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Biogeography Based Optimization based Fuzzy Adaptive Filter for ECG signals denoising.

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Abstract: A novel fuzzy adaptive filter method is presented, which applies fuzzy logic, for electrocardiogram signals denoising. Fuzzy adaptive filter is information processor where both numerical and linguistic information are used in the form of input-output pairs and fuzzy IF-THEN rules. Proposed FAF is based on a recursive procedure to achieve acceptable information extraction in the case where the statistical characteristics of input-output signal are unknown. The filter is displayed as a dual-layered feedback system for the purpose of this study. Each layer has different function: the first layer being the fuzzy autoregressive filter model, the second layer being responsible for the training of the membership functions parameters. The second layer adjusts the fuzzy adaptive filter parameters, which will allow the reaching of the required signal reconstruction by decreasing the fitness based on the biogeography-based optimisation algorithm. For evaluation purposes, various artefacts were added to the ECG signals; these included real and artificial noise. For comparison purposes, the investigation uses both model and non-model-based methods recently published. In addition, the impact of the proposed filtering method on the distortion of diagnostic features of the ECG was investigated using an ECG diagnostic distortion measure called the: Multi-Scale Entropy Based Weighted Distortion Measure.

Keywords: Fuzzy logic, fuzzy filter, ECG signal, ECG denoising, BBO.

1. Introduction

The purpose of an ECG is to measure electrical potential changes in the heart over a specific time period. Particular cells in the heart produce electrical impulses that spread through the heart causing it to contract, thereby controlling the rate of the heart's beating and causing these changes in the electrical potentials [1][2][3][4]. In the ECG, these electrical changes are measured through electrodes positioned on the chest. The electrical impulses are recorded in millivolts. Whilst the idealised heartbeat comprises a number of complexes, three of these complexes are frequently recorded and utilised in medical ECGs Terminology. These are the P complex, which measures the depolarisation of the atrium, the QRS complex, which measures the depolarisation of the ventricles, and the T complex, measures the repolarisation of the ventricles. However, the ECG signal

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frequently becomes contaminated by both internal and external noises. Whilst there are numerous sources of these noises, the ones of primary interest are instrument and EMG noises, electrode contact noise, motion artefacts and power line interference [5]. As such, it is necessary to carry out advanced digital processing of the ECG waveforms in order to utilise the ECG of an individual for identification and diagnosis purposes. Obviously, any noise that appears on the trace of the ECG can complicate diagnosis and identification analysis. Therefore, it is necessary to understand and cancel out the effects of noise from an ECG trace in order to extract the required identifying features of the trace itself. The required identification data can be masked by artefacts introduced by noise. Since its inception, numerous methods have been developed and utilized to denoise ECG signals. The most widely used methods for ECG denoising are the non-model based methods including dual threshold filter and discrete wavelet transform (ADTF-DWT) [6], the empirical mode decomposition and genetic algorithm for adaptive denoising [7], and the adaptive Fourier decomposition (AFD) [8]. Others contributions in this subject are reported in [9][10][11][12] which have been widely used for ECG denoising. Alternatively, a model-based method has been proposed, in [13] the authors uses a three state non-linear dynamical model in Cartesian space for the generation of synthetic ECG signals. Indeed, several papers have used this model in order to denoise the ECG signal. In [14] the authors used this model with Bayesian filtering framework called the marginalized particle-extended Kalman filter (MP-EKF) for ECG denoising purposes, and many others works used this model are reported in [15, 16].

The construction of the fuzzy system encompasses two steps [17]: The first one is concerned with the construction of the fuzzy system model's structure using a set of input-output data pairs. Several contributions in this subject are reported in [18][19][20][21]. The second step is the identification of the constructed fuzzy system model's parameters. Many methods have been discussed in the literature to identify parameters including gradient descent, nonlinear least squares, and Kalman filter [17][18][19][20][21] [22]. Chafaa *et al* [17] have proposed an efficient approach to construct automatically a Takagi-Sugeno fuzzy model's; when the mode's parameters are adjusted using the Kalman filter algorithm twice. Leandro *et al* [19] developed a method for identifying a Takagi-Sugeno fuzzy model based on the chaotic particle Swarm optimization algorithm combined with an efficient Gustafson-Kessel clustering algorithm. Fuzzy Winer model was proposed by Li *et al* in [20] to identify chaotic systems, where the model's parameters are tuned using a particle swarm optimization algorithm. Rahib *et al* [21] in their work presented a new Type2-Fuzzy-neuro system to detect equalizing time-varying channels and detect time-varying systems, where the identification step was achieved using clustering and gradient algorithms.

This paper presents an effective ECG signal denoising method that utilises a combination of fuzzy logic and the biogeography-based optimisation algorithm. In order to prove their efficiency, the combination of metaheuristic methods and fuzzy logic have been exhaustively analysed and reported in [23] [24][25][26]. Four stages are being used to construct the proposed biogeography based optimisation fuzzy adaptive filter (BBOFAF). The first stage, defines the fuzzy sets for the input space of the filter using membership function to cover the entire input space. That were determined by matching input-output data pairs during the adaptation procedure or were gathered from human experts. The third stage was the construction of the filter based on these rules and the fourth stage was where the filter's free parameters were updated using the BBO algorithm. It is envisaged that this method will successfully deal with white Gaussian noise and the real noise and as MA and EM that are taken from the MIT-BIH noise stress test database [27]. By comparing the results of this method with those of other benchmark methods (ADTFDWT, AFD, EEMD and MP-EKF), it can be seen that the proposed method has a statistically significant performance improvement.

This paper is organized as follows, after section1; section 2 presents an overview of type-2 fuzzy system and BBO algorithm. Section outlines the proposed technique. Simulation studies and discussion are presented in sections 3 and 4. Section 5 concludes the paper.

2. Theory

2.1. Fuzzy Adaptive filter

As previously mentioned, the concepts of fuzzy logic are applied by fuzzy adaptive filters [28][29][30][31][32]. These information-processing filters are able to utilise both numerical and linguistic

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information, in the form of input-output pairs and fuzzy IF-THEN rules, respectively. The benefits of using a fuzzy adaptive filter are its non-linear nature and simple design. This simplicity allows human experts to incorporate linguistic information into the filter. Where there is no linguistic information available, it is possible for the fuzzy adaptive filters to be re-defined as non-linear adaptive filters. The parameters of the membership functions are adjusted with the adaptive algorithm in order to characterise the IF-THEN rules of the fuzzy concepts through the reduction of some criterion function.

