International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST

An Improved EMD based ECG Denoising Method using Adaptive Switching Mean Filter

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ARTICLEINFO

Article History:
Accepted: 01 Aug 2023
Published: 16Aug 2023

Publication Issue
Volume 10, Issue 4
July-August-2023

Page Number
457-467

ABSTRACT

In this paper discuss the various Denoising technique in EMD –ECG and discuss the Adaptive Switching Mean filters. Electrocardiogram (ECG) conveys numerous clinical information on cardiac ailments. For the analysis of mutual coupling also focus on the surface current analysis, in this paper shows the surface current analysis of different previous work. In this paper also discuss about the Electrocardiogram (ECG) problem signals are crucial for diagnosing various cardiac abnormalities. However, these signals are often corrupted by various types of noise, including baseline wander, powerlines interference, and muscle artefacts these are the major problem in this paper. The proposed EMD-based ECG denoising method with the Adaptive Switching Mean filter provides an effective approach for removing noise from ECG signals. The last section discusses about Experimental results on both synthetic and real-world ECG signals demonstrate the effectiveness of the proposed method.

Keywords: Space-Time Trellis Code (STTC), Filter, Inter-Carrier Interference, Bit Error Rate (BER), Signal To Noise Ratio (SNR) And Wireless Fading Channe.

I. INTRODUCTION

Electrocardiogram (ECG) is widely utilized tool for the identification of cardiovascular disorders. A typical ECG signal contains following segments, namely P, Q, R, S, and Twave. Due to the rapid growth of population, computer based automated ECG analyzer has a great importance. For reliable and efficient analyzing of ECG signal, a noise free ECG signal is much desired. However, practically during acquisition and transmission, several noises in particular, Gaussian noise, power line interference, muscle artifact, baseline wander, etc. contaminates with ECG signal. Gaussian noise is generated due to the poor channel condition, power line interference appears because of power supply, muscle artifact is introduced by the muscle activity and baseline wander is occurred due to respiration [5]. Elimination of these noises is very much essential for reliable analysis. Hence, the denoising of ECG signal through appropriate algorithms is an important topic in the field of biomedical engineering.

Several researchers contribute a number of research articles on ECG denoising technique, these methods are mainly based on digital filter bank [6, 7], adaptive filter [4], principle component analysis [8], neural network [9], Bayesian filter [10], discrete wavelet transform (DWT), empirical mode decomposition (EMD) [14], EMD+DWT [15, 16]. Digital filter based techniques require suitable cutoff frequency, moreover, they blur the signal by removing P and T waves [6, 7]. Adaptive filter and neural network based methods require additional reference signals and training phase [4, 9]. Bayesian filter based algorithms require complex mathematical calculations [10]. In EMD based denoising methods, the intrinsic mode functions (IMFs) are extracted from the signal [14, 15]. As the high-frequency artifacts are concentrated on only a few lower order IMFs so to discard the noise components and preserve QRS complexes, a window is applied. Then a partial reconstruction is employed by using the windowed IMFs and the others IMFs. As a result, the noises in the frequency range of QRS complex still exist. Hence, a further denoising procedure is essential.

Introduced an improved ECG denoising technique based EMD along with an adaptive switching mean filter (ASMF). The ASMF is commonly used for image denoising. It is inspired by the fact that, there should be a similarity in value in neighborhood pixels.

Here, at the primarystage, the corrupted ECG signal is decomposed into its IMFs and a wavelet denoising operation is performed on first three IMFs to reduce the high-frequency artifacts. Then, the signal is recovered by accumulating the denoised IMFs and remaining IMFs. Now, the ASMF is applied for further improvement of signal quality by reducing the noises those are spread in the lower frequency band. Due to the use of the ASMF, the peaks of the ECG signal are attenuated. Hence a peak restoration operation has been performed. For evaluation of the efficiency of the presented method standard ECG signals of MIT-BIH arrhythmia database have been utilized [17]. Three performance metrics Signal to noise ratio improvement (*SNRimp*), root mean square error (*RMSE*) and percentage root mean square difference (*PRD*) have been used. The efficacy of the presented work is compared with the existing methods.

