Reconstruction of EMG Signals from Noisy Environment Using Sine Adapted Whale Optimization Algorithm

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ABSTRACT

Electromyography (EMG) signals are frequently corrupted by noise during acquisition, impacting the accuracy of clinical diagnoses, particularly in neuromuscular disorder identification. Traditional adaptive noise cancellation filters, such as Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms, face limitations in weight vector updating and parameter tuning, making them ineffective in eliminating common noise sources like electrocardiogram (ECG) noise, baseline wander, and power line interference. To overcome these limitations, we propose LMS-SiWOA and RLS-SiWOA, which integrate the Sine Adapted Whale Optimization Algorithm (SiWOA) to enhance signal-to-noise ratio (SNR) and optimize weight updates. The convergence analysis shows that the method successfully simplifies the optimization of adaptive filter coefficients by utilizing improved search capabilities of SiWOA. The proposed algorithms extract 17 key EMG features while effectively denoising the signal across multiple noise types. Experimental results show that the proposed LMS-SiWOA and RLS-SiWOA methods could improve SNR by 23.75% and 17% compared to conventional algorithms, providing a more reliable solution for clinical EMG signal processing.

Keywords: Adaptive noise cancellation filters, Optimization algorithm, EMG features, Neuromuscular disease

1. INTRODUCTION

Electromyography (EMG) is a technique used to record electrical signals produced by muscle contractions, known as EMG signals. These signals can be converted into quantitative data, sounds, or graphical representations to assess muscle and nerve function. EMG signals are captured using either non-invasive surface electrodes or invasive needle electrodes, depending on the application. These electrodes detect the electrical currents generated by muscle contractions and convert them into electrical signals for further analysis. EMG is widely used in both medicine and engineering, particularly for diagnosing neuromuscular disorders [1].

Accurate EMG signal recording is crucial for diagnosing various neuromuscular conditions, such as myopathy and neuropathy. One commonly studied condition is sciatica, also known as lumbar radiculopathy, which affects nerve conduction and causes characteristic changes in the EMG signal [2]. However, EMG signals, like all biological signals, are susceptible to noise from various sources, including artifacts and electrical muscle stimulation [3]. This noise complicates the analysis, making it necessary to apply noise reduction techniques before processing the signals for clinical or research purposes [4].

Traditional filtering methods, such as low-pass, high-pass, and notch filters, have been used to reduce noise in EMG signals [5]. However, these filters often fail to adequately address the nonlinear and time-varying nature of biological signals, especially when the noise and signal occupy overlapping frequency bands [6]. In response to these limitations, more advanced techniques such as principal component analysis, wavelet transformation, and empirical mode decomposition have been introduced. Yet, these methods still fall short in certain scenarios, particularly in dealing with dynamic noise conditions [7][8].

Adaptive filtering techniques offer a more robust solution by dynamically adjusting filter coefficients based on the input signal and noise characteristics. Common adaptive algorithms like the Least Mean Square (LMS) and Recursive Least Square (RLS) algorithms have been widely applied in EMG signal processing [9]. These algorithms are particularly effective at handling non-stationary noise, such as baseline wander and power line interference (PLI), which are common in EMG recordings. The adaptive nature of these filters allows for better noise reduction while preserving the integrity of the underlying EMG signal [10].

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Baseline wander, typically caused by patient movement, breathing, or variations in electrode-skin impedance, is one of the most challenging sources of noise in EMG signal recordings [11]. Power line interference (PLI) further complicates signal analysis due to the presence of stray currents and differences in electrode impedance [12]. Hardware solutions, such as improving the Common Mode Rejection Ratio (CMRR), have been developed to mitigate the impact of PLI [13]. However, these hardware-based approaches are not always sufficient for achieving clean EMG signals, which is why adaptive filtering techniques are crucial [14].

Given the limitations of both traditional and advanced filtering methods, there is a need for more effective adaptive algorithms that can handle diverse noise conditions. This paper proposes an improved adaptive filtering approach using the Sine Adapted Whale Optimization Algorithm (SiWOA). The SiWOA enhances the performance of LMS and RLS filters by optimizing their weight adjustment process, allowing for more effective noise reduction. The following sections of the paper are structured as follows: Section 2 discusses the materials and methods, including the proposed optimization algorithm; Section 3 presents the experimental results; and Section 4 provides concluding remarks.

2. MATERIALS AND METHODS

An adaptive filter is a digital filter that adjusts its weights dynamically based on the incoming signal and noise characteristics. This adjustment process is governed by an algorithm that minimizes error and improves the convergence rate of the filter. In this work, we present an enhanced version of the Whale Optimization Algorithm (WOA), called the Sine-function Adapted Whale Optimization Algorithm (SiWOA), to optimize the weight update mechanism in adaptive filters. We also utilize traditional algorithms like Least Mean Square (LMS) and Recursive Least Square (RLS) for comparison. To assess the significance of performance differences across algorithms, a statistical analysis using a paired t-test and analysis of variance is conducted after calculating the performance metrics, including signal-to-noise ratio (SNR) and mean square error (MSE). This ensures that improvements are not just observed but are also statistically significant. The suggested LMS-SiWOA and RLS-SiWOA methods save computational load and enhance searching performance. In Fig. 1, the proposed structure is illustrated. The several types of noise in electromyogram signals can be successfully removed by this adaptive noise cancellation framework.

The proposed methodology has the following steps:
Step 1: It starts with the noisy EMG signal, which is collected from a real-world dataset (e.g., the PHYSIONET EMGDB dataset). The signal is contaminated with three types of noise: Baseline Wander (BW), Power Line Interference (PLI), and Electrocardiogram (ECG) noise.

Step 2: Parallel to step 1, a synthetic noise signal is generated in MATLAB to simulate the characteristics of the actual noise contaminating the EMG signal. This noise is uncorrelated and additive to the desired signal.

Step 3: The adaptive filter receives two inputs: the noisy EMG signal and the reference noise signal. The goal of the filter is to estimate the noise and subtract it from the noisy signal to retrieve the clean EMG signal. The filter uses an adaptive algorithm (LMS, RLS, or SiWOA) to continuously update its weights in order to minimize the error signal e(n), which is the difference between the desired signal D(n) and the estimated output Y(n).

Step 4: The sine-function adapted whale optimization algorithm (SiWOA) is employed to optimize the weight updating process in the adaptive filter. This involves using exploration and exploitation phases, controlled by sine and cosine functions, to find the optimal filter weights that minimize the error signal.

