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

[1]MD Khateeb Alam, [2]Dr. Arvind Kaurav, [3]Prof. Nehul Mathur
Department of Electronics and Communication (EC)
Bhopal Institute of Technology (BIT), Bhopal, M.P., INDIA

Abstract: *Electrocardiogram (ECG) signal denoising is a critical preprocessing step in diagnosing cardiovascular disorders. Empirical Mode Decomposition (EMD) is a powerful technique commonly used for ECG denoising. However, traditional EMD-based denoising methods often suffer from certain limitations, such as mode mixing and the loss of high-frequency components. The proposed method comprises two main stages: EMD decomposition and adaptive switching meanfiltering. In this pepar, the noisy ECG signal is decomposed into intrinsic mode functions (IMFs) using EMD. The adaptive switching mean filter is then introduced in the second stage to perform a filtering process on each IMF. The adaptive nature of the filter enables it to selectively suppress noise, while retaining important features in the signal.To evaluate the effectiveness of the proposed method, we conducted extensive experiments on a diverse set of synthetic and real-world ECG signals contaminated with various types of noise and artifacts. Comparative analysis against state-of-the-art denoising methods demonstrates the superiority of our proposed approach in preserving high-frequency components and improving signal-to-noise ratio (SNR).*

Key Words: *Electrocardiogram (ECG), Denoise, EMD, Adaptive switching mean filter, SNR, MIT-BIH database.*

1. INTRODUCTION:

The electrocardiogram (ECG) is a common diagnostic technique for heart problems. A normal electrocardiogram will include the following waves: P, Q, R, S, and T. Rapid population expansion highlights the need for automated ECG analyzers based on computers. A clean ECG signal is highly sought after because it allows for more precise and time- saving analysis. However, in reality, the ECG signal is contaminated by a number of disturbances during recording and transmission, including Gaussian noise, power line interference, muscle artefact, baseline drift, etc. Inadequate power supplies, power line interference, muscular artefacts, and muscle action add Gaussian noise, while breathing introduces baseline drift. For accurate analysis, it is crucial that these distractions be removed.

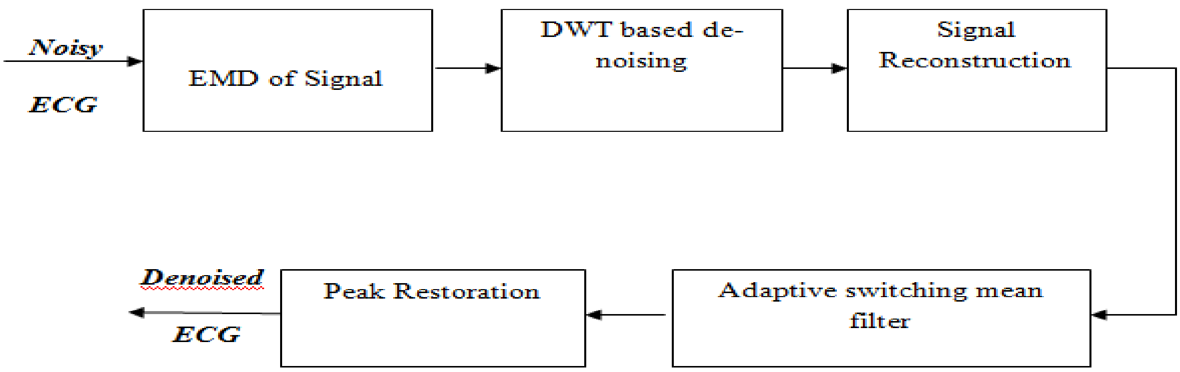

Figure 1 Block Diagram Of The Presented ECG Denoising Technique.

Predominant Noises in ECG:

These aberrations and noises occur within the relevant spectral range and most often take the form of morphological features that are comparable to either the ECG's intrinsic characteristics or any disease-specific characteristics. Below is a synopsis of the most common types of ECG noise WM and Palace Metro Police Station area networks are implemented with the aid of this system, and with it, the locations issues are also taken into account on the network, just like current network-based wireless locations method in the below figure 2 shows MIMO-OFDM architecture.

In an electrocardiogram (ECG), the predominant noises that can be encountered include:

- Baseline wander: This noise appears as small fluctuations or drifts in the ECG baseline. It can be caused by patient movement, breathing, or improper electrode placement.
- 60 Hz/50 Hz interference: Electrical interference from power lines can introduce noise at the power line frequency (60 Hz in the United States and 50 Hz in many other countries). This noise appears as regular spikes or artifacts on the ECG waveform.
- Muscle artifact: Movement or contraction of muscles near the electrode sites can generate noise on the ECG, appearing as random spikes or sharp waves. It can be caused by patient movement or tension in the muscles.
- Electrode contact noise: Poor electrode contact with the skin can lead to noisy signals. This noise can manifest as high-frequency noise or irregular patterns on the ECG.
- Electrical interference: Various electrical devices or machinery present in the environment, such as cell phones, medical equipment, or fluorescent lights, can introduce interference into the ECG signal.
- Respiratory artifact: Breathing can cause fluctuations in the ECG signal, particularly noticeable in the precordial leads. These artifacts usually manifest as rhythmic oscillations in the waveform.
- External interference: Environmental factors like electromagnetic fields or radiofrequency interference can disrupt the ECG signal, leading to additional noise or signal distortion.

