International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3s
DOI: https://doi.org/10.17762/ijritcc.v11i3s.6184
***Article Received**: 15 December 2022 **Revised**: 22 January 2023 **Accepted**: 02 February 2023*

Denoising ECG Signal Using DWT with EAVO

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Abstract— Cardiovascular diseases are the leading cause of death across the world, and traditional methods for determining cardiac health are highly invasive and expensive. Detecting CVDs early is critical for effective treatment, yet traditional detection methods lack accessibility, accuracy, and cost-effectiveness – leaving patients with little hope of taking control of their own cardiac health. Noisy ECG signals make it difficult for health practitioners to accurately read and determine heart health. Unreliable readings can lead to misdiagnosis and needless expense. Despite the importance of ECG analysis, traditional methods of signal denoising are inefficient and can produce inaccurate results. This means that medical practitioners are struggling to obtain reliable readings, leaving them unable to accurately treat their patients and leading to a lack of confidence in the medical field. The Enhanced African Vulture Optimization (AVO) algorithm with Discrete Wavelet Transform (DWT) optimized by adaptive switching mean filtration (SMF) is proven to provide accurate denoising of the ECG signal. With this reliable method, medical professionals can quickly and accurately diagnose patients. Obtaining accurate ECG signals and interpreting them quickly is a challenge for healthcare professionals. Not only it takes a lot of time and skill but also requires specialized software to interpret the signals accurately. Healthcare professionals are facing a serious challenge when it comes to obtaining accurate ECG signals and interpreting them quickly. It requires them to spend extra time and effort, as well as specialize in the field with expensive software. Time is of the essence in healthcare and ECG readings can mean the difference between life and death. Specialized software can be expensive and time-consuming for those who don't have the resources or expertise. Our easy-to-use platform allows healthcare professionals to quickly interpret ECG signals, saving time, money, and lives! Get accurate readings. The EAVO algorithm and MIT-BIH dataset provide an effective solution to this problem. With the proposed filter built using EAVO, businesses can attain significant enhancements in reliable parameters and obtain accurate testing results in terms of SNR, MD, MSE and NRMSE.

Keywords- ECG Signal Denoising, DWT, AVO, Whale Optimization, ASMF and MIT-BIH Dataset, Signal Processing

I. INTRODUCTION

Electrocardiography (ECG) is a representation of the heart's electrical activity, which is demonstrated as a graph. To acquire this data, electrodes are linked to the skin on the chest, legs, and hands. The potentials generated by the cardiovascular muscle are shown on the ECG. Medical practitioners commonly use it to identify and manage heart-related illnesses. On the ECG, there are multiple unique representations, such as the QRS complex, P, T, and U waves. ECG is a common test used to evaluate heart conditions and recondition electrical waveforms that occur during the contraction of cardiac muscle. This can help doctors determine if there is an abnormality with the heart's electrical signals. Most found in the ECG is the QRS complex and QRS duration, known as the Q wave, which may give an indication indicating a condition such as heart disease, stroke, or heart attack. Electrocardiography is a test performed to determine how effectively the heart is pumping. This test measures the electrical activity of the heart, which can show any abnormalities either in the heart muscle or around it. ECG doesn't just measure the heart beating at regular intervals, but it also shows when your heartbeat is irregular. This irregularity may be due to an arrhythmia that occurs from stress or anxiety. If you are suffering from heart failure, chronic high blood pressure, a sedentary lifestyle, or a drug that has caused abnormal heart rhythms such as digoxin, may affect your heart rate. Waveform morphology is the shape of electrical signals within a signal that occurs when the wave moves along its path. Waveform analysis is defined by various parameters such as amplitude, phase, and time-to-peak. A waveform is used to evaluate functional stability and assess numerous disorders from heart disease to seizures (Rutz 2001). In this case study, the axis deviation of the QRS complex was recorded on patient BN00219. The purpose of this study was to determine if these axis deviations were caused by ventriculoarterial disease or baseline wander which can be viewed on an ECG as noise or blips that interfere with accurate waveform morphologies (1). Baseline wander is a phenomenon that affects many electrical signals, including ECG and EEG. The magnitude of noise present in an electrical signal can be used to characterize it with precision and can be assessed through the shapes of these signals. Baseline wander is often derived from changes in the R-S systole and R-S-T segments due to changes in heart rate and breathing rate, among other factors. Baseline wander is a noticeable ECG signal that has a larger effect on the ST segment than any single waveform, such as the QRS complex. This problem results from missing beats when recording signals. Baseline wander can be caused by the gap between heartbeats and a lack of synchronization between monitors or sensors. As a result, there is a mistake in one's diagnosis because it would be difficult to determine which abnormality is causing it since they both appear similar. Many researchers have found that the amplitude of baseline wander is highly related to PS and T waves, making it a convenient method for identifying PS and T waves. In clinical studies, baseline wander has also been shown to improve diagnostic accuracy by identifying STEMI and PEA. In this work, the denoised ECG signals are decomposed by DWT and applied to ASMF filter to get the denoised ECG signal. Then, the proposed method is tested using MIT-BIH dataset and its performance is compared with other existing methods. In addition, experimental results are presented in Section 4 and comparisons are given in Section 5. Finally, this paper contributes to knowledge and provides a new approach to assess features of ECG signals in form of ASMF filters.

