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RESEARCH ARTICLE

A Novel ECG Noise Reduction Technique Employing the Chaotic Adaptive Fish Migration Optimization Algorithm

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ABSTRACT Optimization problems are ubiquitous, and obtaining ideal solutions to optimization problems is a challenging task. In terms of denoising the electrocardiogram (ECG) signal, the weight parameters of the adaptive filtering algorithm determine the quality of the output ECG signal to a large extent. However, adaptive filters need to adjust too many parameters, which is a challenging problem. Heuristic algorithm is a powerful tool for solving various optimization problems, and it is very suitable for solving such complex problems. In this paper, a novel ECG denoising method is proposed, which combines a heuristic algorithm with an adaptive filtering algorithm to adjust the weight parameters of the filter. In addition, a new heuristic algorithm, Chaotic Adaptive Fish Migration Optimization (CAFMO), is proposed to introduce the chaotic strategy into the Adaptive Fish Migration Optimization (AFMO) algorithm. The efficiency of a novel denoising method is validated through the use of synthetic data generated by the FECGSYN toolbox. The CAFMO algorithm exhibits superior performance in noise mitigation in ECG data, outperforming other algorithms such as PSO, ABC, BH, GWO, SO and AFMO. The combination of CAFMO algorithm and adaptive filter produces a significant 28% improvement over traditional LMS adaptive filter, with another 20% improvement over other heuristic algorithms combined with adaptive filter.

INDEX TERMS Intelligence computing, mate-heuristic algorithm, fish migration algorithm, evolutionary computing, ECG signal processing.

I. INTRODUCTION

An electrocardiogram (ECG) is a signal obtained from a patient in an efficient, harmless and acceptable manner. It is considered to be the most powerful diagnostic test in clinical medicine in recent decades and is widely used to detect ischemia, injury and blood [1]. In general, ECG analysis consists of several parts, such as feature selection, feature transformation, preprocessing, feature extraction, and classification [2]. In clinical applications, there are obstacles such as myoelectric noise, baseline drift, power line interference, and motion artifacts that prevent doctors from obtaining sufficient useful information from ECG signals [3]. Therefore, it is very important to eliminate the noise in the original ECG signal, which can help doctors get more useful information and diagnose diseases faster.

Various techniques for extracting noise-free pure signals from raw ECG signals have been proposed in recent decades. Adaptive filtering is a popular method and widely adopted by scholars because of its advantages of high efficiency, simplicity and ease of application. Various structures of adaptive filters have different performances, and many structures have been proposed to remove different noises, such as baseline drift, muscle noise, 60 Hz power line interference, and motion artifacts [4]. Adaptive filter can eliminate the noise signal according to the correlation

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between noise and ECG signal, even if the noise is colored [5]. Denoising ECG signals is a difficult task because the noise is non-stationary and overlaps the requested ECG signal to a large extent. The author uses neural network and discrete wavelet transform to adjust the parameters of the adaptive filter, which removes the noise signal in the ECG signal well [6]. In [7], three algorithms based on Ensemble Empirical Mode Decomposition (EEMD) are proposed, which enhance the convergence performance of traditional adaptive filters based on EEMD. The wavelet transform (WT) method is widely used to suppress the noise signal of ECG because of its advantages in dealing with nonlinear and non-stationary signals. An appropriate discrete wavelet threshold can effectively improve the denoising performance of the algorithm on ECG [8], [9], [10]. Wavelet-based architectures demonstrate faster convergence rates than adaptive filter architectures, but their hardware implementation carries a substantially higher cost. The soft-thresholding methods has great ability in eliminating power line noise and white Gaussian noise, ECG signal is decomposed into many sub-signal in frequency and time [11]. In order to better extract the pure ECG signal, the signal averaging technique is used to separate the ECG signal to obtain the signal averaging ECG signal (SAECG), and then the discrete wavelet transform (DWT) is applied to remove the noise signal [12]. For high-resolution ECG signals, the DWT method combined with the Wiener filter shows excellent performance in reducing the noise of ECG signals [13]. Popescu et al. proposed a method for applying adaptive Bayesian rule to the shrinkage of WT coefficients. Bayesian rule searches for the optimal value of the shrinkage factor according to the maximum likelihood process, and this method can replace many previously proposed complex method [14]. The independent component analysis (ICA) method was first introduced in 1998 to remove artifacts in ECG signals, and the ICA method can blindly separate signals that are mixed together [15]. The ICA method has powerful performance in solving complex task about biomedical signal, especially in the absence of reference signals [16]. But a challenge in ICA methods is the order of independent components, which deeply affects the performance of ICA, and this challenge is addressed by an approach based on simple statistical techniques [17]. The constrained ICA (cICA) method has better performance than traditional ICA or fast ICA in ECG signal denoising, and this method has powerful ability in fetal extraction from abdominal ECG signal [18]. When applying the ICA method for noise reduction, accurately identifying the requisite number of independent sources proves to be a significant challenge that greatly impacts the efficacy of the ICA algorithm.

