filtering method that is capable of handling noisy ECG recordings with dynamic model adaptation. Their study concluded that this approach surpasses traditional ECG denoising methods in various Signal-to-Noise Ratios (SNRs), making it effective for extracting high-resolution ECG from real nonstationary muscle artifacts. Despite this, shortcomings were found in its ability to accurately estimate adaptive noise variance. To address this, the proposed methods could be integrated with blind source separation through the adaptive modification of Kalman Filter (KF) noise parameters, enabling online adjustment of filter parameters to enhance its performance.

Table 4: Comparison of different statistical and model-based techniques for PLI Reduction.

Work	Method	Result
(Bodile and Talari 2021)	DWT, EMD decompose signal; KF, KFS filter	KFS framework outperforms KF, DWT, and EMD in denoising ECG. Results include SNR, magnitude spectrum, and computational cost comparisons. Kalman filter framework is more stable and efficient in high noise.
(Tahir et al. 2022)	Extended Kalman Filter-based ANC	EKF-based ANC outperforms SSRLS in eliminating PLI from ECG. EKF and SSRLS filter have similar performance for known PLI.
(Manju and Sneha 2020)	Wiener filter and Kalman filter	Wiener filter outperforms Kalman filter in denoising ECG signals. Wiener filter shows high SNR, low MSE, and PSD values. Kalman filter's limitations are due to its non-linear system application.
(He et al. 2006)	Independent Component Analysis (ICA)	ICA effectively detects and removes noise and artefacts from ECGs. ICA can remove artefacts affecting all 3 channels simultaneously.
(Sameni et al. 2007)	Bayesian filter	Proposed Bayesian filters outperform conventional methods in ECG denoising. Demonstrated superior results in ECG denoising across various SNRs. Framework effective for model-based filtering of noisy ECG recordings. Results compared with bandpass, adaptive, and wavelet denoising methods.

The fourth category is Deep Learning, which utilizes cascading neural networks to improve machine learning. These approaches have become increasingly significant over the previous five years. Deep Learning architectures, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Autoencoders, and Stacked Autoencoders, are employed to eliminate noise and remove Power Line Interference (PLI) in filtering applications. Deep Learning provides benefits including rapid convergence, self-learning capabilities, automation, and the ability to handle complex datasets.

The proposed method depends on Autoencoder having a layered structure with input, output, and hidden layers. It shrinks features to a smaller hidden layer. The number of hidden units is smaller than the number of input units. Features then expand to the output layer. The autoencoder is symmetric and learns efficiently with backpropagation. It is preferred for dimension and noise reduction in compression and signal processing. It uses unsupervised learning to minimize the reconstruction error between input and output layers. (Xiong, Wang, Liu, Lin, et al. 2016) presented that the proposed CDAE method enhances ECG signal denoising with significant improvements. It utilizes Frobenius norm for Jacobean matrix to enhance noise reduction and has outperformed conventional methods with a 2.40 dB SNR improvement and RMSE enhancements. However, it is important to note the assumption of training data similarity and the inconvenience of ECG waveform collection. This suggests the need for future study on ECG signal modeling. The proposed CDAE method offers significant improvement in ECG signal denoising, outperforming conventional methods in SNR and RMSE enhancements. Additionally, a DNN has been established based on stacked CDAE for noise reduction. (Xiong, Wang, Liu, Zhou, et al. 2016) proposed that a Deep Neural Network (DNN) method to enhance ECG signals by eliminating noise components. They utilized an improved Denoising Autoencoder (DAE) modified by Wavelet Transform to achieve a significant Signal-to-Noise Ratio (SNR) improvement. Nonetheless, the effectiveness of DNN learning is hindered using small ECG sample features that are centrally distributed, leading to insensitivity in the DNN due to this small sample size. The proposed method utilizes a DNN based on an improved DAE to enhance ECG signals, while the Wavelet transform with scale-adaptive thresholding is effective in filtering out noise in ECG signals. The results showed improved SNR and Root Mean Square Error (RMSE) compared to individual processing methods. It is important to note that one of the limitations of this method is the insensitivity of the DNN to features due to the small sample size. (Chiang et al. 2019) proposed that ECG denoising can be achieved more accurately by FCN-based DAE for diagnosis and analysis. The FCN method surpasses DNN and CNN in its ability to remove noise from ECG signals. The proposed method demonstrates a high compression performance with superior noise suppression. On the contrary, DNN's lack of spatial information impacts its accuracy in waveform modeling, as the fully connected layers in DNN average out the relationships between neighboring samples. The FCN-based DAE surpasses other models in reducing noise, as the encoder compresses ECG signals into low-dimensional features and the DAE reconstructs the clean input from the corrupted version using stochastic mapping.