II. RELATED WORKS

Noise-Edge Detection (NED) is a powerful and efficient demodulation method which addresses the problem of noisy ECG signals. Unlike other conventional techniques for noise reduction, NED does not require a preprocessing stage. In fact, it does not even require a linear transformation of the signal! This article presents a novel WT-based filter bank design for ECG signal denoising. Compared to earlier built architectures, in order to reduce noise in ECG data, Hao et al., (2019) [10] have proposed a multi-lead model that utilizes a guided filter. Additionally, a sparse auto-encoder (SAE) is also employed, allowing for the creation of a patient-specific statistical model for everyone. This statistical model is then able to capture the signal features effectively, ultimately leading to a successful outcome. The introduced strategy includes three low-pass filters and one high-pass filter. in the guided filter.

Georgieva-Tsaneva (2019) [11] reviews the WT based denoising method and provides an effectual algorithm for denoising in non-stationary signals that uses an adaptive threshold scheme, detailed and approximate coefficients processing, and the level of decomposition. The proposed design has a minimal level of complexity and low resource utilization. The authors tackle the problem of noise removal in ECG signals, formulated using a Bayesian model. A new Bayesian structure, that does not require a preexisting scheme and is based on the Kalman filter, is presented. It employs two adaptive Kalman filters for denoising the QRS complex and the P wave, respectively.

The EM algorithm is used to estimate and repeatedly update the parameters of these filters. The results suggest that the Wiener filter is an excellent filter for denoising ECG data; however, it necessitates significant amount of computational power due to high frequency processing and massive amount of data. In this paper we present a new filter bank that combines Wiener filtering with the Kalman filtering technique to remove noise from ECG waveforms. We evaluate our strategy by comparing it with several commercial solutions available on the market today; our experiments show promising results compared with commercially available detectors."

Heart rate signals obtained utilizing non-contact radar systems for use in assisted living situations are focused on by Pravin and Ojha (2022) [18]. signals contain more noise than those measured under clinical settings, necessitating the development of a new signal noise removal approach capable of determining adaptive filters. The wavelet and elliptical filtering methods are investigated in this study for the objective of decreasing noise in ECG readings recorded utilizing assistive technology. Currently, the most frequent approach to reducing noise from such a waveform is to utilize filters, with the wavelet filter being the most prominent among them.

III. PROPOSED METHODOLOGY

This paper presents a novel signal denoising framework for the ECG signal. The proposed technique is based on the African Vulture Optimization (AVO) algorithm and adaptive switching Mean Filter (ASMF) which improves the edge information, reduces estimation error and enhances signal quality. First, the white gaussian noise is added to obtain corrupted input ECG signals. Then, the denoised signal is processed with an adaptive switching mean filter to remove noise and improve denoising performance. Finally, AVO algorithm and ASMF are used together to obtain cleaner output ECG signals by finding optimal thresholds. The proposed approach is compared with existing approaches and results show significant improvement over existing methods in terms of quality degradation and acquisition timeMaintaining the Integrity of the Specifications.

Wavelet transforms are a set of techniques for transforming signals in time and frequency domains. The DWT is a sort of wavelet transformation is made up of wavelets that are broken into discrete pieces. The WT process uses individual 1-D wavelet transformations in each direction. In comparison to the Fourier transform, which only gives insight into the frequency of the signal and not its location, the DWT can provide information about both the frequency and the temporal

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resolution of the wave. There are a range of wavelet family options that can be used for applications involving WT.