Step 5: The error signal e(n) is iteratively reduced by adjusting the filter weights. The objective is to make the error as small as possible, which indicates that the filter is effectively removing the noise from the EMG signal.

Step 6: Once the optimization converges, the output of the adaptive filter is the denoised EMG signal, which has minimal interference from the noise sources.

Step 7: From the denoised signal, important EMG features are extracted (such as mean absolute value, root mean square, zero crossings, etc.). These features are essential for further analysis and classification in clinical applications.

2.1 Least-Mean-Square (LMS) algorithm

The least mean square (LMS) algorithm is a traditional adaptive method with minimal computational cost. Because the LMS algorithm was created using a gradient descent methodology, it does not require memory or involve intricate matrix computations. However, the adaptive filter's rate of convergence is constrained by the choice of step size.

Equations (1) and (2) represent the LMS algorithm's error computation and weight modifications.

$$e(n) = S(n) - S(n)^T \times W(n) \tag{1}$$

$$W(n+1) = W(n) - 2\mu S(n) W(n) \tag{2}$$

$S(n)$ is the input vector in this case (signal correlated to noise). where e(n) is the error estimate and Y(n) is the output signal. Equation (1) measures the difference between the true signal and the noisy, filtered signal. The goal is to minimize e(n) as much as possible. The nth iteration weight vector is represented by w(n), and the step size, μ, controls the convergence rate in equation (2). The filter weights are adjusted iteratively using this equation, which seeks to reduce the error signal.

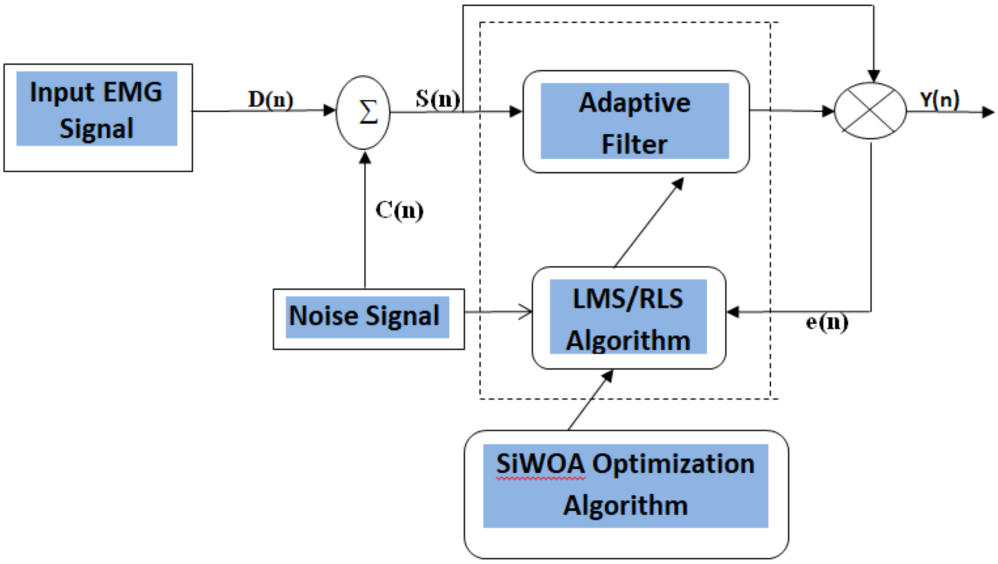

Fig. 1*: Work flow of proposed method.*

2.2 Recursive Least-Squares (RLS) algorithm

The RLS method minimizes errors and has a quick rate of convergence. A correlation matrix is created by the RLS algorithm to alter weight. The filter's convergence rate is increased through this procedure, but it also uses more memory and requires more matrix calculations. The optimization of the error function using the weight updating approach is described in Equations (3) and (4).

$$e(n) = S(n) - D^T(n) \times W(n) \tag{3}$$

$$W(n) = P_M(n)Q_M(n) \tag{4}$$

In Eq. (6), P_M is the input signal correlation matrix, and Q_M is the cross-correlation matrix among filtered and input signals. These values are evaluated using Eqs. (5) and (6).

$$\begin{aligned} P_M(n) = \frac{1}{\lambda}[P_M(n-1) \\ - \frac{P_M(n-1)C(n)D^T(n)P_M(n-1)}{\lambda + P_M(n-1)C^T(n)D(n)}] \end{aligned} \tag{5}$$

$$Q_M(n) = \lambda Q_M(n-1) + D(n)S(n) \tag{6}$$

Here λ is the factor and I is the identity matrix in which the output signal equation is given below Eq. (7).

$$Y(n) = S(n)W^T(n) \tag{7}$$

RLS adjusts the filter weights by taking into account the correlation of past signal values, allowing it to converge faster than LMS. It is particularly useful in scenarios where the noise characteristics change over time, such as in EMG signals contaminated with different types of noise.

The SiWOA algorithm is used in this work to lower the mean square error of an adaptive filter.

2.3 Overview of Sine function adapted improved WOA (SiWOA)

Many motivated optimization strategies are proposed for different types of optimization tasks. Based on the art of bumper whale hunting, Mirjalili and Lewis have devised the Whale Optimization Algorithm (WOA) [31]. Nonetheless, WOA maintains its local optimism and affinity for premature convergence. Therefore, it was suggested in earlier studies to make a few WOA adjustments to improve the effectiveness of the original WOA technique. The results of the current study suggest that the increased WOA (SiWOA) with sine adaptation improves WOA ability. Using the original WOA factor scale factors, SiWOA is changed to define the step in the positioning gradation process. Additionally, it evaluates control parameter 'c' in the WOA process by using the sine function. WOA incorporates these variables in order to strike a reasonable balance between exploration and exploitation. Whales search for food close to the surface of the ocean. This search habit is driven by circular bubbles. Whales obtain their food by swimming in diminishing circles, a process known as food swimming. The whales determine that the new best candidate is nearly the best since the location of the food in the quest field is unknown. Following that, the remaining whales try to get into the ideal posture. There are two approaches: the spiral remodeling role in the WOA usage process, which is controlled by the bubble-net attack strategy, and the decreasing encircling method. The mechanisms are discussed in equations (8)-(10).