The WT method has a good performance in ECG signal denoising, but the choice of decomposition level and wavelet function limits WT to achieve better performance. Genetic Algorithm (GA) as a proven heuristic algorithm can ensure find a suitable parameter of WT, the combination of GA and WT achieve a better results than other version WT method [19]. A GA-based intrinsic mode function (IMF) thresholding method is proposed, which calculates the optimal threshold parameters of the IMF to remove the noise internal in the noisy IMF [20]. The Artificial Bee Colony (ABC) algorithm is employed to calculate the suitable thresholds and shape parameter [21]. In addition, many other excellent heuristic algorithms have been proposed in the past few decades [22]. The particle swarm optimization (PSO) algorithm is a classic population-based heuristic algorithm with strong optimization performance in unimodal and multimodal test problems [23]. In some complex multimodal problem, the PSO is trapped in local optimal and the Artificial Bee Colony (ABC) algorithm is presented. The ABC algorithm divides the population into two subgroups according to different task, and the roulette mechanism is introduced, these operations significantly enhance the performance of ABC algorithm [24]. Differential Evolution (DE) algorithm is a simple and efficient heuristic algorithm, which has attracted the attention of many researchers due to its excellent performance [25]. So many novel heuristic algorithm have been proposed in recent years, such as Grey Wolf Optimization (GWO) algorithm [26], [27], Whale Optimization Algorithm (WOA) [28] and Black Hole (BH) algorithm [29], [30].

Some scholars proposed a new strategy based on primitive heuristic algorithms to achieve specific capabilities. Although the population-based heuristic algorithm can calculate the optimal solution to the optimization problem, it requires huge memory and powerful computing power. The compact strategy uses a single individual instead of a swarm to achieve the same performance under certain memory and computational power constraints [31], [32]. Multi-group strategies can effectively improve the global search ability of heuristic algorithms in multimodal problems, and many novel communication strategies between sub-groups have been proposed in recent years [33], [34]. In high-dimensional and high-complexity problems, the traditional heuristic algorithm takes too long to calculate the solution, which is unacceptable in many cases. The Surrogatte method uses a neural network to estimate the fitness value of most locations in the computational space, so this method can find optimal solutions faster than traditional heuristic algorithms [35].

In this paper, a new ECG denoising method is proposed, which applies the heuristic algorithm to the traditional adaptive filtering algorithm. Like other adaptive filtering algorithms, the new method requires an original signal and a reference signal. Then the weight parameters of the adaptive filter are optimized by a heuristic algorithm, and the output of the new algorithm is processed by a moving average filter. In addition, a new algorithm is proposed, introducing chaotic theory to enhance the global search ability of Adaptive Fish Migration Optimization (AFMO) algorithm in solving the ECG signal denoising problem. The novel denoising method not only depend on high performance of hardware, but also can adjust the parameters of adaptive filter to obtain idearl results. The combination of CAFMO algorithm and adaptive filter produces a significant 28% improvement over traditional LMS adaptive filter, with another 20% improvement over other heuristic algorithms combined with adaptive filter.

The main content of this paper is as follows: Section II introduces the adaptive filtering algorithm and the AFMO algorithm; Section III introduces the new ECG denoising method and the new heuristic algorithm; In order to demonstrate the new ECG denoising method and the new heuristic The performance of the algorithm, Section IV gives the experimental results; Finally, Section V draws conclusions.

II. METHODOLOGY

A. ADAPTIVE FILTER ALGORITHM

Adaptive filters can adjust parameters or structures according to the time-varying statistical properties of the input signal, and it is widely used in noise removal and other signal processing fields, and the structure of this filter is shown in Fig 1. This method has two input signals, the original signal $x(n)$ is needed processed signal, which contains objective signal and noise, the reference signal $d(n)$ is the pure signal which with no noise. The coefficients of this filter are adjusted according to the feedback of the error signal $e(n)$, and the purpose of this filter is to minimize the error signal.

The least mean square (LMS) algorithm is a common method for iterating filter parameters, which has the advantages of low computational complexity, no need for prior knowledge of statistical data, and unbiased convergence of the mean to the Wiener solution. Suppose the length of filter is L, the original signal is $X(n) = [x(n), x(n-1), \ldots, x(n-L+1)]^T$, the n-th sample output signal is can be calculated by the following equation:

$$y(n) = \sum_{j=0}^{L-1} w_{j+1}(n) \cdot x(n-j) = W(n)^T \cdot X(n), \tag{1}$$

$$e(n) = y(n) - d(n), \tag{2}$$

where $W(n) = [w_1(n), w_2(n), \ldots, w_L(n)]^T$ is the weight parameter of this filter and it can be updated by the Eq. 3. The $e(n)$ is the error between reference signal $d(n)$ and output signal $y(n)$, and the error is utilized to iterate the parameter of filter.

$$w(n+1) = w(n) + 2\mu e(n)X(n), \tag{3}$$

where the μ is the step size of the filter, which is a constant value configured by the user before use. Because it is fixed, there is a contradiction between the steady-state error and the convergence speed of the filter, which is difficult to coordinate. The smaller the step size, the better the stability, but the slower the convergence, and vice versa.

B. ADAPTIVE FISH MIGRATION OPTIMIZATION

The AFMO is a modified vision of Fish Migration Optimization (FMO), which can adaptive adjust the parameter of FMO to obtain more comprehensive performance [36]. In AFMO, individuals are divided into four life stages during the iterative process of the algorithm, and different life stages have different habits and survival rates, the details are shown in Fig 2. In the first stage, the fish is just born, there are few individuals that are preyed on, and there is no individual reproduction in the place of birth. After a certain number of iterations, about 15% of the fish are preyed by predatory fish, and these preyed fish are replaced by new individuals in order to maintain the fish population size. In the next stage, more and more fish are predated or die from other causes, and almost 35% of the individuals are replaced by new ones. When the surviving fish become adults, they return to their birthplace to reproduce and end their lives.