The Discrete Wavelet Transform (DWT) with the Daubechies wavelet is a powerful tool for obtaining the greatest number of vanishing moments for a given support. This is done by passing the input signal through a low-pass filter with an impulse response of $g[n]$ and a high-pass filter with an impulse response of $h[n]$. The filter outputs, as expressed in Equations (1) and (2), respectively, are the concatenations of the input signal and the filter's impulse response. The low-pass filter output defines the approximation coefficients, while the high-pass filter output defines the detailed coefficients. These two filters are connected to each other through a single coefficient and referred to as a single wavelet filter bank. DWT with the Daubechies wavelet is used for signal decomposition, denoising, and reconstruction. It is a powerful tool in signal processing that can be used to study the properties of a signal, such as its frequency, time-domain, and statistical properties.

According to Nyquist's rule, when performing the DWT with the Daubechies wavelet, sample data is deleted, as half of the signal's frequency is discarded. This process is then repeated in a hierarchical fashion, with the cut-off frequency of each successive stage of filters decreasing by a factor of two. This is represented by Equations (3) and (4), which show the low-pass and high-pass filter outputs, respectively, after down-sampling the input signal by a factor of two. The detailed and approximation coefficients obtained at each level of filtering can be further used to generate useful information about the input signal, such as its frequency, time-domain, and statistical properties.

The main purpose of the Discrete Wavelet Transform (DWT) is to decompose the input signal into a hierarchical set of coefficient levels, to reduce or remove its high frequency content. This decomposition process can be applied to EEG signals to remove artifacts while preserving important features. To evaluate the results of this process, the Mean Squared Error (MSE) objective function is used as a measure, which is expressed in Equation. In addition to denoising, DWT is also used for signal compression, image fusion, and feature extraction, among other tasks.

The Denoising of ECG signals is an important task, which can be accomplished by optimizing the wavelet parameters. This is done by creating a randomly generated solution, which is then refined iteratively using a metaheuristic technique, such as simulated annealing or genetic algorithms. The resulting optimized solution, $xo' = x1', x2', \dots. xn'$, is then used to filter the original ECG signal, $x(pi)$, in order to obtain a pure denoised signal, $\acute{x}(pi)$.

After applying the Discrete Wavelet Transform (DWT) denoising process, some residual noise can remain in the reconstructed signal. This noise is particularly noticeable in the region of the QRS complexes. To further remove this noise and improve signal quality, an Adaptive Switching Mean Filter (ASMF) can be used. ASMF is a powerful filtering technique which assumes that signal samples in the same neighborhood should be identical. In other words, given a specific window length, the windowed region's standard deviation is used to estimate a threshold value. If the variance between the ECG sample and the mean of the windowed area is higher than the threshold, the sample is considered corrupted, and its value is adjusted to match that of the mean. This operation can be mathematically expressed as in Equation (6) The Adaptive Switching Mean Filter (ASMF) operation can be expressed mathematically as shown in Equation (6). This operation takes the input ECG sample, Xie, and the standard deviation of the windowed region, qi, as input and produces a processed ECG sample, $\bar{X}i$. The upper limit threshold, α, is set empirically and the window length is set to 9 samples. If the difference between the ECG sample and the mean of the windowed region is greater than the threshold value multiplied by the standard deviation, $\sigma 1$, then the sample is considered corrupted and its value is adjusted to match the mean.

The filter parameter $wk(n)$ indicates the time-varying weight coefficients or weights which are used to model the relationship between the input x(n) and the desired output d(n). The open interval for the filter parameter ranges from 0 to N where N is the total number of coefficients or weights. The fitness function for this filter parameter is the minimization of the error function $e(n)$, which is given by Equation (8). The objective is to minimize the error between the desired output d(n) and the actual output y(n). This is done by adjusting the filter parameters $wk(n)$ until the error is minimized. Optimization of Enhanced African Vulture Algorithm (EAVO) is an evolutionary search algorithm that combines characteristics of the African Vulture Optimization (AVO) algorithm, Grey Wolf Optimization (GWO) algorithm, and Whale Optimization Algorithm (WOA). It is designed to simulate the foraging and dwelling behavior of African vultures, with the goal of finding the optimal solution for a given problem. Optimization of Enhanced African Vulture Algorithm (EAVO) is an evolutionary search algorithm that combines characteristics of the African Vulture Optimization (AVO) algorithm, Grey Wolf Optimization (GWO) algorithm, and Whale Optimization Algorithm (WOA). It is designed to simulate the foraging and dwelling behavior of African vultures, with the goal of finding the optimal solution for a given problem. EAVO begins by categorizing the vultures into three groups according to their quality. The first group contains the best solution, the second group has the second-best solution, and the third group contains the remaining vultures. It then uses a roulette wheel mechanism to determine which vulture will move towards the current iteration. This helps to ensure that only the best solutions are selected and that the search process is efficient.