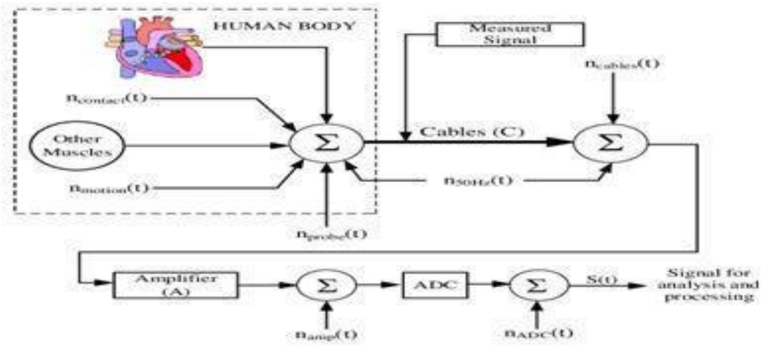

Figure 2: Predominant noises in ECG

2. LITERATURE REVIEW:

Pragya Talwar et.al. (2023) - Here, we looked at how 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 improved signal-to-noise ratio demonstrates the effectiveness of the suggested strategy as a de-noising method for non-stationary signals like ECG. Clearer recordings may be obtained while still maintaining the spikes and other characteristics of an electrocardiogram (ECG) using the suggested threshold and shrinking function, which may increase the signal-to-noise ratio (SNR) during processing. The proposed method accomplishes its goal—recovering a genuine ECG signal from a noisy recording—remarkably well [01].

Yinghao Xia et.al. (2023) - Technology advancements in wearable electrocardiogram (ECG) monitoring have made it possible to keep tabs on heart health in real time, but increased susceptibility to interference from numerous disturbances threatens to compromise diagnostic accuracy. In this paper, we use masked convolution and variation auto encoders to develop a more effective model for reducing noise in ECG data. By enticing the approximate posterior of the latent variables to fit the prior distribution, variational Bayesian inference is used to identify the global features of the ECG signals, and the skip connection and feature concatenation are used to realise the information interacting across each channel. By extracting local features from the ECG signals using the masked convolution module, the model's ability to filter out background noise is improved. Using the MIT-BIH arrhythmia database, experiments indicate considerable improvements in signal-to-noise ratio (SNR) and root mean square error (RMSE) with less signal distortions [02].

Shahid A. Malik et.al. (2023) - 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) - Abdominal electrocardiogram (AECG) signals are combined with maternal ECG (MECG) data to create a composite signal used in noninvasive foetal electrocardiogram monitoring. By maintaining meticulous records, we are able to gather credible data that has a direct impact on foetal well-being. Due to the non-stationary nature of FECG signals, comparable frequency components, poor detection rates, and the possibility of overlap difficulties for abdominal recordings, FQRS detection and FECG extraction are difficult tasks. Improved detection sensitivity with low false positive rates calls for cutting-edge approaches to processing biological signals. The authors offer a state-of-the-art framework that uses a signal decomposition method and enhanced threshold-based detection with an adaptive noise cancelling approach (ANC-SDITD) to recognise QRS waves and extract FECG signals from AECG data. There are three sections to it: In the first stage of AECG signal denoising, the reserved amplitude information is taken into account utilising the powerful VSS-WALMS (variable step size-weighted adaptive least mean square) algorithm. Using empirical wavelet transfer and inverse scattered entropy methods, the underlying FECG indications may be extracted electronically from the complexity of AECG signals [04].

A Narmada et.al. (2023) - 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. Finding the real components in EEG data with the wavelet-ICA approach also requires arbitrary thresholding or eye examination. For this challenge, we detail a deep learning and heuristics-based adaptive artifact wavelet demising method for epilepsy identification that achieves state-of-the-art accuracy [05].

Jaya Prakash Allam et.al. (2023) - 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. Here we offer a deep learning technique tailored to ECG heartbeat detection. Preprocessing and categorization are used in this study. Finding the R-peak in the ECG data allows for its separation into individual beats during preprocessing. Next, the ECG spikes are empirically mode deconstructed (EMD) to get the intrinsic mode functions (IMFs). Selecting relevant IMFs helps filter out unwanted high-frequency components of the ECG signal. At last, an electrocardiogram (ECG) is made, and heartbeats are detected, by means of a deep learning-based custom model for categorization [06].