In AFMO, the action range of one fish is influenced by the best individual and randomly selected neighbors. The former can provide more ideal candidate solutions, but there are also local optimal traps. The latter effectively enhances the population diversity and further improves the global search ability. In addition, the appropriate weight of these two factors is very important to the performance of the AFMO algorithm, and the movement details of a fish's are shown in the Eq 4.

$$p_i^{t+1} = p_i^t + \alpha \times (Best^t - p_i^t) \times \frac{E_i^t}{E_{max}} + \frac{f_i^t - f_r^t}{|f_i^t - f_r^t|} \times \beta \times r \times (R_i^t - p_i^t), \tag{4}$$

$$E_i^{t+1} = E_i^t + \times \delta \times \frac{f_i^t - f_{best}^t}{f_{max}^t - f_{best}^t}, \tag{5}$$

where p_i^t represents the position of i-th individual at the t iteration, f_i^t and f_r^t are the fitness values of i-th individual and its randomly selected neighbor at the t iteration, respectively. The attractiveness weight parameter for the best individuals is α, which is a variable that goes from 2 to 0.4 in decreasing order, and the β is a constant value, which is set $\frac{\pi}{10}$ in this paper, r is a random value between 0 and 1. In the t-th iteration, the positions of the best individual and the randomly selected neighbor of the i-th individual are denoted by $Best^t$ and R_i^t, respectively. E_i^t represents the energy of the i-th individual at the t iteration and E_{max} is a user-defined constant value. The energy of fish is an important parameter to control its activity, and it is updated according to Eq 5. When the energy of one fish increase to E_{max}, it will grow to the next stage shown in Fig 2. In Eq 5, in order to increase the diversity of fish population, δ takes a random number between 0.2 and 0.6, and f_{max}^t and f_{best}^t are the maximum fitness value and minimum fitness value of the population at the t iteration, respectively.

III. THE PROPOSED ECG SIGNAL DENOISING METHOD USING THE CHAOTIC ADAPTIVE FISH MIGRATION OPTIMIZATION ALGORITHM

A. CHAOTIC ADAPTIVE FISH MIGRATION OPTIMIZATION ALGORITHM

In many practical cases, chaotic theory plays an important role, and it has received more and more attention from scholars. Subtle differences in the initial stages of two

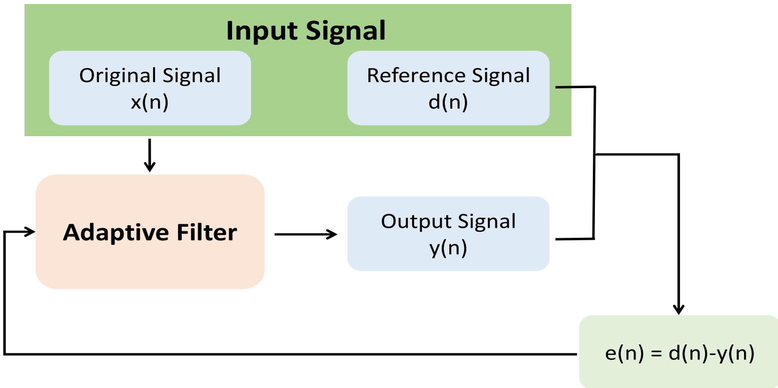


FIGURE 1. Adaptive filter configuration.

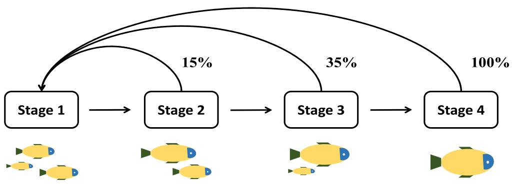


FIGURE 2. Survival rate of fish at different stages.

particles in a chaotic system can lead to vastly different outcomes. Since the chaotic system is very sensitive to the initial state of each particle, it can enhance the diversity of the particle population and amplify the differences between particles after several iterations. Combining chaotic theory and heuristic algorithms is a promising work, and many scholars are working on it [37].

There are many chaotic maps, each with its own advantages and disadvantages. In this paper, the logistic map combined with the AFMO algorithm is used because it is an extremely simple map that can efficiently generate non-periodic and non-convergent sequences. Eq 6 describes the mechanism of logistic chaotic mapping in detail, and Fig 3 intuitively shows its operation effect.

$$m^{t+1} = m^t \times \sigma \times (1 - m^t). \tag{6}$$

In the equation, m^{t+1} represents the chaotic value at the $t+1$-th iteration and the σ is the logistic parameter, which is 4 in this paper. It is worth noting that the initial value of m cannot be any one of 0, 0.25, 0.5, 0.75 and 1. The output sequence of the logical chaotic map is shown in Fig 3, and the 1000 values generated by it are evenly distributed in the range of (0,1).

Although the AFMO algorithm has outstanding performance in optimization problems, especially in unimodal problems [36], getting stuck in a local optimum is an important problem that hinders its further development. To address this challenge, enhancing population diversity is a promising way to avoid most fish congregating in the same place and allow the algorithm to find more interesting places with high probability.

During the operation of the AFMO algorithm, initialization plays an important role, as shown in Eq 7. It is implemented by Matlab's simple "rand" function, which ensures that the algorithm has a good global search ability. But a suitable initialization strategy could further enhance the diversity of population and search performance of AFMO algorithm. In this paper, the logistic map is applied on initialization stage of AFMO and named it is Chaotic Adaptive Fish Migration Optimization (CAFMO) algorithm. In CAFMO, the output sequence of logistic map is used to replace the r in Eq 7.

