JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Literature Survey on Different Denoising Techniques in EMD –ECG - Using Different

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Abstract : In this survey paper discuss the various Denoising technique in EMD –ECG and discuss the multiple 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 survey shows the surface current analysis of different previous work. In this survey 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 survey paper. The last section discusses about the ECG signal or electrocardiogram is a widely used exam in cardiology field. It describes the electrical activity of the human heart and has a high clinical value for diagnosing cardiac arrhythmias.

Keywords — Electrocardiogram (ECG), Denoise, EMD Adaptive switching mean filter, SNR, MIT-BIH database).

I. 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[5]. For accurate analysis, it is crucial that these distractions be removed. As a result, biomedical engineers have found denoising the ECG signal with the right techniques to be an essential area of study. Digital filter banks, adaptive filters, principal component analysis, neural networks, Bayesian filters, Discrete Wavelet Transforms, Empirical Mode Decomposition, and Empirical Mode Decomposition plus Discrete Wavelet Transforms are just some of the methods used in the numerous research articles on ECG denoising technique contributed by various researchers. Methods based on digital filters need a certain cutoff frequency and muddy the signal by cancelling out P and T waves. Additional reference signals and a training phase are needed for systems based on adaptive filters and neural networks[6, 7], Algorithms based on the Bayesian filter are computationally intensive. Extraction of the intrinsic mode functions (IMFs) is performed in EMD based denoising algorithms. Due to the concentration of high-frequency artefacts in a small number of lower-order IMFs, a window is used to filter out the noise and keep the QRS complexes intact. Then, the windowed IMFs and the other IMFs are used to do a partial reconstruction. Thus, the QRS complex sounds persist at their original frequencies. Therefore, an additional denoising process is required. In this work, we provide an adaptive switching mean filter (ASMF) based EMD for enhanced ECG denoising [4], The ASMF is widely used in the denoising of images. It's based on the idea that nearby pixels should have a similar colour or brightness. First, the damaged ECG signal is decomposed into its IMFs, and then the first three IMFs undergo a wavelet denoising operation to attenuate the high-frequency artefacts. After the IMFs have been denoised, the remaining IMFs are added to them to recover the signal. Recently, the ASMF has been used to improve signal quality by cutting down on low-frequency noise. The ECG signal's peaks are weakened because of the ASMF's presence. As a result, a peak restoration procedure was executed. Standard ECG signals from the MIT-BIH arrhythmia database have been used to assess the effectiveness of the provided technique. There are three measures of success Methods such as reducing noise, minimising RMSE, and minimising the PRD have all been employed to boost the signal-to-noise ratio. Existing approaches are compared to the submitted study for effectiveness [8] [9][10],

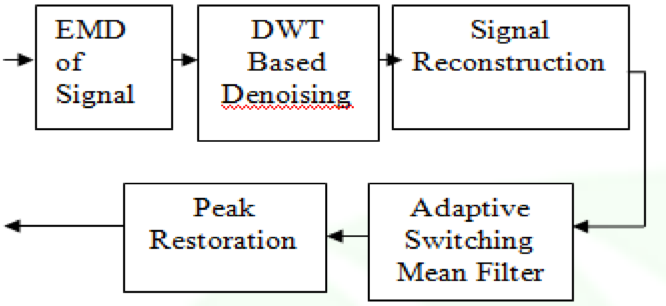

Figure 1. Block diagram of the presented ECG denoising technique

II. LITERATURE SURVEY

Pragya Talwar et.al. (2023) – 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 signal [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].

III. ECG SIGNAL PROCESSING

The electrocardiogram (ECG) signal is a common diagnostic tool in the area of cardiology. Its clinical relevance for identifying cardiac arrhythmias is excellent since it depicts the heart's electrical activity [9]. It is possible to get numerous parameters by analysing the ECG signal. Generally speaking, problems in the heart might be indicated by waves of varying lengths and forms. The ECG signal, seen in Fig. 2, is generated in response to the patient's heart's various deflections and contractions, allowing for a diagnosis of the patient's cardiac status.
In order to make the most of the abundant ECG data, clever diagnostic algorithms have emerged. These technologies may improve signal quality, retrieve relevant data, and provide a diagnostic to aid in treatment planning.
Recent technical advances in the field of biomedical engineering have allowed for the optimisation of ECG processing algorithms for real-time monitoring of cardiac data to be implemented on embedded systems.