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Additionally, the algorithm incorporates a limitation on the number of groups members, and takes the top three highest solutions instead of just one. This helps to reduce the search space, thus making the process faster and more efficient.

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Overall, EAVO is a powerful and efficient optimization algorithm that combines characteristics of several other algorithms to find the best solution for a given problem quickly and accurately. Vultures are scavenging birds that are known for their impressive hunting skills, allowing them to find food in some of the harshest areas. They have a unique ability to recognize food sources from miles away, making them excellent predators. To further maximize their chances of finding food, vultures employ a strategy known as "the hunger of vultures". This strategy relies on the degree of hunger of each individual vulture to indicate when they are transitioning from the search to the exploitation stage. At each given iteration, the hunger degree of each vulture is calculated by considering factors such as the distance traveled, random numbers, and the probability of vultures finding food. This allows the vultures to optimize their chances of finding food by adjusting their behavior based on the level of their hunger. With this strategy, vultures are able to quickly adapt to their environment and maximize their chances of finding food. AVO is an optimization algorithm that combines exploration and exploitation stages. In the exploration stage, a random value between 0 and 1 is generated, and if this value is greater than or equal to a parameter called $p1$, the vulture's exploration strategy is determined by the Equation (14). The exploitation stage uses a random search agent to pick the best solution from the group. This is done by creating a vector A with random values higher than 1 or lower than -1 (Equations 16 & 17). This vector drives the search agent away from the optimal solution to ensure enough exploration is done. The exploitation stage works to update the best solution and ensure the algorithm converges to a better local optimum. The Enhanced AVO algorithm is an optimization method used to find the most optimal solutions for a given problem. This algorithm works by creating a random population of solutions and then analyzing the fitness function to determine the best solutions. After the optimum solution is found, the algorithm repeats the same steps until a certain end condition is met.

The Enhanced AVO uses a best solution discovered to update the location of the remaining resolutions, ensuring the convergence of the algorithm. The pseudo code for this algorithm is as follows:

Inputs: population size N and maximum iterations T
Outputs: Best fitness value

Initialize the random population.

while (stopping condition is not met) do
Compute fitness
Set PBestVulture1 as the position of Vulture (First best solution)
Set PBestVulture2 as the position of Vulture (Second best solution)

for (each Vulture (Pi)) do
Select X using Eq. (10)
Update the H using Eq. (12)
if (|H| ≥ 1) then
if (≥ rand) then
Update the location Vulture using Eq. (14)
else

Chose a random search agent ()
Update current search agent position by the Eq. (17)
end if
end if
end for

Check for any solutions that go beyond the limit and make necessary changes.
Compute fitness
Update X if there is a better solution.
$t = t + 1$
end while
return best.

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IV. RESULT AND DISCUSSION

This paper proposes a denoising approach for ECG signals using MATLAB2018a software running on a Windows 8.1 operating system. White Gaussian noise is added to the ECG signals with varying variances to create a noisy signal. The proposed approach is tested with three standard datasets: MIT-BIH ARR, MIT-BIH NSR, and BIDMC-CHF.

A. As can be seen in Figure 4, the ECG signals are presented as clean, noisy, and denoised. The MIT-BIH dataset is well-known for being the first set of standard test material for recognizing the occurrence of arrhythmias. The BIH Arrhythmia Laboratory was responsible for collecting 48 half-hour fragments of 2-channel, 24-hour ECG recordings from 47 test subjects for the purpose of this database. Each ECG data set includes information about the patient such as age, gender, and illness status. The MIT-BIH dataset has a wide range of ECG abnormalities and more data types, enabling different organizations to share services and technical aid while reducing R&D costs. To measure the efficacy of the proposed strategy for noise reduction, the following metrics are used: SNR, ME, MSE, MD, peak reconstruction error (PRE), normalized root-mean-square error (NRMSE), correlation coefficient (CC), and normalized root maximum error (NRME) [17]. The values of these parameters are determined by comparing the pure signal $x(p)$ to the output of the filter $y(p)$.The proposed denoising method is a valuable approach for improving the quality of signals and making them more suitable for various applications. It incorporates multiple metrics such as SNR, ME, MSE, MD, PRE, NRMSE, CC, and NRME to evaluate its performance. Moreover, it has been compared to several existing approaches, such as RLS-based adaptive filter, Multichannel LMS, IMVO with AT, EWT with HBO, and DWT-based baseline wander, and it has shown that it outperforms the existing techniques. This makes the proposed method a reliable choice for denoising signals.

