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Optimal ECG Signal Denoising Using DWT with Enhanced African Vulture Optimization

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Abstract—Cardiovascular diseases (CVDs) are the world's leading cause of death; therefore cardiac health of the human heart has been a fascinating topic for decades. The electrocardiogram (ECG) signal is a comprehensive non-invasive method for determining cardiac health. Various health practitioners use the ECG signal to ascertain critical information about the human heart. In this paper, the noisy ECG signal is denoised based on Discrete Wavelet Transform (DWT) optimized with the Enhanced African Vulture Optimization (AVO) algorithm and adaptive switching mean filter (ASMF) is proposed. Initially, the input ECG signals are obtained from the MIT-BIH ARR dataset and white Gaussian noise is added to the obtained ECG signals. Then the corrupted ECG signals are denoised using Discrete Wavelet Transform (DWT) in which the threshold is optimized with an Enhanced African Vulture Optimization (AVO) algorithm to obtain the optimum threshold. The AVO algorithm is enhanced by Whale Optimization Algorithm (WOA). Additionally, ASMF is tuned by the Enhanced AVO algorithm. The experiments are conducted on the MIT-BIH dataset and the proposed filter built using the EAVO algorithm, attains a significant enhancement in reliable parameters, according to the testing results in terms of SNR, mean difference (MD), mean square error (MSE), normalized root mean squared error (NRMSE), peak reconstruction error (PRE), maximum error (ME), and normalized root mean error (NRME) with existing algorithms namely, PSO, AOA, MVO, etc.

Keywords- ECG signal denoising; discrete wavelet transform; African Volture optimization; whale optimization; adaptive switching mean filter; and MIT-BIH dataset.

I. INTRODUCTION

The heart activity is represented by electrocardiography (ECG), which is primarily an electrical signal. It's presented as a graph. Electrodes (3 or 12 leads) are linked externally to the surface of the thorax, legs, and hands to record the data. The potentials generated by cardiovascular muscle action are plotted on the ECG. Physicians utilize it widely to anticipate and treat a variety of cardiovascular disorders. On an ECG, there are numerous distinct entities that may be identified: the QRS complex, as well as P, T, and U waves, each of which is connected with a specific phenomenon that occurs during a single cardiac cycle. The combination of these entities and knowledge of the ECG scale allows for the calculation of heart rate and the detection of rhythm disorders such as atrial fibrillation, atrial flutter, cardiac arrhythmia, sinus tachycardia, and sinus bradycardia, among other things. The axis deviation of the QRS complex, for example, is a symptom of ventricular hypertrophy, anterior and posterior fascicular block, and other disorders that can be detected by shape analysis [1-2].

To ensure that the information collected from a signal is accurate, waveform morphologies must be well characterized and free of noise. On the other hand, ECG is a relatively faint electric signal, with amplitudes typically in the mill volt range. Interference from the instrument, human activities, baseline wander, and other elements in the signal are all examples of ECG noise. The most prevalent noise in ECG data is baseline wander, which has the largest interference to its magnitude. It frequently causes the signal to diverge from its regular baseline level, disturbing the ST segment as well as tiny waves like the P and T waves, among other things. As a result, many approaches for minimizing signal noise have been presented by researchers. The wavelet transform (WT) is a commonly used signal processing method [3] that uses parameters to represent signals in the time-frequency domain such as wavelet function name, thresholding methods, selection rule, decomposition level and threshold rescaling approaches to obtain a smooth signal. Several strategies for dealing with ECG components contaminated by various noises have been published in the literature. WT, adaptive filter, neural networks, and non-linear filter bank architectures are some of the solutions that have been presented.

In recent years, a number of ECG compression algorithms have been established, most of them are established on lossy methods because of their greater compression ratio. Moreover, these methods have been applied to the extraction of a noise-free signal from a noisy ECG signal. The scientific community has intensively investigated ECG signal processing in the biomedical field, notably its denoising for trustworthy diagnosis [4]. Several denoising strategies have been investigated in the signal processing literature. Traditional filtering based on finite impulse response (FIR) filters was proposed by Van Alste and Schilder (1985) [5]. To remove electrical noises from the ECG signal, least squares-based adaptive filtering is utilized in [6]. An adaptive Kalman filter is utilized to enhance the ECG signal quality in the same scenario. Furthermore, the frequency of the relevant components of the ECG frequently overlaps with the typical frequencies of noises. Filtering the signal becomes difficult as a result of this. Over the years, a number of approaches for filtering various types of noise have been created. For filtering away baseline wandering noise, examples include band pass/notch filters (used mostly to remove power line interference), wavelet transform-based approaches, and empirical mode decomposition [7].

The contribution of the work is as follows,

- The ECG signals from the MIT-BIH dataset are considered as the input of the architecture. The white Gaussian noise is added with a pure signal and gets the noisy signal.
- The denoised ECG signal is decomposed by the DWT and its parameters are optimized by the proposed Enhanced AVO algorithm. The AVO algorithm exploration phase is enhanced by the WOA optimization approach.
- After the decomposition, the noisy signal is transferred into the ASMF filter and its weight parameters are adjusted by the EAVO algorithm. Finally, the denoised ECG signals are obtained from the proposed strategy.
- The effectiveness of the proposed method is verified in terms of NRMSE,SNR, MD, NRME, PRE, ME ,and CC with various existing approaches.

The remainder of the paper is laid out as follows: Section 2 is a review of the related research on the subject. The proposed strategy and corresponding methods are explained in Section 3. Section 4 contains performance evaluations and experimental results. Finally, Section 5 summarizes the research findings.