Monisha Lodh et.al. (2022) - 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. There is an immediate need for a robust strategy for filtering out background noise in ECG measurements. In this research, we present a novel approach to de-noising ECG data by combining an EMD with an adaptive switching mean filter. In this study, ASMF operation was employed to further enhance signal quality, in contrast to traditional EMD based de-noising techniques, which only de-noise lower-order IMFs. In order to preserve the QRS complexes while reducing the high-frequency artefacts, the lower-order IMFs are filtered using the wavelet de-noising method. Then, adaptive switching mean filtering (ASMF) is used to further improve the quality of the signal. Tests are conducted using the MIT-BIH arrhythmia database to assess the effectiveness of the presented method. Gaussian noise is superimposed on the original data at varying signal-to-noise (SNR) levels [07].

Punitkumar Bhavsar et.al. (2022) – 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. In this research, we present a novel approach to de-noising ECG data by combining an EMD with an adaptive switching mean filter. To further increase signal quality, ASMF procedures were used, as opposed to the traditional EMD-based de-noising techniques that only de-noise lower-order IMFs. In order to preserve the QRS complexes while reducing the high-frequency artefacts, a wavelet de-noising approach is used to the IMFs of lower order. Then, adaptive switching mean filtering (ASMF) is used to further improve the quality of the signal. Tests are conducted using the MIT-BIH arrhythmia database to assess the effectiveness of the presented method. A Gaussian signal is superimposed over the original data at various signal-to-noise ratios (SNRs) [08].

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Table 1: Comparison of Different ECG signal Filters

S.No	Ref./Year	Authors	Title	Method
1	[01]/2023	Pragya Talwar et.al.	Adaptive Filter and EMD Based De-Noising Method of ECG Signals	Kalman Adaptation Algorithm
2	[02]/2023	Yinghao Xia et.al.	A Denoising Method Of ECG Signal Based On Variational Autoencoder And Masked Convolution	Wavelet Based Methods
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	A novel adaptive artifacts wavelet Denoising for EEG artifacts removal using deep learning with Meta-heuristic approach	Deep Learning
6	[06]/2023	Jaya Prakash Allam	4 - Patient-specific ECG beat classification using EMD and deep learning-based technique	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	De-noising Method
8	[08]/2022	Monisha Lodhi et.al.	Design of Kalman Adaptive Filter Thresholding and EMD based De-noising Method for ECG Signals	De-Noising Method

3. PROPOSED METHOD:

Overview:

Figure 4.1 depicts the whole model of the system. To recover the ECG signal from the noisy ECG wave is the primary goal of the suggested technique. In order to get those ECG signals back, we need to do a number of different processes. Empirical mode decomposition has been applied to the supplied ECG wave. The resulting function, called an IMF (Intrinsic Mode Function), is derived from this decomposition. These IMFs are compressed and then decompressed to provide sound waves for further processing. The spline function was used to calculate the Reverse Intrinsic Mode Functions (RIMFs) that have been developed. Mathematically, a spline function is one that has a high level of smoothness at the intersections of its polynomial definition's individual components. We get the desired recovered signals after all processes are complete.

Important Parts of Proposed Method:

Explain in further detail the pivotal step in the proposed procedure. The suggested study focuses on the

electrocardiogram (ECG) reading. The suggested work would have needed an ECG signal as an input. The e lectrocardiogram (ECG) signal in medicine has been studied extensively for many years. Speech recognition, speaker identification, and voice detection are three well-studied areas of speech categorization.

EMD:

Using EMD, a signal may be dissected without ever having to leave the temporal domain. It's similar to wavelet decomposition and the Fourier transform, for example. Complex signals, which are often both non-linear (NL) and non-stationary (NS), benefit from this kind of analysis. This goes against the grain of everything we've learned thus far about how to approach problems (specifically, that the systems in issue are LTI, at least approximately)