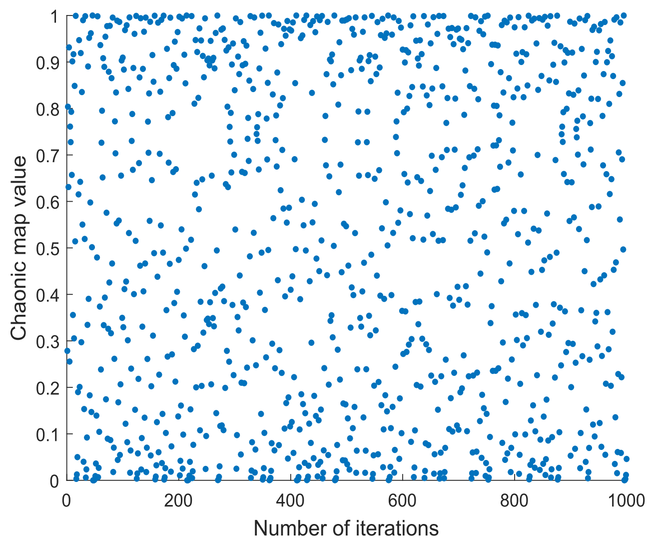


FIGURE 3. The dynamics of logistic map with σ equals 4.

$$p_{i,d} = p_{min} + 2 \times r \times p_{max}, \tag{7}$$

where p_{min} and p_{max} are the minimum and maximum values of the fish active range, respectively, and the position value of the i-th individual in the d-dimension is represented by $p_{i,d}$. The pseudo code is given in Algorithm 1 to share the algorithm in more detail:

B. NOVEL ECG SIGNAL DENOISING METHOD

In the traditional LMS algorithm, the weight parameters are updated according to Eq 3, which is a simple and efficient method. When the error is small enough to not affect the

Algorithm 1 The Chaotic Adaptive Fish Migration Algorithm

Initialization: i = 1, t = 1, $E_{max} = 200$, $\beta = \pi/10$, D, n, T
$p_{max}, p_{min}, v_{max} = p_{max}/10, v_{min} = p_{min}/10$;
while $i \leq n$ **do**
  $p_i^t = p_{min} + (p_{max} - p_{min}) \times$ rand(1, D);
  Calculated f_i^t (The fitness value of p_i^t);
  $E_i^t = 0$;
  $Stage_i = 1$;
$Best^t = p_1^t$;
$f_{best}^t = f_1^t$;
while $t \leq T$ **do**
  α = 2.0 - 1.6· t/T;
  while $i \leq n$ **do**
    Update the population according to Eq 4;
    $p_i^{t+1} = \min(p_{max}, \max(p_{min}, p_i^{t+1}))$;
    Calculated f_i^{t+1};
    if $f_i^{t+1} \geq f_{best}^t$ **then**
      Update E_i^{t+1} according to Eq 5;
      if $E_i^{t+1} \geq 2+10 \cdot rand \cdot t/T$ **then**
        $Stage_i = Stage_i + 1$;
    else
      $Best^{t+1} = p_i^{t+1}$;
      $f_{best}^{t+1} = f_i^{t+1}$;
    According to Eq 7, fish migrate to their birthplace according to Chaotic strategy;
    i = i + 1;
  t = t + 1;
Output: $Best^{t+1}, f_{best}^{t+1}$;

Algorithm 2 The Novel ECG Signal Denoising Method Which Employed Heuristic Algorithms

Input:Original signal x(n), Reference Signal d(n);
Employ heuristic algorithms to process the noise signal according to Eq 8;
The output results of heuristic algorithm is processed by moving average filter;
Output:Processed signal;

update of the weight parameter, the weight parameter will become constant, and the weight parameter obtained at this time is the most suitable. But this is an ideal situation, which is difficult to achieve in ECG signal denoising, because there are too many signal samples in ECG signals, and the noise signal is complex. In this paper, the novel ECG signal denoising method based CAFMO algorithm is proposed. The weight of each signal sample is assigned to one dimension of individual of the CAFMO algorithm, and the optimal weight parameter is obtained through algorithm iteration. In order to evaluate the candidate solution of weight parameter, the fitness function is introduced:

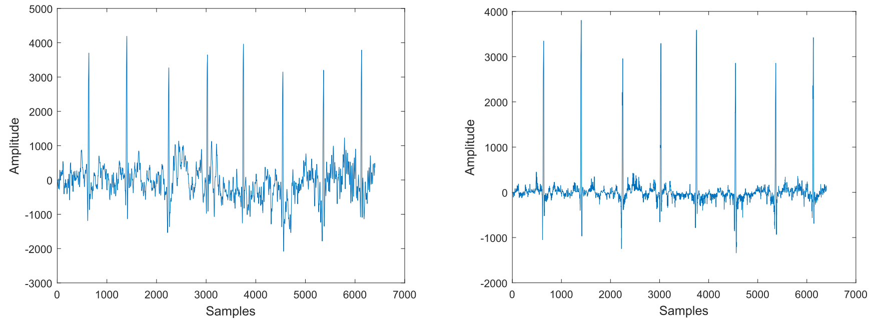
$$f_i = \frac{1}{n} \times \sum_{n=1}^{N} |w_n \times x_n - d_n|. \tag{8}$$

In Eq 8, N is the samples number of ECG signal, w_n, x_n and d_n are the weight value, original and reference signal at n-th sample. The new method can choose the optimal weight parameters, and the original signal is processed to make it as close as possible to the reference signal. In order to improve the quality of the denoised signal, the output of the new method is filtered by moving average filter.