A dual-layered feed forward network structure can be used to represent the fuzzy adaptive filter [33] [34] [35]. As a result, it is possible to train the fuzzy ad adaptive filter to determine the required input-output relationship through the utilisation of a number of learning algorithms. One such algorithm is the biogeography based optimisation algorithm (BBO).Within this study, the fuzzy adaptive filter's input ($(x(k), x(k+1), \ldots, x(K-n+1))$ is equal to the previous output, therefore the new input x_n becomes y. Hence, at the sampling instant k, the role of the fuzzy adaptive filter is to estimate the measured signal $\hat{y}(k)$ through the use of various estimated signals.

The input-output equations for the fuzzy adaptive filter that have product inference, singleton fuzzifier and centroid defuzzifier are expressed by the following terms:

$$f\big(x(k)\big) = \frac{\sum_{l=1}^{M} \theta^l (\prod_{i=1}^{n} \mu_{F_i^l}(x_{i-1}))}{\sum_{i=1}^{M} (\prod_{i=1}^{n} \mu_{F_i^l}(x_{i-1}))} = \sum_{l=1}^{M} \theta^l \emptyset^l(X) \tag{1}$$

where :

$$\emptyset^l(X) = \frac{\prod_{i=1}^{n} \mu_{F_i^l}(x_{i-1})}{\sum_{i=1}^{M} (\prod_{i=1}^{n} \mu_{F_i^l}(x_{i-1}))} \tag{2}$$

where the fuzzy basis functions are represented as $\emptyset^l(Y)$. An expression for the fuzzy adaptive filter is given in equation 1 that uses a fuzzy auto regressive (AR) model. This uses the following input vectors:

$$x = [x_1 \quad x_2 \quad \cdots \quad x_{n-1}] = [y(k) \quad y(k-1) \quad \cdots \quad y(k-n+1)] \tag{3}$$

For the purpose of this paper, a Gaussian radial basis function has been chosen for the membership function as follows:

$$\emptyset^l(x) = \frac{u_l(X)}{\sum_{l=1}^{M} u_l(X)} \tag{4}$$

where:

$$u_l(x) = \left(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\right) = \prod_{i=1}^{n} exp\left(-\frac{1}{2}\left(\frac{x_i - \tilde{x}_i^l}{\sigma_i^l}\right)\right) \tag{5}$$

where the membership function after product inference is represented as $u_l(x)$ and the centre of the i^{th} membership function is $\tilde{x}_i^l$ and the width of the i^{th} membership function is represented as σ_i^l.

2.2. Biogeography based optimization (BBO)

Inspired by studies of the spatial distribution of species of plants and animals together with the causes of their distribution and extinctions, BBO is a global optimization algorithm [36][37]. The algorithm considers island habitats and species populations and the habitat's ability to support the populations. When an island cannot sustain the population of a species easily, members migrate to new islands and undergo speciation. Each island is a potential solution to the problem. Island fitness is determined by its habitat suitability index (HSI), which considers features such as rainfall, temperature, and vegetation and is a measure of the quality of a

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candidate solution. These features are suitability index variables (SIVs). An optimal solution to a problem of optimization is a low HSI island with a large number of species. In BBO, each habitat has its own immigration (γ) and emigration (μ) rates representing the species coming to and leaving the island. These parameters are influenced by the number of species (S) on the island [38].

3. Design procedure of the BBO- based Fuzzy adaptive filter (BBOFAF)

Figure.1 shows the proposed BBOFAF framework:

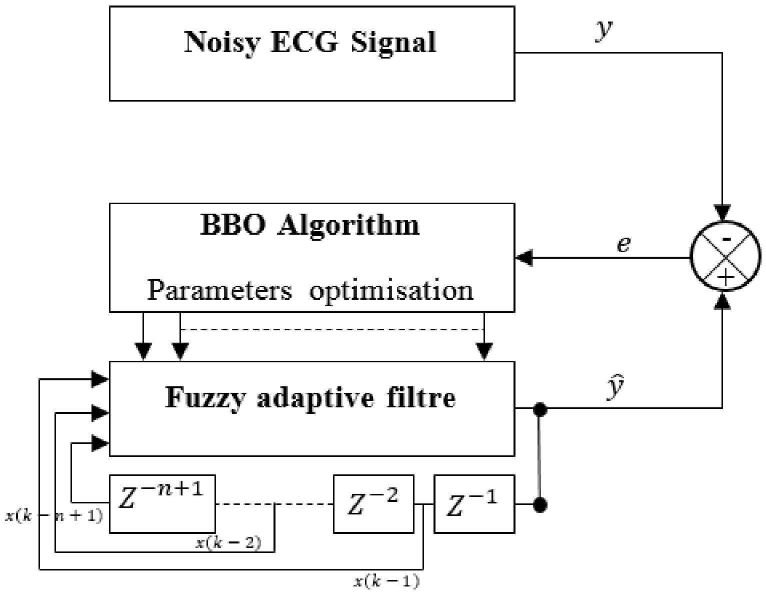

Figure.1 Proposed framework of the BBOFAF.

Four steps are followed to construct the BBOFAF:

- **Step. 1** M fuzzy sets F_i^l are defined for each of the input space intervals $[C_{i^-}, C_{i^+}]$ with Gaussian membership functions:

$$\mu_{F_i^l} = exp\left[-\frac{1}{2}\left(\frac{x_i - \tilde{x}_i^l}{\sigma_i^l}\right)\right] \tag{6}$$

where $l = 1, 2, \cdots, M$, $i = 1, 2, \cdots, n$, the input to the filter is represented as $x_i = x(k - I + 1)$, the centre of the i^{th} membership function in the l^{th} rule is represented as $\tilde{x}_i^l$, and the width of the i^{th} membership function in the l^{th} rule is represented as σ_i^l . Within this study, the sets σ_i^l are 0.75 and the free parameters, $\tilde{x}_i^l$, will be optimized using the BBO algorithm. The Gaussian membership function (eq.6) was chosen over triangular, trapezoidal or other shapes because is a universal approximator that is able to uniformly estimate a compact set's continuous functions [35]. Nevertheless, when this type of network employs the other membership function types, verification of the universal approximation capability is difficult. Additionally, in order to complete a function approximation, a large number of rules are required.

- **Step. 2** A set of changeable fuzzy IF-THEN rules are constructed using either numerical or linguistic information derived from the training input-output data pairs:

$$\begin{gathered} R^l: if\ x_1\ is\ F_1^l\ and\ \cdots\ x_n\ is\ F_n^l\ then \\ \hat{y} = \bar{Y}^l \qquad l = 1, 2, \cdots, M \end{gathered} \tag{7}$$

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where the desired output is denoted as $\hat{y}$, F_i^l are defined in step 1, the fuzzy sets of the R^l defined output are represented as $\bar{Y}^l$ having a singleton membership function $\mu_{\bar{Y}^l}$ of the output space. There will be a change of the membership function parameters $\mu_{F_i^l}$ and $\mu_{\bar{Y}^l}$ during the adaptation process.

