Research article

Technology and Health Care
1–14

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/09287329241302749
journals.sagepub.com/home/thc
Sage | IOS Press

An efficient sparse code shrinkage technique for ECG denoising using empirical mode decomposition

Vibha Tiwari[1], Divya Jain[2], Deepak Sharma[3], Mohamed M Hassan[4], Fayez Althobaiti[5], Akshay Varkale[6], Mahmoud Ahmad Al-Khasawneh[7,8] and Ravi Kumar Tirandasu[9]

Abstract

Accurate denoising of Electrocardiogram (ECG) signals is essential for reliable cardiac diagnostics, but traditional methods often struggle with high-frequency noise and artifacts, leading to potential misinterpretations. It is often impeded by interference such as power line interference (PLI) and Gaussian noise. To address this challenge, we suggest a novel ECG denoising technique that combines empirical mode decomposition (EMD) with wavelet domain sparse code shrinking. Our approach first decomposes the noisy ECG signal into Intrinsic Mode Functions (IMFs) using EMD. These IMFs are then transformed into the wavelet domain, where a sparse code shrinking function is applied to effectively reduce both Gaussian noise and PLI while preserving the integrity of the original signal. The effectiveness of the technique is assessed on the MIT-BIH database, where it shows marked improvements in Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Percentage Root Mean Square Difference (PRD). The suggested approach demonstrates improved SNR and reduced MSE when compared to prior approaches, which suggests that the ECG signals are clearer and more precise. This method presents a rather effective approach to enhancing ECG analysis as it is important for diagnosis and interpretation. At 10 dB SNR, the suggested technique achieves an MSE of 0.005, which is much less than the 0.076 and 0.0025 MSEs obtained by EMD wavelet adaptive thresholding and soft thresholding correspondingly. This indicates that the proposed approach effectively eliminates noise while preserving significant signal characteristics, leading to an improved and less erroneous signal reconstruction. Furthermore, the proposed method outperformed conventional techniques and demonstrated improved noise reduction and signal clarity, achieving an SNR of 19.24 and a PRD of 20.38 at 10 dB SNR.

Keywords

ECG, EMD, PLI, SNR, Wavelet transform

Received: 6 May 2024; accepted: 1 November 2024

[1]Assistant Professor, Centre for Artificial Intelligence, Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh, India
[2]Associate Professor, Electronics and Communication Department, Technocrats Institute of Technology, Bhopal, Madhya Pradesh, India
[3]Assistant Professor, Department of Computer Science, Aryabhatta College, University of Delhi, New Delhi, India
[4]Department of Biology, College of Science, Taif University, Taif, Saudi Arabia
[5]Department of Biotechnology, College of Science, Taif University, Taif, Saudi Arabia
[6]Department of Computer Science and Engineering, IES Institute of Technology and Management, IES University, Bhopal, Madhya Pradesh, India
[7]School of Computing, Skyline University College, University City Sharjah, Sharjah, United Arab Emirates
[8]Jadara University Research Center, Jadara University, Irbid, Jordan
[9]Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India

Corresponding author:
Deepak Sharma, Assistant Professor, Department of Computer Science, Aryabhatta College, University of Delhi, New Delhi 1100021, India.
Email: deepaksharma@aryabhattacollege.ac.in

1 Introduction

The ECG is a form of biological signal that is employed in clinical practice for the identification of heart disorders. P, S, Q, R, and T waves in the ECG are the display of bioelectric potential that is created by the muscular contractions of the heart. In particular, ECG interpretation is considered to be very important for a cardiologist as each wave contains numeric clinical data.[1] Surface electrodes are often placed on the limbs and chest to record the ECG. There are normally two types of artefacts that are common in an electrocardiogram recording and these are the power line interference and Gaussian noise. A high-frequency interference resulting from electromagnetic interaction between the current-carrying conductor and the recording equipment is referred to as PLI. It is therefore important to remove such noise from the ECG signal for proper diagnosis of the patients. Therefore, the extraction of high-quality ECG signals is very important. The objective of this paper is to remove noise from an electrocardiogram signal. The main purpose of Denoising is to eliminate the artefacts in the ECG signal while keeping the signal properties intact. Filtering approaches based on linear filters are unable to eliminate artefacts without compromising signal quality because of the spectrum overlap between desired ECG signals and artefacts. This creates room for the application of adaptive algorithms for filtering the ECG signal in case it is noisy.[2]

To define ECG components in the background noise, ECG denoising is a necessary procedure. Digital filtering is the conventional method used in the elimination of artefacts in the ECG signal. It is possible to employ either a time-domain or a frequency-domain digital filter. Knowledge of the relative position of the signal and noise allows one to design such a filter. The most common method of signal processing is known as data smoothing and is applied to filter out high-frequency noise in the biological signal.[3] In this way, the data can be made more uniform by averaging together multiple data points. The Moving Average (MA) filter is one of the filters that is used for this purpose. The MA filter is a low-pass time-domain filter that is used to eliminate the random noise from the ECG signal. The high-frequency component above 40% of the sampling frequency needs to be reduced to smooth and minimize noise. Hence, the application of a low-pass filter is not feasible for ECG data processing.

The Butterworth filter, while commonly used for its simplicity and flat frequency response, has limitations. It exhibits a trade-off between the sharpness of the cutoff and passband ripple. Additionally, it introduces phase distortion, particularly near the cutoff frequency. Furthermore, it is sensitive to parameter choices, requiring careful selection of order and cutoff frequency to balance between attenuation and distortion, which may not always be achievable for all desired filtering characteristics.

Where We Started A derivative-based high pass filter is used to the ECG signal to eliminate the stray artefacts. This filter attenuates low-frequency noise while amplifying high-frequency information.[4] High pass filtering of the ECG data modifies the QRS shape and eliminates the sluggish P and T waves. The time-domain digital filter's limited utility is due to its uneven attenuation in the stopband and its non-linear phase characteristics. To achieve a filter with desired properties, however, a frequency-domain filter is presented. To create the desired band characteristics, poles and zeros are located on the unit circle in the Z domain. The Butterworth filter is the most widely employed in the frequency domain. Data-driven and locally adaptive, EMD is a time-space analytic technique that may be applied to non-linear and non-stationary time series.[5] Unlike the Fourier transform and the Wavelet transform, which both rely on a specified basis function, EMD is a data-driven method for signal decomposition. The EMD uses the signal itself as its basis function. With this EMD, every signal may be broken down into a collection of discrete oscillatory components called IMFs. IMFs are the oscillatory functions that provide the signal with an orthogonal foundation.[6] Because of its adaptability and data dependence, EMD is a powerful technique for studying biological signals.

An alternative to the EMD for decomposing multicomponent signals into a finite number of IMFs is the recently created flexible transform known as the Synchrosqueezing Transform (SST). There are two main problems with EMD: mode mixing and noise sensitivity. When two parts of a signal share very similar instantaneous frequencies, the EMD technique treats them as though they were just one.[7] As a result, it can't tell them apart. Because of this, a method is needed to disentangle the parts whose instantaneous frequencies are so close together.

EMD is more appropriate for ECG signal analysis than Fourier or Wavelet transforms because EMD is more suitable for non-stationary and nonlinear signals like ECG. It breaks signals into Intrinsic Mode Functions, which are good for analyzing signal dynamics, and therefore used in denoising and feature extraction in ECG.

A combined ECG denoising model based on EMD and Wavelet domains is developed to eliminate high-frequency interferences from the ECG signal. The method employs a two-stage process: Mode Decomposition that was followed by wavelet thresholding to minimize high-frequency noise in the signal.