IV. RESULTS AND DISCUSSION

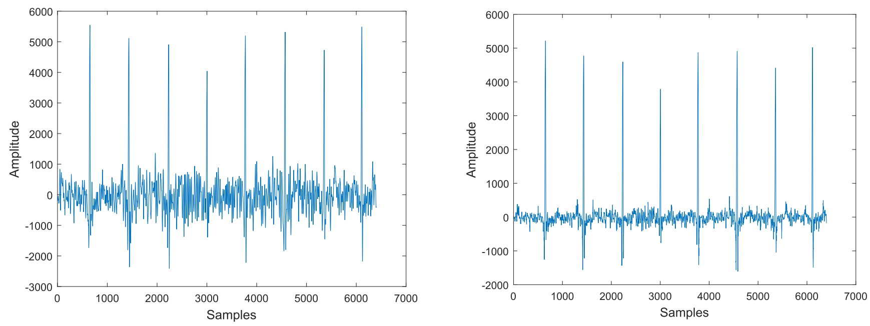
A. DATASET

In this work, synthetic data generated by the FECGSYN toolbox is used to validate the performance of a novel ECG denoising method [38]. FECGSYN can generate maternal and fetal ECG signals and simulate signals acquired from different positions in the mother. This toolbox has been widely used in the denoising and extraction of ECG signals and the research of fetal ECG monitoring [39]. The data is 205Hz, including 32 signals collected from the female abdomen and 2 signals collected from the female chest. We selected 9 channels of maternal ECG signals from 34 channels at 2 different signal-to-noise ratio (SNR) levels,



(a) Original ECG signal. (b) Denoised ECG signal

FIGURE 4. **Comparison of original and denoised signals SNR in 3dB.**



(a) Original ECG signal. (b) Denoised ECG signal

FIGURE 5. **Comparison of original and denoised signals SNR in 6dB.**

and added simulated noise signals to form test data to verify the performance of the new ECG denoising method. The noise-added signal will be processed by different signal denoising methods and their output results will be compared.

B. RESULTS

The experimental platform is a laptop computer with i9-12900HK (16 core and 24 threads) CPU and 128Gb memory. In order to avoid one accidental interference to the final experimental results, each experiment was carried out 40 times, and the experimental results listed in this paper are the average value of 40 experiments. The rank sum test is a non-parametric statistical procedure used to determine differences between datasets. This article utilizes it to analyze experimental results. The significance level for the test is set at 0.05. The symbol '=' is used to indicate that the difference between the data is not significant, while '-' indicates that the new algorithm is superior to others. The symbol '+' implies that the new algorithm is less effective than other alternatives. In this section, the new denoising method is compared with the traditional LMS algorithm, and the CAFMO algorithm is compared with other well-known heuristic algorithms. The length of filter L of LMS algorithm is set to 64, and the heuristic algorithm parameters involved in the comparison are shown in Table 1. The original signals and denoised signals of SNR in 3 dB and SNR in 6 dB levels are shown in Fig 4 and 5, all signals contain 6500 samples and ECG waves can be clearly displayed in the denoised signal. These pictures show that the new method can effectively eliminate baseline drift noise and muscle artifact-like noise. The amplitude of the signal is not compressed or amplified, and the main information of the signal is preserved.To demonstrate the novel method and CAFMO has the better performance than tradition LMS algorithm and other heuristic algorithms, the detail experimental data is presented in Tables 2 to 4.

The data shown in the tables is the average value of the output results of different denoising methods. The test data is roughly divided into SNR in 3 dB and SNR in 6 dB according to the SNR of the ECG signal, and the signal of each SNR level contains 9 channel signals (SNR0301 indicates that the signal is the first channel with a SNR of 3db). Among the results for each test data, the best experimental result is marked in bold for clarity. The error between output and real ECG signal is used to verify the performance of different denoising methods, in addition, the SNR and percentage root mean square difference (PRD) are utilized in this work, and the experimental results of these parameters are shown in Tables 2 to 4. The SNR is calculated by the Eq 9,

$$SNR = 10 \times log_{10} \frac{\sum_{k=1}^{K}(x(k) - d(k))^2}{\sum_{k=1}^{K}(y(k) - d(k))^2}, \tag{9}$$

TABLE 1. Parameter setting of algorithms.

Algorithms	Common Parameters	Unique Parameters
Particle swarm optimization [23]		c = 2.0, w =0.9, Velocity Range ∈ [-0.1, 0.1];
Grey wolf Optimization [26]	Population size = 30	a ∈ [0, 2];
Artificial bee colony [21]	Iterations = 3500	Limit = 20;
Black Hole [29]	Dimensions = Length of signal	NULL;
Adaptive Fish migration optimization [36]	Limited areas ∈ [-1, 1]	Velocity Range ∈ [-0.05, 0.05], E_{max} = 200, $\beta = \pi/10$, α in [0.4, 2];
Snake Optimization [40]		T_1 = 0.25,T_2 = 0.6, C_1=0.5,C_2=0.05,C_3=2.

TABLE 2. The comparison of error between denoised signal and noise-free signal.

