Performance analysis of swarm intelligence algorithms in removal of ECG artefact from tainted EEG signal

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ABSTRACT

Electroencephalogram (EEG) is the recording of electrical activities of the brain. It is contaminated by other biological signals, known as artefacts. In this research paper, the performance analysis of three swarm intelligence incorporated adaptive neuro fuzzy inference system (ANFIS) - based techniques is made with respect to ECG artefact removal from the corrupted EEG signal. Swarm intelligence algorithms such as improved artificial immune system (IAIS), artificial immune system (AIS) and particle swarm optimization (PSO) are employed for artefact removal, by tuning the parameters of ANFIS individually. The performances of the methods are experimentally validated for both simulated and real data sets. Measures such as signal to noise ratio (SNR), mean square error (MSE) value, correlation coefficient, power spectrum density plot, sensitivity, specificity and accuracy are used for analysing the performance of the methods of simulated data set. The sensitivity, specificity and accuracy of ANFIS-tuned IAIS (ANFIS-IAIS), are found to be 94.9%, 100% and 99.2%, respectively. The sensitivity, specificity and accuracy of ANFIS-AIS and ANFIS-PSO are 91.9%, 100%, 98.7% and 87.9%, 100%, 98.3%, respectively. From the results, it is found that ANFIS-IAIS is more effective in removing ECG artefacts from EEG signals than ANFIS-AIS and ANFIS-PSO.

1. Introduction

The EEG is recorded by placing the electrodes along the scalp, and these recordings are used to detect the abnormalities associated with the electrical activities of the brain [1]. Even though EEG is designed to capture cerebral signals, it also records signals that are not of cerebral origin such as Electrocardiogram (ECG), Electrooculogram (EOG), Electromyogram (EMG), etc. generally called artefacts. The existence of artefacts makes interpretation of EEG signals difficult by doctors and causes critical errors and inaccuracies [2,3]. Hence elimination of artefacts from contaminated EEG signals is essential for better diagnosis. Optimization is a procedure for attaining best solution among the given solutions. Farmer et al introduced AIS in the year 1980. The advantages of AIS are (i) it is suitable for non-linear problems [4] (ii) free from local optima and (iii) self adaptive [5]. In this research work, Improved Artificial Immune System (IAIS), Artificial Immune System (AIS) and Particle Swarm Optimization (PSO) are applied to remove ECG artefacts from the EEG signals individually and their performances are compared with each other.
2. Related works

Several methods have been proposed by researchers for the ECG artefact removal process from EEG signals.

In this section, a brief review of some important contributions from the existing literature is presented. Sijbers et al. [6] suggested a method to remove ECG artefact from EEG signals based on adaptive filtering. Before filtering, this method necessitates to detect ECG artefact and to estimate the template of ECG artefact. Stephane Devuyst et al. [8] applied modified Independent Component Analysis (ICA) approach for eliminating ECG artefacts from EEG signals and attained the correction rate of 91%. On the other hand, the technique was found to have high computational complexity. In [9] ANFIS tuned by particle Swarm Optimization (PSO) was applied to eliminate ECG artefact from EEG signal and compared the results with that of ANFIS. It was proved that, ANFIS tuned by PSO technique performed better than original ANFIS.

Adaptive filtering method based on ANFIS, is employed in this research work to remove ECG artefact from EEG signal by optimizing the parameters of ANFIS by IAIS, AIS and PSO individually and their performances are compared. The algorithm IAIS is implemented by modifying the existing AIS algorithm. Simulation results illustrate the effectiveness and advantages of IAIS algorithm over AIS and PSO. This paper is organized as follows: Section 3 explains the concept of cancelling the artefacts from the EEG signal and describes the different techniques employed. The performance evaluation is shown in Section 4. Conclusion is discussed in Section 5.

3. Problem formulation

The corrupted EEG signal, EEG\(_c\)(n), recorded from the scalp is the combination of original EEG signal, EEG(n) due to brain activity and the artefact signal. The signal from the noise source (heart) ECG(n) becomes non-linear and distorted interference signal (artefact) ECG\(_N\)(n), as it passes through the non-linear passage of the human body. The method employed uses the concept of adaptive noise cancellation for removing artefacts from the EEG signal. In the present work, the adaptive filter is replaced by swarm intelligence incorporated ANFIS-based technique, that estimates the ECG artefact present in the corrupted EEG signal by identifying non-linear model between measurable ECG(n) and the corresponding immeasurable interference signal ECG\(_N\)(n). The estimated interference signal is deducted from the corrupted EEG signal to obtain the estimated EEG signal. In this work, the non-linear function of the human body is modelled as sigmoidal function, based on the transfer function of the biological neuron [10].