- **Step. 3** Through the use of centroid defuzzification and product inference, the fuzzy filter $f(x)$ is constructed around the set of M rules:

$$f\big(x(k)\big) = \frac{\sum_{l=1}^{M} \bar{Y}^l \Big(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\Big)}{\sum_{i=1}^{n} \Big(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\Big)} \tag{8}$$

where the Gaussian membership function, as defined in (6) is represented as $\mu_{F_i^l}$, $x = [x_1, \cdots, x_n]^T = [y(k), y(k-1), \cdots, y(k-n+1)]$, and the crisp output value of the l^{th} rule is determined as $\bar{Y}^l \in R$.

- **Step. 4** Figure 1 shows the fuzzy adaptive filter scheme that is based mainly on the online adaptation of the filter's parameters $f(x)$. Therefore, the BBO algorithm is able to adjust the filter's parameters so that the fitness function error e attains its minimum value between the fuzzy adaptive filter output $\hat{y}$ and the noisy ECG signal y. The filter parameters to be trained are the consequence intervals $\bar{Y}^l$ and the Gaussian centre of the premise membership functions $\mu_{F_i^l}$, which are trained by the optimisation algorithm block. The fitness function that is used throughout the study to be the cost function of the optimization algorithm (BBO) is the mean square error (MSE) criterion that uses the actual and estimated values as follows:

$$MSE = \frac{\sum_{k=1}^{N}(y_k - \hat{y}_k)^2}{N} = \frac{\sum_{k=1}^{N} e^2}{N} \tag{9}$$

where y_k is the actual measure, $\hat{y}_k$ is its estimate, and N is the length of the data.

4. Results and discussion

This section provides the results gained after using the proposed method to filter ECG signals. For this purpose, 200-signal segments of real ECG signals from different subjects that were selected from the MIT-BIH normal sinus rhythm database and the MIT-BIH arrhythmia database [40][41]. The suggested method was simulated with $M = 40$ rules. Consequently, the filter was structured according to a set of 40 rules leaving $40 \times 3 = 120$ adjustable parameters. Therefore, there was one interval output and two regressors to every rule. This means that there were 2×40 premise parameters and 1×40 consequence parameters. The fuzzy adaptive filter's initial input vector x is set as $x = [x1, x2] = [0,0]$. The following setting values for the BBO algorithm parameters were used: a mutation rate of $m = 0.01$ whilst the immigration rate γ_k and emigration rate y_k mimicked the linear migration curve shown in figure.2. The effectiveness of the proposed approach was fully investigated by assessing its performance in a number of noisy environments. These included the typical noises associated with ambulatory ECG recordings, which involve MA and EM. These were individually selected from the MITBIH stress data [27]. In addition, the proposed method was tested with artificially generated white Gaussian noise, which was added to the original ECG segments with a number of input SNR levels. In general, evaluation of signal denoising methods usually involves a measure of similarity between the denoised signal to the original signal. In order to assess the obtained fuzzy filter output fit, four of the frequently used criteria from other experimental studies have been applied:

- ***Signal-to-noise output ration:***

$$SNR_{output} = 10log\left(\frac{\sum_{k=1}^{N}(x_k)^2}{\sum_{k=1}^{n}(\hat{y}_k - x_k)^2}\right) \tag{10}$$

- ***The SNR improvement:***

$$SNR_{imp} = SNR_{output} - SNR_{input} \tag{11}$$

- ***Mean Square Error:***

$$MSE = \frac{1}{2}\sum_{k=1}^{N}(\hat{y}_k - x_k)^2 \tag{12}$$

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✓ ***The Root Mean Square Error:***

$$RMSE = \sqrt{\frac{1}{2}(\hat{y}_k - x_k)^2} \tag{13}$$

where x_k is the clean signal, $\hat{y}_k$ is its estimate and N is the length of the data.

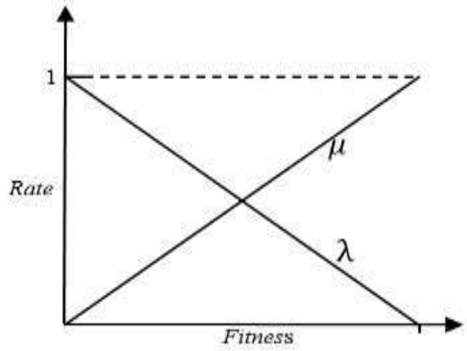

Figure.2 Linear migration curves for BBO.

4.1. Denoising

In order to study the outcomes from the proposed method, three types of noise were utilised. The denoising results for the different noise types are shown in Figures.3 – 6. These include the real and white noises that were added to the real ECG data that were selected from the MIT-BIH normal sinus rhythm database [41], which is referenced 18177.dat. The results show that, with the addition of white Gaussian noise at $3dB\ SNR$ level, the clean ECG morphology is followed by the denoised signal (Figure. 3). Meanwhile, Figure. 4 shows that the denoised signal does not show any EMG artefacts with real MA noises at $3dB\ SNR$ level. Nevertheless, whilst the most troublesome noise to emit is generally agreed to be EM, due to its ability to mimic ectopic beats, there was a successful outcome in this experiment. Normally, undesired notches are seen on the ST segment with EM noise that are difficult to remove using simple bandpass filters; however, with the proposed method, the BBOFAF was able to remove these motion artefacts (EM), as shown in Figure. 5, whilst also preserving the signal's diagnostic morphology information. In order to assess the proposed method's ability to remove more complicated noise, all three noises (EM, MA and white Gaussian noise) were added to the same signal (18177.dat). When comparing the noised ECG with the denoised signal following application of the BBOFAF, is can be seen that the method produces a very smooth signal (Figure.6).