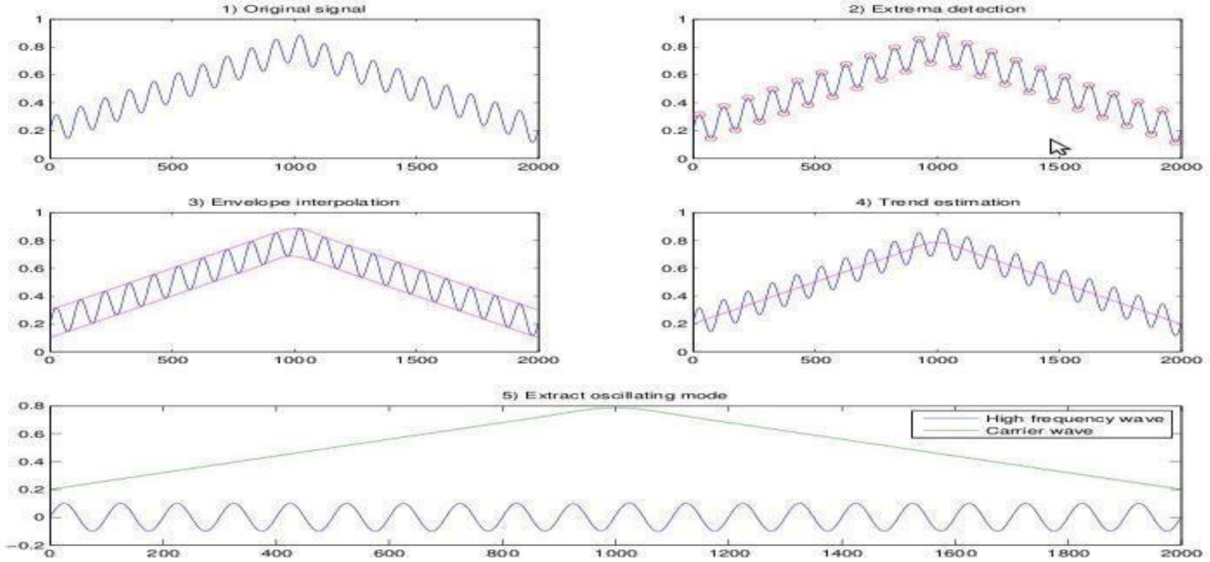


Figure 3: Shows the steps of EMD

A. *Intrinsic Mode Functions (IMF)*

Only the initial IMF and residual of a data stream may be calculated using the IMF object. This is done in a manner similar to the offline method in that input data is gathered and stored until there is enough to compute a portion of the IMF and the residual. As long as new input data is provided, we will keep computing new sections of the IMF and residue and appending them to the existing sections and residue. The catch is that smooth connections between blocks are required for the calculation of each new block to begin just where the preceding block left off. Two factors complicate this:

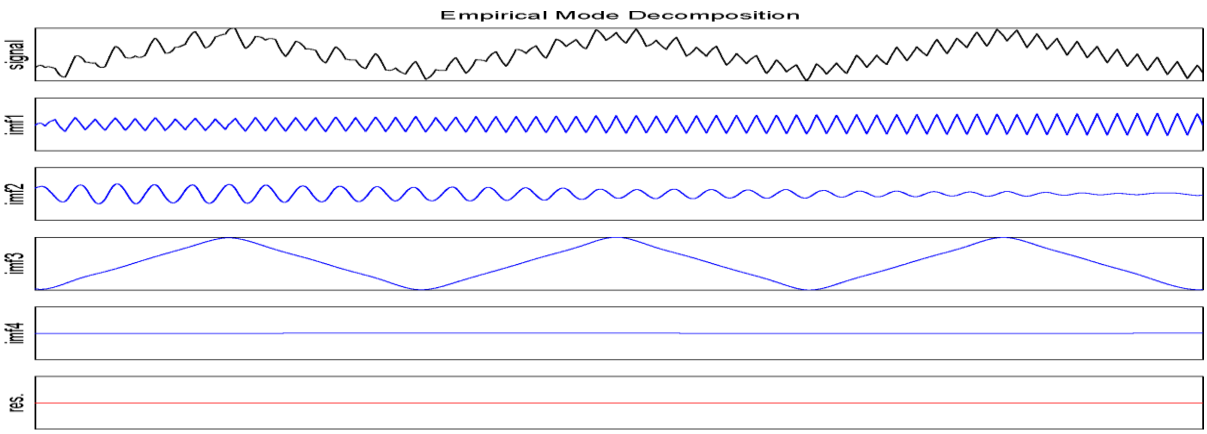


Fig 4 Empirical Mode Decomposition

4. SIMULATION AND RESULT:

Introduction:

The anticipated results of the suggested approach are discussed below. MATLAB R2015b (8.0.0.783) is required for simulation of the suggested technique. Our system's most fundamental setup is Hewlett-Packard is the manufacturer. HP 4540s Powered by a 2.40 GHz, Intel(R) Core(TM) i3-3110M processor with 4.00 GB (2.64 GB usable) of RAM. RAM: A 64-bit operating system setup.

A. Performance Parameter

The following table displays the proposed work's performance parameters.