II. RELATED WORKS

Several researchers have published several ways for denoising electrocardiographic data in recent years. The ECG signal is now utilized to diagnose a wide range of heart problems. The significance of an ECG signal in the practice of cardiology cannot be emphasized. It must be completely noise-free. ECG signals are frequently distorted by numerous sorts of disturbances throughout the recording and transmission process. The reduction of these disturbances allows for more precise detection of numerous irregularities. In Verma et al., (2018) [8], the Alexander fractional differential window (AFDW) filter is introduced for ECG signal denoising. This principle is applied to the creation of a forward filtering window. After that, the backward filter is built by reversing the forward filter's coefficients. After that, the forward and backward filter coefficients are averaged to produce the suggested AFDW filter. WT-based filter bank design for ECG signal denoising was proposed by Kumar et al., (2018) [9]. In comparison to earlier built architectures, the introduced strategy only has three low-pass filters and one high-pass filter. A multi-lead model has been suggested by Hao et al., (2019) [10], in which to denoise ECG data a guided filter is essentially fitted. A sparse auto-encoder (SAE), which can effectively maintain particular signal attributes, will be used to create a patient specific statistical model for each person. As a result, the statistical model's directed signal can accomplish well 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 denoising procedures allow specifying the decomposition level, wavelet basis, and testing signal size, as well as calculating the denoising process assessment features. The Adaptive Dual Threshold Filter (ADTF) was presented by Jenkal et al., (2018) [12] for ECG signal denoising. The proposed design has a minimal level of complexity and low resource utilization. Wavelet denoising is one of the most common denoising algorithms for ECG signals. However, due to the frequency overlap between the EMG and the ECG, the faint properties of ECG signals may be decreased throughout the noise filtering process. Wang et al. (2019) [13] offer a modified wavelet design method and apply it to ECG signal denoising. The optimized filter coefficients are calculated by estimating the ideal filter's amplitude-frequency response, and the wavelet is built using the optimized filter coefficients.

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Hesar and Mohebbi (2020) [14] present a new Bayesian structure based on the Kalman filter that does not require a preexisting scheme and is adopted to various ECG morphologies. It employs a filter bank with two adaptive Kalman filters for denoising the QRS complex and the P and T waves, respectively. The expectation-maximization (EM) algorithm is used to estimate and repeatedly update the parameters of these filters. And also Manju and Sneha (2020) [15] proposed two filters to remove the noises by Wiener filter and the Kalman filter. The simulation results suggest that the Wiener filter is an excellent filter for denoising the ECG data. However, ECG analysis is a time-consuming operation that necessitates a significant amount of computational power due to the vast amount of data that is essentially evaluated in parallel at high frequencies. As a result, Mejhoudi et al., (2021) [16] use several embedded architectures to assess the Adaptive Dual Threshold Filter (ADTF) method for ECG signal denoising. This method is utilized in MIT-BIH Arrhythmia dataset with a sampling frequency of 360 Hz were used to validate the evaluation.

Swarm intelligence approaches are used in the biomedical signal processing sector by Yadav et al., (2021) [17], in the optimization of adaptive noise cancellers. The particle swarm optimization (PSO), symbiotic organisms search (SOS), and harmony search (HS) optimization was used to evaluate and update the adaptive filter parameters. Heart rate signals obtained utilizing non-contact radar systems for use in assisted living situations are focused on by Pravin and Ojha (2022) [18]. Such 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. However, in some cases, applying a different filtering approach can result in a waveform with a greater SNR.

III. PROPOSED METHODOLOGY

In the proposed technique the ECG signal is denoised based on Discrete Wavelet Transform (DWT) optimized with African Vulture Optimization (AVO) algorithm and ASMF is proposed. Initially, the input ECG signals are obtained from the MIT-BIH ARR dataset and white Gaussian noise is added to the obtained ECG signals. Then the corrupted ECG signals are denoised using Discrete Wavelet Transform (DWT) in which the threshold is optimized with an Enhanced African Vulture Optimization (AVO) algorithm to obtain the optimum threshold. AVO algorithm is enhanced by the Whale optimization algorithm exploitation phase. Finally, the denoised signal is again processed with an adaptive switching mean filter for enhancing the edge information and improving the denoising performance. The filtered error is also minimized by the Enhanced AVO algorithm. Moreover, the proposed approach is compared with existing denoising techniques. Figure 1 demonstrates the proposed ECG signal denoising approach.