SST has some benefits over EMD for filtering out high-frequency noise from the ECG signal. In contrast to EMD, SST offers a more accurate time-frequency representation of signals, which allows for more accurate identification of the high-frequency components. Also, SST provides better flexibility in terms of the nature of the signal and the level of noise present in the signal. Due to its capacity to track the instantaneous frequency changes, it is very useful in the analysis of non-stationary signals like ECG and improves the denoising ability and feature extraction.

This study aims to propose a novel approach to ECG signal denoising that can overcome the previous methods' shortcomings in processing high-frequency noise and artifacts including PLI and Gaussian noise. The major contribution of the study is as follows:

- The proposed hybrid model integrates EMD with wavelet thresholding to remove high-frequency noise effectively. By utilizing a two-stage approach—Mode Decomposition followed by wavelet thresholding—the method excels in separating signal components from noise, offering an improved denoising solution for ECG signals.
- A major innovation in this study is the introduction of an adaptive sparse code shrinkage function, which enhances traditional wavelet shrinkage methods. The function adaptively selects coefficients for thresholding based on their sparse representations, providing better noise suppression while preserving significant ECG signal features. This adaptive approach outperforms conventional hard or soft wavelet shrinkage, making the denoising process more accurate.
- The study demonstrates the utility of lower-order IMFs in EMD for effective noise reduction. By focusing on lower-order IMFs and discarding higher-order ones, the method simplifies computation without sacrificing signal fidelity, making it well-suited for real-time ECG signal processing.
- The performances of the proposed method are measured with MSE, SNR, and PRD, and compared with other filtering approaches. The analysis of the outcomes proves the superiority of the suggested technique as the SNR is higher and MSE and PRD are lower in the proposed method for ECG denoising.
- The improvement in ECG denoising has significant clinical implications. The clearer and more accurate ECG signals produced by this method enhance the reliability of diagnostics, aiding in the detection of subtle cardiac abnormalities. This contribution is critical for improving patient care and outcomes in clinical settings.

The rest of the paper is organized as follows: The review of the literature is presented in Section 2. The suggested methodology for this study is presented in Section 3. The findings of the thorough experimentation are presented in Section 4. The discussion of the results, the study's practical implications, and its limitations are presented in Section 5. Section 6 offers the study's conclusion.

2 Literature review

To manage non-stationary and non-linear signals, scientists develop EMD. The EMD is an adaptive decomposition approach that is data-driven and doesn't need a known foundation like the Fourier or wavelet transform. EMD excels over conventional methods because the basis function is inferred from the input signal.[8] The EMD can separate any signal into a residue and a collection of IMFs. Fast-oscillating IMFs were placed at the top of the decomposition, whereas slow-oscillating IMFs were placed at the bottom. Using EMD, the obtained IMFs can be utilized to break down a noisy ECG signal into its frequency components. Several EMD-based approaches for removing noise from an electrocardiogram have been published.

An approach to filtering PLI from the ECG signal was explored in the articles. When the SNR is low, the PLI is extracted as the first IMF using this method, but when the SNR is large, the decomposed IMF includes some of the signals in addition to the PLI.[9] To eliminate PLI, a pseudo-noise is superimposed at a higher frequency than the peak frequency of the signal. This method has the drawback of introducing pseudo-noise into the signal, which would significantly alter the QRS complex shape of the denoised ECG signal.

Empirical mode decomposition (EMD) was offered as a means of cancelling out Baseline drift and high-frequency Gaussian noise. The windowing technique can be used to get rid of the high-frequency noise in the early IMFs.[10] Using a partial signal reconstruction technique to filter such noise after estimating the number of IMFs generating baseline wandering noise employing statistical testing.

The authors suggested a new method for ECG denoising using EMD and Wavelet Transform (WT) after which the WT adaptive thresholding was used to remove residual noise.[11] This approach has the potential to be a great way of improving the quality of ECG signals. Nevertheless, the effectiveness of this technique is based on the selection of the corresponding parameters and the type of noise in the signal.

However, there is a drawback of using EMD and WT together for the removal of noise from non-stationary signals like ECG. Thus, the selection of the denoising methods and filters should be based on the kind of noise that exists in ECG signals. Furthermore, the effectiveness of the denoising may well depend on the richness and variability of the underlying cardiac activity.[12]

The hybrid approach described by the authors eliminates some of the shortcomings of standard EMD denoising techniques by keeping the initial IMFs to maintain important characteristics such as the QRS complex.[13] However, the effectiveness of this approach in providing accurate preservation of the ECG morphology while minimizing noise has yet to be tested and compared with other methods.

Furthermore, the use of adaptive thresholding in the wavelet domain assists in reducing additional residual disturbances, although the choice of the thresholding parameters and the choice of the wavelet functions may affect the denoising effectiveness.[14] Future work is required to fine-tune these parameters and assess the stability of the suggested hybrid denoising on other ECG databases and different types of noise.

Although the use of the hybrid EMD-WT denoising method is identified as a potential solution to enhance the quality of ECG signals, it is crucial to assess and verify the efficiency and applicability of the method through empirical testing and comparison with the existing denoising methods. The EMD technique was studied by researchers about its application for filtering the white Gaussian noise in ECG data. First, the noisy ECG signal is decayed by EMD into a set of IMFs with noise. The IMFs that are contributing to the noise are isolated using a spectral flatness-based approach.[15–17] They talked about a method for reducing high-frequency Gaussian noise from an ECG signal that combines EMD with a Moving Average (MA) filter.

When EMD is applied to an imperfect ECG signal, a finite set of IMFs and residue are produced.[18] Since high-frequency noise is covered in the first few low-order IMFs, this method employs the EMD algorithm on the noisy ECG signal before resorting to the adaptive windowing technique to maintain the QRS complex.[19] The windowing approach can be used to clean up noisy IMF, but only on the outside of the QRS complex's boundaries; noises inside the boundaries will remain. By applying an MA filter, we can remove these disturbances and create a smoother QRS complex.[20]

The research[21] examines the analysis of ECG signals using artificial neural networks in conjunction with morphological and discrete wavelet transform properties. We presented a method that uses several neural classifiers to accurately categorize ECG signal data into two classes: abnormal and normal. Based on the kinds of beats contained in each of the 48 files, the MIT-BIH arrhythmia database was used to pick 45 one-minute recording files (25 files of normal class and 20 files of abnormal class). To categorize the ECG signal, three neural network classifiers are used: Back Propagation Network (BPN), Feed Forward Network (FFN), and Multilayered Perceptron (MLP). Sensitivity (Se), Positive Predictivity (PP), and Specificity are the metrics used to assess the performance of the classifier (SP). Using MLP, the system performance is attained with 100% accuracy.

Using a Modified Sigmoid Thresholding Function (MSTF), Empirical Mode Decomposition (EMD), and Ensemble Empirical Mode Decomposition (EEMD), the authors of work[22] suggests new techniques for noise reduction and QRS identification for ECG data. The denoising performance of the results was much better than that of the traditional approaches, such as wavelet denoising, conventional EMD and EEMD, Stockwell Transform, and CEEMDAN-HIT.

While SST and EMD show promise for high-frequency ECG noise reduction, their widespread adoption in practice remains limited. Challenges include the complexity of implementation, the need for validation in diverse datasets, and comparison against established methods, hindering broader community uptake and application.