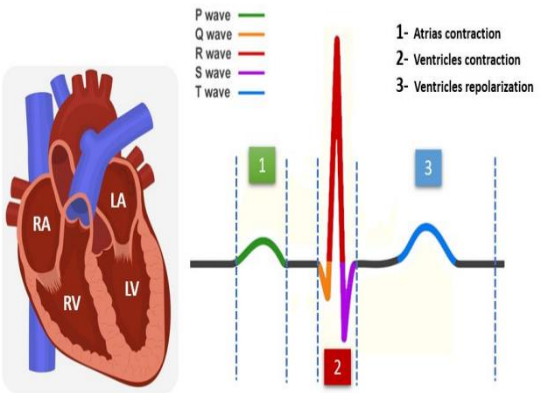

Figure 2. ECG Signal Formation

Both the frequency and amplitude of the ECG signal are often rather modest. Because of this, its morphology is easily distorted by noises like electrical equipment interference, the high-frequency sounds made by active muscles, and the low-frequency sounds made by the body in relation to breathing [5,20]. To get around this issue, the ECG signal must undergo careful and efficient pre-processing.

The purpose of the pre-processing stage is to attenuate or eliminate the various sounds. Digital Filters (FIR/IIR) [21, 22], Empirical Mode Decomposition (EMD) and Ensemble EMD (EEMD) based approaches, DWT, DT-WT, and Adaptive Filtering are all employed in this context.

A. Related Works based ECG Denoising

Finite- and infinite-impulse-response digital filters are the two most common types. To remove background noise from an electrocardiogram. The mathematical definitions are initially associated with their names, and their expressions are presented in (1) and (2):

$$Y(n) = \sum b(q)X(n-q) \qquad (1)$$

$$y(n) = \sum ak\, y(n-k) + \sum bk\, x(n-k) \qquad (2)$$

As can be seen in Fig. 2, where X(n) represents the input signal, Y(n) represents the filtered signal, Z(-1) operator represents a delay in the Z transformation, N represents the filter order, and b(q) represents the coefficients of the filter transfer function, FIR filters may be implemented without feedback. Different kinds of windows, such as the rectangular window and the Kaiser.

window, the Hannay window, the Blackman window, the Hamming window, etc. Chebyshev filters, Butterworth filters, and Inverse Chebyshev filters [30] are used in the construction of IIR filters. FIR filters, on the other hand, are invariant with respect to the nature of the input signal. However, as demonstrated in Fig. 3, IIR filters may become unstable owing to feedback. Coefficients of the filter transfer function (an and bm).

Most of these studies employed FIR or IIR filters, using a bandwidth appropriate for extracting useful information from the ECG signal. It has been inferred from several articles that the sounds in an ECG signal may be removed using a FIR filter with a Kaiser Window with little change to the waveform. The primary difficulty in real-time systems is the high processing requirements of FIR filters owing to the large number of coefficients required to get a good denoising result and a group of delay in response.

Wavelet techniques have surpassed FIR and IIR filters in popularity and efficiency. Time and frequency information may be characterised using the same wavelet technique. As shown in Fig. 4, the signal is decomposed into approximations (A) and details (D) using low pass filters (H[n]) and high pass filters (g[n]). Using thresholding methods, the ECG signals are cleaned up. However, they do have certain restrictions since they weaken the signal and hence may alter the R waves. Methods based on EMD are employed to get over this restriction; the signal is decomposed into a series of intrinsic mode functions (IMFs), and the noisy IMFs are filtered out. However, this process may also filter out some relevant data. To get around this issue, EEMD is employed to eliminate the mode-mixing. W. Jenkal et al. created a novel method of ECG denoising based on the principles of picture denoising to address the complexity issues that had previously plagued the field. An adaptive dual threshold filter, it is specifically designed to filter out interference at very high frequencies. This technique seeks to correct the median value of the selected window by applying thresholding, after first computing three components for that window (the average of the window, the higher threshold, and the lower threshold). Fig. 4 is a block diagram that explains the procedure. In [8], the SNRimp comparison between the ADTF and EEMD-based approaches is used to evaluate the method's performance. The results of this study reveal that the ADTF outperforms the EEMD denoising technique described in and the extended EEMD approach described in in terms of SNRimp. The ADTF algorithm's key feature is its simplicity in comparison to the approaches mentioned. The ADTF has a complexity that is linear in n, where n is the size of the signal. In [8], the authors examine the relative difficulty of the EMD, the EEMD, and the ADTF procedures. This research concludes that ADTF has a low complexity compared to EMD and EEMD, where the complexity increases with signal length, the number of noisy signals, the number of IMFs, and the number of sifting processes. Its complexity is comparable to that of the DWT and is connected to additional parameters in an EMD/EEMD-style. Not only do we have to consider the magnitude of the signal, but also the coefficients of the wavelet mother, the depth of the decomposition, and the thresholding method. In the next part, we offer the results of our simulations and a comprehensive analysis of the ADTF..