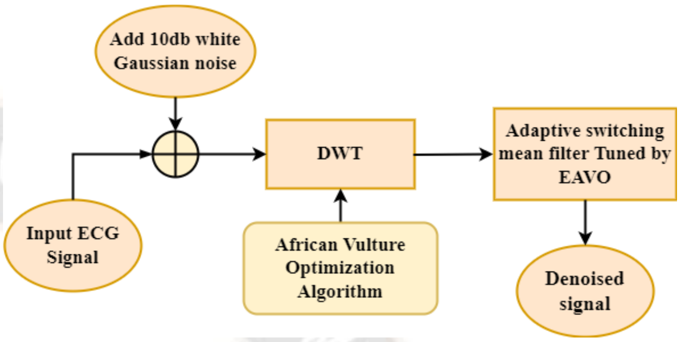

Figure 1. Proposed Approach Flow Diagram

A. *Discrete Wavelet Transform*

The WT is a mathematical technique for analyzing a signal with changing frequency components. The DWT is a sort of wavelet transform in which the wavelets are sampled in discrete intervals. In each dimension, DWT uses 1-D wavelet transforms. When discussing other transformations like the Fourier transform, it only offers details about the signal's frequency domain, not its position. On the other hand, DWT can accomplish both frequency and temporal resolution, which means it, can offer detail on the wave's frequency components as well as its location. There are a variety of wavelet families that can be employed in particular applications of the WT. The mother wavelet of these WT families is used to identify them. Haar, Spline, Daubechies, Shannon, Biorthogonal, Mexican hat, and other wavelets are among the more popular. In this research, we used the Daubechies wavelet (db4), which has four vanishing moments. Daubechies wavelets are a wavelet family that includes orthogonal wavelets. The greatest number of vanishing moments for a given support can be obtained by using DWT with the Daubechies wavelet as the wavelet function. The input signal is sent into a low pass filter with an impulse response of $g[n]$ to conduct DWT. The approximation coefficients are defined by the low pass filter output. This filter's output is the concatenation of the input signal ($x[n]$) and the filter's impulse response ($g[n]$) which is expressed in Equation (1) [19],

$$y_g[n] = x[n] * g[n] = \sum_{-\infty}^{\infty} x[k]g[n-k] \qquad (1)$$

At the same time, the input is sent via a high pass filter with an impulse response of h[n]. The integration among

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the input and filter's impulse response is the filter's output. The detailed coefficients of the high pass filter are defined by the output of the high pass filter.

$$y_h[n] = x[n] * h[n] = \sum_{-\infty}^{\infty} x[k]h[n-k] \quad (2)$$

It's worth noting that the low pass and high pass filters are connected to one another and are therefore referred to as a quadrature mirror filter.

As stated by Nyquist's rule, half of the samples are deleted because half of the signal's frequency is discarded. The level-2 detailed and approximation coefficients are then obtained by down-sampling the low pass filter g[n] output signal by a factor of 2 and passing it through another series of low pass and high pass filters. The cut-off frequency of the current set of filters is half that of the prior stage filter. The following equation can be used to represent this process.

$$y_{low}[n] = \sum_{-\infty}^{\infty} x[k]g[2n-k] \quad (3)$$

$$y_{high}[n] = \sum_{-\infty}^{\infty} x[k]h[2n-k] \quad (4)$$

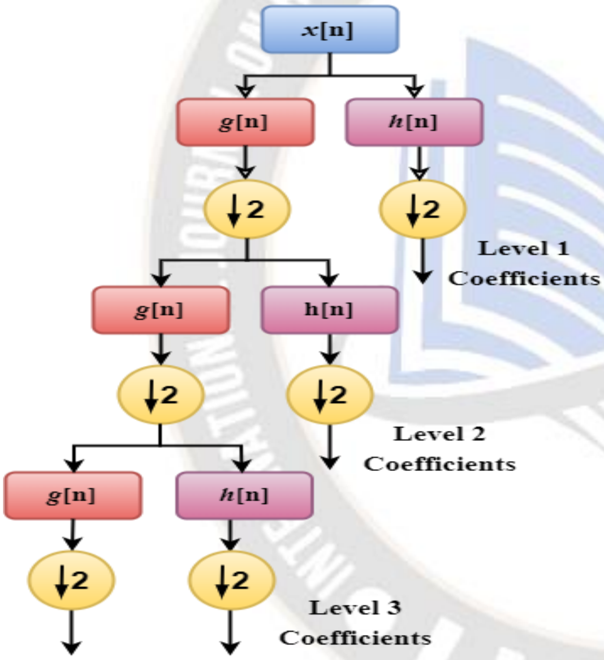

Figure 2. 3-level DWT block diagram

The main goal of employing DWT is to divide the input signal into various coefficient levels in order to adjust the input signals' high frequency. To put it another way, DWT divides the EEG signal into numerous frequency bands based on the assumption that the artifacts will have substantial amplitudes in each band. Fig. 2illustrates the decomposition level L = 3 for denoising. In signal processing, signal noise removal is regarded as a difficult task. As a result, researchers have devised a number of solutions to this challenge, including the use of the filtering process. The solution is evaluated by the selected metaheuristic algorithm using the MSE objective function. It can be expressed in Equation (5) [20].

$$obj1 = MSE = \frac{1}{N}\sum_{n=1}^{N}[x(p_i) - \hat{x}(p_i)]^2 \quad (5)$$

Where,$x(p_i)$ is the original ECG signal and $\hat{x}(p_i)$ is the pure denoised ECG signal attained using the meta-heuristic approach to tune the wavelet parameters. The randomly created solution is refined iteratively by the chosen metaheuristic technique. This phase's ultimate output is an optimized solution $x'_o = x'_1, x'_2, \dots . x'_n$, which will be used as a filter in the next phase.

B. Adaptive switching mean filter

Some noises remain in the reconstructed signal after DWT-based denoising. The region amongst QRS complexes shows these disturbances very clearly. As a result, an ASMF filter is used to improve signal quality even more. ASMF is a powerful filtering technique that is utilized to eliminate impulse noise from signals [21]. The core premise of ASMF is that signal samples in the same neighborhood should be identical. In this procedure, a specific window length is chosen, and the window center is put on an ECG sample at each iteration. The windowed region standard deviation is now used to estimate a threshold value. If the variance among the ECG sample and windowed area's mean value is more than the threshold limit, the sample is considered corrupted, and its value is adjusted to match that of the mean. The ASMF operation's mathematical formulation is expressed in Equation (6).

$$\overline{X}_\iota = \begin{cases} q_i, & if\ |X_i^e - q_i \geq \alpha * \sigma_1| \\ X_i^e, & else \end{cases} \quad (6)$$

Where, ASMF operation input and processed ECG samples are represented into $X_i^e$and $\overline{X}_\iota$, respectively. The windowed region standard deviation denoted as$q_i$and i. Then the upper limit threshold value is chosen and the value varies from 0 to 1. The value of 0.1 is chosen empirically in this study, and a window of length of 9 samples is used.