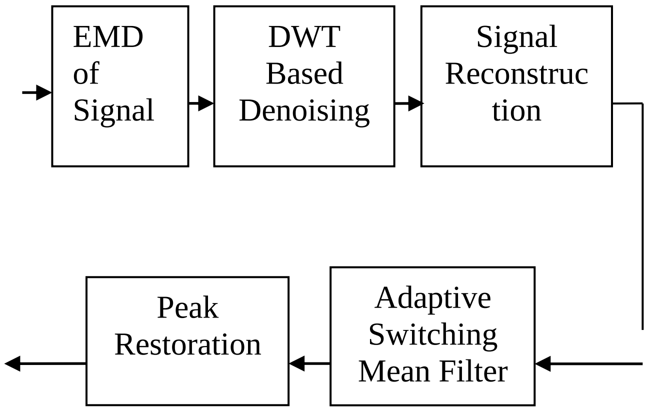


Figure 1. Block diagram of the presented ECG denoising technique

II. LITERATURE SURVEY

Pragya Talwar et.al. (2023) – In this research work the different de-noising methods performed on noisy ECG data. It is shown that the proposed shrinkage function is very successful in de-noising noisy ECG data. In addition to improving the signal-to-noise ratio, this technique may also preserve the continuity and uniformity of the signals themselves. In fact, many sorts of signals can have their noise removed using this method. The signal-to-noise ratio is increased, proving the proposed approach is an efficient de-noising technique for irregular signals like ECG. The proposed threshold and shrinking function may improve the signal-to-noise ratio (SNR) while processing an electrocardiogram (ECG), leading to clearer recordings while preserving the signal's spikes and other properties. The suggested technique does an excellent job of doing what it sets out to do, which is recover a real ECG signal from a noisy recording [01].

ghao Xia et. al. (2023) –In this research work Wearable Electrocardiogram (ECG) technology has made it feasible to continuously monitor cardiovascular problems; nevertheless, these devices are more susceptible to interference from multiple disturbances, which would drastically reduce the diagnostic accuracy. In this work, we provide an improved noise reduction model for ECG data using masked convolution and variation auto encoders. We use the skip connection and feature concatenation to realize the information interacting across each channel, and variational Bayesian inference is used to identify the global features of the ECG signals by encouraging the approximate posterior of the latent variables to fit the prior distribution. To further enhance the model's noise reduction capability, the masked convolution module is used to capture local feature data from the ECG signals. Experiments done on the MIT-BIH arrhythmia database show significant gains in performance measures such as signal-to-noise ratio (SNR) and root mean square error (RMSE) with less signal distortions. [02].

Shahid A. Malik et.al. (2023) - In this researchwork the use of adaptive data-driven iteration filtering for denoising electrocardiogram (ECG) signals has been shown to be beneficial. ECG signals have been deconstructed into a band of IMFs using the IF approach in the presence of both narrow-band PLI at 50 Hz or 60 Hz and wideband low-frequency baseline wander. Denoising techniques is the process of removing the IMFs that contribute to the noise and recreating the signal using the remaining IMFs. The noise order, which quantifies the number of IMFs contributing to the noise, has been tuned to a target value. QRS maintenance through the Tukey window method was also used. Denoising has also been achieved by applying a discrete wavelet transformation on the wavelet parameters of the noise-affected IMFs according to a lifting scheme. In order to accurately retain the QRS complex after compression with the signal components, an R-peak location detection technique was employed to establish a window function [03].