The original EEG signal EEG(n) is corrupted by the interference signal ECG\(_N\)(n), and it becomes corrupted EEG signal, which is the measured EEG signal:

\[
EEG_c(n) = EEG(n) + ECG_N(n),
\]

The estimated EEG signal is given as:

\[
\hat{EEG}(n) = EEG_c(n) - \hat{ECG}_N(n),
\]

\[
EEG(n) = \hat{EEG}(n) + ECG_N(n) - \hat{ECG}_N(n).
\]

where \(\hat{ECG}_N(n)\) is the estimated artefact signal [9].

3.1. Particle swarm optimization (PSO)

The PSO algorithm is based on the biological and the sociological behaviour of birds searching for their food. PSO searches for optima by updating generations. For each iteration, each particle is updated by two “bt” values. The first one is the best position (fitness) the particle has achieved so far. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is a global best and is called gbest. The PSO algorithm is as follows:

**Step 1:** Initialize particles each with dimension \(k\) randomly. Set the values for \(c_1\), \(c_2\), \(w\), \(r_1\) and \(r_2\).

where \(w\) is the inertia weight; \(c_1\), \(c_2\) are acceleration constants both set equal to or less than 2.0, and \(r_1\), \(r_2\) are random numbers.

**Step 2:** Initialize position \(P\) and velocity \(V\) of the particles randomly.

**Step 3:** Calculate fitness for each particle.

**Step 4:** For each generation, select particle’s best value (pbest) by comparing the performance of each particle to its best performance.

**Step 5:** Select particle with best fitness (minimum mean square error) among all particles as gbest.

**Step 6:** Update new velocity and new position of the particle by using pbest and gbest values in the velocity and position equations of PSO.

**Step 7:** Steps 3 to 6 are repeated until stopping criterion (maximum iterations set) is met [9].

\[
V_k(i) = wV_k(i-1) + (P_{pbest} - P_k(i)) + c_2r_2(P_{gbest} - P_k(i)),
\]

\[
P_k(i) = P_k(i-1) + V_k(i),
\]

\[
i = i + 1.
\]
Step 2: Evaluation: Calculate affinity value (objective function or fitness) for antibodies.
Step 3: Cloning: Clone the antibodies from the initial population, after evaluation. The number of clones is fixed suitably in such a way to get better performance.
Step 4: Hypermutation: Hypermutate the cloned population.
Step 5: Receptor editing: Randomly replace any one antibody from each group of mutated clones with the corresponding initial one.
Step 6: Evaluation and Selection: Evaluate the affinity value for every antibody in each group, and select the best one from each group which serves as the new population for the next iteration.
Step 7: Continue Step 2 to 6 till stopping condition (maximum number of iterations) is satisfied. In this work, stopping condition is the maximum number of iterations set. At the end of maximum iteration, antibody with the best fitness in memory is selected as the optimum parameter set for the membership function [12].

3.3. Improved artificial immune system (IAIS)

The performance of AIS increases as the number of clones produced for each antibody increases. However, as the number of clones increases, the time taken for completing single iteration of cloning, mutation and receptor editing process increases. Thus, the time consumed by AIS to reach the desired stopping condition also increases based on the different applications. Hence in order to deal with this disadvantage an improved artificial immune system is proposed by altering the general AIS algorithm by the inclusion of two selection mechanisms. In this method, instead of cloning all the initial antibodies, tournament selection [13] is employed to select the best antibodies among the initial antibody pool. Cloning and mutation are performed on the selected antibodies and are regulated to produce memory cell. Objective function or affinity of memory cell is calculated. From each group, antibody with high affinity is selected in such a way that the population size is the same as that of the initial population. Next to this, unlike AIS, a comparative selection is applied to select antibodies for the next iteration. In comparative selection, the affinity of the antibodies in the pool thus formed is compared with that of the initial antibodies and the antibody which has a high affinity is selected as the next generation antibodies. Due to these selection mechanisms, the chance of retaining the best antibodies is increased and thus IAIS reaches the stopping condition earlier when compared to AIS [12].