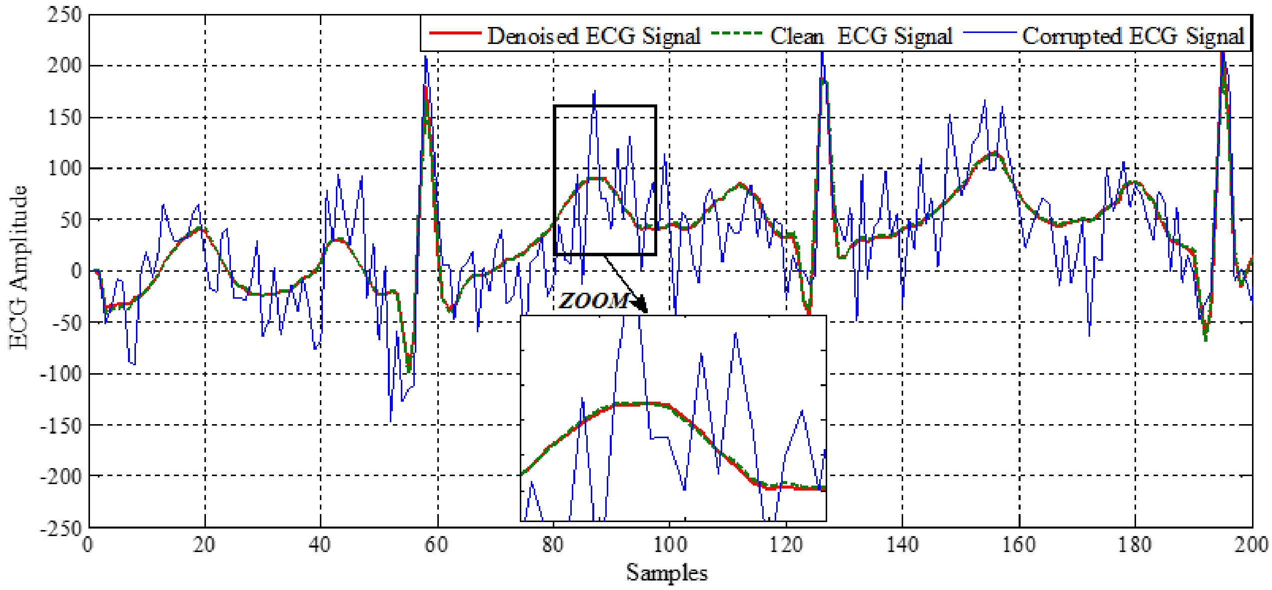

Figure 3 Typical filtering of BBOFAF for the recorded 18177.dat from MIT-BIH database with an added white Gaussian noise (WGN) at a 3dB SNR level.

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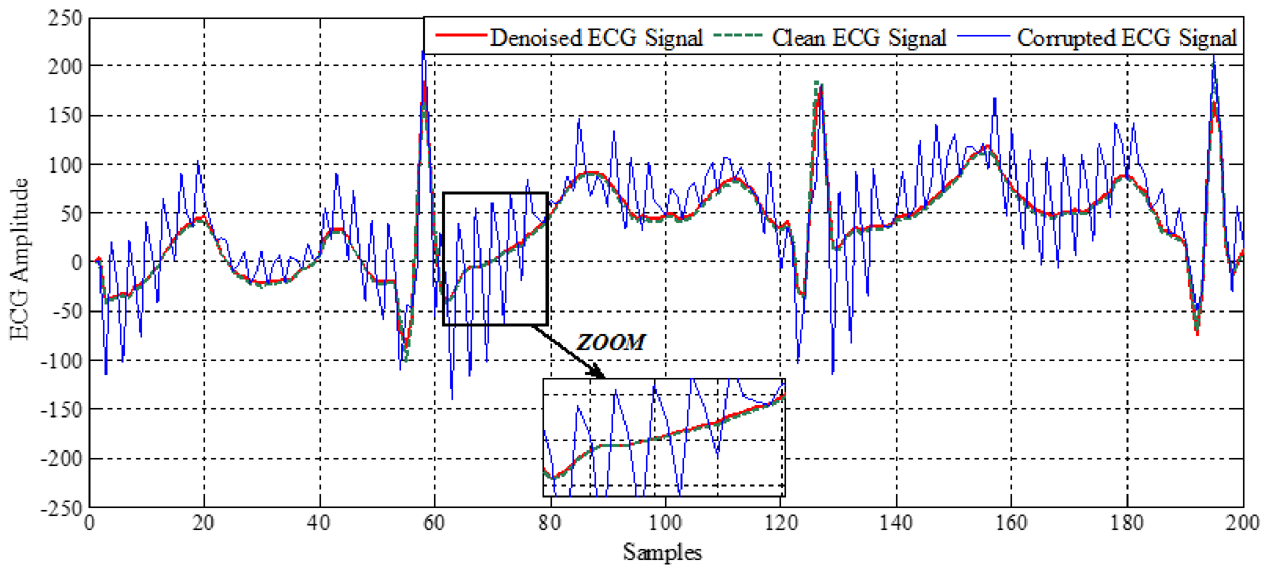

Figure 4 Typical filtering of BBOFAF for the recorded 18177.dat from MIT-BIH database with muscle (EMG) artifact (MA) at a 3dB SNR level.

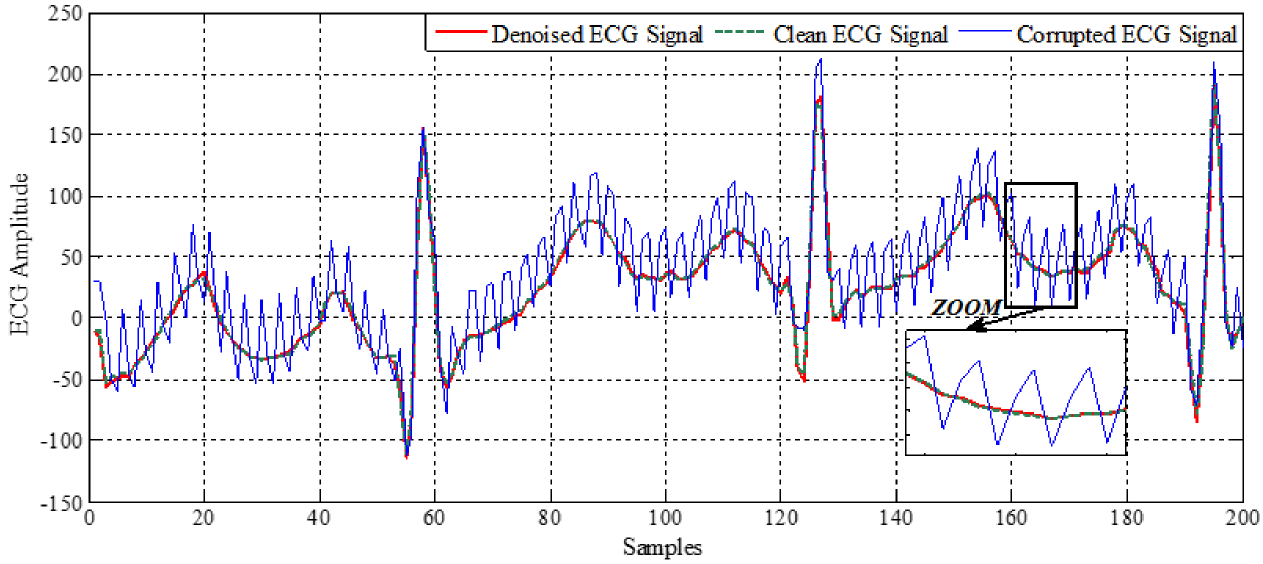

Figure 5 Typical filtering of BBOFAF for the recorded 18177.dat from MIT-BIH database with electrode motion artifact EM at a 3dB SNR level.