$$\vec{G} = \left| \vec{F} \times \vec{Y}^*(t) - \vec{Y}(t) \right| \tag{8}$$

$$\vec{Y}(t+1) = \vec{Y}^*(t) - \vec{D}\vec{G} \tag{9}$$

$$\vec{Y}(t+1) = \vec{G'} e^{lm} \cos(2\pi m) + \vec{Y}^*(t) \tag{10}$$

where $\overrightarrow{G'} = \left|\overrightarrow{Y}^*(t) - \overrightarrow{Y}(t)\right|$ and $'k'$ stands for the shape of the logarithmic spiral from the ith whale to the finest whale since then. $'m'$ is an arbitrary number in [-1,1]. Eqs. (11) and (12) are used to estimate $\overrightarrow{D}$ and $\overrightarrow{F}$ vectors that regulate the area where whales can be found in close proximity to prey. $\overrightarrow{Y}^*(t)$is the current best solution until the present iteration t and $\overrightarrow{Y}(t)$ is the location vector. Equation (10) guarantees that whales will shift positions in the vicinity of the greatest outrage. The optimal locations to enter are updated by an agent in accordance with Equation (11). In Eq. (10), $\overrightarrow{F}$ represents the difference between i^{th} whale and the best solution so far achieved.

$$\overrightarrow{D} = 2\vec{d}\vec{s} - \vec{c} \tag{11}$$

$$\overrightarrow{F} = 2\vec{s} \tag{12}$$

where $\vec{s}$ is a chosen random number in the range [0, 1]. The distance control parameter is denoted by $\vec{c}$. Its value falls linearly during the optimization process from 2 to 0. As $\vec{c}$ decreases, the shrinking feature is assured.

$$\vec{d} = 2 - t\frac{2}{ITER_{MAX}} \tag{13}$$

Whereas $\vec{d}$ is the parameter for the distance control, t is the current iteration, and the limit is ITERMAX. Proposed SiWOA uses sine to pick $\vec{d}$ for iteration as depicted in Eq. [14].

$$\vec{d} = 2 - 2\sin\frac{t\pi}{2ITER_{MAX}} \tag{14}$$

Parameter $\vec{d}$ weighs combinations of exploration and exploitation using the sine and cosine functions. An agent could be repositioned in the region of another agent thanks to the sine function cyclic molds. This method ensures that the right stage of exploration and exploitation is followed. Whales are searching for the optimal solution in the prediction step of WOA. Early on, it's difficult to determine which alternative is ideal. Whales will therefore initially move away from the ideal location in big stages. Scaling factors (SF) are used in SiWOA to control whale movement during the search. The equations have been updated as:

$$\overrightarrow{G} = \left|\overrightarrow{F} \times \overrightarrow{Y}^*(t) - \overrightarrow{Y}(t)\right| /SF \tag{15}$$

$$\overrightarrow{Y}(t+1) = (\overrightarrow{Y}^*(t) - \overrightarrow{D}\overrightarrow{G})/SF \tag{16}$$

$$\overrightarrow{Y}(t+1) = (\overrightarrow{G'}e^{lm}\cos(2\pi m) + \overrightarrow{Y}^*(t)/SF \tag{17}$$

In the WOA approach, the whale's objective is to be the best whale in the area while other whales attempt to update their positions in close proximity to it. The most probable search agent is not known at first, and this method's modification takes big steps at first. These changes might not have the optimum effect on whale movement. The following equations describe how the introduction of scaling factors (SF) in SiWOA during the exploration stage regulates the movement of search agents during the search process.

$$\overrightarrow{G} = \left|\overrightarrow{F} \times \overrightarrow{z_{rand}}(t) - \overrightarrow{Y}\right| /SF \tag{18}$$

$$\overrightarrow{Y}(t+1) = (\overrightarrow{\mathrm{z_{rand}}}(\mathrm{t}) - \overrightarrow{\mathrm{D}}\overrightarrow{\mathrm{G}})/\mathrm{SF} \tag{19}$$

Where $\overrightarrow{z_{rand}}(t)$ is a random vector at time t, which introduces stochasticity into the search process, enhancing the diversity of agent movements.
The scaling factor is varied as given below:

$$SF = \begin{cases} 2 - t\frac{2}{ITER_{MAX}} & if \text{ RND} < 0.5 \\ 1/(2 - \frac{t}{ITER_{MAX}}) & if \text{ RND } \geq 0.5 \end{cases} \tag{20}$$

where RND is a random value that lies in the interval [0, 1]. Whale behavior during the initial stages of the selection process is altered by the integration of both the activity and scan elements, which enhances the process's exploration capabilities. Later on, whales use improved techniques to go past them at a regular speed. It is demonstrated that SiWOA efficiently scans the search space to identify the optimal solution. Whales have significant changes in the early stages before eventually converging. Figure 2 compares the SiWOA to WOA convergence curves for a few functions. To improve the convergence function definition, only six search agents and one hundred iterations are taken into account.

Figure 2 illustrates the greater convergence of SiWOA with respect to WOA. When sine and cosine characteristics are employed in SiWOA iterations instead of the current WOA technique, the parameter '$\vec{c}$' exhibits better behavior. In order to achieve optimal outcomes, it improves integration by offering a better balance between extraction and exploration. Phase variance scales are adjusted by scaling factors. This enables SiWOA to quickly converge and explore challenging regions in search space during the initial iteration. We attribute the great exploration capability of SiWOA to an enhanced update process using scaling factors.

3. RESULTS AND DISCUSSIONS

In the present study, the neuropathy EMG signal is denoised, and its features are recovered using the suggested optimum adaptive filter structure. The simulation results of current and suggested methodologies are also contrasted. Here, MATLAB software is used to create and mix the test EMG signal with noise signals (PLI, BW, and ECG noise) and test EMG signals obtained from PhysioBank. According to the reviewed results, the adaptive noise cancellation filter based on the sine function-adapted improved Whale Optimization Algorithm (SiWOA) performed better than the current approaches in terms of SNR, convergence rate, and extraction of 17 valid EMG signal characteristics.