Recent studies on ECG denoising utilizing EMD have some limitations in handling various types of noises such as Gaussian noise and PLI. Although EMD can be applied for processing nonlinear and nonstationary signals, most of the existing methods fail to denoise while preserving the ECG characteristics such as the QRS complex. The combination of EMD with other methodologies like the Wavelet Transform (WT) has been attempted and yields good results but the main problem is in the determination of the suitable threshold values and wavelet functions to be used. Moreover, some methods bring in pseudo-noise or artifacts during the process of denoising and hence add more noise to the signal and complicate the diagnosis. The use of sparse coding which is capable of preserving useful signal components has not been applied in EMD-based denoising, which is a missed opportunity for improvement. Furthermore, the majority of the research works fail to provide adequate cross-validation on different datasets and varying levels of noise, which decreases the generalization of the results obtained. It is also not often compared with more traditional denoising methods, and therefore it is challenging to determine the relative efficiency and real-world applicability of newer approaches. These limitations are resolved in this study by presenting an ECG denoising technique that integrates EMD with sparse code shrinkage to present a new solution that effectively removes noise while maintaining important ECG characteristics, especially the QRS complex. The study shows that the suggested approach is superior to the current methods regarding noise reduction and signal preservation, and as a result, it has a great deal of potential to enhance ECG analysis and clinical diagnosis. It also offers a thorough validation of the suggested approach via the MIT-BIH database.

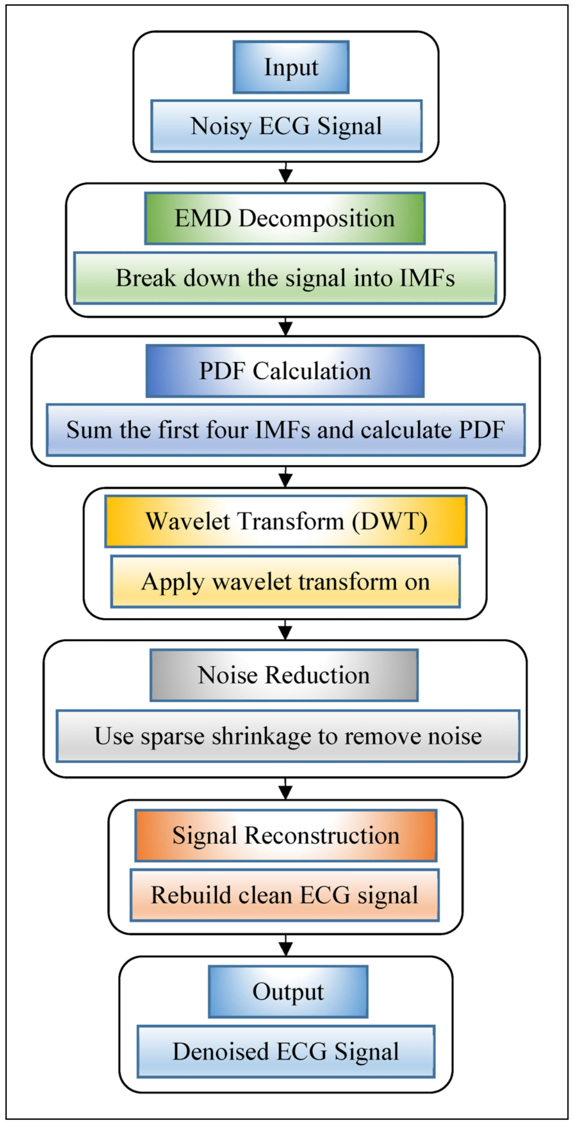

Figure 1. Proposed ECG denoising method using EMD and sparse shrinkage function.

3 The proposed method

The proposed approach combines EMD with wavelet thresholding to enhance ECG signal denoising. Utilizing the MIT-BIH Database, the method first decomposes the ECG signal into IMFs via EMD, focusing on the lower-order IMFs where noise is prevalent. It then employs an adaptive sparse code shrinkage function in the wavelet domain, which surpasses traditional hard and soft thresholding by selectively preserving significant coefficients and suppressing noise. The model involves training to create a sparse code shrinkage function from noise-free data, followed by testing where noisy signals are cleaned using wavelet-based thresholding. The inverse wavelet transform reconstructs the denoised ECG signal, significantly improving SNR, MSE, and PRD, and demonstrating a robust enhancement in ECG signal quality for accurate cardiac diagnostics. Figure 1 demonstrates the proposed ECG denoising method.

We have utilized the MIT-BIH database. The first set of commonly available standard test data for evaluating arrhythmia detection was the MIT-BIH Database. Approximately 500 sites worldwide have been using this database for basic research on cardiac dynamics since 1980. 48 half-hour segments of a 24-h, two-channel ECG recording, gathered from 47 participants inspected by the BIH Arrhythmia Laboratory, are included in this collection. There were two groupings of these 48 half-hour excerpts: Twenty-three (the "100 series") were randomly selected from a pool of over four thousand Holter tapes; the other twenty-five (the "200 series") were chosen to contain infrequent but clinically relevant arrhythmias that would not be adequately shown in a small arbitrary sample.

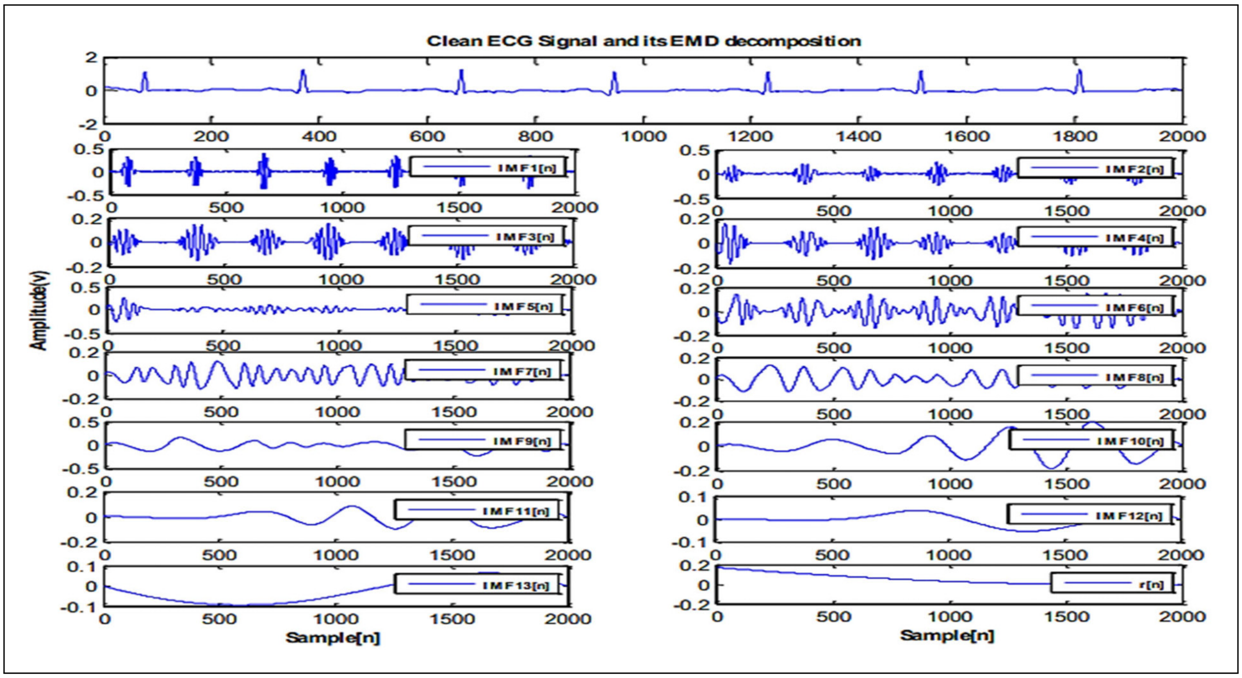

Figure 2. Pure ECG data EMD.