J. Jebastine et.al. (2023) - In this research work the noninvasive foetal electrocardiogram monitoring method uses a composite signal consisting of maternal ECG (MECG) and foetal ECG (FECG) data acquired from abdominal ECG (AECG) signals. This record-keeping makes it possible to collect crucial and reliable information that improves foetal health. FQRS detection and FECG extraction are challenging due to the non-stationary complexity of FECG signals, similar frequency components, low detection rates, and potential overlap problems for abdominal recordings. Enhanced detection sensitivity with minimal false positives requires novel biological signal processing methods. In order to identify QRS waves and extract FECG signals from AECG data, the authors describe a state-of-the-art framework that employs a signal decomposition technique and improved threshold-based detection utilizing an adaptive noise cancelling approach (ANC-SDITD). It consists of three parts: The first phase of AECG signal denoising involves using a potent VSS-WALMS (variable step size-weighted adaptive least mean square) algorithm, which accounts for the reserved amplitude information. The underlying FECG indicators may be electronically retrieved from the complexity of the AECG signals using the empirical wavelet transfer and inverse scattered entropy techniques [04].

A Narmada et.al. (2023) - In this research work It has been suggested that electroencephalography (EEG) is a standard method for diagnosing and treating neurological conditions and conducting cognitive studies. However, artefacts of different types often contaminate EEG, making it even more difficult to decipher the data. Wearable or portable EEG recording methods are hampered by these artefacts. The implementation of "neurologically oriented mobile health solutions" is therefore subject to extra difficulties. The use of EEG in the diagnosis of epilepsy exceeds that of the next five most common neurological disorders put together. A technique for cleaning up EEG data that combines "Independent Components Analysis (ICA) and the Discrete Wavelet Transform (DWT)" was recently developed and suggested. The wavelet-ICA method also involves arbitrary thresholding or visual inspection to find the factual constituents in EEG data. In this competition, we describe an adaptive artefact wavelet denoising approach that uses deep learning and heuristics to achieve state-of-the-art accuracy in the detection of epilepsy [05].

Jaya Prakash Allam et.al. (2023) - In this research work In order to diagnose cardiac diseases and their severity, an electrocardiogram (ECG) is used. It might be challenging to manually identify critical events in an ambulatory electrocardiogram. This highlights the necessity for a diagnostic technique that can automatically detect heartbeats. While high-quality ECG data is essential for reliable ECG beat categorization, the multiple noise sources presented by wearable sensors significantly degrade such signals in real-time. In this chapter, we propose a deep learning method specifically designed to detect heartbeats in an ECG. This research makes use of (i) preprocessing and (ii) classification. During preprocessing, the ECG data is segmented into individual beats by locating the R-peak. Then, the inherent mode functions (IMFs) are derived from the ECG spikes using the empirical mode decomposed (EMD) technique. Important IMFs are selected to remove high-frequency noise from the ECG signal. In the end, an ECG is created and heartbeats are identified using a deep learning-based bespoke model for classification [06].

Monisha Lodh et.al. (2022) - In this research work A variety of noise sources could tamper with an ECG signal. Power line interface noise, electrosurgical noise, instrument noise, and electromyography noise are all examples. An efficient method of removing unwanted noise from ECG readings is urgently required. Using an EMD in combination with an adaptive switching mean filter, we propose a new method for de-noising ECG data in this study. In contrast to conventional EMD based de-noising approaches, which only de-noise lower-order IMFs, ASMF operation has been applied to further improve signal quality in this investigation. The lower-order IMFs are filtered using the wavelet de-noising technique to keep the QRS complexes while lowering the high-frequency artefacts. To further enhance the signal quality, adaptive switching mean filtering (ASMF) is then performed. The given technique is evaluated by running tests on the MIT-BIH arrhythmia database. At different ratios of signal to noise (SNR), a Gaussian signal is added on top of the raw data [07].