3.1 Dataset Description

The electrical activity of muscles and nerve conduction is measured by the EMG test. Compression on

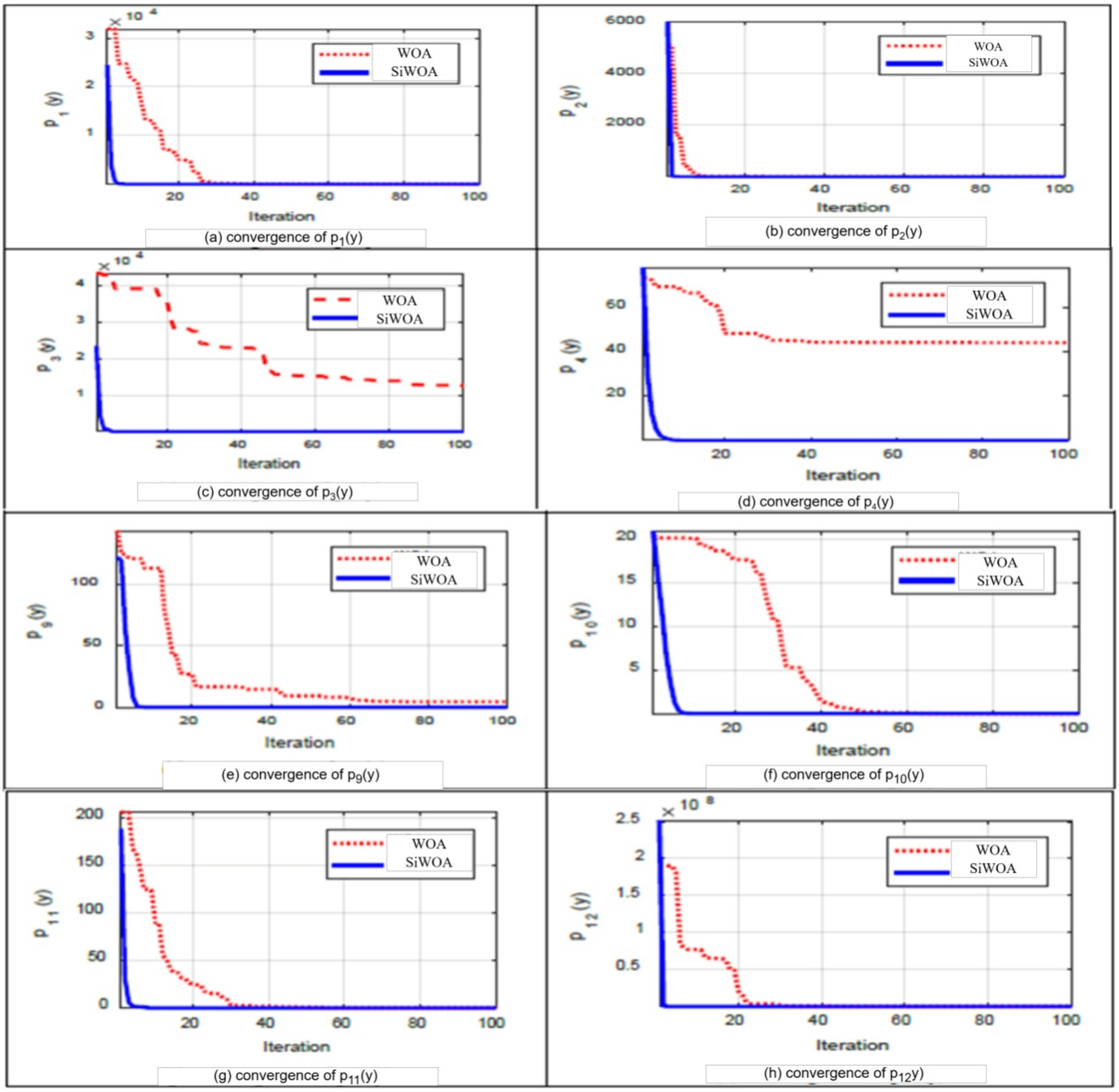

***Fig. 2**: Comparing several test function convergence properties using WOA and SiWOA methods.*

the spinal root causes sciatica, a disease that falls under the group of neuropathic disorders. A test EMG signal was obtained from a male individual aged 62 who was experiencing low back discomfort as a result of right L5 radiculopathy, sometimes known as sciatica. The waveform was captured at an amplitude of 1 mV per cm and a sweeping intensity of 10 milliseconds per centimeter. The Medelec Synergy N2 EMG monitoring system is where the EMG signals are captured and gathered. After inserting a 25 mm needle electrode into the anterior tibialis muscle, the patient was told to gently dorsiflex their foot. After notifying the patient of the sharp increase in the EMG signal, the needle is repositioned and removed from the patient. Following a 50 kHz note, the data was sampled down to 4 kHz. It allows for the effective analysis of relevant muscle activity without introducing aliasing while also simplifying data handling and improving computational performance.

3.2 Evaluation and Analysis of Filtered EMG signal

The LMS and RLS filters usually offer one solution since updating the weights for noise reduction in EMG signals is not a suitable use of a typical procedure. The assessment is thus described using the SiWOA algorithm. For the efficient weight updating procedure, SiWOA generates additional solutions; choose the best one from the group. When parameters are evaluated, the original signal and the noise signal are typically displayed alongside the filtered signal. This study compared the results with previously published techniques after evaluating the output SNR, MSE, maximum error, standard deviation, and mean. Based on the following equations, all of these parameters are computed. Table 1 presents a comparative assessment of the proposed filter structure performance in terms of SNR, MSE, mean, standard deviation, and maximum error. In table 1, significant improvements are indicated with * (which indicate $p < 0.05$), very significant improvements are indicated with ** (which indicate $p < 0.01$), and high significant improvements are indicated with *** (which indicate $p < 0.001$).

$$SNR_{out} = 10\log_{10}\left(\frac{EMG_{original\ out}}{(EMG_{filter\ sig.} - EMG_{original\ sig.})^2}\right) \tag{21}$$

$$Maximum\ error = abs\left(EMG_{noise\ sig.} - EMG_{original\ sig.}\right) \tag{22}$$

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n}(EMG_{noise\ sig.} - EMG_{original\ sig.})^2 \tag{23}$$

In terms of signal-to- noise ratio (SNR), the RLS-SiWOA and LMS-SiWOA algorithms achieve the highest SNR values of 78.944 dB and 77.254 dB, respectively, indicating their superior noise suppression capabilities. These values are significantly higher than those of the LMS and RLS algorithms, which are around 35-36 dB (p<0.001), indicating a highly significant difference. Despite showing notable gains in SNR (76.432 dB and 72.846 dB, respectively), the LMS-ESS and RLS-ESS algorithms were unable to match the performance levels of SiWOA-based techniques. Additionally, LMS-SiWOA outperforms the worst-performing optimization algorithm, LMS-SS, by 23.75%. Similarly, RLS-SiWOA performs 17% better than the RLS-SS technique.