The recorded 18177.dat from the MIT-BIH database was used to assess the performance of the proposed technique. As such, different SNR input levels of EM, MA and white Gaussian noise were added in order to assess that method's performance where severe distortion occurs. To assess the obtained fuzzy filter output for each noise power case, the following criteria formulas were used: 7, 8, and 9. The $SNRoutput$, $SNRimp$, MSE and $RMSE$ generated by the BBOFAF framework for white Gaussian noise, MA and EM versus different $SNRinputs$ are shown in Figures. 7, 8 and 9, respectively. These results show that the proposed method achieves positive results in all different noise environments for a number of $SNRinput$ levels. This can be seen where the slope of the different criteria, particularly the $SNRoutput$, are not flat and there is an obvious increase of the $SNRoutput$ with a corresponding decrease in $SNRinput$. As such, it appears that the BBOFAF

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framework is capable of optimally filtering the ECG signal even in the presence of artefacts such as white Gaussian noise, MA and EM.

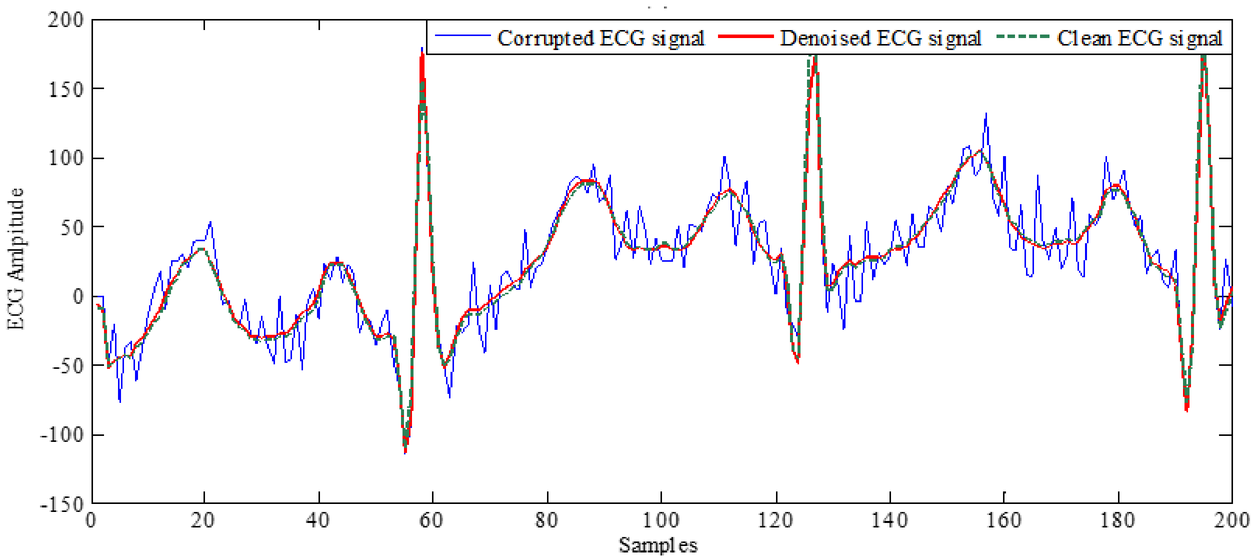

Figure 6 Typical filtering of BBOFAF for the Recorded 18177.dat from MIT-BIH database. with the three noises type (WGN+MA+EM).