Punitkumar Bhavsar et.al. (2022) – In this research work A variety of noise sources could tamper with an ECG signal. Power line interface noise, electrosurgical noise, instrument noise, and electromyography noise are all examples. An efficient method of removing unwanted noise from ECG readings is urgently required. Using an EMD in combination with an adaptive switching mean filter, we propose a new method for de-noising ECG data in this study. In contrast to conventional EMD-based de-noising approaches, which only denoise lower-order IMFs, ASMF operations have been applied to further improve signal quality in this investigation. The lower-order IMFs are filtered using a wavelet de-noising technique to keep the QRS complexes while lowering the high-frequency artifacts. To further enhance the signal quality, adaptive switching mean filtering (ASMF) is then performed. The given technique is evaluated by running tests on the MIT-BIH arrhythmia database. At different signal-to-noise ratios (SNRs), a Gaussian signal is added on top of the raw data [08].

TABLE-1 COMPARISON OF DIFFERENT PREVIOUS METHODS

S.No	Ref./Year	Authors	Title	Method
1	[01]/2023	Pragya	Adaptive Filter And EMD Based	EMD Based De-

		Talwar et.al.	De-Noising Method Of ECG Signals	Noising Method
2	[02]/2023	Yinghao Xia et.al.	A Denoising Method Of ECG Signal Based On Variational Autoencoder And Masked Convolution	DeepCED NetAE Method
3	[03]/2023	Shahid A. Malik et.al.	An Iterative Filtering Based ECG Denoising Using Lifting Wavelet Transform Technique	Iterative Filtering (IF) Method
4	[04]/2023	J. Jebastine et.al	Fetal ECG Extraction And QRS Detection Using Advanced Adaptive Filtering-Based Signal Decomposition And Peak Threshold Technique From Abdominal ECG Signals	signal processing methods
5	[05]/2023	A Narmada et.al.	distributed DL-based attack detection framework	Artifacts Removal Using Deep Learning
6	[06]/2023	Jaya Prakash Allam et .al	Patient-Specific ECG Beat Classification Using EMD And Deep Learning-Based,	EMD and deep learning-based technique
7	[07]/2022	Monisha Lodhi et.al.	Design Of Kalman Adaptive Filter Thresholding And EMD Based De-Noising Method For ECG Signals	ECG signal method
8	[08]/2022	Punitkumar Bhavsar et.al.	Improved ECG Denoising Using CEEMAN Based On Complexity Measure And Nonlocal Mean Approach	ECG with Normal Sinus Rhythm

III.PROPOSED METHOD

The proposed method for ECG denoising using an improved Earth Mover's Distance (EMD) and Adaptive Switching Mean Filter (ASMF) involves a two-step process to effectively remove noise from ECG signals. This method aims to enhance the quality of ECG signals for more accurate analysis and diagnosis.

Step 1: Improved EMD-based Denoising

The first step of the proposed method utilizes an improved version of EMD for denoising the ECG signal. EMD is a widely used technique for decomposing signals into Intrinsic Mode Functions (IMFs) and residual noise. The traditional EMD method can sometimes generate noise artifacts known as mode mixing.

To address this issue, the improved EMD method incorporates additional criteria to select the IMFs and effectively eliminate mode mixing. The improved EMD algorithm ensures that the extracted IMFs contain relevant ECG components while minimizing noise artifacts.

Step 2: Adaptive Switching Mean Filter

After the EMD-based denoising, the proposed method employs an Adaptive Switching Mean Filter (ASMF) to further enhance the denoising process. The ASMF adaptively filters the ECG signal by dynamically selecting between a mean filter and a median filter based on the characteristics of the signal.

The ASMF algorithm continuously monitors the local statistical properties of the ECG signal to determine whether the mean or median filter should be applied. The mean filter is effective in reducing Gaussian noise, while the median filter is more suitable for Suppress

By adaptively switching between these two filters, the ASMF can effectively reduce different types of noise present in the ECG signal. This adaptive approach ensures that the denoising process is optimized for various noise conditions encounTERED IN REAL-WORLD ECG SIGNALS

Overall, the proposed method combines the improved EMD-based denoising technique with the adaptive switching mean filter to achieve robust noise reduction in ECG signals. This two-step approach aims to preserve the important features of the ECG waveform while removing unwanted noise, enabling more accurate analysis and interpretation of the signals for clinical applications.

