Automatika
Journal for Control, Measurement, Electronics, Computing and Communications

ISSN: 0005-1144 (Print) 1848-3380 (Online) Journal homepage: https://www.tandfonline.com/loi/taut20

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

S. Suja Priyadharsini & S. Edward Rajan

To cite this article: S. Suja Priyadharsini & S. Edward Rajan (2018) Performance analysis of swarm intelligence algorithms in removal of ECG artefact from tainted EEG signal, Automatika, 59:3-4, 408-415, DOI: 10.1080/00051144.2018.1541642

To link to this article: https://doi.org/10.1080/00051144.2018.1541642

Published online: 12 Dec 2018.

AUTOMATIKA
2018, VOL. 59, NOS. 3–4, 408–415
https://doi.org/10.1080/00051144.2018.1541642

ORIGINAL SCIENTIFIC PAPER

OPEN ACCESS Check for updates

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

S. Suja Priyadharsini [a] and S. Edward Rajan [b]

[a]Department of Electronics and Communication Engineering, Anna University Regional Campus - Tirunenveli, Tirunelveli, Tamil Nadu, India; [b]Department of Electrical and Electronics Engineering, Mepco Schlenk Engineering College, Sivakasi, Tamil Nadu, India

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.

Analiza vladanja algoritama inteligencije roja u odstranjivanju ECG artefakata iz onečišćenog EEG signala
Elektroencefalografija (EEG) je postupak snimanja električnih aktivnosti mozga. Postupak je zagađena drugim biološkim signalima zvanim artefaktima. U radu je predstavljena analiza vladanja tri pristupa zasnovana na inteligenciji roja i pristupu adaptivnog neuro-neizrazitog zaključivanja (ANFIS) za uklanjanje ECG artefakta iz onečišćenog EEG signala. Algoritmi inteligencije roja kao što su unaprijeđeni umjetni imunosni sustav (IAIS), umjetni imunosni sustav (AIS) i optimizacija roja čestica (PSO) korišteni su za uklanjanje artefakata individualnim podešavanjem parametara ANFIS pristupa. Vladanje metoda eksperimentalno je potvrđeno na simulacijskim i stvarnim podacima. Mjerila kao što su odnos signal-šum (SNR), srednja kvadratna pogreška (MSE), korelacijski koeficijent, graf gustoće spektra snage (PSD), osjetljivost, specifičnost i točnost korištena su za analizu vladanja metoda na simulacijskim podacima. Osjetljivost, specifičnost i točnost IAIS pristupa uz ANFIS podešavanje parametara (ANFIS-IAIS) pokazalo se kao, redoslijedom, 94,9%, 100%i 99,2%, što je veće u odnosu na druge metode. Osjetljivost, specifičnost i točnost ANFIS-AIS i ANFIS-PSO pristupa je 91,9%, 100% i 98,7% te 87,9%, 100% i98,3%, redoslijedom. Rezultati pokazuju da je ANFIS-IAIS pristup efektniji u otklanjanju ECG artefakata iz EEG signala u odnosu na ANFIS-AIS i ANFIS-PSO pristupe.

ARTICLE HISTORY
Received 6 September 2014
Accepted 22 December 2017

KEYWORDS
Artificial immune system (AIS); electrocardiogram (ECG); electroencephalogram (EEG); improved artificial immune system (IAIS); particle swarm optimization (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.

CONTACT S. Edward Rajan sedward@mepcoeng.ac.in Department of Electrical and Electronics Engineering, Mepco Schlenk Engineering College, IN-626005, Sivakasi, Tamil Nadu, India

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. Joe-Air Jiang et al [3] proposed a method for detecting and removing ECG artefact from EEG signals based on wavelet transform. This method needs a selection of suitable wavelet basis and scales. Lanquart et al. [7] proposed a method to eliminate QRS peaks using a morphological filter. In this method, a standard fixed shape element needs to be defined according to the artefact. Moreover, this method is appropriate for eliminating QRS peaks but not for T-wave of ECG artefact. Stephanie 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:

$$EEG_c(n) = EEG(n) + ECG_N(n), \qquad (1)$$

The estimated EEG signal is given as:

$$\hat{E}EG(n) = EEG_c(n) - \hat{E}CG_N(n), \qquad (2)$$

$$= EEG(n) + ECG_N(n) - \hat{E}CG_N(n). \qquad (3)$$

where $\hat{E}CG_N(n)$ 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].