Regarding mean square error (MSE), both LMS-SiWOA and RLS-SiWOA exhibit the lowest MSE values, showcasing their effectiveness in minimizing prediction errors during the denoising process. The lower MSE values reflect a significant increase in accuracy for signal recovery (p<0.001), indicating a highly significant difference compared to other algorithms. In comparison, algorithms such as LMS-CS and RLS-CS display higher MSE values, underscoring the superior accuracy of the SiWOA-based methods.

The maximum error is also notably smaller for the LMS-SiWOA and RLS-SiWOA algorithms compared to other methods, indicating that these algorithms provide more stable and precise filtering, effectively reducing large deviations between the true and estimated signals (p<0.01), signifying a very significant difference.

Furthermore, both SiWOA-based algorithms yield much lower mean and standard deviation values than other methods, indicating more consistent performance with fewer fluctuations during the denoising process. This stability leads to more reliable results in noisy environments (p<0.01), indicating a very significant difference in performance.

Figure 3 shows how different algorithms differ in terms of standard deviation, maximum error, mean, mean square error, SNR, and convergence rate. The convergence plot primarily shows that the error function lowered well. The suggested adaptive filter structure with LMS-SiWOA and RLS-SiWOA algorithms offers higher performance in every parameter than the LMS-ESS and RLS-ESS algorithms. Power line interference, baseline drift, and ECG have the greatest effects on the EMG signal. The comparative study of several optimization techniques with adaptive filters put in consideration of MSE and SNR is displayed in Figure 4. Here, the enhanced squirrel search (ESS), squirrel search (SS), and cuckoo search (CS) algorithm-based LMS& RLS algorithms are compared with the LMS-SiWOA and RLS-SiWOA algorithms. Figure 4 suggests that the adaptive filter may effectively remove all noise, but the adaptive algorithm's efficacy determines how much the SNR and MSE vary.

3.3 Analysis in terms of EMG feature extraction

The process of converting the unprocessed EMG data into a condensed set of features is called feature extraction. A quality attribute should include pertinent details that aid in cleaning up noise-contaminated EMG signals. Seventeen widely used EMG characteristics are employed in this investigation. These elements were selected for earlier works because they were straightforward and produced positive outcomes.

Mean Absolute Value (MAV): This is one of the commonly used features throughout the analysis of EMG trends. MAV is defined as the EMG signal average of absolute signal value.

$$MAV = \frac{1}{L}\sum_{N=1}^{L} Z_N \tag{24}$$

Here Z_N is the signal coefficient, and L is the total number of coefficients.

Wavelength (WL): It is a widely used function that represents the cumulative EMG waveform duration over time. WL can be represented as:

$$WL = \sum_{N=1}^{L} Z_N - Z_{N-1} \tag{25}$$

Enhanced Mean Absolute Value (EMAV):

$$EMAV = \frac{1}{L}\sum_{N=1}^{L}\left|(Y_N)^p\right|$$

$$Y_N = \begin{cases} 0.75, \text{ if N} \geq 0.2\text{L and N} \leq 0.8\text{L} \\ 0.5, \text{ otherwise} \end{cases} \tag{26}$$

Root mean square (RMS): It is modeled as a Gaussian random phase modulated by amplitude; those lead to relentless energy and tireless contraction. The mathematical description of the RMS function can be given as:

$$RMS = \sqrt{\left(\frac{1}{L}\sum_{N=1}^{L} {Z_N}^2\right)} \tag{27}$$

***Table 1**: Parameters comparison for different algorithms.*

Algorithm	Signal to Noise Ratio (dB)	Mean Square Error	Maximum Error	Mean Error	Standard Deviation
LMS	35.626	0.0005	0.984	5.325	1.8131
RLS	36.502	0.00055	0.889	4.325	1.8129
LMS-ESS	76.432*	4.19E-04*	1.20E-01*	0.523*	0.3264*
RLS-ESS	72.846**	5.38E-04**	1.50E-01**	0.523**	0.3269**
LMS-SS	59.121	3.99E-03	0.547	1.458	0.789
RLS-SS	65.268*	3.35E-03*	0.525*	1.325*	0.872*
LMS-CS	62.458	2.11E-02	0.488	3.248	1.245
RLS-CS	66.584*	2.52E-02*	0.489*	3.998*	1.478*
LMS- SiWOA	77.54***	2.80E-04***	3.40E-02***	0.132***	0.1258***
RLS- SiWOA	78.944**	1.19E-04**	2.90E-02**	0.132**	0.1224**