To eliminate the high-frequency disturbances from the ECG signal, a hybrid ECG denoising model is suggested, which combines the EMD and Wavelet domains. To get rid of high-frequency sounds in the ECG signal, the suggested method uses a two-stage operation, such as Mode Decomposition followed by wavelet thresholding.

The proposed method filters sound in the lower-order IMFs by converting them into the wavelet domain, where the coefficients analogous to the noise are thresholded. Thresholding by conventional shrinkage function, whether hard or soft wavelet shrinkage in the wavelet domain, does not improve the denoising result since the high-frequency components of the decomposition are sparse and super-Gaussian. Accurate denoising can be attained with the use of a data-dependent shrinkage function.

The proposed sparse code shrinkage function enhances conventional hard or soft wavelet shrinkage by adaptively selecting coefficients for thresholding based on sparse representations. Unlike hard or soft wavelet shrinkage, which treats all coefficients uniformly, the sparse code shrinkage function identifies and preserves significant coefficients while suppressing noise. This adaptive approach improves denoising performance, effectively distinguishing between signal and noise components, leading to more accurate signal reconstruction and noise reduction.

This proposed solution makes use of the non-linear sparse code shrinkage function. The sparse code shrinking is adaptive, meaning it is built from the ground up with knowledge of the PDF of noise-free data. There are two stages to the actual execution of the proposed method: training and testing. After applying EMD to a cleaner ECG signal, the training phase involves estimating the model parameter necessary for creating the sparse code shrinkage function from the probability density function (PDF) of lower-order IMFs. In the EMD testing phase, the noisy ECG signal is broken down into a collection of IMFs. The following is the algorithm for the suggested sparse shrinkage denoising of the ECG signal:

1) Clean up the ECG signal with EMD, and then calculate the total of the first four IMFs, denoted as d(n).

The formula for $d(n)$ is:

$$c1(n) + c2(n) + c3(n) + c4(n) \tag{1}$$

The EMD decomposition of a clean ECG signal is presented in Figure 2. The original ECG signal, which illustrates the heart's electrical activity throughout time, is shown at the top. Below the original signal, the figure illustrates the IMFs, each labeled from IMF1 to IMF13, along with a final residual component (r). Each IMF represents a specific frequency component extracted from the ECG signal, with the higher-frequency components captured in the earlier IMFs (such as

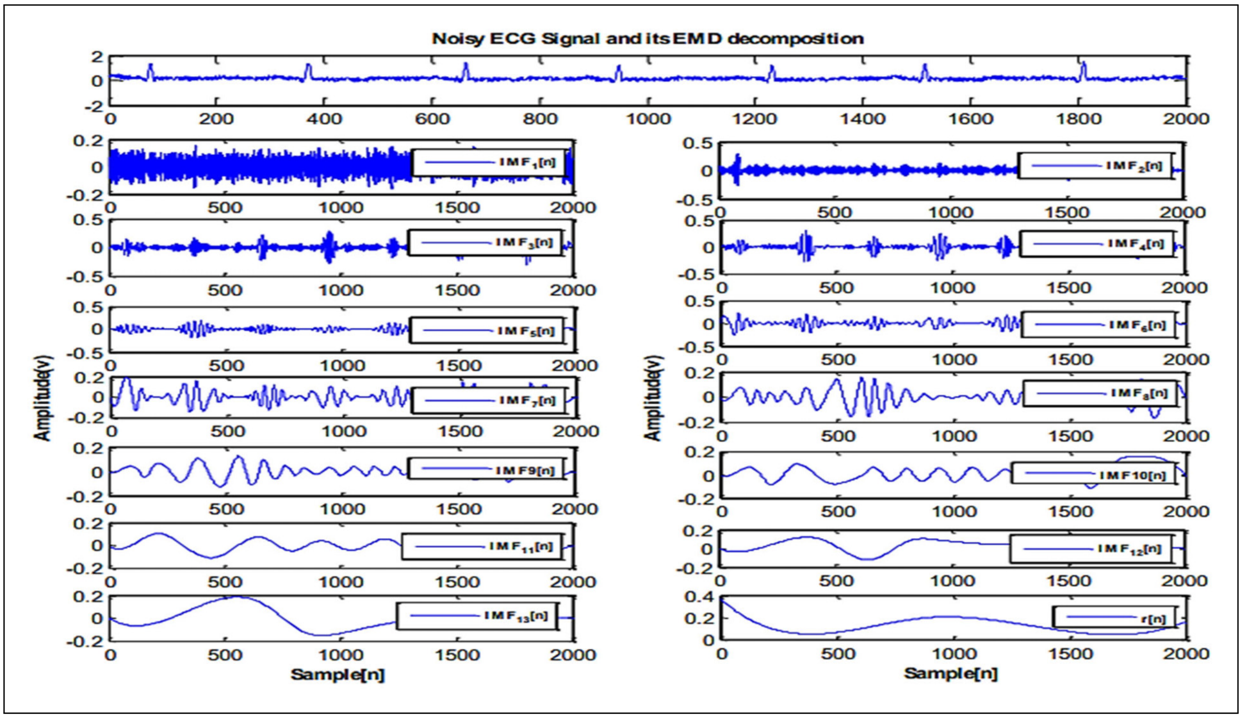

Figure 3. The decomposition of a noisy ECG signal using EMD.

IMF1 and IMF2), and progressively lower-frequency components found in the later IMFs (such as IMF12 and IMF13). The residual (r) represents the remaining trend of the signal after all oscillatory components have been extracted. This decomposition enables a clearer understanding of the various frequency elements of the ECG, helping to isolate noise or specific features relevant for analysis in heart rate monitoring or detecting abnormalities.

Figure 3 illustrates the breakdown of a noisy ECG signal employing EMD. The top panel shows the original contaminated ECG signal, which exhibits both signal and noise components. Below it, the signal is progressively broken down into several IMFs, each representing different frequency components of the original noisy ECG data. On the left and right sides of the figure, multiple IMFs are presented, showcasing the different modes extracted from the noisy signal. Each IMF captures oscillatory modes with decreasing frequencies, starting with higher frequencies and moving to lower ones. The first few IMFs, particularly IMF1 and IMF2, contain the highest frequency components and are dominated by noise. As the decomposition progresses, the IMFs represent progressively smoother oscillations, with lower frequencies and lesser noise, ultimately isolating the essential features of the ECG signal, such as heartbeats. The last component, often referred to as the "residual" or trend (denoted by $r(t)$), contains the slowest variations, which could represent baseline wander or other low-frequency trends in the ECG signal. The EMD technique is thus effective in separating noise from the underlying signal, enabling improved ECG signal analysis and subsequent denoising processes.