B.1 Mean Square Error (MSE)

Standard deviation of the difference between the original picture (X) and the final processed image (Y) is what the Mean Squared Error (MSE) quantifies

$$\text{MSE} = \frac{1}{N}\sum_{j-0}^{N-1}(X - Y)_y$$

B.2 Root Mean Square Error (RMSE)

The root-mean-squared error (RMSE) is a popular statistic for assessing the reliability of experimental results. How much a model or estimate is off from the actual value is quantified by the root-mean-squared error (RMSE).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{j-0}^{N-1}(X - Y)_y}$$

B.3 Mean Absolute Error (MAE)

Two continuous variables may be differentiated from one another using a metric called the mean absolute error (MAE). In this hypothetical set of paired observations describing the same phenomenon, we will treat X and Y as though they were variables that were separate.

$$\text{MAE} = \frac{1}{N}\sum_{j-0}^{N-1}\|X_J - Y_y\|$$

B.4 Signal to Noise Ratio (SNR)

The SNR is a measurement of how much signal is there in relation to how much noise there is. The higher the ratio, the less noticeable the background signal. Decibels (db) are the units of measurement:

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

Where 2 is the variance of the true picture and _e2 is the variance of the error (the gap between the true and denoised images, denoted by (X-Y)).

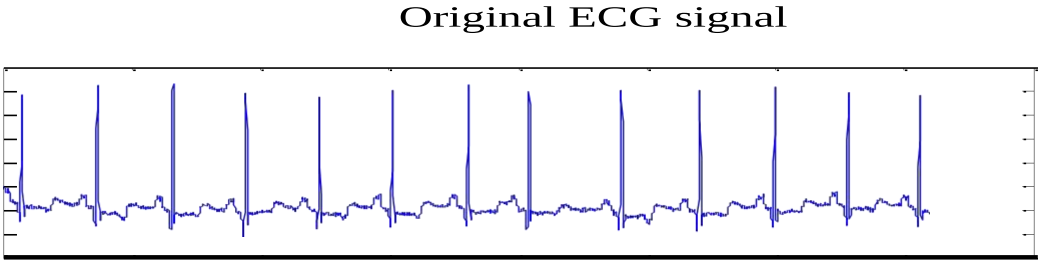
B.5 Percentage Root-Mean-Square Difference (PRD)

For simplicity, we'll refer to N as the length of the original signal and the reconstructed signal as x[n] and y[n], respectively. To explain the PRD formula, we say that:

$$\text{PRD} = \sqrt{\frac{\sum_{j-0}^{N-1}(X_J - Y_y)^2}{\sum_{j-0}^{N-1} Y_y^2}} \times 100 \qquad 5.5$$

B. Data set

The reported work [17] has been evaluated using electrocardiogram (ECG) data from the industry-standard MIT-BIH arrhythmia database. The 100m, 101m, 103m, 105m, 115m, and 215m ECG signals are used. There are both typical and atypical heartbeats and QRS geometries in these ECG data. Various amounts of Gaussian noise (-6dB, -10dB, - 15dB, & -20dB) are superimposed on the ECG signals.