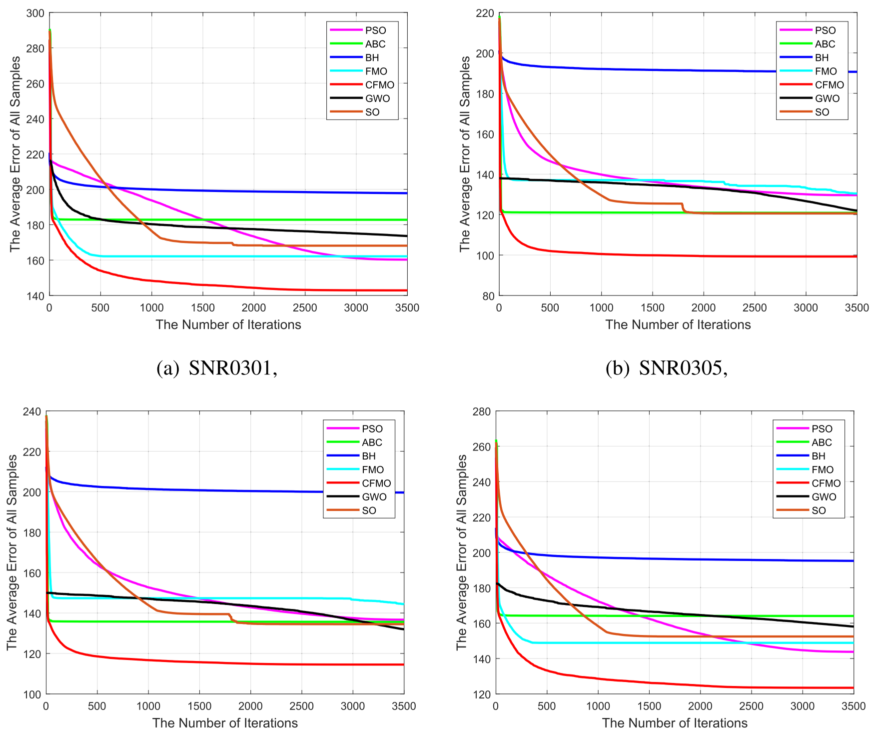
Test Data	LMS		PSO		ABC		BH		AFMO		GWO		SO		CAFMO
SNR0301	205.2228	-	158.9481	-	182.7313	-	197.8221	-	162.3535	-	173.1453	-	205.2228	-	**142.2997**
SNR0302	157.3211	-	125.4932	-	146.8518	-	185.7614	-	144.4733	-	136.3040	-	157.3211	-	**112.2999**
SNR0303	43.2258	-	148.9077	-	20.1977	-	184.9253	-	91.2716	-	87.3489	-	43.2258	-	**20.1893**
SNR0304	315.0544	-	201.7675	-	246.8108	-	244.9739	-	214.9444	-	214.8300	-	315.0544	-	**185.1029**
SNR0305	130.4039	-	130.1884	-	120.9247	-	190.7062	-	131.3311	-	122.1431	-	130.4-39	-	**98.4195**
SNR0306	101.7847	-	140.3229	-	91.2291	-	195.7473	-	118.1710	-	110.9783	-	101.7847	-	**87.1393**
SNR0307	140.3655	-	137.2725	-	135.6295	-	199.8295	-	144.6360	-	132.6431	-	140.3655	=	**106.7010**
SNR0308	164.3370	-	134.9213	-	151.0109	-	195.9234	-	150.4793	-	141.7750	-	164.3370	-	**117.6520**
SNR0309	182.5381	-	143.2391	-	164.0923	-	195.2644	-	146.8584	-	157.1969	-	182.5381	-	**123.8484**
SNR0601	164.6133	-	126.0309	-	156.2590	-	186.6543	-	141.9770	-	144.1318	-	164.6133	-	**113.2263**
SNR0602	132.6527	-	127.7866	-	109.5696	=	188.7905	-	124.5814	-	116.2068	-	132.6527	-	**99.3581**
SNR0603	91.0125	-	141.4364	-	76.3325	-	189.6800	-	110.1133	-	104.3104	-	91.0125	-	**74.9322**
SNR0604	257.9164	-	188.5195	-	227.7423	-	260.7698	-	199.6741	-	212.4795	=	257.9164	-	**171.6533**
SNR0605	119.3559	-	116.5191	-	109.7024	-	172.1976	-	119.1539	-	109.4712	-	119.3559	-	**92.7694**
SNR0606	66.5677	-	149.3599	-	48.0333	=	189.9621	-	101.6415	-	96.3500	-	66.5677	=	**48.0415**
SNR0607	204.7097	-	158.0763	-	181.6546	-	194.2686	-	165.8638	-	171.0478	-	104.7097	-	**143.3949**
SNR0608	186.9355	-	144.4362	-	172.0434	-	195.4945	-	149.7222	-	160.1524	-	186.9355	-	**129.8206**
SNR0609	165.2958	-	135.1567	-	163.0902	-	182.0870	-	141.3803	-	153.3880	=	165.2958	-	**123.6989**

TABLE 3. The comparison of signal to noise ratio of denoised signal.