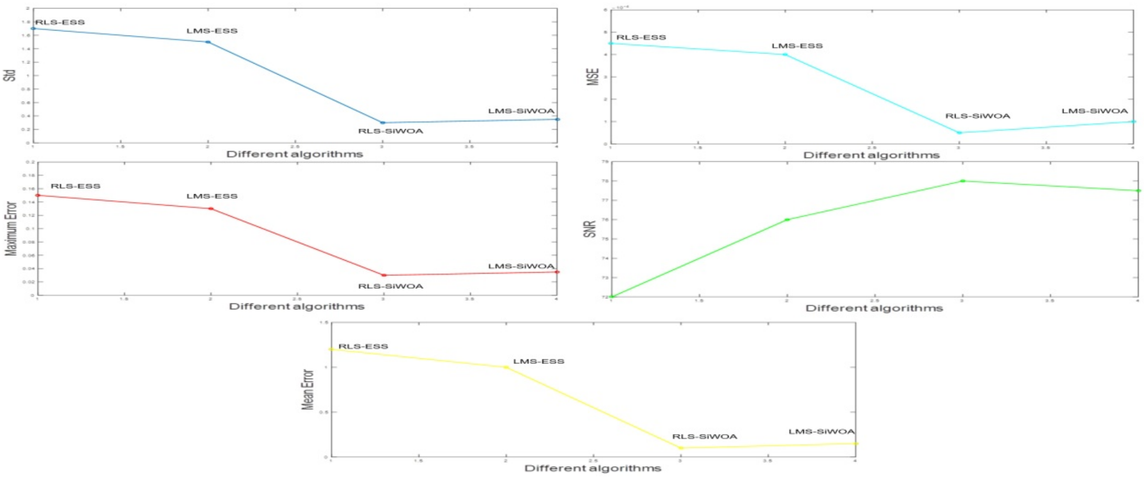

***Fig. 3**: Signal quality assessment metrics of different algorithms.*

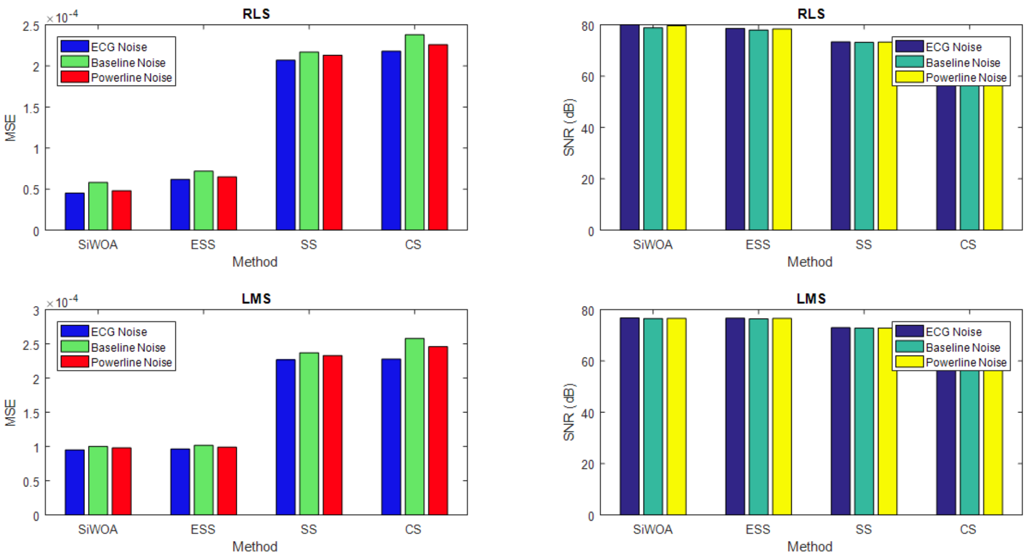

***Fig. 4**: Performance analysis of MSE, SNR due to the influence of noises in the adaptive filter.*

Enhanced Wavelength (EWL): one of the EMG characteristics and is measured as

$$EWL = \sum_{N=2}^{L} \left|(Y_N - Y_{N-1})^p\right| \tag{28}$$

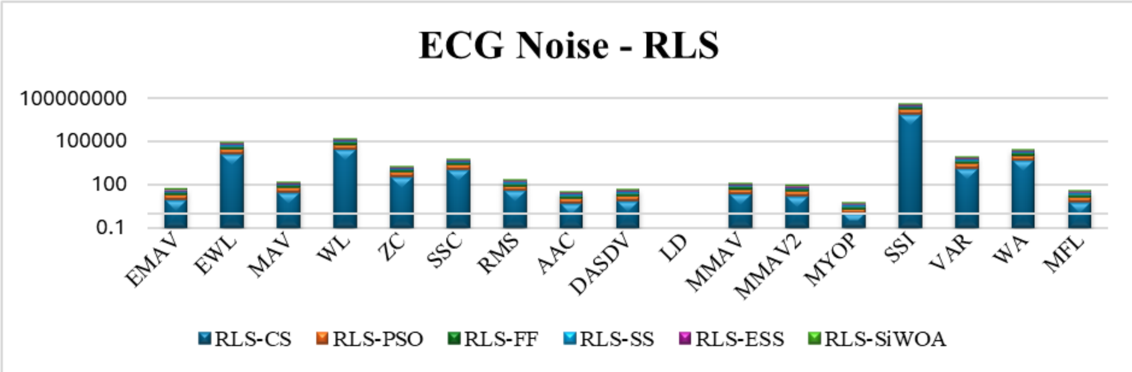

***Fig. 5**: EMG features after de-noising with various RLS algorithms for ECG noise.*

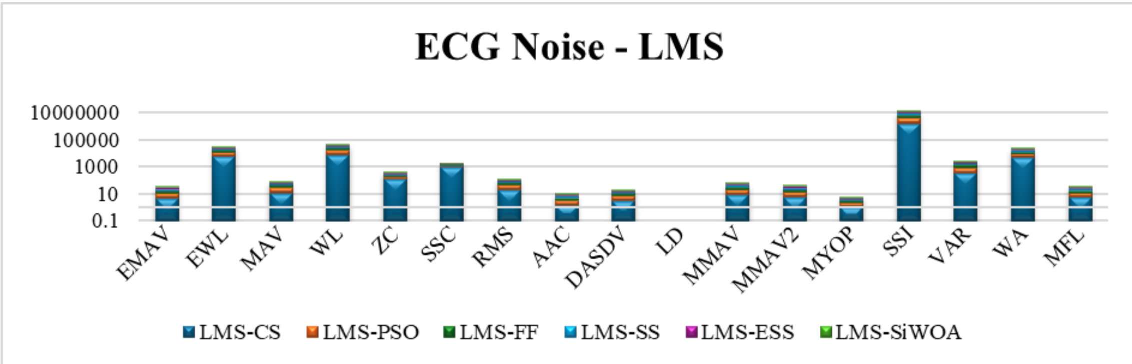

***Fig. 6**: EMG features after de-noising with various LMS algorithms for ECG noise.*

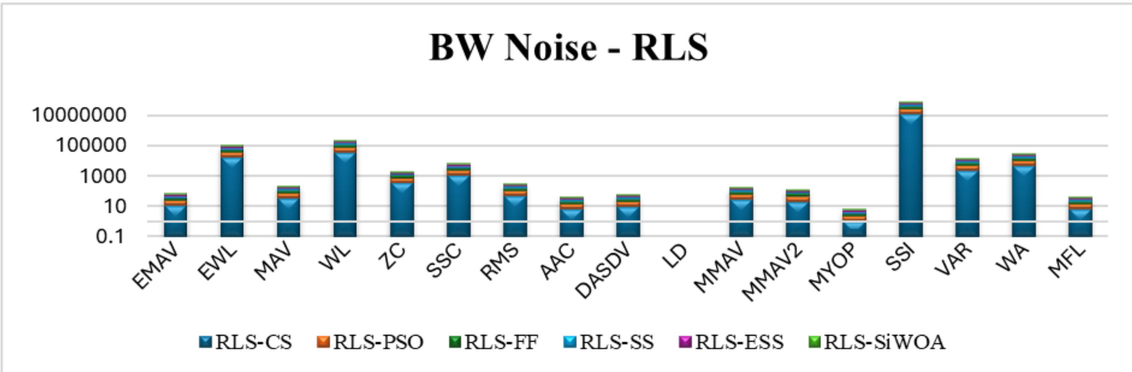

***Fig. 7**: EMG features after de-noising with various LMS algorithms for ECG noise.*

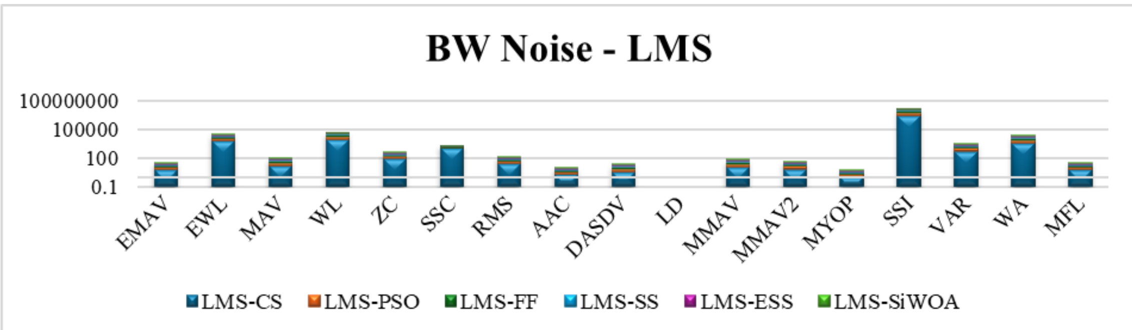

***Fig. 8**: EMG features after de-noising with various LMS algorithms for BW noise.*

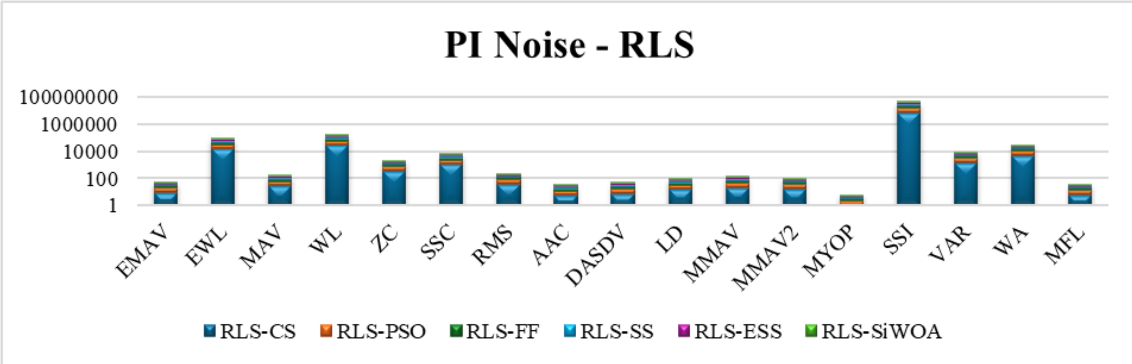

Fig. 9: *EMG features after de-noising with various RLS algorithms for PL noise.*

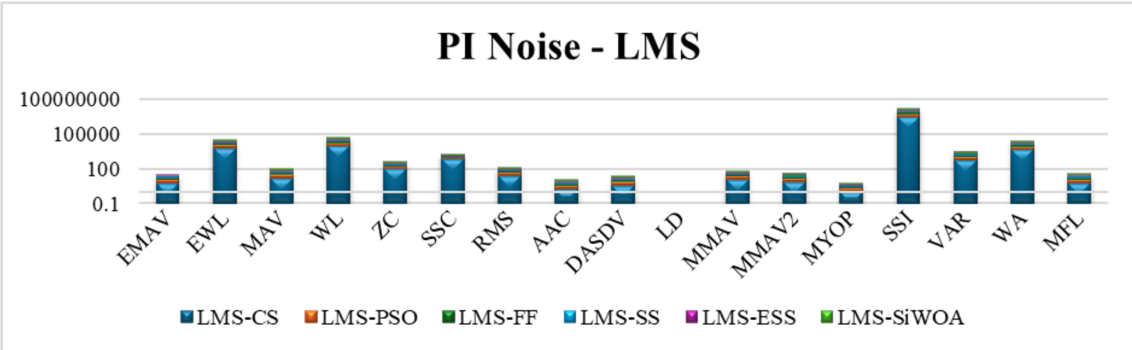

Fig. 10: *EMG features after de-noising with various LMS algorithms for PL noise.*

where Y_N is as given in equation (26).

Maximum fractal length (MFL): It is an EMG characteristic used to measure low-level muscle contraction activation. Mathematically, MFL is definable as:

$$MFL = \log_{10}\left(\sqrt{\sum_{N=1}^{L}(Z_{N+1} - Z_N)^2}\right) \tag{29}$$

Zero crossing (ZC): It measures the information regarding the frequency of the signal and is measured with the following equation:

$$ZC = \sum_{N=1}^{L-1} Y_N$$

$$Y_N = \begin{cases} 1, & \{(Z_N > 0 \;\&\; Z_{N+1} < 0) \mid \{(Z_N < 0 \;\&\; Z_{N+1} > 0) \\ & \{|Z_N - Z_{N+1}| \geq T) \\ & 0, \text{ otherewise} \end{cases} \tag{30}$$

Slope sign change (SSC): SSC is a commonly measured biosignal feature. The number of sign changes in the EMG waveform is determined as:

$$SSC = \sum_{N=2}^{L-1} Y_N$$

$$Y_N = \begin{cases} 1, & \{(Z_N > Z_{N-1} \& \; Z_N > Z_{N+1}) \mid \{(Z_N > Z_{N-1} \& \; Z_N > Z_{N+1}) \\ & \{|Z_N - Z_{N+1}| \geq T) \mid (|Z_N - Z_{N-1}| \geq T) \\ & 0, \; x \geq 0 \text{ otherwise} \end{cases} \tag{31}$$

Average amplitude change (AAC): It is another amplitude-related EMG feature, and it can be framed as:

$$AAC = \frac{1}{L}\sum_{N=1}^{L}|Z_{N+1} - Z_N| \tag{32}$$

Log detector (LD): To measure the exerted force of muscle, it can be represented as:

$$LD = \frac{1}{L}\sum_{N=1}^{L}\log(Z_N) \tag{33}$$

Difference absolute standard deviation value (DASDV): DASDV is one of the frequently used EMG features, and it is measured with the equation below.