5 (a) – Shows 100m ECG Signal

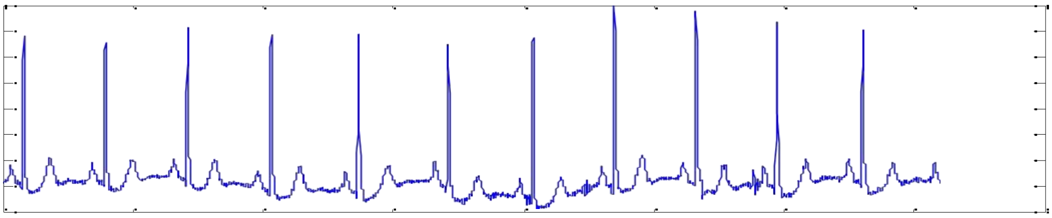


Fig. 5 (b) – Shows 101m ECG Signal

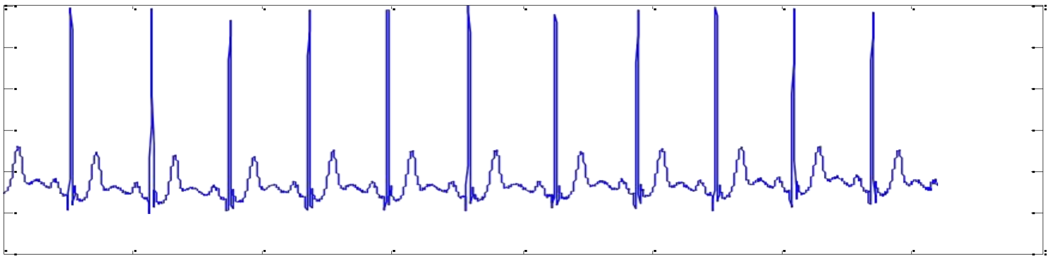


Fig. 5 (c) IMF -2

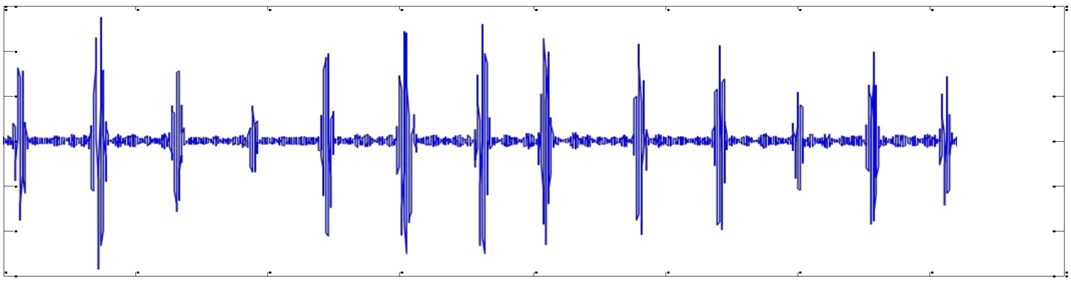


Fig. 5 (d) IMF -3

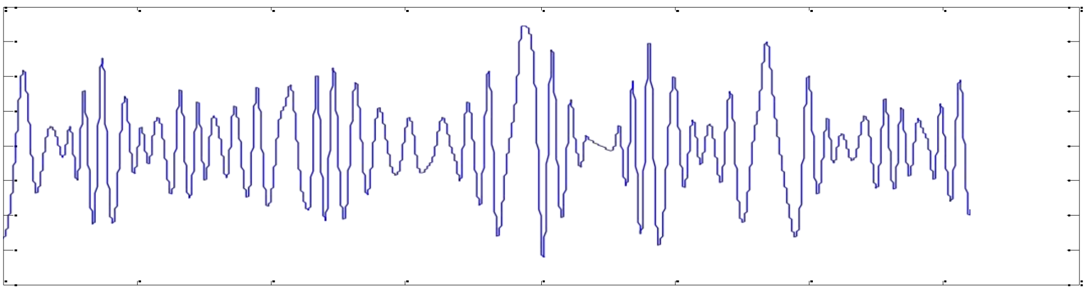


Fig. 5 (i) IMF -8

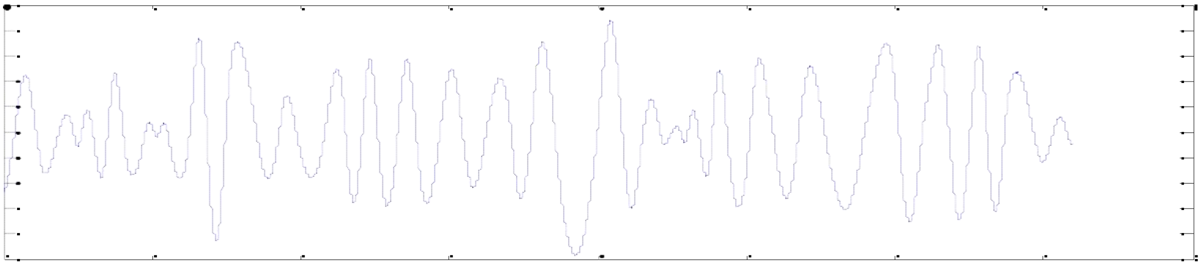


Fig. 5 (j) IMF -9

From figure 5.2 (a) to 5,2 (j) received various Intrinsic Mode Functions (IMFs) of given input audio signal. There are different IMF's generated in compression which are represented as IMF-1, IMF-2, IMF-3, IMF-4, IMF-5, IMF-6, IMF-7, IMF-8, IMF-9, IMF 10, IMF 11 and IMF- 12 respectively. From the above diagrams it clearly shows that the frequency became broader than every slot of signal to signal. Now apply mean filter and apply peak restoration then apply reconstruction of the signal. Now discuss the result in terms of result parameters.

Table: 1 Shows the RMSE comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper	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

The suggested method is tested on a set of ECG signals that have been filtered using 6, 10, 15, and 20 decibels of signal-to-noise ratio (SNR). Root Mean Square Error (RMSE) is shown above for various signal-to-noise ratios (SNRs). The RMSE of the proposed de-noising method is the smallest of the available options. All other methods, including wavelet soft threshold, EMD, EMD wavelet, and modified EMD (IEEE, 2017), perform worse in terms of signal-to-noise ratio than the proposed method. The following outcome, signal-to-noise ratio (SNR), has been released. Table 5.2 below displays the results after using many alternative approaches. Results of the suggested technique are shown in the table below for various signal-to-noise ratios (6, 10, 15, and 20 dB).

Table 2 Shows the SNR comparison of Proposed Method

Input SNR	Wavelet soft threshold	EMD	EMD wavelet	Base Paper	Proposed work
6	5	6.2	8	9.1	8.1
10	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

Talk about the next finding that PRD Table 3 shows the results after using many alternative approaches. This table displays the output of the suggested approach at six, ten, fifteen, and twenty dB SNR.