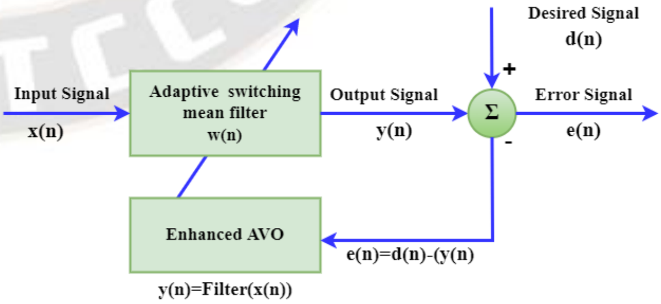

Figure 3. Adaptive switching mean filter

$$y(n) = \sum_{i=0}^{N-1} w_i(n) * x(n-i) \quad (7)$$

The total number of coefficients or weights is indicated by N. The $w_k(n)$ filter parameter signifies a specific

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time n and is valid for k weight sequences. The open interval ranges from 0 to N this specific time changes.The fitness function is minimization of $e(n)$, which is given in Equation (8),

$$obj2 = \min\{e(n)\} = d(n) - y(n) \tag{8}$$

C. Optimization of Enhanced African Vulture Algorithm

Modeling and simulating the foraging activity and dwelling behaviors of African vultures led to the development of AVO [22]. The African vulture population has N vultures, and size of N is determined by the algorithm user based on the current scenario. Each vulture's position space has D dimensions, and the size of D is determined by the problem dimension. Equation (9) can be used to express the position of each vulture.

$$X_i^t = [x_{i1}^t, \dots\dots x_{id}^t, \dots x_{iD}^t] \tag{9}$$

All vultures in AOV aim to come near to the best vultures while avoiding the worst vultures. To imitate diverse vulture behaviors, AOV can be categorized into population grouping, the hunger of vultures, and the exploration and exploitation Stage. The key benefit of GWO is that the top three highest values from each cluster are examined, and these values indicate the first three best solutions from that group while keeping in mind that the group that represents the cluster is limited. However, the WOA does not have a limit on the number of group members, and it also does not have the top three highest solutions instead of one. From these considerations, the Enhanced AVO is presented as a mixture of these two algorithms, applying the WOA algorithm [23] to bypass the group team member limitation and take the top highest solutions. The proposed EAVO algorithm proceeds as follows,

1) Population Grouping: The vultures must be categorized according to their quality after startup or before proceeding to the next operation. The first group vulture corresponds to the optimal solution, while the second group contains the second optimal solution. The remaining vultures are in the third group. Based on these facts, the second and first group has a guiding effect that is given in Equation (10), in which vulture moves towards the current iteration.

$$X_i^t = \begin{cases} B_1^t, P_i^t = r_1 \\ B_2^t, P_i^t = r_2 \end{cases} \tag{10}$$

Here, best vulture is $B_1^t = [b_{1i}^t, \dots b_{1d}^t, \dots b_{1D}^t]$, the second best vulture is $B_2^t = [b_{2i}^t, \dots b_{2d}^t, \dots b_{2D}^t]$, the random numbers $(r_1 and\ r_2)$ are in 0 to 1 range and sum of the two numbers is $1, P_i^t$ which is gotten by roulette wheel mechanism is in Equation (11),

$$P_i^t = \frac{F_i^t}{\sum_{i=1}^m F_i^t} \tag{11}$$

Where F_i^t signifies first group fitness value and 2^{nd}group vultures, and its total is denoted bybm. Whereα, β, γindicates vultures group of first, second and third groups, respectively. Then, the optimal vulture is gained via relevant parameters.

2) The Hunger of Vultures: If the vulture isn't starving, it has enough strength to travel far in search of food. However, if the vulture is very hungry right now, it lacks the physical power to support its long-distance journey. As a result, the degree of hunger is utilized to indicate when vultures are transitioning from the search to the exploitation stage. At the t^{th}iteration, ith vulture hunger degree H_i^tiscomputed by Equation (12),

$$H_i^t = (2 \times r_{i1}^t + 1) \times z^t \times \left(1 - \frac{t}{T}\right) + g^t \tag{12}$$

Where, z^t is random number lies in [-1, 1] range. Then g^t is computed by Equation (13),

$$g^t = h^t \times \left(sin^k\left(\frac{\pi}{2} \times \frac{t}{T}\right) + cos\left(\frac{\pi}{2} \times \frac{t}{T}\right) - 1\right) \tag{13}$$

Where, h^t is random number lies in [-2, 2] range, probability of vulture denoted into k. With a greater k, the exploration phase is more likely to occur after the final optimization step. A lesser$k$ means that it's more likely that the last optimization stage will lead to the exploitation phase.