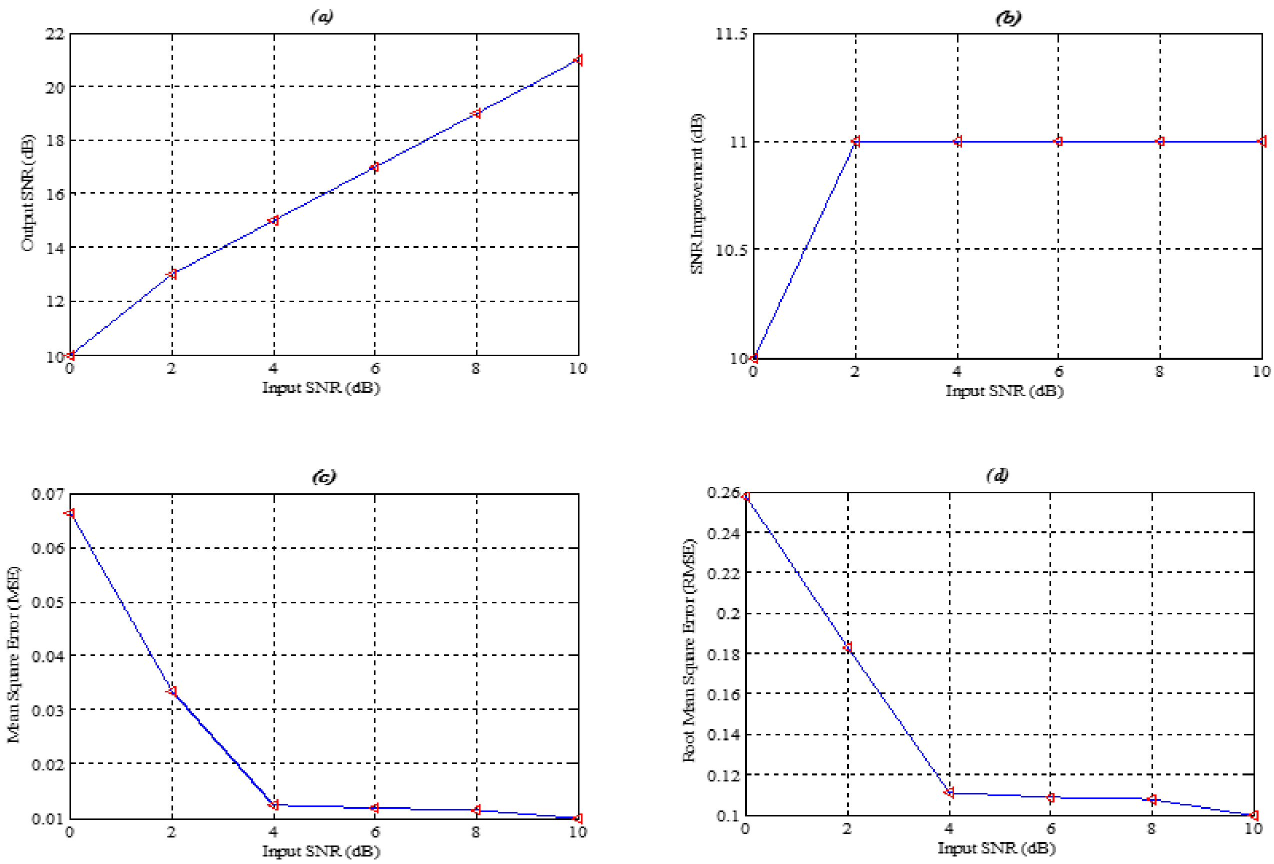

Figure 7 Measures performances of BBOFAF versus different input SNRs for white Gaussian noise (*a*) SNR output (*b*) SNR Improvement (*c*) Mean square error (*d*) Root mean square error.

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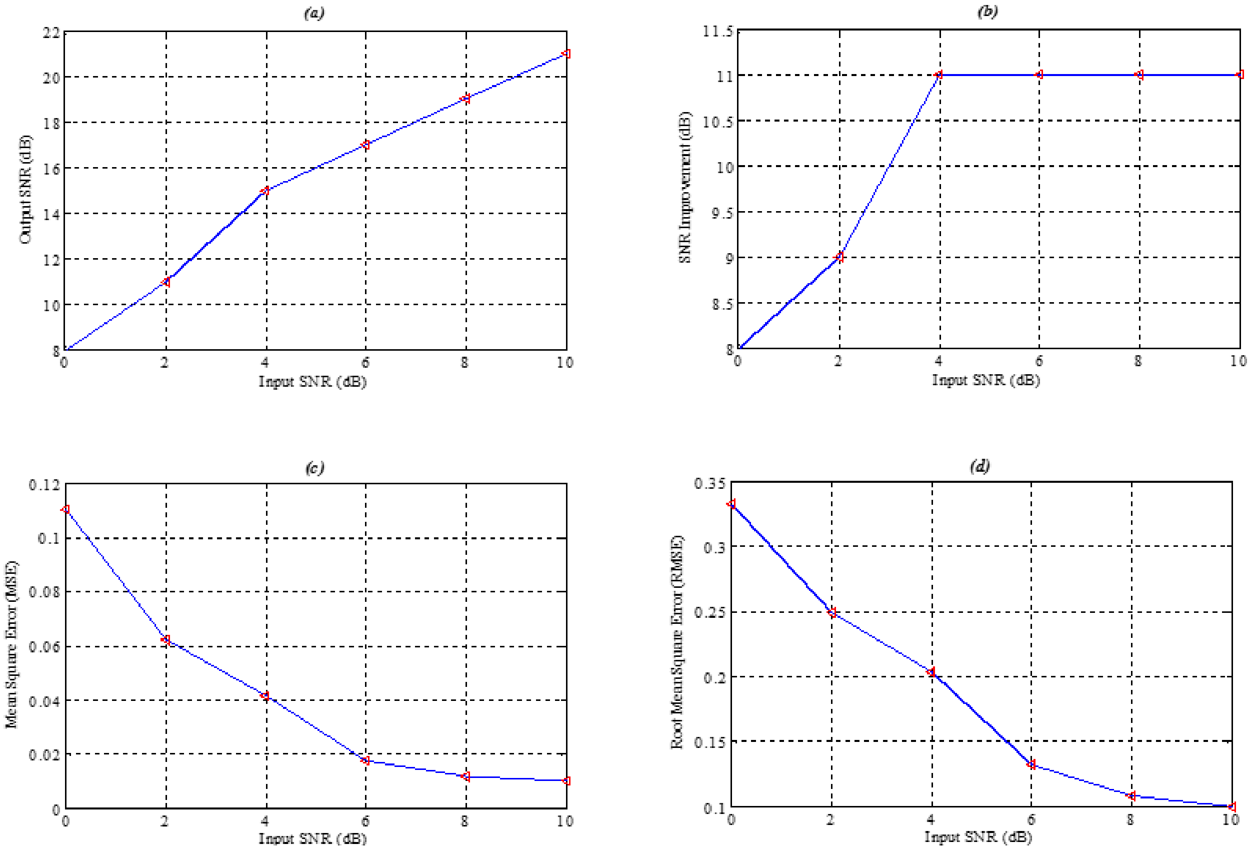

Figure 8 Measures performances of BBOFAF versus different input SNRs level for MA noise (*a*) SNR output (*b*) SNR Improvement (*c*) Mean square error (*d*) Root mean square error.

4.2. Comparison

In order to evaluate the performance of the proposed method against other benchmark methods of ECG signal denoising, the results of this study have been compared to the results obtained by recently published methods, where these methods have been compared to other methods. In order to produce a valid comparison, the proposed method has been simulated with the same parameters, test signals and noise, and under the same conditions using the same evaluation criteria as those used in the comparison studies with the benchmark methods. Tables.1 – 4 detail results generated with a comparison between the proposed method and the adaptive dual threshold filter and discrete wavelet transform (ADTF-DWT) method [6]. These results of [6] were validated by the works of several authors who compared the ADTF-DWT with the parallel type fractional zero-phase filtering (FZP) [9], the Reimann- Liouville (RL) integrator [10], and the zero-phase average window filter (AZP) [9]. The EMG artefact comparison results are shown in Table. 1. The noises were simulated in the same manner as the experiment described in [6]. Denoising comparison of 5dB of white Gaussian noise from the selected entries of the MIT-BIH arrhythmia database [40] is shown in Table. 2. The original paper compares its results with a number of different methods, including the adaptive dependent wavelet thresholding technique (ADWT) and the multi-adaptive bionic wavelet transform (MABWT) [11]. Tables. 3 and 4 show the results of the comparison between the proposed method and the benchmark method at the same levels of white Gaussian noise.

Table 1 The comparison of the denoising results of the EMG artefact in the signal 115 of the MIT-BIH arrhythmia database.