2) Then, using Equation (2), create a Sparse PDF to approximatively represent $d(n)$. Estimate the parameters needed to build the sparse shrinkage function once you get the sparse PDF.

$$P(d) = \frac{1}{2\,SD}\frac{(S+2)[s(s+1)/2]^{\left(\frac{s}{2}+1\right)}}{\left[\sqrt{\frac{S(S+1)}{2}} + |d/SD|\right]^{(S+3)}} \tag{2}$$

where,

$$SD = \sqrt{E(d^2)} \tag{3}$$

$$S = \left(2 - k + \frac{\sqrt{k(k+4)}}{2k} - 1\right) \tag{4}$$

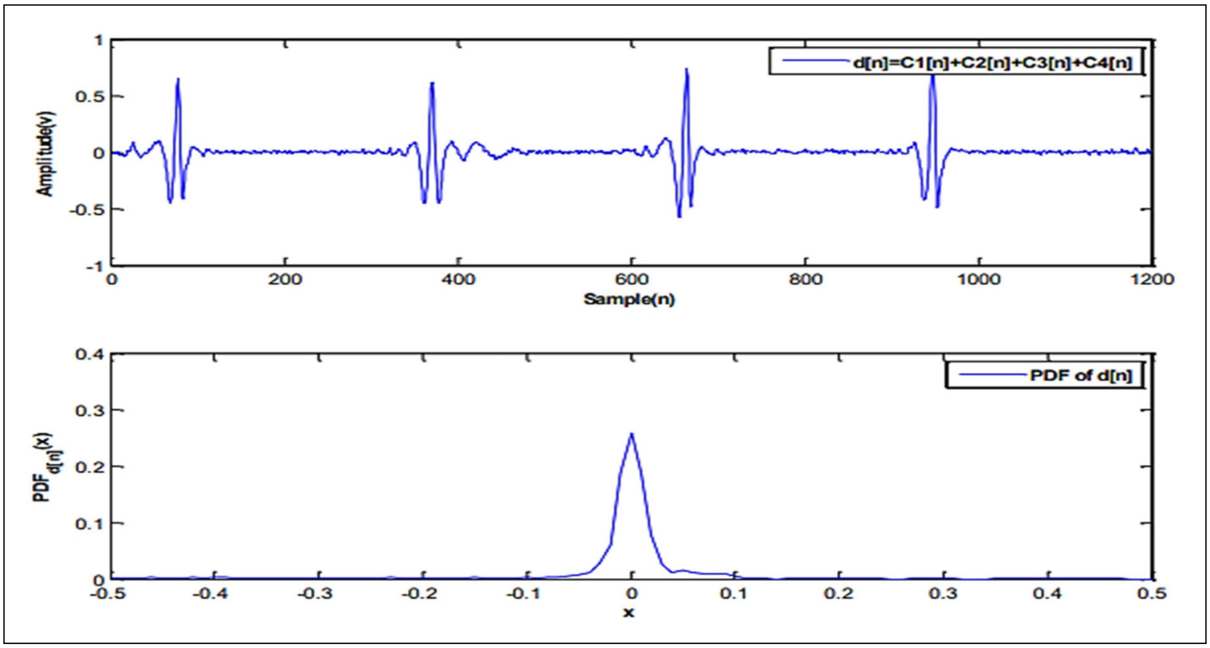

Figure 4. Sum of first four IMFs (d[n]) and its PDF.

where *SD* is Standard Deviation and *S* is the sparsity parameter that defines the distribution type.

3) Apply EMD to the noisy ECG signal to compute d(n) by incorporating the first several lower-order IMFs and disregarding the higher-order ones.
4) With the sparse shrinkage function computed in the first stage, apply DWT on d(n) to reduce the size of the wavelet coefficients.
5) Subsequently, shrinking the wavelet coefficients, use inverse DWT to get noise-free d(n) values for the intermediate and lower-order IMFs.
6) Denoising the ECG signal is as simple as adding d(n) using IMFs of higher order in the EMD domain.

As shown in Figure 4, the PDF of d(n) can be used as an approximation to the Hyvarine Sparse PDF specified by Equation (2) to generate the shrinkage function. Adjusting some of Sparse PDF's settings will get you there. See Figure 5 for an illustration of the Sparse PDF for the case of = 0.1 r 0.18. With a parameter value of 0.1, 0.18, the Hyvarine Sparse PDF is found to have a shape that is analogous to the PDF of d(n).

The PDF of the noise-free signal is used in the construction of this sparse shrinkage function. If a signal has a sparse distribution, this shrinkage function can help get rid of the Gaussian noise. It is also comparable to Donoho's hard and soft shrinking functions. The spare shrinkage function is predicted to keep a middle ground between hard and soft shrinking.

Hyvarinen Sparse PDF approximation improves the artifact removal process from ECG signals by modeling the signal distribution. This method identifies sparse structures within the ECG, effectively separating informative features from noise. Hyvarinen Sparse PDF approximation can capture the sparse structure of ECG signals and therefore, artifact removal is accurate in avoiding the loss of signal components, while noise is effectively reduced, making denoising processes more effective.

The PDF of the noise-free signal is used in the construction of this sparse shrinkage function. If a signal has a sparse distribution, this shrinkage function can help get rid of the Gaussian noise. It is also comparable to Donoho's hard and soft shrinking functions. The spare shrinkage function is predicted to keep a middle ground between hard and soft shrinking.

To enhance the ECG signal's degradation in noise, we apply sparse code thresholding in the wavelet domain, with a threshold value customized to the unique coefficients of every level. The definition of the adaptive sparse shrinkage function is

$$D_d(1) = STHR\ (D_d(w),\ \partial(w)) \tag{5}$$

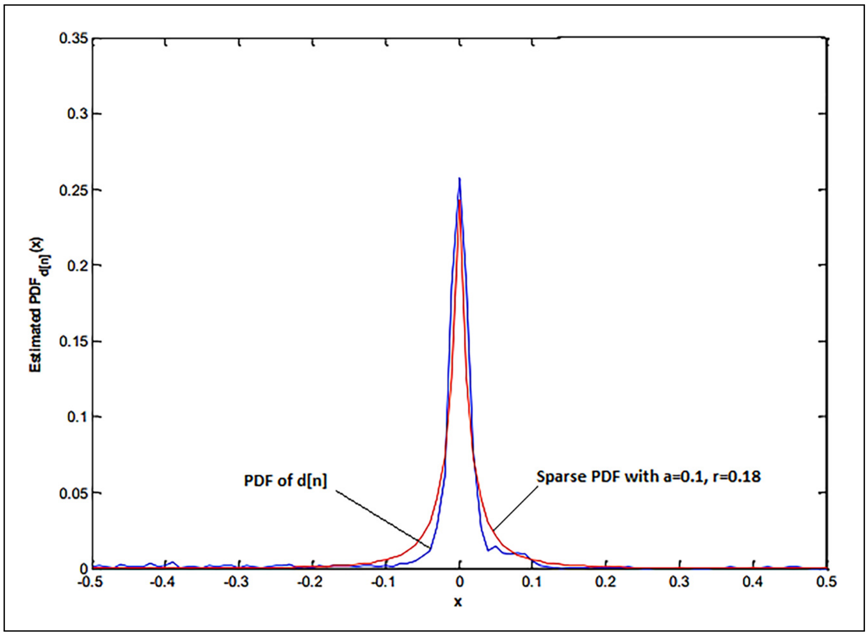

Figure 5. PDF of d[n] and its equivalent model PDF.

The calculated threshold at wavelet level w is denoted as $\partial(w)$, where D_d is the thresholded detailed *DWT* coefficients. The thresholded coefficient for a wavelet decomposition with two levels looks like

$$D = [D_d(1),\ D_d(2), D_a(2)] \tag{6}$$

At last, the $d(n)$ data beforehand noise is projected by accomplishing an inverse wavelet transform on D, as designated by

$$d(n) = Inverse\ DWT[D] \tag{7}$$

4 Experimentation

4.1 Experimental setup

The Experiments were conducted employing Python 3.3 and TensorFlow version 2.13.0. The hardware setup featured an 11th Gen Intel® Core™ i5 processor with 16 GB of memory, which facilitated efficient computation. The system operated on Windows 11 and had a total storage capacity of 145 GB, providing ample space for data and processing tasks. To boost the performance, an NVIDIA GTX 750 GPU was used to train models and to perform computations for the experiments. This configuration formed a good basis for assessing the proposed ECG denoising method.