Test Data	LMS		PSO		ABC		BH		AFMO		GWO		SO		CAFMO
SNR0301	1.8754	-	3.8535	-	-0.0359	-	-1.5480	-	3.9454	-	1.1746	-	1.8754	-	**4.9718**
SNR0302	0.4452	-	1.9448	-	-1.4110	-	-5.8972	-	0.3366	-	-0.8120	-	0.4452	-	**2.5396**
SNR0303	**-10.9932**	+	-21.7513	-	-12.5783	+	-24.6444	-	-19.8553	-	-16.8395	-	-10.9932	+	-12.5800
SNR0304	2.7039	-	4.5858	=	0.1773	-	-0.6313	-	4.3772	=	2.0460	-	2.7039	-	**5.4221**
SNR0305	-0.9182	-	-0.5396	-	-1.4424	-	-8.7842	-	-1.6643	-	-2.1995	-	-0.9182	-	**0.6662**
SNR0306	**-1.6058**	+	-4.6115	-	-2.2650	=	-11.7770	-	-4.9634	-	-4.4835	-	-1.6058	+	-1.9944
SNR0307	-0.9740	-	0.4427	-	-1.1351	-	-7.1228	-	-1.1834	-	-1.0907	-	-0.9740	-	**1.7581**
SNR0308	-2.3966	-	1.7214	-	-0.7763	-	-5.6673	-	0.3827	-	-0.4516	-	-2.3966	-	**2.4086**
SNR0309	1.1113	-	2.9568	-	-1.0332	-	-3.6334	-	2.7562	-	0.2025	-	1.1113	-	**3.9604**
SNR0601	0.2812	-	2.3503	-	-1.8987	-	-5.1976	-	1.3021	-	-0.7858	-	0.2812	-	**2.8557**
SNR0602	-1.6402	-	-1.5349	-	-1.3655	-	-9.2748	-	-2.1620	-	-2.5904	-	-1.6402	-	**-0.5708**
SNR0603	**-2.2831**	+	-6.9103	-	-3.4681	-	-13.0073	-	-6.7835	-	-5.8302	-	**-2.2831**	+	-3.3702
SNR0604	0.8949	-	3.3442	-	-1.3608	-	-3.8585	-	2.8895	=	-0.0942	-	-0.8949	-	**3.8767**
SNR0605	-0.2238	-	-0.4292	-	-1.0875	-	-8.5751	-	-1.6661	-	-1.9910	-	-0.2238	=	**0.5444**
SNR0606	-4.6449	-	-12.5301	-	-6.0115	-	-17.1137	-	-11.6933	-	-4.6449	=	**1.1746**	+	-6.0104
SNR0607	2.0415	-	3.7721	=	0.0537	-	-1.2198	-	3.6284	-	1.3482	-	2.0415	-	**4.6128**
SNR0608	-0.8196	-	2.6877	=	-1.2872	-	-3.5645	-	2.6754	-	-0.0175	-	-0.8196	-	**3.4133**
SNR0609	0.8583	-	4.2271	=	-0.6400	-	-2.5045	-	3.8515	=	0.8867	-	0.8583	-	**4.8819**

TABLE 4. The comparison of peak root mean square difference of denoised signal.

Test Data	LMS		PSO		ABC		BH		AFMO		GWO		SO		CAFMO
SNR0301	63.1177	-	50.2878	-	78.6568	-	93.6099	-	49.8233	-	68.4380	-	63.1177	-	**44.2058**
SNR0302	43.7933	-	36.8562	-	54.2467	-	90.8928	-	44.5900	-	50.6308	-	**43.7933**	+	**34.4118**
SNR0303	**18.3757**	-	63.6143	-	22.0546	+	88.4779	-	51.4552	-	36.0367	-	18.3757	+	22.0588
SNR0304	62.6388	-	50.4607	=	83.8059	-	91.9605	-	51.7139	=	67.5807	-	62.6388	-	**45.8175**
SNR0305	36.3553	-	34.8246	-	38.6262	-	89.9243	-	39.8094	-	42.1441	-	36.3553	-	**30.3194**
SNR0306	**27.7050**	+	39.1956	-	29.8893	=	89.3560	-	40.9691	-	38.6077	-	**27.7050**	+	28.9814
SNR0307	44.5804	-	37.8796	-	45.4211	-	90.4877	-	45.7923	-	45.1942	-	44.5804	-	**32.5688**
SNR0308	62.8723	-	39.1366	-	52.1795	-	91.6212	-	45.8964	-	50.2793	-	67.6021	-	**36.2418**
SNR0309	53.3859	-	43.1757	-	68.3420	-	92.1854	-	44.2573	-	59.2846	-	53.3859	-	**38.4635**
SNR0601	48.5594	-	38.2756	-	62.4266	-	91.2470	-	43.3729	-	54.9277	-	48.5594	-	**36.1107**
SNR0602	37.3460		36.9213	-	36.1837	-	89.9453	-	39.7706	-	41.6739	-	37.3460	-	**33.0665**
SNR0603	**25.8777**	+	44.1215	-	29.6606	-	88.9506	-	43.7241	-	38.9588	-	**25.8777**	+	29.3305
SNR0604	52.9642	-	39.9604	-	68.6835	-	91.5496	-	42.1986	=	59.3734	-	52.9642	-	**37.5886**
SNR0605	34.4336	-	35.2935	-	38.0359	-	90.0641	-	40.8169	-	42.2234	-	34.4336	=	**31.5947**
SNR0606	**21.1351**	+	52.4874	-	24.7362	-	88.8091	-	47.9427	-	37.1634	=	**21.1351**	+	24.7330
SNR0607	63.5408	-	52.0894	=	79.8845	-	92.4960	-	53.0136	-	68.8334	-	63.5408	-	**47.2688**
SNR0608	67.6021	-	45.1502	=	71.3462	-	92.7269	-	45.3286	-	61.6583	-	67.6021	-	**41.5325**
SNR0609	62.9292	-	42.7111	=	74.7813	-	92.6815	-	44.7075	=	62.7410	-	62.9292	-	**39.6023**