Table 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

Different ECG signals processed using a variety of filters at SNR levels of 6, 10, 15, and 20 are used to evaluate the

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proposed approach. The graphic above displays PRD (percentage root mean square error) calculations for a range of signal-to-noise ratios (SNRs). When compared to existing approaches, the suggested de-noising technique yields higher PRD. At varying levels of signal-to-noise ratio (SNR), the suggested technique outperforms alternatives such as Wavelet soft threshold, EMD, EMD wavelet, and enhanced EMD.

C. Visual Result Compare

We could that the demised result has a correct peak and is noise free by referring to Figure 5.6 below. The picture below shows the output at a signal-to-noise ratio of 6 dB.

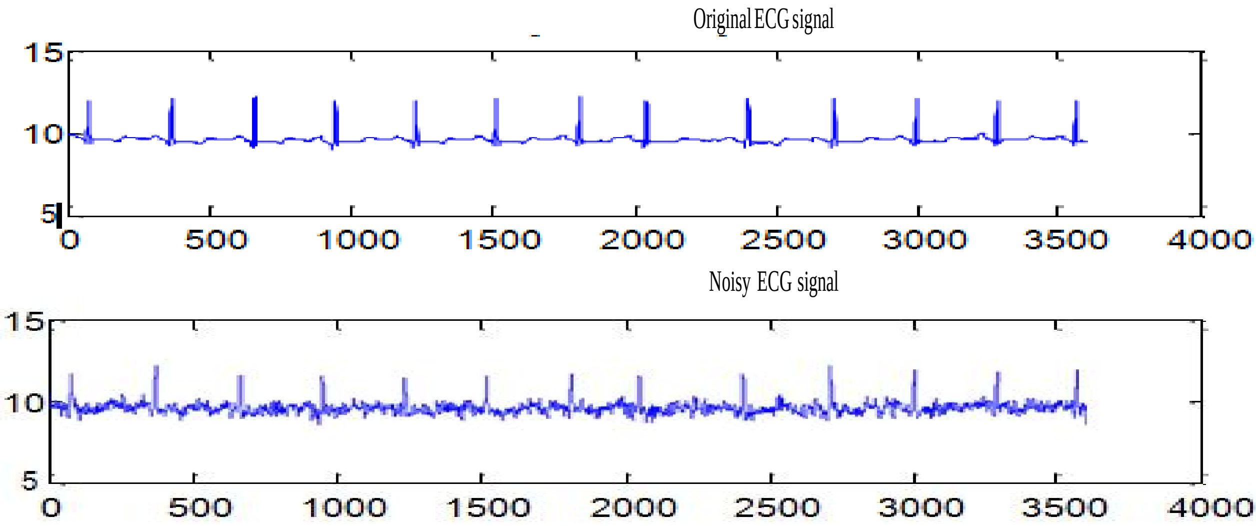

Fig. 6 shows the output of denoised ECG signal 6dB SNR value

We would see that the denoised result has a correct peak and is noise free in Figure 7 below. The output at a signal-to-noise ratio of 10 dB is shown in the image below.