IV. SIMULATION RESULT

In this section we are analyzing projected outcomes of the proposed method. For simulation of proposed method we have to use MATLAB R2015b (8.0.0.783) software. Basic configuration of our system is Manufacturer: Hewlett-Packard HP 4540s Processor: Intel(R) Core(TM) i3-3110M CPU @ 2.40 GHz 2.40 GHz with 4.00 GB (2.64 GB usable) RAM : System type: 64-bit Operating System.

Mean Square Error (MSE)

The MSE measures the standard amendment between the actual image (X) and processed image (Y) and is given by:

$$MSE = \frac{1}{N}\sum_{j-0}^{N-1}(X_J - \overline{Y_J})^2 \qquad 5.1$$

Root Mean Square Error (RMSE)

The **root-mean-square error (RMSE)** is a frequently used measure error observation in results. RMSE shows differences between values (sample and population values) predicted by a model or an estimator and the values actually observed.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j-0}^{N-1}(X_J - \overline{Y_J})^2} \qquad 5.2$$

Signal to Noise Ratio (SNR)

The SNR compares the amount of desired signal to the amount of background noise. The upper the proportion, the less obtrusive the background signal is. It's expressed in decibels (db) as:

$$SNR = 10\log_{10}\left(\frac{\sigma^2}{\sigma_e^2}\right) \qquad 5.3$$

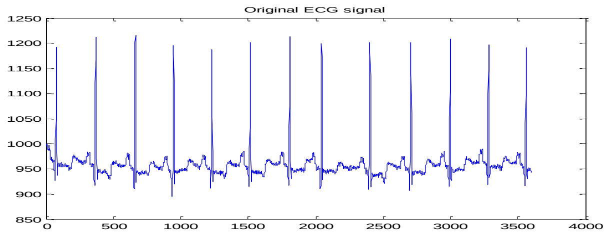
Where σ^2 is that the variance of the actual image and σ_e^2 is that the variance of error (Difference between the actual and denoised image i.e. *|X - Y|*).

Percentage Root-Mean-Square Difference (PRD)

Let x[n] and ˆy[n] be the original and the reconstructed signals, respectively, and N its length. The PRD formula is defined as:

$$PRD = \sqrt{\frac{\sum_{j-0}^{N-1}(X_J - \overline{Y_J})^2}{\sum_{j-0}^{N-1}(\overline{Y_J})^2}} \times 100 \qquad 5.4$$

Now shows the original audio signal of input data. We will compress this audio signal by using empirical mode decomposition (EMD) technique to generate different Intrinsic Mode Functions (IMFs).