3) Exploration stage: In AVO, the author creates two different exploring behaviors and utilizes a parameter called $p_1$to determine which one the vulture will perform this time. The range of this parameter p_1 is [0, 1] and it is given with the algorithm's initialization. The vulture's exploration strategy is determined by AVO based on a random value in the range [0, 1] that is larger than or less thanp_1.

The vulture exploration function can be stated as in Equation (14),

$$X_i^{t+1} = \begin{cases} X_i^t - D_i^t \times H_i^t, P_1 \geq r_{P1}^t \\ X_i^t - H_i^t + r_{i2}^t \times \left((ub - lb) \times r_{i3}^t + lb\right), P_1 < r_{P1}^t \end{cases} \tag{14}$$

At the $t + 1$th iteration,ith vulture position denoted byX_i^{t+1}.r_{P1}^t,$r_{i2}^t$and $r_{i3}^t$are random numbers which is lies between 0 and 1, ub and lbsignifies the upper and lower boundary, and D_i^t is computed by Equation (15) to denotes the distance among vulture and current optimal vulture.

$$D_i^t = |C \times X_i^t - X_i^{t+1}| \tag{15}$$

As previously stated, AVO is a population-based metaheuristic algorithm. On the other hand, this method may lead to solutions that are local optima. This is why random variables are used to update the position of the solutions. The

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WOA position update function is used to strike a compromise between exploration and exploitation. It will encourage exploitation in direct proportion to the number of iterations.

4) Exploitation stage: To improve the exploration in AVO, a random search agent is picked to lead the search instead of changing the locations of the candidate solutions depending on the role of the best one thus far.The WOA exploitation stage is used to update the best solution in this case. To drive a search agent to transfer away from the optimal recognized search agent, a vector A with random values higher than 1 or <-1 is utilized.It can be demonstratedby Equations (16) and (17) [23].

$$\vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \tag{16}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{17}$$

Here, $\overrightarrow{X_{rand}}$ is random whale which is selected from the current population.

Once the optimization process begins, EWOA makes a random, initial population and analyses the fitness function. Following the discovery of the optimum solution, the algorithm repeats the stages until the end condition is met. The main parameters are first updated. Finally, the method returns the optimal solution. The use of the best solution discovered so extreme to update the location of the remainder of the resolutions ensures the convergence of this algorithm. As a result, the Enhanced AVO offers the most optimal solutions.

Pseudo code for Enhanced AVO

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 (P_i)) ***do***
Select $X(i)$ using Eq. (10)
Update the H using Eq. (12)
if *($|H| \geq 1$)* ***then***
if *($p_1 \geq randp_1$)* ***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 solution

IV. RESULT AND DISCUSSION

The proposed denoising approach is simulated by MATLAB2018a software running on a Windows8.1 operating system. The White Gaussian noise is included in the ECG signals with the variances of 10dB to create a noisy signal. For experimentation purposes, the proposed approach is tested with three standard datasets MIT-BIH ARR, MIT-BIH NSR and BIDMC-CHF. Figure 4 illustrates the clean, noisy, and denoised ECG signals. The MIT-BIH dataset was the first set of standard test material for detecting widely available arrhythmias. Since 1980, this database has been used for fundamental cardiac dynamics research at over 500 locations across the world. The BIH Arrhythmia Laboratory obtained 48 half-hour snippets of 2-channel, 24-hour ECG recordings from 47 participants for this database. Each ECG data set includes information such as the patient's age, gender, and illness status. The database has a broader spectrum of ECG abnormalities and more data kinds, allowing affiliated institutions to share services and technical assistance while lowering R&D costs.

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

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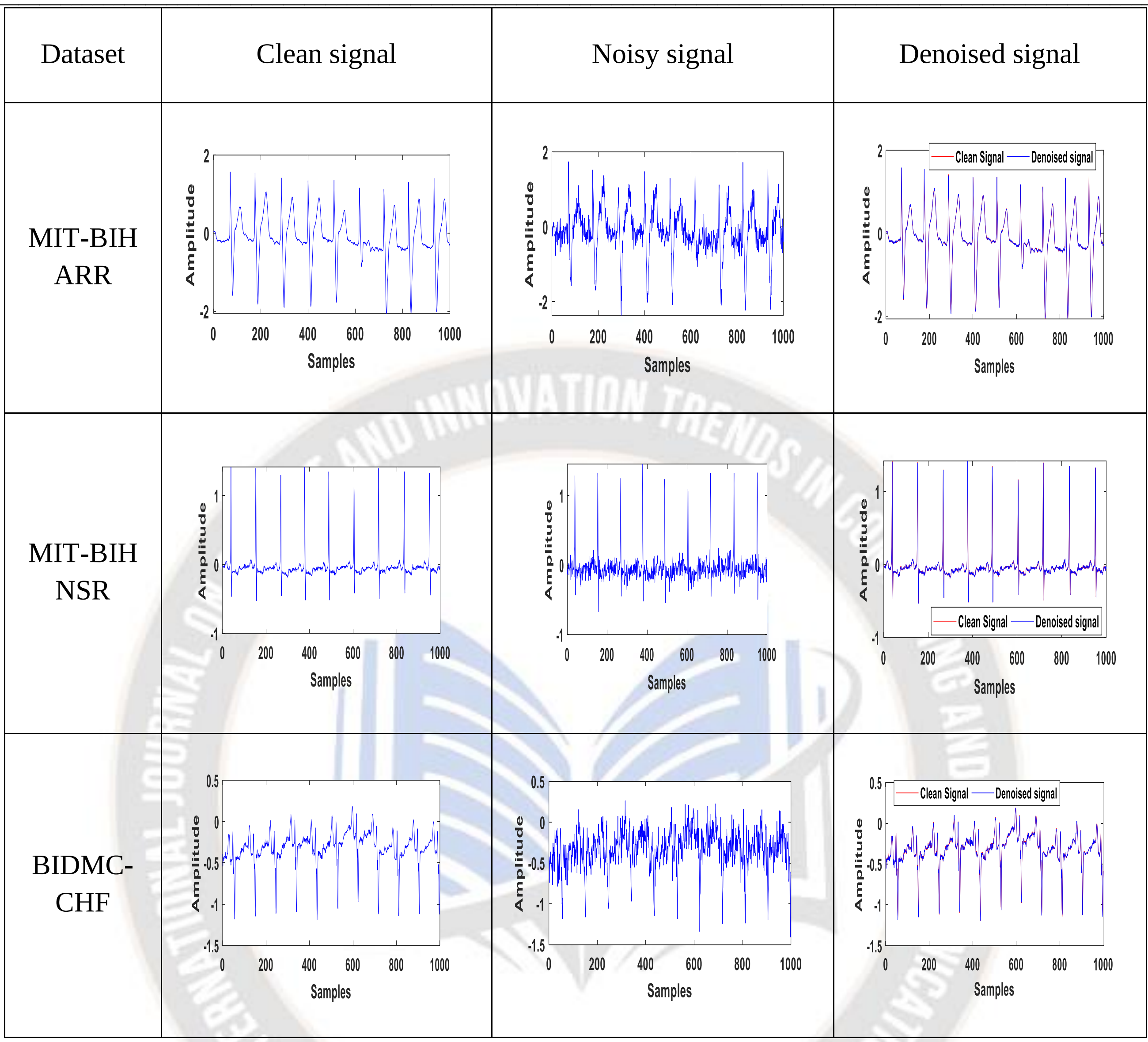