The average time taken by the ANFIS-IAIS is 22 seconds and ANFIS-AIS is 35 seconds respectively to produce its better results.

In this research work, the parameters of ANFIS are tuned using PSO, AIS and IAIS optimization algorithms individually as it was done in ANFIS-tuned PSO [9]. The input and output Membership Function (MF) used in this work, are gbell and linear respectively. Hence the input and the output MF parameters are initialized randomly and optimized by the optimization algorithms individually until stopping criterion. Table 1 shows the parameter values used for IAIS, AIS and PSO algorithms.

4. Results and discussion

The following section discusses the results obtained from the simulated data sets and real polysomnograph data set with ECG artefact. Table 2 shows the experimental setup for implementation of both simulated and real data sets.

4.1. Simulated data

The simulation studies have been carried out to evaluate the performance of the different techniques. The
reference signal (ECG) is delayed twice and non-linearly transformed using sigmoidal function [10] to generate artefact signal, which is then added with EEG signal to generate EEG signal with artefact (contaminated EEG signal). To illustrate the performance of different techniques, a sample set of ten data sets are considered for evaluation. The EEG signals are obtained from CHB/MIT database, and ECG signals are obtained from the Apnea ECG database (a01,a05,a09,a10,a11,a13,a14,a16) and MIT-BIH polysomnograph database (slp03,slp37) of the Physionet [14,15]. For experimental verification, EEG signals minimally corrupted with artefacts and ECG signals with varying number of QRS peaks are identified from the database. The details of the simulated data sets are shown in Table 3.

### 4.1.1. Performance analysis

To evaluate the performance of different techniques in artefact removal, output Signal to Noise Ratio (SNR), Mean Square Error (MSE) and Correlation coefficient (CC) are calculated. The output SNR is calculated using the following formula:

\[
SNR = 10 \log_{10} \left( \frac{\sum (EEG(n))^2}{\sum (EEG(n) - \hat{EEG}(n))^2} \right),
\]

(7)

where \(\hat{EEG}(n)\) is the estimated EEG signal, \(EEG(n)\) is the standard EEG signal. MSE is calculated using the following formula

\[
MSE = \frac{\sum (EEG(n) - \hat{EEG}(n))^2}{\text{length}(EEG(n) - \hat{EEG}(n))}.
\]

(8)

To examine the match between the standard EEG signal and the extracted EEG signal, the concept of correlation is used. The correlation coefficient is a normalized measure whose value varies from 0 to 1. It is used to find the match between the standard EEG signal and the extracted EEG signal. Higher correlation coefficient implies better signal extraction [12]. Correlation Coefficient is calculated using the formula

\[
\text{Correlation Coefficient}(CC) = \frac{\text{Cov}(EEG(n)\hat{EEG}(n))}{\sigma_{EEG(n)}\sigma_{\hat{EEG}(n)}}
\]

(9)

The performances of the various techniques in removing ECG artefact from EEG signal for the data sets mentioned in Table 3 are tabulated in Table 4.

The Figures 1 and 2 depict the ECG artefact suppression of two data sets I and X. From the results, it is found that the technique ANFIS-IAIS provides higher SNR, smaller MSE and higher correlation coefficient in relation to the other techniques.

The performance measures such as specificity, sensitivity and accuracy are also determined and evaluated with respect to the correction rate.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%.
\]

(10)

\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100\%.
\]

(11)

### Table 2. Experimental settings of ANFIS-IAIS, ANFIS-AIS, ANFIS-PSO and ANFIS.

| Parameters | ANFIS-IAIS | ANFIS-AIS | ANFIS-PSO | ANFIS |
|------------|------------|------------|-----------|-------|
| Number of linear parameters | 12 | 12 | 24 | 24 |
| Number of non-linear parameters | 12 | 12 | 24 | 24 |
| Total number of parameters | 24 | 24 | 24 | 24 |
| Number of fuzzy rules | 4 | 4 | 4 | 4 |
| Training Method | IAIS/AIS/PSO | Hybrid | Hybrid | Hybrid |
| Type of input MF | Gbellmf | Gbellmf | Gbellmf | Gbellmf |
| Type of output MF | Linear | Linear | Linear | Linear |