Criteria	RL	AZP	FZP	ADTF-DWT	**Proposed Method**
SNRoutput	6.83	11.82	13.68	15.59	30.65
MSE	0.0705	0.0223	0.0146	0.0146	0.0051

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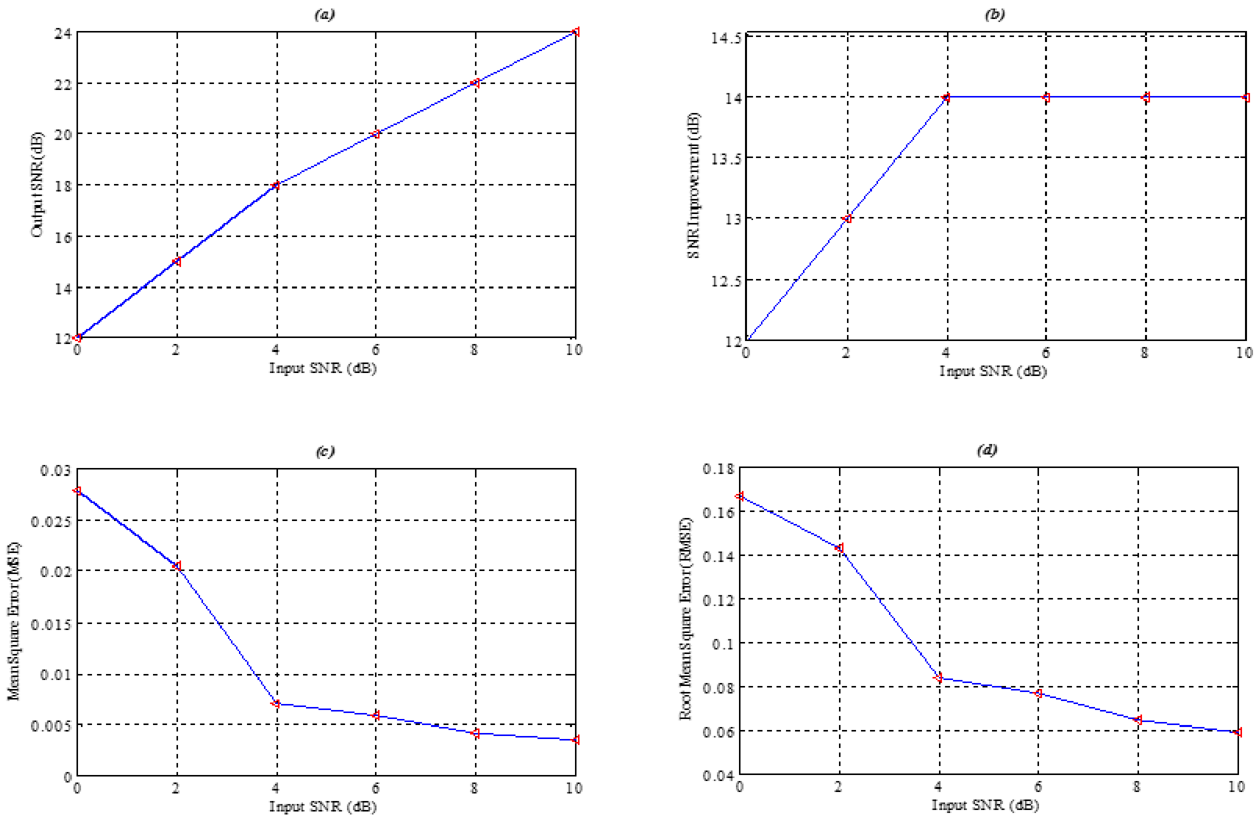

Figure 9 Measures performances of BBOFAF versus different input SNRs for EM noise (*a*) SNR output (*b*) SNR Improvement (*c*) Mean square error (*d*) Root mean square error.

Table 2 The comparison of the denoising results of the WGN noise of 5dB In some of the MIT-BIH arrhythmia database.

MIT-BIH Record N°	CRITERION	ADTF-DWT	Proposed Method
100	*MSE*	0.0044	0.0026
	RMSE	0.066	0.0511
	SNR_{imp}	9.70	20.59
101	*MSE*	0.0042	0.0019
	RMSE	0.04	0.0440
	SNR_{imp}	10.23	20.72
103	*MSE*	0.0058	0.0023
	RMSE	0.076	0.0480
	SNR_{imp}	9.10	20.68
113	*MSE*	0.0088	0.0015
	RMSE	0.093	0.0388
	SNR_{imp}	9.33	22.18
115	*MSE*	0.0122	0.0056
	RMSE	0.110	0.0751
	SNR_{imp}	9.45	16.81
117	*MSE*	0.0283	0.0081
	RMSE	0.168	0.0899
	SNR_{imp}	9.34	14.08
119	*MSE*	*0.0459*	*0.0084*
	RMSE	*0.214*	*0.0914*
	SNR_{imp}	*8.13*	*14.49*

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Table 3 The comparison of the denoising results of the WGN (5dB) in the signal 101 of the MIT-BIH arrhythmia database.

Criteria	ADWT	ADTF-DWT	Proposed Method
MSE	0.005	0.0042	0.0019
RMSE	0.072	0.064	0.0440
SNRimp	9.098	10.23	20.72

Table 4 The SNRimp comparison of the denoising results of the WGN (5dB) in some of the MIT-BIH database signals.

MIT-BIH Record N°	ADWT	MABWT	ADTF-DWT	Proposed Method
100	9.90	7.80	9.70	20.59
101	9.09	6.90	10.23	20.72
103	7.13	7.70	9.10	20.68
113	7.82	7.90	9.33	22.18
115	7.19	7.80	9.45	16.81
117	8.62	7.90	9.34	14.08
119	7.27	7.60	8.13	14.49
122	7.86	6.90	8.07	17.34