Figure 4. Original, noisy and denoised ECG Signal

For quantitative evaluation in denoising performance, the proposed strategy is utilized the following metrics such as SNR, ME, MSE, MD, peak reconstruction error (PRE), normalized root-mean-square error (NRMSE), correlation coefficient (CC) and normalized root maximum error (NRME) are separately computed [17]. These parameters are computed using $x(p)$ is the pure signal; $y(p)$ is the filter output.

$$SNR = 10log_{10}\frac{\sum_{i=0}^{N-1}(x(p_i))^2}{\sum_{i=0}^{N-1}(y(p_i)-x(p_i))^2} \tag{18}$$

It's worth noting that the SNR measures noise suppression; consequently, the greater the SNR, the greater the denoising performance.

$$MD = \frac{1}{N}\sum_{i=0}^{N-1} x(p) - y(p) \tag{19}$$

$$NRMSE = \sqrt{\frac{\sum_{i=0}^{N-1}(y(p_i)-x(p_i))^2}{\sum_{i=0}^{N-1}(x(p_i))^2}} \tag{20}$$

$$PRE = \frac{x(p)-y(p)}{x(p)} \tag{21}$$

$$ME = \max\left[abs(x(p) - y(p))\right] \tag{23}$$

$$NRME = 100 \times \sqrt{\frac{abs(x(p)-y(p))}{abs(x(p))}} \tag{24}$$

The proposed method performance is evaluated in various matrices with existing approaches such as RLS-based adaptive filter [24], Multichannel LMS [25], improved multiverse optimization (IMVO) with adaptive thresholding (AT) [26], Empirical Wavelet Transform (EWT) with honey badger optimization (HBO) and DWT- based baseline wander [27]. From the readings, it is evident that the proposed approach

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produces better-denoised signals than the other existing approaches.

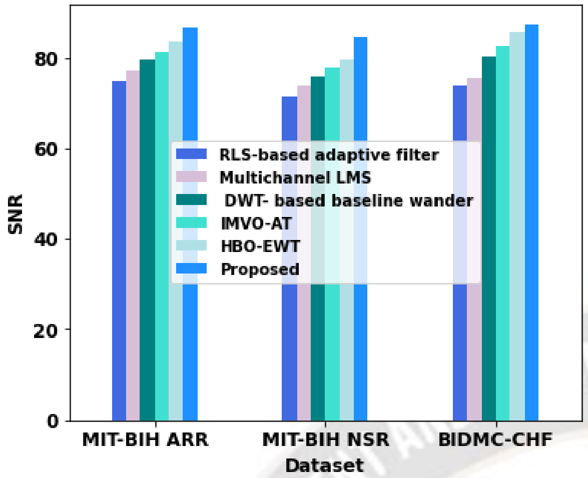

Figure 5. Performance evaluation of SNR

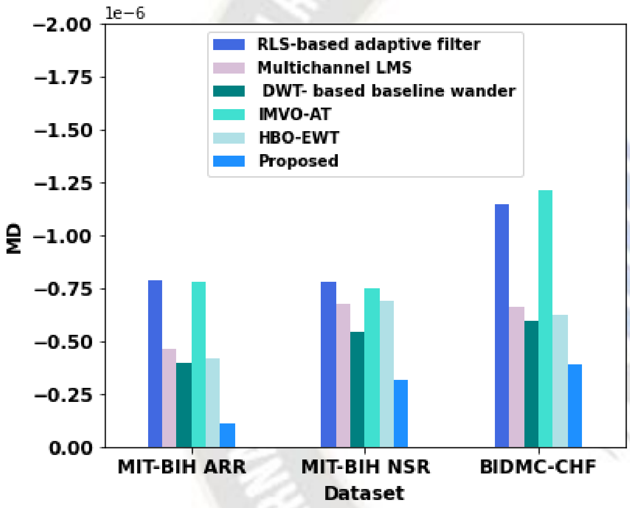

Figure 6. Performance evaluation of MD

Figures 5 and 6 depict the SNR and MD of various approaches such as RLS-based adaptive filter, Multichannel LMS, IMVO-AT, HBO-EWT, and DWT- based baseline wander compared with the proposed approach. From this Figure, it is evident that the suggested approach gives a higher SNR value than other existing approaches. The experimental findings illustrate that the proposed approach is superior to all other denoising techniques.