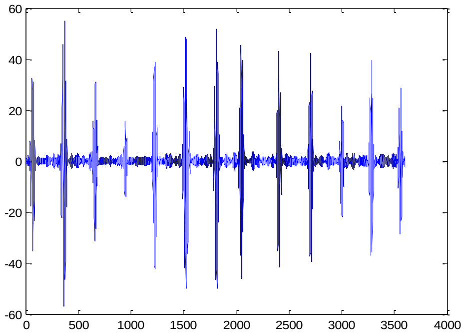


Fig.2.ECG Signal

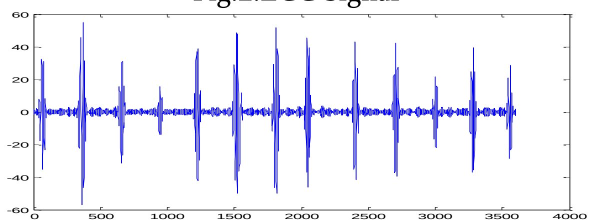


Fig. 3 IMF -1

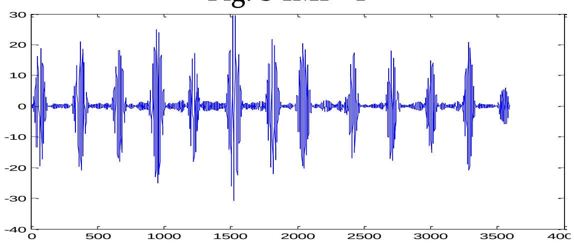


Fig. 4 IMF -4

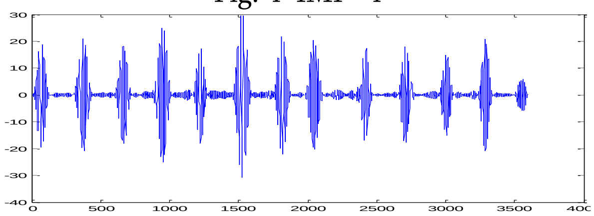


Fig. 5 IMF -4

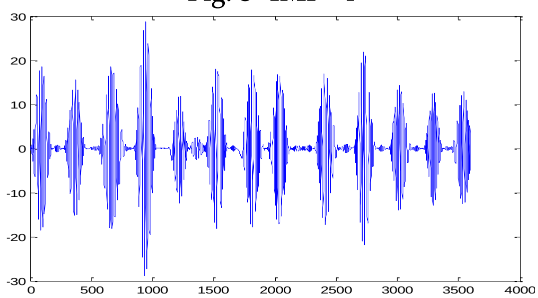


Fig. 6 IMF -5

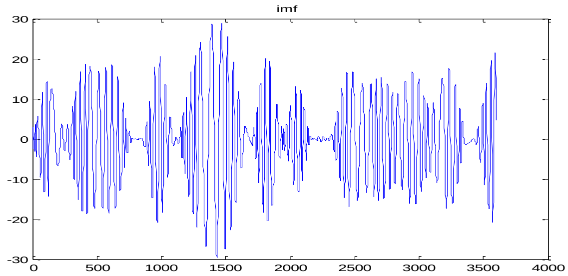


Fig. 6.1(1) IMF -6

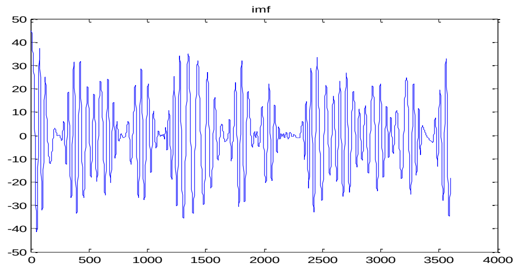


Fig. 6.2(b) IMF -7

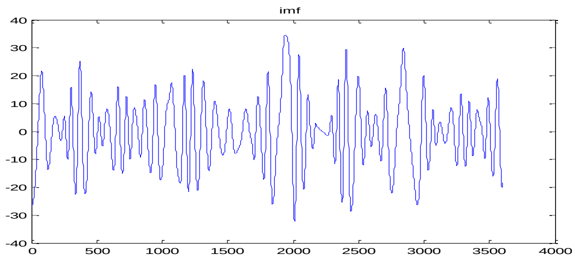


Fig. 6.3 (c) IMF -8

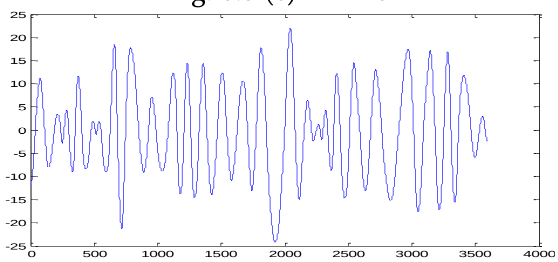


Fig. 6.4 (d) IMF -9

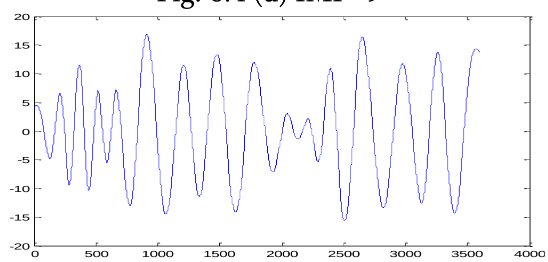


Fig. 6.5 (e) IMF -10

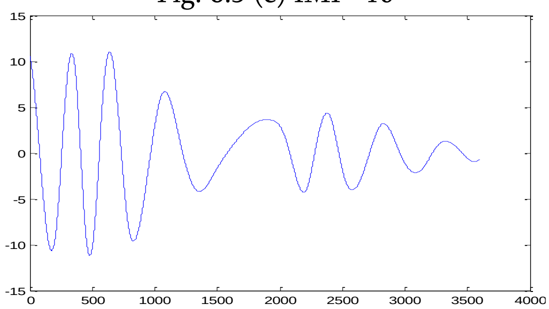


Fig.6.6 (f) IMF -11

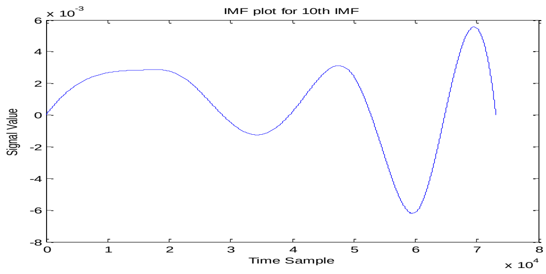


Fig. 7. Shows the IMF-10

There are different IMF's generated in de-nosing method which are represented as IMF-1, IMF-4, IMF-7, and IMF-10 respectively. From the above diagrams it clearly shows that the frequency became broader than every slot of signal to signal.

Table 5.1 Shows the RMSE comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	0.25	0.2	0.17	0.11	0.04
10	0.21	0.16	0.14	0.08	0.03
15	0.14	0.13	0.09	0.04	0.01
20	0.09	0.05	0.04	0.03	0.009

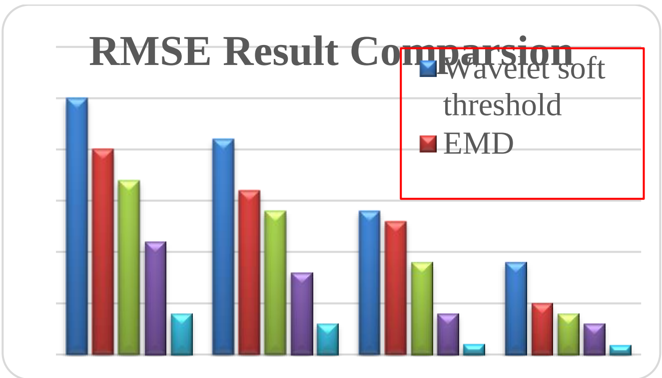


Fig. 5.3 Graphical analysis of RMSE of Proposed Method

The propose method is tested on different ECG signal performed with different filters at different SNR values 6, 10, 15 and 20. In the above figure shows calculated RMSE (Root mean square Error) on different SNR values. RMSE of proposed de-noising method is least than other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) gives lower results as compare to proposed method at different SNR values.

Now moved out the next result that signal to noise ratio (SNR). Compare the resultant output with different pervious methods, which is shown in below table 5.2 In this table shows the resultant output of proposed method at different SNR values 6, 10,15 and 20db.

Table 5.2 Shows the SNR comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	5	6.2	8	9.1	8.1
10	5.2	6.1	7	8.9	9.87
15	5.1	5	6.2	8.2	12.43
20	4.1	4.2	5.5	6.7	14.86

The propose method is tested on different ECG signal performed with different filters at different SNR values 6, 10, 15 and 20. In the above figure shows calculated SNR (signal to noise ratio) on different SNR values. SNR of proposed de-noising method is least than other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) gives lower results as compare to proposed method at different SNR values.