4.2 Results

In this work, we have implemented and tested the proposed ECG enhancement approach in a few different scenarios to determine the efficiency of the method. It is possible to show the usefulness of the suggested method by comparing its findings to those achieved by other, more well-known methods through the application of conventional performance indicators. To perform analysis and to remove noise, we used an ECG recording which was obtained from the Physionet MIT Arrhythmia database. This database comprises 48 ECG records with a duration of 30 min and each record contains 360 samples per second. Each recording also has its unique identifier.

Because it determines when the sorting process ends, choosing the SD value is more crucial in the EMD. The typical range for the SD value is 0.2–0.3. Our proposed EMD analysis uses a standard deviation of 0.2. Sparse code shrinking requires knowledge of parameters approximating the signal's sparse distribution. Since the sparse distribution shifts depending on the signal, choosing the right set of parameters is more crucial than before. Using the sparse distribution of numerous ECG signals and the parameters that approximate each of them, we were able to determine the best parameters for building a sparse code shrinking function.

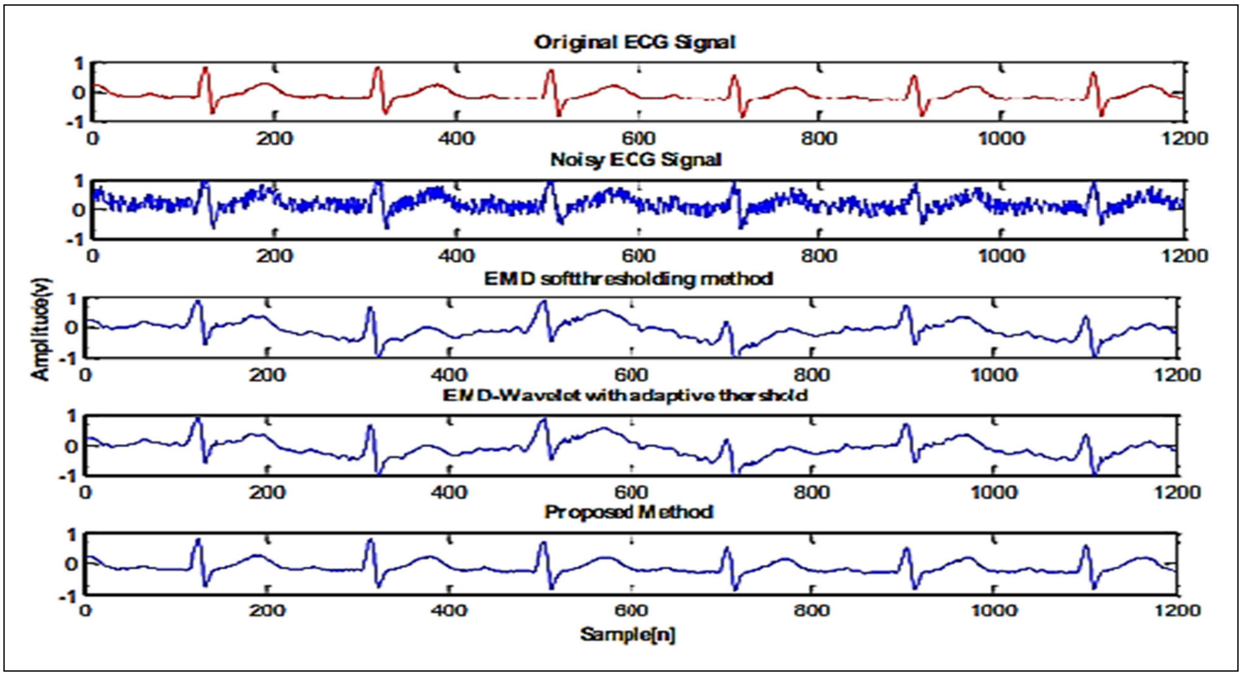

Figure 6. Cleaned ECG data (101.mat) Degraded with Gaussian noise using the diverse ECG filtering methodology.

In this investigation, we apply the suggested filtering technique to ECG data. Both the EMD soft thresholding method and the EMD wavelet filtering with an adaptive threshold method are used to assess the proposed approach's performance.

Neglecting higher-order IMFs in EMD simplifies computational burden and maintains interpretability. However, this choice risks losing potentially relevant signal details. Higher-order IMFs might capture finer variations, contributing to signal fidelity. Their exclusion could lead to a less accurate reconstruction, particularly in complex signals. Balancing computational efficiency with signal fidelity is crucial in choosing the appropriate level of IMF decomposition in EMD.

Figure 6 displays time-domain representations of the initial ECG signal and the enhanced signal following the elimination of Gaussian noise. Our suggested filtering method performs exceptionally well in reducing high-frequency Gaussian noise in the ECG signal, and it is clear that the enhanced ECG signal obtained using the other filtering methods under discussion is more distorted. It should be noted that, in comparison to ECG signals derived from existing EMD-based filtering methods, the pattern of the improved ECG signal resulting from the suggested technique seems smoother and closely matches the original ECG signal.

Existing filtering methods were compared qualitatively with the proposed PLI filtering approach, and its performance was also examined visually. After applying the suggested filtering method to a PLI-corrupted ECG signal, the resulting denoising results are displayed in Figure 7. The outcomes of the tests display that the suggested filtering strategy is effective in reducing PLI while maintaining the integrity of the initial ECG signal.

To evaluate and contrast the efficacy of the recommended filtering strategy with alternative filtering strategies, a quantitative study employing measures like SNR, MSE, and PRD was conducted. The SNR, MSE, and PRD values that result from a superior filtering technique would all be improved. For the sake of a quantitative comparison, we will use the following criteria.

$$SNR = 10 * log_{10} \frac{\sum_{i=1}^{N} (d[n])^2}{\sum_{i=1}^{N} (d[n] - x[n])^2} \tag{8}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(d[n] - \widetilde{d[n]} \right)^2 \tag{9}$$

$$PRD = \frac{\sum_{i=1}^{N} \left(d[n] - \widetilde{d[n]} \right)^2}{\sum_{i=1}^{N} (d[n])^2} * 100 \tag{10}$$

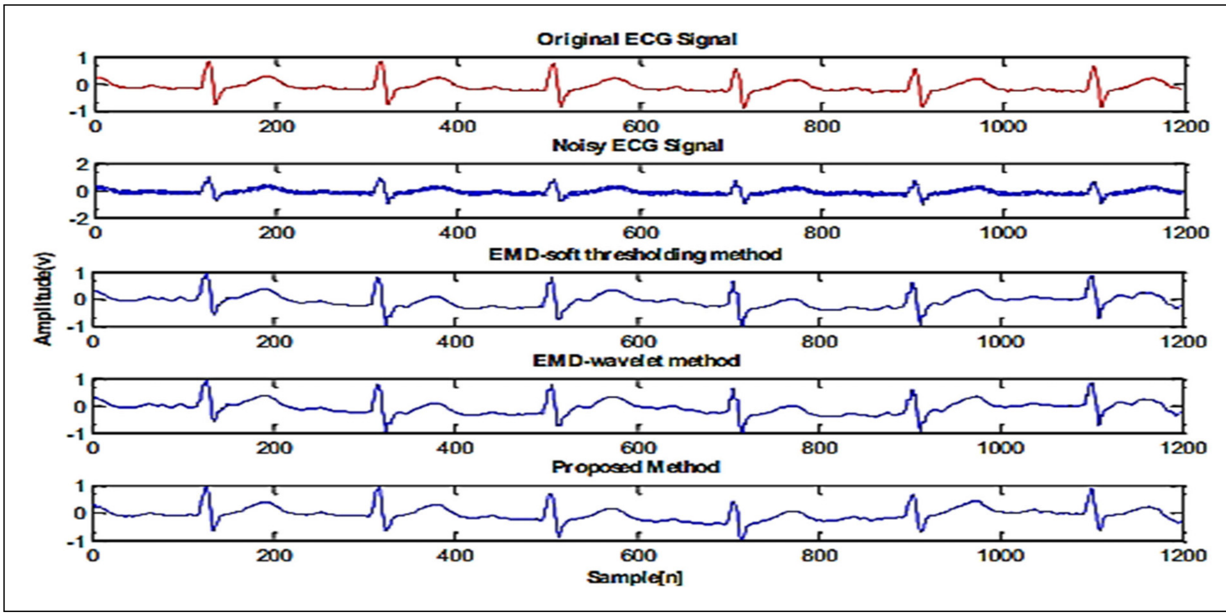

Figure 7. Elimination of PLI using the different ECG denoising method.