The NRME and NRMSE between the suggested approach and other optimization algorithms like RLS-based adaptive filter, Multichannel LMS, IMVO-AT, HBO-EWT, and DWT-based baseline wander is shown in Figure 7 and 8. The suggested approach produces a lower NRME and NRMSE value than existing denoising techniques, as seen in this graph. The results of the experiments reveal that the proposed strategy outperforms all other denoising strategies.

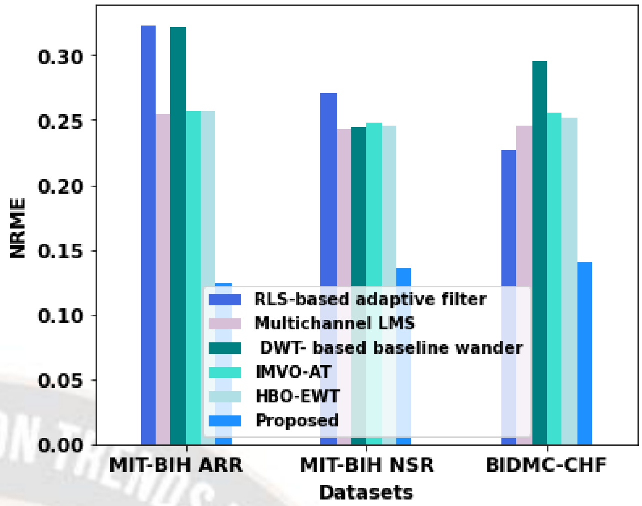

Figure 7. Performance evaluation of SNR

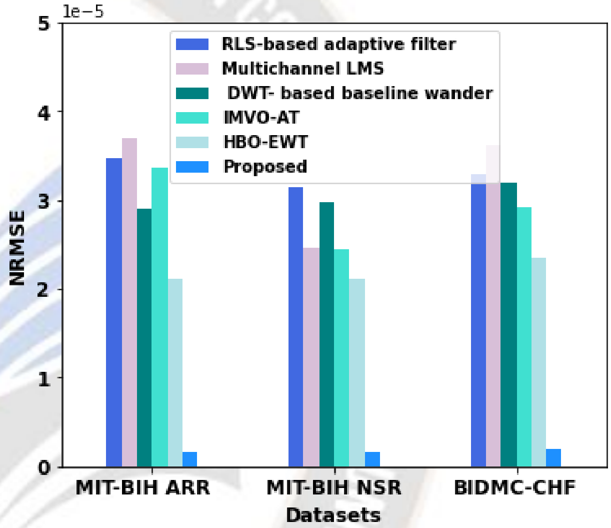

Figure 8. Performance evaluation of MD

The PRE and ME between the suggested approach and other optimization algorithms like RLS-based adaptive filter, Multichannel LMS, IMVO-AT, HBO-EWT, and DWT- based baseline wander is shown in Figure 9 and 10. The suggested approach produces a lower PRE value than existing denoising techniques, as seen in this graph. From figure 10 it is evident that the suggested approach gives a lesser ME value than other denoising techniques. The results of the experiments reveal that the proposed strategy outperforms all other denoising strategies.

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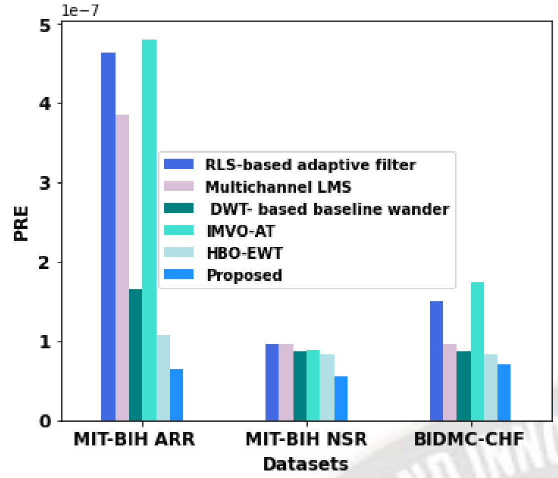

Figure 9. Performance evaluation of PRE

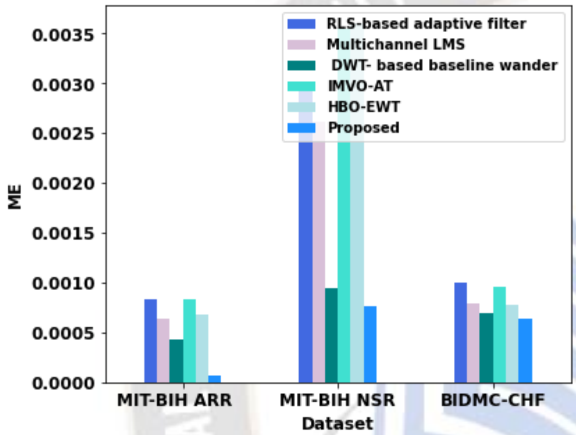

Figure 10. Performance evaluation of ME

Figure 11 depicts CCof various denoising methods such as RLS-based adaptive filter, Multichannel LMS, IMVO-AT, HBO-EWT, and DWT- based baseline wander compared with the proposed approach. From this Figure it is evident that the suggested approach gives better CC than other denoising methods.