TABLE I. PARAMETER DESCRIPTION OF PROPOSED ALGORITHM

Parameters	Value
Population size	40
Maximum iteration	200
r_1	0.8
r_2	0.2
k	2.5
p_1	0.6
Random search ability	0.1

The proposed approach is seen to produce lower NRME and NRMSE values than the other denoising techniques, as suggested by the graph. The experiments demonstrate that the proposed strategy is more effective than the other denoising strategies. Similarly, the PRE and ME values of the proposed approach with the other optimization algorithms are depicted in Figures 9 and 10. The proposed approach is seen to generate a lower PRE than the other denoising techniques, as highlighted by the graph. From Figure 10 it is evident that the proposed approach has a lower ME value than the other denoising techniques. The experiments thus demonstrate that the proposed strategy outperforms the other denoising strategies. Figure 1 displays the capability of several denoising techniques, including the RLS-based adaptive filter, the Multichannel LMS, the IMVOAT, the HBO-EWT, and the DWT-based baseline wander, to produce CC, in comparison to the proposed approach. It is evident from this Figure that the proposed approach yields a superior CC than the other denoising methods.

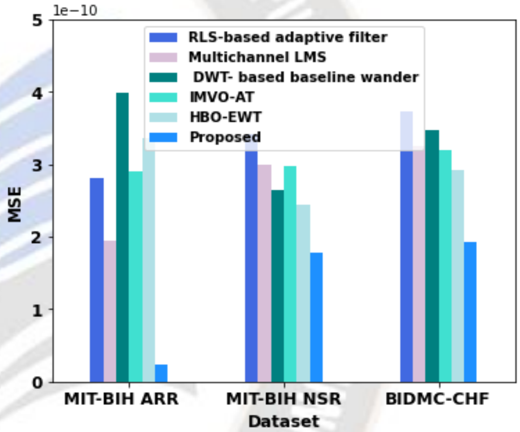

Figure 1. Performance evaluation of MD

The findings of the experiments conducted show that the proposed approach is an effective denoising strategy and outperforms other existing techniques. The proposed strategy produces lower NRME and NRMSE values than existing algorithms, as seen in Figure 7 and 8. Similarly, the proposed approach yields a lower PRE value, as seen in Figure 9. Figure 10 shows that the proposed approach gives a lesser ME value than other denoising techniques. Finally, Figure 11 reveals that the proposed strategy yields better CC than other denoising methods. Therefore, the proposed strategy is a viable solution for denoising signals and can be used for various applications.

ABLE III. FRIEDMAN'S ANOVA TEST

Source	SS	Df	MS	F	Prob>F
Columns	30.2333	2	15.2667	4.04	0.1324
Interaction	2.2333	2	1.3667		
Error	87.2333	12	7.2878		
Total	120	17			

V. CONCLUSION

A new metaheuristic, called Enhanced AVO (EAVO), has been developed to use bio-inspired methods for denoising, which does not necessitate the labor-intensive process of parameter alteration. The DWT wavelet parameter of the window and the ASMF filter are both optimized by the EAVO algorithm. To demonstrate the effectiveness of the suggested denoising filter, a comparison has been made with the RLS-based adaptive filter, multichannel LMS, IMVO-AT, HBO-EWT, and DWT-based baseline wander techniques. As compared to earlier results, the EAVO-based adaptive switching mean filter has obtained noteworthy improvements in NRMSE, SNR, MD, NRME, PRE, ME, and CC. Consequently, it can be concluded that the proposed combination of DWT and filter, which is the hybrid algorithm, is a useful approach for denoising cardiovascular signals.

ACKNOWLEDGMENT

Acknowledging the efforts, hard work, and dedication from the employees of ADEEP, PA, USA, and AMIGOSTECH, DE, USA.

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