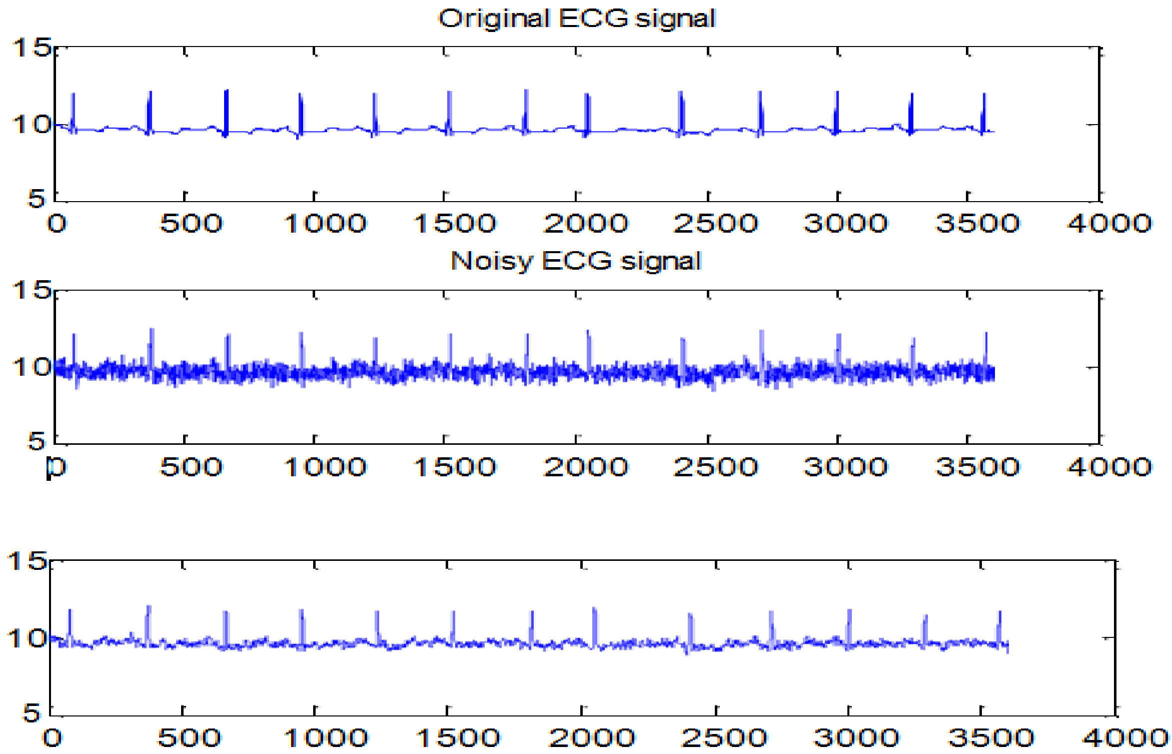

Fig. 7 Shows the Output of Denoised ECG Signal 10db SNR Value

Figure 7 illustrates that the denoised result has an accurate peak and is free of noise. The output at a signal-to-noise ratio of 15 dB is shown in the image below.

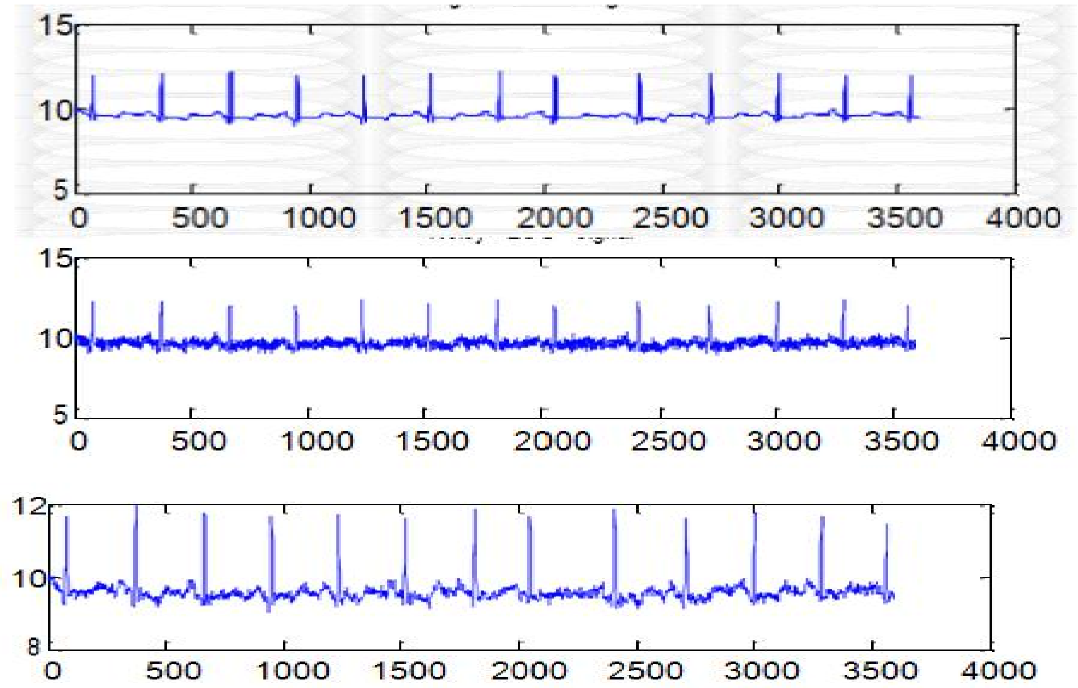

Fig. 8 Shows output at 15db SNR value

5. CONCLUSION:

The primary goal of this study is to develop a means of producing artificial, noise- free ECG readings. To construct Intrinsic Mode Functions (IMFs), our proposed approach employs a modified version of EMD and a mean filter with an adjustable feature. Modified EMD outperforms competing approaches in terms of RMSE, SNR, and PRD. The Mean Absolute Error and Mean Standard Error should also fall within respectable margins of error. The proposed method, an adaptive-mean-filter and error-correcting-mean-discard (EMD) based novel approach to de-noising of ECG data, produces visually beautiful outcomes. Unlike conventional EMD-based de-noising processes, which only denoise lower orders of IMFs, an ASMF operation has been utilised in this research to further improve signal quality.

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