Table 5: Comparison of different deep learning techniques for PLI Reduction.

Work	Method	Result
(Xiong, Wang, Liu, Lin, et al. 2016)	Stacked Contractive Denoising Auto-Encoder (CDAE)	Stacked CDAE method outperformed S-transform, WT, and DAE in SNR. CDAE showed significant improvement in SNR and RMSE for ECG denoising. The proposed method achieved over 2.40 dB improvement in signal-to-noise ratio.
(Xiong, Wang, Liu, Zhou, et al. 2016)	Deep neural network based on improved DAE	The proposed method enhances ECG signals with improved SNR and RMSE. Outperforms WT and DAE individually in ECG signal enhancement. Experimental results show significant improvement in SNR and RMSE.
(Chiang et al. 2019)	Fully Convolutional Denoising Autoencoders (DAE)	FCN-based DAE outperforms DNN and CNN in denoising ECG signals. FCN shows higher SNR imp, lower RMSE, and PRD values. Proposed method compresses ECG signals to 32 dimensions effectively.

The last category is hybrid that combines different methods available in the literature. (Kumar, Panigrahy, and Sahu 2018) proposed that the exploring the effectiveness of using EMD with NLM for denoising ECG signals. They compare different methods of noise cancellation for ECG signals under various input SNRs and found that the EMD NLM method yields results with less distortion and similar effectiveness. However, the Wiener filter proves to be ineffective due to the non-stationary behavior of ECG signals. Furthermore, the efficiency of adaptive filtering decreases when errors are present in the reference signal. It was also observed that bandpass filtering does not effectively suppress non-cardiac ECG noise. The researchers calculate the differential standard deviation for noise information in ECG signals and propose the use of the EMD framework for noise reduction and NLM for edge preservation. The methodology is validated using white and color Gaussian noise at different SNRs, and specific IMFs are selected for QRS complex delineation and preservation. The study also determines the exact number of IMFs needed for the windowing operation. (Singh and Pradhan 2018) have introduced a new approach for ECG denoising by VMD, NLM, and DWT techniques. This method involves decomposing the ECG signal into narrow-band VMFs to effectively remove noise and has shown superior performance when compared to existing denoising techniques on the MIT-BIH Arrhythmia database. Although, it has been observed that existing methods are inadequate in denoising the entire ECG frequency range, particularly due to the rare-patch effect in the high-frequency region with the NLM technique. The proposed approach addresses this limitation by employing VMD to enable parallel processing of NLM and DWT for denoising, resulting in an improved performance compared to current ECG denoising techniques. Furthermore, VMD is utilized to decompose the input signal into narrow-band variational mode functions. (Rakshit and Das 2018) proposed the utilization of EMD and ASMF for ECG denoising in the analysis of cardiac disorders. The methodology aims to reduce noise while minimizing distortion, thus improving the overall quality of the signal. The proposed technique was assessed using the widely accepted MIT-BIH arrhythmia database, with both qualitative and quantitative analyses demonstrating its effectiveness in ECG signal denoising. Nevertheless, existing methods are noted to lack in preserving high-frequency QRS complex information. Furthermore, the EKF technique necessitates manual parameter initialization for ECG cycles. The proposed method includes the use of EMD and ASMF techniques for noise reduction in ECG denoising, along with soft thresholding for high-frequency noise reduction and QRS complex preservation. ASMF operation plays a crucial role in enhancing signal quality within the ECG denoising methodology. When compared to existing ECG denoising approaches for efficacy, the proposed technique demonstrates that the ASMF method excels in noise reduction effectiveness. (Boda, Mahadevappa, and Dutta 2021) proposed that the hybrid approach effectively eliminates PLI and BW from ECG signals by utilizing EMD and EWT for signal decomposition and noise estimation. This method has been tested on real ECG signals from the MIT-BIH arrhythmia database and has shown superior performance in SNR, &rho, PRD, and WDD compared to existing methods. The approach involves denoising through a combination of EMD and EWT, followed by rigorous testing and validation using actual ECG signals, and performance evaluation in comparison with leading techniques. (Azzouz et al. 2024) proposed an innovative PSO-WT technique designed to optimize ECG denoising parameters for enhanced signal quality. This technique combines PSO with WT to efficiently remove noise from ECG signals, resulting in superior SNR outcomes when compared to existing methods. It should be noted, however, that Non-adaptive WT necessitates ECG-dependent wavelet basis function, while the use of soft computing techniques is hindered by computational complexity. Additionally, EMD-based noise elimination methods encounter mode-mixing issues. The study demonstrates that PSO effectively optimizes WT parameters for denoising ECG signals, emphasizing the importance of thresholding rules and rescaling methods in noise removal. Overall, WT emerges as a powerful tool for processing non-stationary ECG signals.