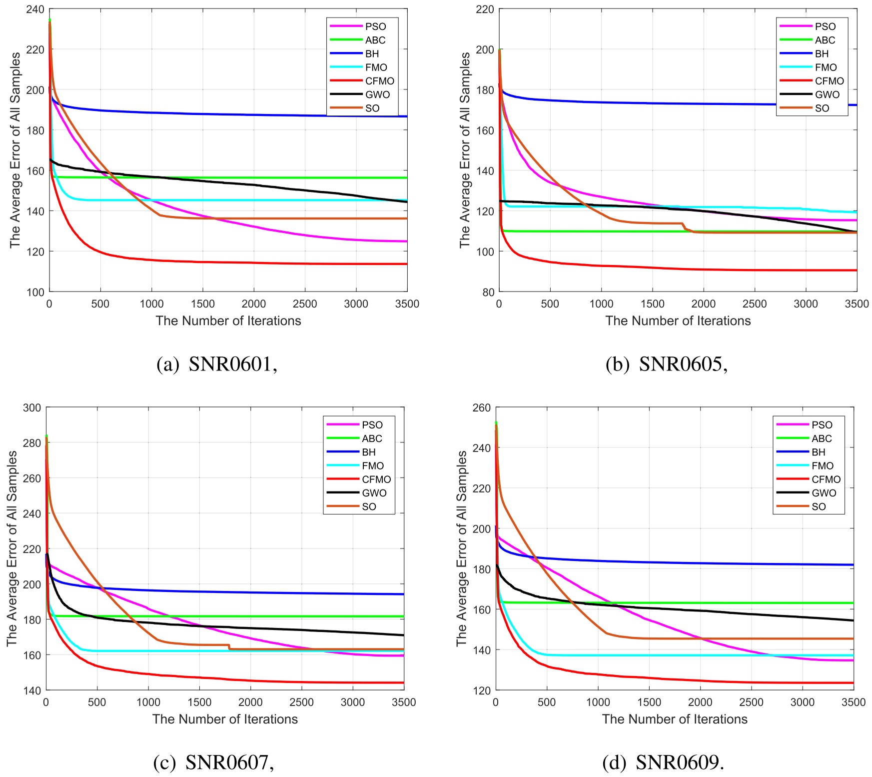
(a) SNR0301, (b) SNR0305, (c) SNR0307, (d) SNR0309.

FIGURE 6. The variation in the number of iterations and fitness values in the SNR03 test data.

where the K represents the length of ECG signal, $x(k)$, $d(k)$ and $y(k)$ are the original signal, reference signal and denoised signal at k-th sample, respectively. This parameter can indicate which denoising method's output has the least noise component, and which denoising method can provide the most useful information. The PRD parameter is usually used to verify the distortion of denoised signal of different methods, which is calculated by the Eq 10.

$$PRD = 100 \times \sqrt{\frac{\sum_{k=1}^{K}(d(k) - y(k))^2}{\sum_{k=1}^{K} d(k)^2}}, \tag{10}$$

the k, K, $d(k)$ and $y(k)$ represent the same meaning as in Eq 9. The PRD is also a significantly parameter to evaluate



(a) SNR0601,

(b) SNR0605,

(c) SNR0607,

(d) SNR0609.

FIGURE 7. The variation in the number of iterations and fitness values in the SNR06 test data.

the performance of denosing method, and it is widely used in other papers [10], [41].

From the tables, the novel denoising method obtains the best results in most experiments and enhances the performance by about 20% more than the traditional LMS algorithm. On the SNR0303, SNR0306, SNR0603, and SNR0606 test data, the new method performs worse than the LMS algorithm on the SNR and PRD parameters, but CAFMO also outperforms other heuristic algorithms. These data indicate that CAFMO has excellent global search ability and is more suitable for solving complex signal processing problems than other heuristic algorithms. In most test data, compared with the traditional LMS algorithm, the output of the new method is closer to the reference signal, with higher SNR and lower PRD, which can provide higher quality ECG signals.

Line graphs on iterations and fitness values can be used to further reveal the performance details of the heuristic algorithms, and it can provide powerful evidence to proof the performance of novel algorithm better than other algorithms. In Figure 6 and 7, show the optimization process for the four cases in SNR in 3 dB and 6 dB test data, respectively. In these plots, we can see that AFMO can find good candidate solutions before 500 iterations, and it outperforms or close to most of the other heuristics except the new one. However, in subsequent iterations, the AFMO algorithm is prone to fall into local optimum, and its optimization effect is surpassed by the PSO and GWO algorithms. In this ECG signal processing problem, the global search ability of AFMO is inferior to that of PSO and GWO algorithms.

Therefore, this paper proposes a new algorithm combining chaotic theory and AFMO to overcome this problem, and the performance improvement of the new algorithm is obvious. The new algorithm not only converges faster, but also is good at solving complex ECG signal processing problems. Compared with other heuristic algorithms, the new algorithm can obtain the best candidate solution at an early stage without falling into local optimum. That is to say, after 3500 iterations, the gap between the fitness value of the new algorithm and other algorithms becomes larger. Comparing Figure 6 and Figure 7, the complexity of the situation does not affect the effect of the new algorithm on different SNR situations than other heuristic algorithms. The novel denoising method employs heuristic algorithms' excellent optimization ability to eliminate noise signals from raw data. Its performance surpasses that of traditional LMS filters. Additionally, the proposed CAFMO algorithm is tailored specifically for denoising problems and yields better results than other well-known heuristic approaches. However, the novel denoising method's complex structure limits its applicability on low-memory and computation equipment.

V. CONCLUSION

This paper proposes a new ECG signal denoising method, which combines the traditional LMS algorithm and the CAFMO heuristic algorithm. The experimental results show that the performance of the new method is more than 20% higher than the traditional LMS algorithm. CAFMO is a heuristic algorithm based on AFMO algorithm, which introduces chaotic theory to overcome the problem of insufficient global search ability of AFMO in the process of ECG signal denoising. Thanks to its robust global search capabilities, the CAFMO algorithm is capable of extracting distinct signal components from diverse and intricate original signals. This paper proves that the heuristic algorithm with high global search ability can effectively improve the performance of traditional denoising algorithms, and can provide ECG signals with higher SNR, lower PRD and closer to noise-free ECG signals. In addition, the design of the fitness function has a great influence on the performance of the new denoising method, and a suitable fitness function can greatly improve the denoising effect of the ECG signal. In future, the suitable fitness function need be designed and the denoising problem can be extended to be a multi-objective optimization problem.

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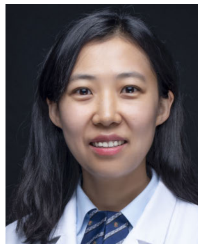

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