### Table 3. Details of signal source.

| Data set | Source of EEG | Source of ECG |
|----------|---------------|---------------|
| I        | chb01_01_edfm | a01           |
| II       | chb01_11_edfm | a05           |
| III      | chb01_02_edfm | a09           |
| IV       | chb01_21_edfm | a11           |
| V        | chb01_04edfm  | a13           |
| VI       | chb01_03edfm  | a14           |
| VII      | chb01_11_edfm | a16           |
| VIII     | Chb01_10_edfm | Slp03         |
| IX       | Chb01_20_edfm | Slp37         |
| X        | chb01_16_edfm | Slp37         |

### Table 4. Comparison of various swarm intelligence incorporated techniques with ANFIS for the removal of ECG artefact from the corrupted EEG signal of simulated data sets.

| Input | ANFIS-IAIS | ANFIS-AIS | ANFIS-PSO | ANFIS |
|-------|------------|------------|-----------|-------|
| SNR (dB) | OSNR (dB) | MSE | CC | SNR (dB) | OSNR (dB) | MSE | CC | SNR (dB) | OSNR (dB) | MSE | CC | SNR (dB) | OSNR (dB) | MSE | CC |
| I     | 1.0289 | 21.8617 | 0.00044 | 0.9967 | 21.7215 | 0.00045 | 0.9966 | 21.6343 | 0.00045 | 0.9966 | 18.6213 | 0.00091 | 0.9931 |
| II    | 1.7232 | 24.0887 | 0.00047 | 0.9981 | 24.0246 | 0.00048 | 0.9980 | 23.4541 | 0.00050 | 0.9937 | 17.9839 | 0.00091 | 0.9921 |
| III   | 1.692  | 24.3051 | 0.00044 | 0.9981 | 23.5138 | 0.00052 | 0.9977 | 23.0454 | 0.00055 | 0.9976 | 19.0457 | 0.00145 | 0.9938 |
| IV    | 2.3531 | 22.6110 | 0.00098 | 0.9972 | 22.9521 | 0.00097 | 0.9974 | 22.4832 | 0.00101 | 0.9972 | 21.4454 | 0.00128 | 0.9964 |
| V     | 1.2399 | 23.0424 | 0.00044 | 0.9976 | 22.8722 | 0.00046 | 0.9974 | 21.4800 | 0.00063 | 0.9964 | 18.5055 | 0.001245 | 0.9929 |
| VI    | 2.4032 | 27.0876 | 0.00035 | 0.9990 | 26.1931 | 0.00044 | 0.9988 | 24.7616 | 0.00062 | 0.9983 | 16.9121 | 0.00370 | 0.9989 |
| VII   | 1.7313 | 25.3116 | 0.00036 | 0.9986 | 24.0365 | 0.00048 | 0.9980 | 24.7142 | 0.00041 | 0.9975 | 22.9710 | 0.00062 | 0.9975 |
| VIII  | 1.3758 | 25.5780 | 0.00016 | 0.9991 | 27.3872 | 0.00017 | 0.9990 | 27.5135 | 0.00016 | 0.9991 | 17.7564 | 0.00160 | 0.9917 |
| IX    | 1.2741 | 21.6573 | 0.00036 | 0.9966 | 18.7668 | 0.000110 | 0.9933 | 18.5039 | 0.00116 | 0.9929 | 16.0614 | 0.00200 | 0.9878 |
| X     | 1.4887 | 23.9266 | 0.00042 | 0.9979 | 23.3849 | 0.000516 | 0.99733 | 22.6741 | 0.00057 | 0.9972 | 20.7281 | 0.00082 | 0.9958 |
| Mean  | 2.14501| 24.0062 | 0.000462 | 0.9979 | 23.3849 | 0.000516 | 0.99733 | 22.6741 | 0.00057 | 0.9972 | 20.7281 | 0.00082 | 0.9958 |

Note: OSNR: output signal to noise ratio; MSE: mean square error; CC: correlation coefficient.
Figure 1. Comparison of various swarm intelligence incorporated techniques with ANFIS applied to remove the ECG artefact from the corrupted EEG signal of the data set I [Extracted EEG signals (blue), standard EEG signal (red)] (color online).