The comparison results show that the outcomes of the proposed method are much better than those generated from the other benchmark methods, namely the ADTF-DWT, RL, AZP, FZP, ADWT, MABWT methods as detailed in [6]. Indeed, the results show that the BBOFAF method displayed an increased SNR improvement and a reduced mean square error (*MSE*). In order to generate further validity in our results, we also compared the BBOFAF performance against another recently proposed method in [8] that is based on the adaptive Fourier decomposition (AFD). In [8], the authors made comparisons of the AFD based method with a number of other EMD and EEMD based methods described in [12]. The results of our comparison between the AFD method and the BBOFAF are presented in Table 5. The results show that again, the BBOFAF method performs better in terms of *MSE* criterion (These results that are presented in Table 5 is calculated with signal magnitude that has been increased by 200 times from its original value). Following this analysis, the BBOFAF method was further tested against a model based method described by [14], which detailed an ECG signal denoising method that utilised a marginalised particle extended Kalman filter. This used an automatic particle weighting strategy. The BBOFAF was compared to this method in terms of an ECG diagnostic distortion measure called theMulti -Scale Entropy based Weighted Distortion Measure (MSEWPRD) [14] [42]. We used a similar method as that utilised in [14] to calculate this measure. A weighted percentage root square difference (WPRD) is used for the metric, which is generated by comparing the original sub-band wavelet coefficient with the filtered signals. This uses weights that are the same as the corresponding sub-band's multi-scale entropies. Using the measure, it is possible to achieve an accurate representation of the distortion of the filtered signal at all sub-bands. It was necessary to decompose both signals using wavelet filters up to L levels in order to calculate this metric. Both the sampling frequency and the nature of the signal dictate the number of levels. An accurate ECG trace will include a sharp QRS complex segment and the slow P and T waves, therefore, effective decomposition of an ECG should display an effective representation of the detail coefficients of the QRS complexes and the approximation coefficients of the P and T waves. As such, Daubechies 9/7 bi-orthogonal wavelet filter [43] was used for decomposition purposes. This led us to choose $L = 4$ for sampling frequency of $128Hz$ [44]. The results of the comparison between our BBOFAF method and that of MP-EKF, EKF and EKS, as detailed in [14], using a MSEWPDM with various input SNR levels, are shown in Table 6. These results were generated by determining the MSEWPDMs of 200 filtered ECG segments that were selected from the MIT-BIH normal sinus rhythm database. However, the chosen segments used in our algorithm can be not the same as those segments used in [14].

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Table 5 ECG denoising performance (*MSE*) comparison between filtered results on the AFD, EEMD , EMD and the proposed method with noisy signal at the 10dB SNR level.

MIT-BIH Record N°	101	102	103	104	105	106	107	108	109
EMD	126.9	83.3	189.4	151.6	180.6	245.6	771.6	103.2	237.2
EEMD	97.4	60.0	147.0	109.5	128.1	192.5	574.9	76.9	179.7
AFD	36.0	32.6	76.0	55.7	73.6	98.9	572.6	24.0	112.1
Proposed Method	23.42	18.46	42.9	27.28	47.5	56.8	88.00	13.3	96.2

Table 6 ECG denoising performance (MSEPWRD) comparison between filtered results on the MP-EKF, EKS, EKF and the proposed method in the presence of white Gaussian noise and real muscle artefact.

		MSEPWRD (mean±SD) (mv)		
Noise type	**Method**	**0 dB**	**-1dB**	**-3 dB**
White Gaussian Noise	MP-EKF	1.284±0.225	1.329±0.224	1.434±0.231
	EKS	1.358±0.180	1.458±0.196	1.678±0.237
	EKF	1.677±0.183	1.824±0.200	2.158±0.242
	Proposed Method	0.306±0.047	0.4184±0.078	0.4866±0.0597
Real Muscle Artefact	MP-EKF	1.468±0.199	1.552±0.200	1.747±0.223
	EKS	2.933±0.455	3.247±0.514	3.992±0.656
	EKF	3.057±0.473	3.393±0534	4.188±0.681
	Proposed Method	0.3880±0.0599	0.4320±0.0499	0.5437±0.0546

4.3. Discussion

Using a set of fuzzy IF-THEN rules, we constructed a fuzzy adaptive filter that was able to adaptively change in order to reduce the criterion functions upon availability of new information. The results show that the proposed method is highly effective in denoising the ECG signal; however, the efficiency of the method's performance is determined by the number of fuzzy adaptive filter rules and the parameters of the optimisation algorithm. The effectiveness of the proposed BBOFAF method were compared to simulation results from both model and non-model based methods using *SNR* and *MSE* criteria, with the *SNR* being the power ratio between signal and noise. As such, a larger *SNR* indicates reduced background noise and, therefore, an increase signal denoising performance. Conversely, the *MSE* is a tracking accuracy measurement of the filtered signal compared to the original signal. Therefore, the performance of the signal information retention is better when the *MSE* is smaller. Figures. 3 – 6 show that the proposed BBOFAF method is effective at dealing with real noises, white Gaussian noise and a combination of all of these noise environments. As such, it can be deduced that this proposed method is both accurate and robust. Furthermore, by filtering, the EMG artefact using the BBOFAF method and comparing the outcomes with those of other benchmark methods, it can be seen that the BBOFAF method is statistically more effective than that of ADTF-DWT and other methods described in [6][9][10] . Comparison results between the BBOFAF method's denoising performance of white Gaussian noise of 5dB on selected MIT-BIH arrhythmia database samples with that of the ADTF-DWT and other methods [6][11] are shown in Tables 2 – 4. These results show that the BBOFAF method has improved results in *MSE*, RMSE and *SNRimp* when compared to ADTF-DWT, ADWT and MABWT methods. Furthermore, the BBOFAF method provides an important solution for the problem of high-density noise as shown with the results of the 5dB of white Gaussian noise. Table 5 displays a more in depth comparison of the filtered results of the ECG denoising performance (*MSE*) using the BBOFAF approach and the AFD, EEMD and EMD methods detailed in [8][12]. These results also show that the proposed approach is, again, more effective. Moreover, the results displayed in Table 6 shows the comparison between the proposed BBOFAF method and the MP-EKF and EKF/EKS [14] performance evaluation using the *MSEPWRD* on two types of noise with four different input SNRs. These results show that the MP-EKF and EKF/EKS had higher *MSEPWRDs* for each of the noise types and at all of the *SNRinput* levels compared to BBOFAF method indicating that the BBOFAF method is more effective than the MP-EKF and EKF/EKS at preserving the diagnostic information and morphology of the ECG signals.

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5. Conclusion

A novel adaptive fuzzy filter for ECG signal denoising was presented in this paper. The fuzzy adaptive filter utilised a biogeography based optimisation algorithm and was therefore termed the BBOFAF. The main characteristics of the BBOFAF are the fuzzy system of the fuzzy adaptive filter, which is developed with the use of a number of fuzzy IF-THEN rules and adaptive algorithm that is capable of updating fuzzy system parameters. The BBOFAF was utilised to denoise ECG signals and was found to be highly effective at removing electrode motion noise, EMG noise and white Gaussian noise. In addition, a number of comparisons were made between the performances of the BBOFAF with a number of other methods that have been presented in previously published studies. The results of these comparisons show that the BBOFAF method has better outcomes, which include a higher SNRout put and improved SNRimp, MSE, RMSE and MSEPWRD than the other model based and non-model based methods detailed in [6][8][12][14] . In addition, the BBOFAF method was able to preserve the morphology of the ECG signal and maintain the diagnostic performance.

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