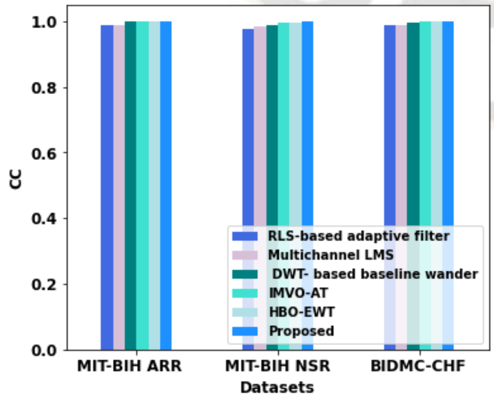

Figure 11. Performance evaluation of CC

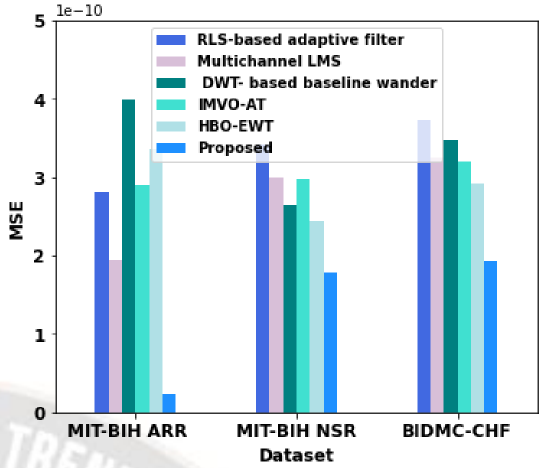

Figure 12. Performance evaluation of MSE

Figure 12 compares the Mean Square Error (MSE) of several optimization techniques to the proposed methodology, including RLS-based adaptive filter, Multichannel LMS, IMVO-AT, HBO-EWT, and DWT- based baseline wander. The recommended technique provides a less MSE value than previous denoising strategies, as seen in this graph. The experimental results show that the suggested method outperforms all existing denoising methods.

Friedman and the Wilcoxon test were used to analyze the results statistically. The null theory supposed that all of the strategies were correspondingly effective. Friedman test is used to rank each method, and the p-value is then determined. A statistically significant difference between the results is confirmed by the lower p-value. As a result, the null hypothesis is ruled out. Wilcoxon signed-rank test for the suggested strategy vs the existing approaches is shown in Table 2. The proposed method received the highest ranking in the analysis. From the table, the p-values are less than $\alpha = 0.05$. Comparing the proposed approach produces the best diagnosing value than the existing approaches. The Wilcoxon test was used after the Friedman test, and the method with the highest rank was chosen as the regulatory method. Because it had the highest ranking, the proposed approach was chosen as the governing method. As a result, the proposed strategy produces statistically superior outcomes when compared to previous methods such as PSO, AOA, MVO, IMVO and HBO.

TABLE II. WILCOXON SIGNED RANK TEST

Comparative hypothesis	Proposed Vs PSO	Proposed Vs AOA	Proposed Vs MVO	Proposed Vs IMVO	Proposed Vs HBO
P-value	0.164	0.157	0.125	0. 125	0.05

For discovering interaction effects or significant factors, Friedman's analysis of variance (ANOVA) is recommended. ANOVA is a useful method for separating overall variability into useable components such as a sum of squares (SS), degree of freedom (Df), mean sum of squares (MS), and F-value. The output parameters and values acquired during the ANOVA test for various optimization algorithms using the proposed denoising approach are shown in Table 3.

TABLE III. FRIEDMAN'S ANOVA TEST

Source	SS	Df	MS	F	Prob>F
Columns	30.3333	2	15.1667	4.04	0.1324
Interaction	2.3333	2	1.1667		
Error	87.3333	12	7.2778		
Total	120	17			

V. CONCLUSION

This study uses Enhanced AVO, a novel bio-inspired metaheuristic algorithm, to implement an adaptive switching mean filter-based denoiser and demonstrate WOA-AVO capacity to find high-quality solutions that outperform other metaheuristic algorithms such as PSO, AOA, MVO, IMVO, and HBO. The Enhanced AVO algorithm not only maintains a correct poise among exploration and exploitation but it is control parameter-free algorithm, which eliminates the need for a time-consuming control parameter tweaking process. The DWT wavelet parameter of window function and ASMF filter is optimized by the Enhanced AVO algorithm. To prove the effectiveness of the proposed denoising filter, EAVO method comparative analysis has been conducted with the RLS-based adaptive filter, multichannel LMS, IMVO-AT, HBO-EWT, and DWT- based baseline wander techniques. When compared to prior reported results, estimated results show that the proposed EAVO-based adaptive switching mean filter achieves a considerable improvement in NRMSE, SNR, MD, NRME, PRE, ME, and CC. As a result, the proposed strategy for denoising the cardiovascular signal is quite effective. As a consequence of the examined results and discussions, it can be concluded that the proposed hybrid algorithm supported by DWT and filter can be employed efficiently for cardiovascular signal denoising.

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