$$DASDV = \sqrt{\sum_{N=1}^{L-1}(Z_{N+1} - Z_N)^2 / L - 1} \tag{34}$$

Myopulse percentage rate (MYOP): It is the mean of the Myopulse rate where the absolute EMG signal value exceeds the predefined threshold value. Mathematically, MYOP can be represented as:

$$MYOP = \frac{1}{L}\sum_{N=1}^{L-1} Y_N$$

$$Y_N = \begin{cases} 1, & |Z_N| \geq T \\ 0, & \text{otherwise} \end{cases} \tag{35}$$

Simple square integral (SSI): It can be measured by adding the EMG signal amplitude square values. Mathematically it can be represented as:

$$SSI = \sum_{N=1}^{L} Z_N^2 \tag{36}$$

Variance of EMG signal (VAR): It is an essential feature to calculate the signal strength. It can be represented as:

$$VAR = \frac{1}{L-1} \sum_{N=1}^{L} Z_N^2 \tag{37}$$

Modified mean absolute value (MMAV): MMAV is the extension feature of MAV. Mathematically, by allocating a weight window function to MAV, it can be calculated as:

$$MMAV = \frac{1}{L} \sum_{N=1}^{L} W_N \left| Y_N \right|$$

$$Y_N = \begin{cases} 1, & \text{if } 0.25\text{L} \leq \text{N} \leq 0.75\text{L} \\ 0.5, & \text{otherwise} \end{cases} \tag{38}$$

Modified absolute mean value 2 (MMAV2): The extension of the MMAV method is MMAV2. Allocate the constant weight window function to the MMAV results.

$$MMAV2 = \frac{1}{L} \sum_{N=1}^{L} W_N \left| Y_N \right|$$

$$Y_N = \begin{cases} 1 & \text{if } 0.25\text{L} \leq \text{N} \leq 0.75\text{L} \\ 4\text{N/L} & \text{if N} < 0.25\text{L} \\ 4(\text{i}-\text{L})/\text{L} & \text{otherwise} \end{cases} \tag{39}$$

Willison amplitude (WA): To indicate muscle engine firing unit action potential, Wilson amplitude is measured, and it can be calculated as:

$$WA = \sum_{N=1}^{L-1} Y_N$$

$$Y_N = \begin{cases} 1, & \left| \text{Z}_\text{N} - \text{Z}_{\text{N}+1} \right| \geq \text{T} \\ 0, & \text{otherwise} \end{cases} \tag{40}$$

This paper determines seventeen important EMG characteristics for use in rehabilitation and physiotherapy. We looked into the effectiveness of using several adaptive algorithms to extract EMG features. A number of algorithms with various properties for signals with noise reduced were assessed. Iowa is still a useful technique for feature extraction that can be used to achieve high classification accuracy. All algorithms have an LD of zero, with the exception of those connected to RLS. With the exception of RLS and LMS for ECG, BLW, and PI noise, ZC, SSC, MYOP, and WA are constant in the case of PI noise for all methods. Out of the seventeen feature extraction parameters, ZC, SSC, MYOP, and WA are algorithm-dependent constants. When the value of an algorithm's parameters is high, it is rich in feature extraction. This study demonstrates that SiWOA outperforms other algorithms in denoising, which allows it to extract more features from the EMG signal than the ESS approach. After de-noising the EMG signal impacted by PI, BW, and ECG noise, Fig. 5 displays the acquired EMG features using various techniques. A logarithmic scale is used along the y-axis to provide a more visually appealing representation. Improved features help with classification, which helps with disease diagnosis. However, the features derived from EMG signals that are noisy are not good; thus, before extracting the features, we used various optimization methods to eliminate the noise from the EMG signals. In the first phase of the study, the effectiveness of the two single features (EMAV and EWL) is assessed, and the outcomes are compared with 17 specific standard EMG features. Fig. 5 to Fig. 10 shows the average precision of 17 features for three noise patterns. RLS-SiWOA and LMS-SiWOA clearly outperform the other methods in reducing ECG noise. The bars representing these methods show significantly lower noise compared to the other techniques. LMS-CS and RLS-CS show the least performance, having the highest noise levels across all EMG features. This suggests that these methods are not as effective for ECG noise suppression. ESS-based methods (LMS-ESS and RLS-ESS) perform better than CS-based methods but are still less effective than SiWOA-based algorithms. In case of BW noise, SiWOA-based methods perform the best, showing minimal levels of BW noise in the processed EMG signals. Similar to the ECG and BW noise graphs, SiWOA-based methods (LMS-SiWOA and RLS-SiWOA) excel in reducing PI noise, with significantly lower values than the other methods. ESS methods provide an intermediate level of performance, while CS-based methods are the least effective in suppressing PI noise.

4. CONCLUSION

This work presents an improved whale optimization algorithm-based adaptive filter method for de-noising ECG noise, baseline wander noise, and power line interference aberrations in EMG signals. It has been demonstrated through experiments that the suggested LMS-SiWOA and RLS-SiWOA perform better at denoising EMG signals when assessing parameters such as SNR in dB, maximum error, MSE, etc. The modified whale optimization technique successfully removes the complexity involved in optimizing adaptive filter coefficients, as evidenced by the convergence graph. Eventually, the various types of noise-affected neuropathy signals are used to obtain 17 valid EMG signal features. The remarkable homogeneity of the derived features makes it possible to accurately forecast the EMG signal in a noisy environment. These results demonstrated the superiority of the LMS-SiWOA and RLS-SiWOA adaptive filters over other optimization algorithm-based adaptive filters. These can be used to estimate signals from any type of noise condition and are useful for the identification of neuropathy illnesses such as sciatica.

The contribution and usefulness of the retrieved features to classification accuracy should be examined further, perhaps using sophisticated machine learning classifiers or feature importance ranking. A wider applicability could be evaluated by investigating adaptability to other biomedical signals, including ECG or EEG. Last but not least, clinical validation via actual trials or case studies will be necessary to support the diagnostic value of the proposed approach for neuropathic diseases. Future research can improve and expand the use of LMS-SiWOA and RLS-SiWOA adaptive filters by tackling these issues, hence expanding their use in biomedical signal processing and diagnostics.

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