Figure 2. Comparison of various swarm intelligence incorporated techniques with ANFIS applied to remove the ECG artefact from the corrupted EEG signal of the data set X [Extracted EEG signals (blue), standard EEG signal (red)] (color online).
Table 5. Performance evaluation of various swarm intelligence incorporated techniques and ANFIS applied to remove ECG artefact from the corrupted EEG signal using sensitivity, specificity and accuracy in terms of correction rate.

| Data set | ANFIS-IAIS | ANFIS-AIS | ANFIS-PSO | ANFIS |
|----------|------------|-----------|-----------|-------|
| I        | TP         | FN        | FP        | TN    | TP         | FN        | FP        | TN    | TP         | FN        | FP        | TN    |
| I        | 9          | 2         | 0         | 60    | 9          | 2         | 0         | 60    | 8          | 3         | 0         | 60    |
| II       | 10         | 0         | 0         | 60    | 10         | 0         | 0         | 60    | 10         | 0         | 0         | 60    |
| III      | 12         | 0         | 0         | 64    | 12         | 0         | 0         | 64    | 12         | 0         | 0         | 64    |
| IV       | 10         | 2         | 0         | 48    | 10         | 2         | 0         | 48    | 9          | 3         | 0         | 48    |
| V        | 13         | 0         | 0         | 41    | 13         | 0         | 0         | 41    | 12         | 1         | 0         | 41    |
| VI       | 11         | 0         | 0         | 47    | 10         | 1         | 0         | 47    | 9          | 2         | 0         | 47    |
| VII      | 13         | 0         | 0         | 68    | 13         | 0         | 0         | 68    | 13         | 0         | 0         | 68    |
| VIII     | 5          | 0         | 0         | 55    | 5          | 0         | 0         | 55    | 5          | 0         | 0         | 55    |
| IX       | 5          | 1         | 0         | 46    | 4          | 2         | 0         | 46    | 4          | 2         | 0         | 46    |
| X        | 6          | 0         | 0         | 40    | 5          | 1         | 0         | 40    | 5          | 1         | 0         | 40    |
| Average  | 9.4        | 0.5       | 0.0       | 52.9  | 9.1        | 0.8       | 0.0       | 52.9  | 8.7        | 1.2       | 0.0       | 52.9  |

Sensitivity = TP / (TP + FN) × 100%, (12)
Specificity = TN / (TN + FP) × 100%
Accuracy = (TP + TN) / (TP + TN + FP + FN) × 100%

where:
- TP represents True positive. It is counted as the number of artefact peaks corrected. Moreover, it corresponds to the correction rate.
- FN represents False Negative. It is counted as the number of artefact peaks not corrected.
- TN represents True Negative. It is counted as the number of peaks (excluding artefact) present in the signal reproduced as such without distortion.
- FP represents False Positive. It is counted as the number of signal peaks distorted or any additionally added peaks during the correction process.
- The above measures are tabulated in Table 5 and they are found by superimposing the standard EEG signal with the extracted EEG signal. Moreover, the FN and FP peaks for data set I and X are exposed in the Figures 1 and 2 by marking it by the ellipse. The specificity represents the extraction of EEG signal without distortion in the area other than the artefact.

The power spectrum density (PSD) plot is used to analyse the efficiency of the technique in the frequency domain. It is used to find the nearness of the standard EEG signal and extracted EEG signal. The Figures 3 and 4 show the PSD plot of the extracted EEG signals of various techniques and the standard EEG signal of the dataset I and X. From Figures 3 and 4 it is obvious that the PSD plot of ANFIS-IAIS is closer to the standard EEG signal than the PSD plot of extracted EEG signals using other techniques.

4.2. Real data

Contaminated EEG signal with ECG artefact and reference ECG signal are taken from MIT-BIH polysomnograph data base and UCD Sleep Apnea databases of Physionet [14]. The MIT-BIH Polysomnographic Database is a collection of recordings of multiple physiologic signals during sleep [15].

In the entire available data set, all the EEG signals corrupted by ECG artefact are included for testing purpose and the results are tabulated. The EEG signals that are not corrupted by ECG artefacts are excluded from the analysis.