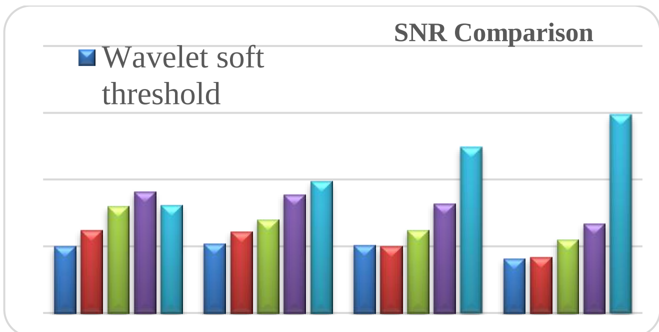


Fig. 5.4 Graphical analysis of SNR of Proposed Method with different methods

Now discuss the next result that PRD Compare the resultant output with different pervious methods, which is shown in below table 5.3 In this table shows the resultant output of proposed method at different SNR values 6, 10, 15 and 20db.

Table 5.3 Shows the PRD comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	57	51	48	18	16.15
10	47	43	41	11	10.3
15	32	30	24	6	5.5
20	20	18	12	4	3.2

The propose method is tested on different ECG signal performed with different filters at different SNR values 6, 10, 15 and 20. In the above figure shows calculated PRD (percentage root mean square error) on different SNR values. PRD of proposed de-noising method is better as compare to other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) gives lower results as compare to proposed method at different SNR values.

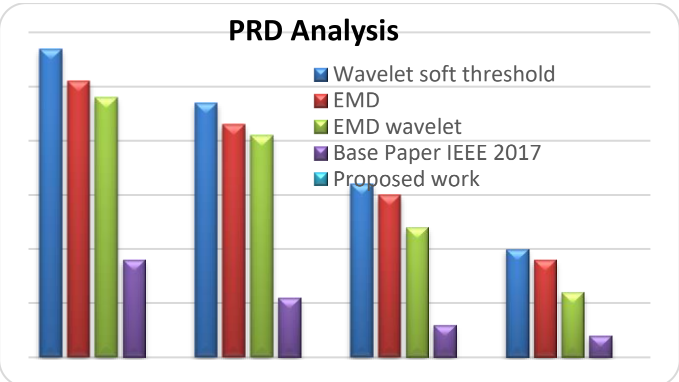
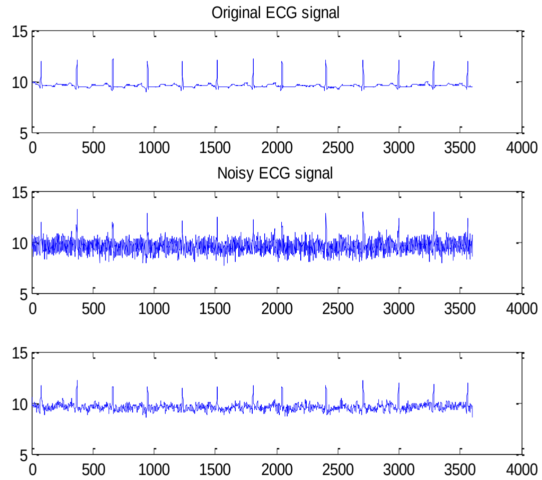


Fig. 5.5 Graphical analysis of PRD of Proposed Method with different methods



V. CONCLUSION

In this paper discuss on the Improved EMD based ECG Denoising Method using Adaptive Switching Mean Filter offers several advantages for ECG signal denoising. It achieves enhanced denoising performance by effectively removing noise while preserving important signal details. The adaptive nature of the switching mean filter allows it to adaptto different noise characteristics, making it suitable for a wide range of ECG signals. This method has the potential to improve the accuracy of ECG analysis and diagnosis, contributing to better patient care and clinical decision-making in cardiology. However, it's important to note that further research and validation are needed to assess its performance across different datasets and compare it with existing denoising method.

Cite this article as :

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Cite this article as :

Tanushree Patel, Prakash Saxena, Seema Kirar, "An Improved EMD based ECG Denoising Method using Adaptive Switching Mean Filter ", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 10 Issue 4, pp. 457-467, July-August 2023.

Journal URL : https://ijsrst.com/IJSRST52310417