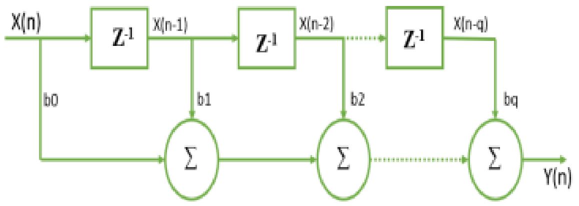

Figure 3 FIR Filter Conceptions

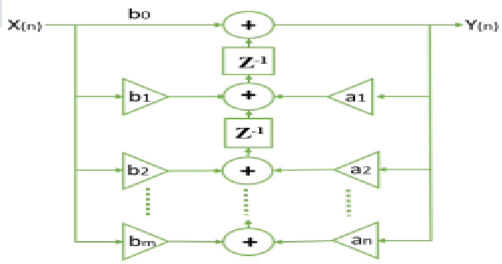

Figure 4 IIR Filter Conceptions

IV. PROBLEM STATEMENT

Signals from an electrocardiogram (ECG) are essential for identifying a wide range of heart problems. However, noise such as baseline drift, powerline interference, and muscular artefacts often contaminate these signals. Noise in ECG signals may prevent proper analysis and interpretation, which can lead to erroneous diagnosis and inappropriate treatment.

One common signal processing method for ECG denoising is the Empirical Mode Decomposition (EMD). With EMD, the signal is broken down into its component frequencies, which are represented as intrinsic mode functions (IMFs). Traditional EMD-based denoising approaches, on the other hand, have drawbacks such mode mixing and end effects that may cause distortion in ECG signals and poor denoising performance.

To get over these restrictions, we suggest using an Adaptive Switching Mean (ASM) filter in an enhanced EMD-based ECG denoising approach. The study's goal is to improve EMD's denoising performance by making it more adept at eliminating noise without distorting the essential characteristics of the ECG signal.

Its process is excellent if they utilise its procedure for research work, but it cannot promise to perform accurately in real settings since the authors never generate a novel procedure, instead studying and selecting an acceptable procedure from known ways based on the input ECG signal. creates its own Thresholding technique and employs a single-stage filtering system A couple of issues: first, they employ the more traditional Daubechies wavelet for Thresholding, which might lead to inaccurate findings if the filtering is incorrect; and second, they use conventional Daubechies wavelet. Since the ECG signal is a function of time, it contains important data on cardiac conditions; yet, this data is often masked by background noise. Suppressing sounds from an electrocardiogram is a challenging but crucial operation since noise contaminates the signal. In order to estimate the unknown signal from the existing noisy data, de-noising is used. employ a single stage of filtering that they've developed themselves in order to create an adaptable EMD filter; this presents a difficulty since erroneous results might be generated by an improper threshold in the adaptive filter's later iterations. Adaptive switching mean filtering (ASMF) and empirical mode decomposition (EMD) are used to remove noise from an electrocardiogram (ECG). While this is a decent approach, it takes a long time, further lowering the threshold.

V. CONCLUSION AND DISCUSSION

In this survey paper discuss on different Denoising and multiple filters. In this work EMD based denoising approaches, where only lower orders IMFs are denoised in this work, along with EMD, ASMF operation has been employed for further signal quality improvement. The lower order IMFs are filtered through wavelet denoising technique to reduce high-frequency artifacts and retain the QRS complexes. Then considering the effectiveness of ASMF, for further enhancement of signal quality adaptive switching mean filtering is performed. In this survey paper observe that the Electrocardiogram (ECG) 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.

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