Table 1. Comparison of SNR and PRD values obtained from different denoising methods.

	SNR			PDR		
Input SNR (in dB)	EMD soft thresholding	EMD wavelet adaptive threshold method	Proposed approach	EMD wavelet adaptive threshold method	Proposed approach	EMD soft thresholding
−5	16.12	19.67	19.41	34.11	32.23	33.69
0	15.55	19.33	19.22	32.26	29.81	32.78
5	15.38	19.24	19.12	30.28	24.29	32.15
10	15.27	19.36	19.24	25.47	20.38	27.26
15	14.92	18.76	19.16	14.34	12.49	16.75
20	13.28	18.83	19.32	14.28	5.64	16.34
25	12.86	18.85	19.26	10.53	5.94	14.29

where,

x[n] signifies the original and noisy ECG signal .
d[n] refers to enhanced ECG signal,
N is the total number of samples.

4.3 Comparative analysis

In Table 1, we see how different filtering techniques are performed on the same set of ECG records in terms of signal-to-noise ratios. For an input SNR of −5 dB, the proposed approach achieved an output SNR of 19.41 dB, outperforming both EMD Soft Thresholding (16.12 dB) and the EMD Wavelet Adaptive Threshold Method (19.67 dB). Additionally, in terms of percentage root mean square difference (PRD), the proposed approach produced a value of 32.23%, which is significantly better than EMD Soft Thresholding (33.69%) but slightly higher than the EMD Wavelet Adaptive Threshold Method (34.11%). This indicates that the proposed method effectively reduces noise while preserving essential signal components at very low SNR levels. For an input SNR of 0 dB, the proposed approach also demonstrated superior performance, with an output SNR of 19.22 dB, close to the EMD Wavelet Adaptive Threshold Method (19.33 dB) and outperforming EMD Soft Thresholding (15.55 dB). The PRD for the proposed method was 29.81%, which is better than both EMD Soft Thresholding (32.78%) and the EMD Wavelet Adaptive Threshold Method (32.26%). At an input SNR of 5 dB, the proposed method achieves an SNR of 19.12, which is close to the 19.24 obtained by the EMD wavelet adaptive threshold method

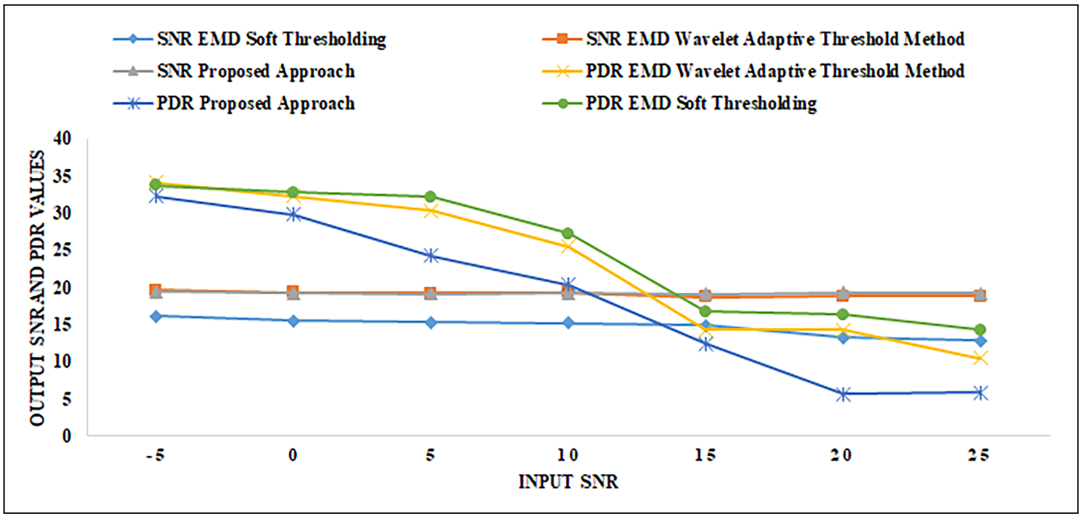

Figure 8. Comparison of SNR and PRD values obtained from various denoising methods.

Table 2. Comparison of MSE values obtained from various denoising methods.

	Mean Square Error		
Input SNR	EMD soft thresholding	EMD wavelet adaptive threshold method	Proposed method
5	0.083	0.016	0.006
10	0.076	0.0025	0.005
15	0.081	0.0031	0.005
20	0.086	0.002	3.2E-04
25	0.091	0.004	2.7E-04

and significantly higher than the 15.38 from EMD soft thresholding. In terms of PRD, the proposed method outperforms both alternatives with a value of 24.29, lower than the 32.15 and 30.28 from EMD soft thresholding and EMD wavelet adaptive thresholding, respectively.

The results show that for a range of ECG signals, the recommended filtering strategy yields a better SNR value. The proposed filtering approach produces a higher mean SNR value than the other comparison methods, as shown in the table below. This implies that the suggested approach is better than the others. In Figure 8, the input SNR was set to 15 dB, and a bar diagram displaying the PRD results produced by applying diverse denoising approaches was shown for all of the ECG data. The suggested techniques yield the lowest PRD value for any particular ECG signal in comparison with the comparative methods that are currently in use, as the bar graph illustrates.

These ECG recordings were used in a comparison study at a standard input SNR of 10 dB. In Table 2, we see the MSE results from a variety of denoising techniques applied to the same set of ECG signals. At an SNR of 5 dB, the suggested technique achieves a significantly lesser MSE of 0.006 compared to 0.083 and 0.016 for EMD soft thresholding and EMD wavelet adaptive thresholding, respectively, indicating better noise suppression. As the SNR increases, the proposed method continues to outperform the other two approaches. For example, at 10 dB SNR, the MSE for the suggested method is 0.005, which is lower than 0.076 and 0.0025 for EMD soft thresholding and EMD wavelet adaptive thresholding, respectively. Likewise, at 20 dB SNR, the proposed technique has a low MSE of 3. 2E-04, compared to 0. 086 for EMD soft thresholding and 0. 002 for EMD wavelet adaptive thresholding. The proposed filtering method yields a lower MSE than the existing state-of-the-art technologies being implemented today. The Sparse Code Shrinkage Technique improves ECG denoising by minimizing noise and at the same time maintaining the relevant characteristics of the cardiac signal. This improvement has important clinical implications as it improves diagnosis by giving clearer ECG traces, and helps in spotting minor abnormalities. Clinicians can make more informed decisions on the care of the patients hence increasing the chances of early interventions. It helps improve the effectiveness of using ECG in diagnostics in clinical practice and increases the accuracy of the results obtained.