Also, a few EEG data corrupted with ECG artefact are selected randomly from Sleep Apnea database and included in the analysis. The sleep apnea database contains overnight polysomnograms from adult subjects with sleep-disordered breathing. Databases of EEG signal with ECG artefact, mentioned in Table 6 are considered, and the artefact removal is carried out using ANFIS-IAIS, ANFIS-AIS, ANFIS-PSO and ANFIS. In the case of real data, the EEG signal to be extracted is...
Table 6. Performance evaluation of various swarm intelligence incorporated techniques and ANFIS applied for the removal of ECG artefacts from the corrupted EEG signal of real data sets.

| Data sets   | ANFIS-I AIS | ANFIS-AIS | ANFIS-PSO | ANFIS |
|-------------|-------------|-----------|-----------|-------|
| Slp02b      | 16.382      | 14.964    | 14.337    | 13.448|
| Slp01      | 12.068      | 11.719    | 11.612    | 11.027|
| Slp01a     | 12.103      | 12.062    | 7.679     | 7.298 |
| Slp037     | 9.425       | 8.441     | 8.275     | 7.980 |
| Slp041     | 12.397      | 12.015    | 11.473    | 10.706|
| Slp045     | 11.386      | 10.587    | 9.535     | 9.294 |
| Slp067x    | 11.131      | 10.125    | 10.246    | 9.672 |
| Ucddb005   | 10.503      | 9.581     | 9.321     | 9.150 |
| Ucddb002   | 17.005      | 15.508    | 15.005    | 14.741|
| Ucddb009   | 14.396      | 12.607    | 12.728    | 10.874|
| Ucddb021   | 16.172      | 16.128    | 16.587    | 11.822|
| Ucddb024   | 9.062       | 9.066     | 8.7613    | 7.6528|
| Ucddb026   | 13.704      | 13.340    | 12.603    | 9.7121|
| Ucddb028   | 14.067      | 13.014    | 12.898    | 11.301|
| Mean       | 12.843      | 12.083    | 11.504    | 10.334|

unknown. Hence a suitable measure, ratio $R^2$ used in [1] is used to evaluate the performance of the artefact removal. The ratio $R^2$ is defined as:

$$R^2 = \frac{\sum (EEG_e(n) - \hat{EEG}(n))^2}{\sum EEG(n)^2}. \quad (13)$$

The ratio $R^2$ represents the ratio of the power of ECG artefact removed from the corrupted EEG signal to the power in the estimated EEG signal. The value of $R^2$ computed for different ECG corrupted EEG data, in MIT-BIH polysomnograph and Sleep Apnea database is tabulated in Table 6.

The value of $R^2$ computed for different ECG corrupted EEG data, in MIT-BIH polysomnograph and Sleep Apnea database is tabulated in Table 6. Figures 5 and 6 show the comparison of the extracted EEG signal, after removing ECG artefact using ANFIS-I AIS, ANFIS-AIS, ANFIS-PSO and ANFIS along with reference ECG signal, corrupted EEG signal for the data set slp67x and Ucddb028, respectively.

It is perceptible from the plot that ANFIS-I AIS, ANFIS-AIS and ANFIS-PSO are proficient at removing ECG artefact peaks from the corrupted EEG signals in real-time applications. Moreover, ANFS-I AIS produces a highest average value for the ratio $R^2$ as shown in Table 6.

5. Conclusion

Electroencephalography (EEG) finds an important role in the diagnosis of cerebral disorders. However, EEG signal is contaminated by ECG artefacts predominantly in short-necked persons, and causes difficulty in the diagnosis of EEG especially for persons with epilepsy. Hence the elimination of the artefacts from EEG signal is essential for the better diagnosis. In this work, the performances of various swarm intelligence incorporated ANFIS-based techniques are compared in eliminating ECG artefacts from corrupted EEG signal.
Swarm intelligence algorithms such as Particle Swarm Optimization, Artificial Immune System and Improved Artificial Immune System are used along with ANFIS to remove ECG artefact. It is evident from the results that the method ANFIS-IAIS excels other techniques. Furthermore, the sensitivity, specificity and accuracy of ANFIS-IAIS are 94.9%, 100% and 99.2% respectively, which is higher than current state-of-the-art approaches. The performance of the techniques is evaluated for simulated data sets, and tested for real data set with ECG artefact.

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No potential conflict of interest was reported by the authors.

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