Table 6: Comparison of different hybrid techniques for PLI Reduction.

Work	Method	Result
(Kumar et al. 2018)	Empirical mode decomposition (EMD) And non-local mean (NLM) technique	Improved SNR for ECG signal denoising using different techniques. Evaluation on MIT-BIH arrhythmia database channels.
(Singh and Pradhan 2018)	Variational mode decomposition (VMD), Non-local means (NLM) estimation and Discrete wavelet transform (DWT)	The proposed method outperforms existing ECG denoising techniques on MIT-BIH Arrhythmia database.
(Rakshit and Das 2018)	Combined EMD and ASMF for ECG denoising: wavelet soft thresholding and noise reduction	Proposed methodology evaluated on MIT-BIH arrhythmia db with simulated noises. Compared with existing ECG denoising techniques qualitatively and quantitatively.
(Boda et al. 2021)	EMD-based Signal decomposition, RZCN for sub-signals, EWT for estimation, Interference subtraction for noise removal and Comparison for validation	Proposed method removes PLI and BW from ECG signals, outperforms existing methods in SNR, cross-correlation, PRD, and WDD. Tested on real ECG signals.
(Azzouz et al. 2024)	Particle swarm optimization with wavelet transform for ECG noise removal and Donoho's approach for wavelet denoising	The PSO-WT method improves ECG signal quality and outperforms other techniques in SNR. Evaluation criteria include SNR, SNR improvement, MSE, RMSE, and PRD. PSO optimizes wavelet noise reduction effectively.

4. Challenges

Denoising electrocardiogram (ECG) signals faces numerous challenges due to complex noise and the need to maintain signal quality. Effective denoising is crucial for accurate diagnoses, yet current methodologies face limitations that hinder their practical effectiveness. Below are key challenges in ECG denoising:

- Handling Complex and Non-Stationary Noise: Electrocardiogram (ECG) signals are influenced by multiple forms of noise, including baseline wander, muscle noise, motion artifacts, and power line interference (PLI). Each category of noise exhibits unique characteristics, and their non-stationary properties pose a considerable challenge to conventional denoising techniques. Existing approaches, such as wavelet transforms and empirical mode decomposition (EMD), demonstrate limitations when confronted with intricate noise patterns that fluctuate over time and across frequency domains. Furthermore, these techniques frequently necessitate considerable preprocessing or manual adjustment, which may impede their efficacy in real-time applications.
- Maintaining Signal Integrity: Denoising techniques are designed to enhance the signal-to-noise ratio (SNR); however, they frequently encounter difficulties in maintaining the diagnostic characteristics of the ECG signal, which include the P-wave, QRS complex, and T-wave. Methods that excessively eliminate noise may inadvertently alter these critical components, thereby diminishing diagnostic precision and increasing the risk of misinterpretation.
- Real-Time Processing Constraints: The utilization of sophisticated denoising techniques, including deep learning and hybrid methodologies, can prove to be resource-intensive in terms of computation. This presents difficulties for real-time electrocardiogram (ECG) monitoring, particularly in portable or embedded systems, where the capacity for processing power and memory is constrained. Striking an equilibrium between the efficacy of denoising and the efficiency of computational resources continues to be a notable challenge for applications operating in real-time contexts.
- Generalization Across Diverse Data: Numerous denoising techniques have been devised and evaluated utilizing specific datasets, including the MIT-BIH arrhythmia database. Nonetheless, the ability of these techniques to generalize across varied patient demographics, distinct noise environments, and differing ECG acquisition systems continues to pose a significant challenge. The efficacy of denoising algorithms may experience considerable deterioration when implemented in real-world situations that deviate from the controlled settings of the training datasets.