5 Discussion

This work shows enhanced results in ECG signal denoising through the integration of EMD with wavelet thresholding. The proposed approach results in an MSE of 0.005 at 10 dB SNR, significantly less than the 0.076 achieved with EMD soft thresholding and the 0.0025 with EMD wavelet adaptive thresholding. This indicates that our method delivers a more accurate signal reconstruction with reduced error, effectively suppressing noise while preserving crucial signal features. Moreover, our method yielded an SNR of 19.24 and a PRD of 20.38 at 10 dB SNR outperforming traditional methods and providing better noise and signal enhancement.

The consequences of these findings for practice are significant for clinical environments. A high-quality ECG signal facilitates accurate diagnosis as it can distinguish between even the least noticeable abnormalities in the heartbeat that can be masked by noise. These lead to accurate diagnosis and timely interventions hence enhancing patients' health status. As our method gives clearer ECG signals, it helps in improved monitoring and evaluation of cardiac health, which in turn, enhances patient care.

However, there are some drawbacks to the above approaches. We also found that the selection of SD for EMD and the parameters used for sparse code shrinkage can affect the performance of our method. While we used a standard SD of 0.2, the optimal parameters may also be different in different ECG signals, which means that the parameters may need to be adjusted and tested again. Further, excluding higher-order IMFs during EMD leads to a reduction in computational complexity but at the same time may lead to loss of signal details. This balance between effectiveness and precision could affect the ability of reconstructing signals with high fidelity, in the more complicated cases. Future research should consider these limitations to enhance the method and its applicability even further.

6 Conclusion and future scope

This study proposes a new method of using EMD with wavelet thresholding for the elimination of high-frequency noise from ECG signals. Compared to the other methods, the proposed method performs well in filtering out noise while retaining the significant features of the signal through the Mode Decomposition and wavelet thresholding. The use of an adaptive sparse code shrinkage function, which selectively thresholds coefficients based on their sparse representations, offers a significant improvement over traditional hard or soft thresholding methods. The results have shown that this approach yields better SNR, MSE and PRD, which means that the ECG signals obtained are clearer and more accurate for diagnostic purposes.

The Sparse Code Shrinkage Technique for ECG denoising has potential future uses such as real-time monitoring in wearable devices, telemedicine, and as a data input to automated diagnostic systems. Its applicability is in increasing the accuracy and effectiveness of the ECG interpretation to increase patient outcomes and clinical management across different healthcare facilities.

Acknowledgements

The authors extend their appreciation to Taif University, Saudi Arabia, for supporting this work through project number (TU-DSPP-2024-74).

ORCID iD

Vibha Tiwari https://orcid.org/0000-0002-9772-4392

Statements and declarations

Author contributions

Vibha Tiwari: Idea and concept generation, Divya Jain: Methodology, Deepak Sharma: Implementation: Mohamed M. Hassan, Literature Review, Fayez Althobaiti: Modelling, Akshay Varkale: Supervision, Mahmoud Ahmad Al-Khasawneh: Editing and formatting, Ravi Kumar Tirandasu: Mathematical Modeling.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was funded by Taif University, Saudi Arabia, Project No. (TU-DSPP-2024-74).

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Availability of data and materials

The data that support the findings of this study are available on request from the corresponding author.

Data availability

The datasets used are cited within the manuscript.

References

1. Ahrabin A and Mandic DP. A class of multivariate denoising algorithm based on synchrosqueezing. *IEEE Trans Signal Process.* 2015; 63: 2193–2208.
2. Chen C, Shu M, Zhou S, et al. Wavelet-domain group-sparse denoising method for ECG signals. *Biomed Signal Process Control.* 2023 May 1; 83: 104702.
3. Dmytro L, Peter V and Stefanovska A. Linear and synchrosqueeed time-frequency representation revisted: overview, standards of use, resolution, reconstruction, concentration, and algorithm. *J Digital Signal Process* 2015; 42: 1–26.
4. de Vries IR, de Jong AM, van Laar JO, et al. Deep learing for sparse domain kalman filtering with applications on ECG denoising and motility estimation. *IEEE Trans Biomed Eng.* 2024 Feb 21; 71: 2321–2329.
5. Roy V, Shukla S, Shukla PK, et al. Gaussian Elimination-Based novel canonical correlation analysis method for EEG motion artifact removal. *J Healthc Eng.* 2017; 2017: Article ID 9674712, 11 pages.
6. Yu L, Yu C and Song F. Time-Frequency analysis of sunspot numbers using synchrosqueezing transform. In: IEEE International Conference Proceeding on Chinese Control and Decision Conference, 2017, pp.5204–5208.
7. Roth GA, Mensah GA, Johnson CO, et al. Global burden of cardiovascular diseases and risk factors, 1990–2019: update from the GBD 2019 study. *J Am Coll Cardiol* 2020; 76: 2982–3021.
8. Moridani MK and Marjani S. A review of the methods for sudden cardiac death detection: a guide for emergency physicians. *Int J Online Biomed Eng* 2020; 16: 137–158.
9. Ullah H, Amir M, Iqbal M, et al. De-Noising of sparse signals using mixture model shrinkage function. *IEEE Access* 2023 Jan 16; 11: 7551–7563.
10. Stalin S, Roy V, Shukla PK, et al. A machine learning-based big EEG data artifact detection and wavelet-based removal: an empirical approach. *Math Probl Eng.* 2021; 2021: Article ID 2942808, 11 pages.
11. Roy V and Shukla S. Effective EEG motion artifacts elimination based on comparative interpolation analysis. *Wireless Pers Commun* 2017; 97: 6441–6451.
12. Hua J, Zou J, Rao J, et al. ECG signals deep compressive sensing framework based on multiscale feature fusion and SE block. *IEEE Access* 2023 Sep 18.
13. Sharma RR and Pachori RB. Baseline wander and power line interference removal from ECG signals using eigenvalue decomposition. *Biomed Signal Process Control* 2018; 45: 33–49.
14. Bing P, Liu W and Zhang Z. DeepCEDNet: an efficient deep convolutional encoder-decoder networks for ECG signal enhancement. *IEEE Access* 2021; 9: 56699–56708.
15. Tan X, Ye J, Zhang X, et al. Application of improved wavelet threshold in ECG signal de-noising. *Chin J Med Devices* 2021; 45: 1–5.
16. Muduli PR and Kumar V. A proximity operator-based method for denoising biomedical measurements. *Circuits Syst Signal Process.* 2023 Oct; 42: 6253–6277.
17. Roy V and Shukla S. Designing efficient blind source separation methods for EEG motion artifact removal based on statistical evaluation. *Wireless Pers Commun* 2019; 108: 1311–1327.
18. Halidou A, Mohamadou Y, Ari AA, et al. Review of wavelet denoising algorithms. *Multimed Tools Appl.* 2023 Nov; 82: 41539–41569.
19. Mazumder R, Radchenko P and Dedieu A. Subset selection with shrinkage: sparse linear modeling when the SNR is low. *Oper Res.* 2023 Jan; 71: 129–147.
20. Mavaddati S. Classification of ECG arrhythmia using wavelet packet transform analysis and sparse learning method. Iranian journal of science and technology. *Trans Electr Eng* 2023 Dec; 47: 1583–1593.
21. Rai HM, Trivedi A and Shukla S. ECG Signal processing for abnormalities detection using multi-resolution wavelet transform and artificial neural network classifier. *Measurement (Mahwah N J).* 2013 Nov 1; 46: 3238–3246.
22. Mohguen O. Noise reduction and QRS detection in ECG signal using EEMD with modified sigmoid thresholding. *Biomed Eng/Biomedizinische Technik* 2024 Feb 26; 69: 61–78.