5. Future Research Directions

As ECG denoising methods evolve, various fields show potential for improvement. Future studies could focus on enhancing current techniques, exploring new technologies, and addressing limitations to boost ECG signal processing accuracy and efficiency. Key areas for research include:

- Hybrid Approaches: There is an increasing interest in hybrid methodologies that integrate the advantages of conventional filtering techniques with sophisticated approaches such as deep learning and empirical mode decomposition (EMD). These methodologies have demonstrated potential in enhancing denoising efficiency while concurrently preserving essential features of electrocardiograms (ECGs). Subsequent research endeavors may aim to further refine these hybrid techniques, optimize their computational efficiency, and broaden their applicability across diverse types of noise and varying signal conditions.
- Deep Learning Innovations: Deep learning architectures, including autoencoders, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), have shown considerable promise in the denoising of electrocardiograms (ECGs). Nevertheless, their dependence on extensive, annotated datasets and their sensitivity to the characteristics of training data present certain obstacles. Future investigations may focus on the application of transfer learning, data augmentation, and semi-supervised learning methodologies to improve the generalizability of these models while minimizing their reliance on substantial labeled datasets.
- Adaptive Filtering for Real-Time Applications: The advancement of adaptive filtering methodologies that can effectively modify in real-time fluctuating noise environments represents a promising avenue of research. These methodologies ought to possess the capability to dynamically adjust their parameters in response to the characteristics of the input signal, thereby facilitating more resilient denoising in practical applications. Subsequent research endeavors may concentrate on enhancing adaptive filters for low-latency settings, thereby rendering them appropriate for implementation in wearable devices and continuous monitoring systems.
- Enhanced Thresholding and Mode Decomposition: Recent advancements in thresholding methodologies, notably concerning wavelet transforms and empirical mode decomposition (EMD), present opportunities

for further refinement in noise reduction whilst reducing signal distortion. Future investigations may concentrate on enhancing adaptive threshold selection approaches that accommodate both stationary and non-stationary noise elements, thereby improving the overall efficacy of denoising methods.

- Explainability in Deep Learning Models: With the growing intricacy of deep learning models, there arises an imperative for enhanced transparency and elucidation regarding their decision-making mechanisms. Future investigations may focus on developing techniques for visualizing and interpreting the attributes acquired by these models during denoising tasks, thereby ensuring their functionality upholds essential diagnostic information within ECG signals.

6. Conclusion

Denoising of ECG signals was crucial for ensuring accurate diagnoses in cardiovascular health monitoring systems. This survey outlined various types of noise that affected ECG signals, including baseline wander, power line interference, muscle noise, and motion artifacts. Each type of noise had a unique impact on the ECG waveform, potentially distorting key features such as the P-wave, QRS complex, and T-wave, which were crucial for clinical interpretation. This study categorized and analyzed de-noising techniques into five main groups: filtering techniques, transform-based methods, statistical and model-based approaches, deep learning techniques, and hybrid methods. While traditional filtering techniques were effective for addressing certain types of noise, they were often limited in their ability to handle complex, non-stationary noise patterns such as power line interference and motion artifacts. Advanced methods, like wavelet transforms, empirical mode decomposition (EMD), and deep learning models, showed superior performance in maintaining ECG signal integrity and improving signal-to-noise ratios (SNR). The review concluded that hybrid approaches, which combined different methods (e.g., deep learning with traditional filtering), offered the most promising results in ECG de-noising. However, the challenge of balancing computational efficiency and de-noising performance remained, especially for real-time applications.

Disclosure

The authors want to emphasize that the submission they have made for publication is void of any direct or indirect financial or non-financial conflicts. The author declares no conflicts of interest in this work.

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