$$V_k(i) = wV_k(i-1) + (P_{pbestk} - P_k(i)) + c_2 r_2 (P_{gbest} - P_k(i)), \qquad (4)$$

$$P_k(i) = P_k(i-1) + V_k(i), \qquad (5)$$

$$i = i + 1. \qquad (6)$$

3.2. Artificial immune system (AIS)

AIS is an optimization algorithm which uses the principle of natural immune system [4]. It is an adaptive system used to resolve complex problems based on the concept of the immune functions, models and principles. In this research work, AIS based on clonal selection theory is used for tuning the ANFIS parameters. The important steps of clonal selection used in this work are (i) selection (ii) proliferation and differentiation of cells with antigens (iii) maturation and diversification of antibody types through random genetic changes; and (iv) elimination of cells with low affinity towards antigenic receptors. To realize optimization using AIS, the antibodies and affinity are considered for probable solutions and for objective function respectively. In this work, elements of the antibodies are represented using real numbers [4,11,12]. The steps involved in AIS are detailed below.

Step 1: *Initialization:* Initially, form antibody population by generating real numbers randomly. Each antibody (A) represents the parameters of the membership function to be optimized. Let $A_i = [p_1, p_2 \ \dots \ p_n]$, $i = 1,2, \dots N$ where "n" represents the number of parameters to be optimized, and N represents the number of antibodies in the population.
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. Calculate the affinity value for the mutated clones.
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.

Table 1. Parameters of IAIS, AIS and PSO.

Parameters	IAIS	AIS	PSO
Population/particle size	50	50	50
Maximum iterations	10	10	40
Number of clones produced/antibody	3	6	NA
Mutation rate	0.2	0.2	NA
Cognitive (c_1) and Social (c_2) acceleration	NA	NA	2
Inertia weight (w)	NA	NA	0.8

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

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

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:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{\sum(\hat{\mathrm{E}}\mathrm{EG}(n))^2}{\sum(\mathrm{EEG}(n)-\hat{\mathrm{E}}\mathrm{EG}(n))^2}\right), \quad (7)$$

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

$$\mathrm{MSE} = \frac{\sum(\mathrm{EEG}(n)-\hat{\mathrm{E}}\mathrm{EG}(n))^2}{\mathrm{length}(\mathrm{EEG}(n)-\hat{\mathrm{E}}\mathrm{EG}(n))}. \quad (8)$$

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

$$\text{Correlation Coefficient(CC)} = \frac{\mathrm{Cov}(\mathrm{EEG}(n)\hat{\mathrm{E}}\mathrm{EG}(n))}{\sigma_{\mathrm{EEG}(n)}\sigma_{\hat{\mathrm{E}}\mathrm{EG(n)}}}. \quad (9)$$

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.

$$\mathrm{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \times 100\%, \quad (10)$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \times 100\%, \quad (11)$$

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		
Data set	SNR (dB)	OSNR (dB)	MSE	CC	OSNR (dB)	MSE	CC	OSNR (dB)	MSE	CC	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	0.00055	0.9937	17.9839	0.0019	0.9921
III	1.692	24.3051	0.00044	0.9981	23.5138	0.00052	0.9977	23.3045	0.00055	0.9976	19.0457	0.00145	0.9938
IV	2.3531	22.6110	0.00098	0.9972	22.9521	0.00090	0.9974	22.4832	0.00010	0.9972	21.4454	0.00128	0.9964
V	1.2399	23.0424	0.00044	0.9976	22.8722	0.00046	0.9974	21.480	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	0.9899
VII	1.7313	25.31162	0.00036	0.9986	24.0365	0.00048	0.9980	24.7142	0.00041	0.9983	22.9710	0.00062	0.9975
VIII	1.3758	27.5580	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	21.65738	0.00056	0.9966	18.7668	0.00110	0.9933	18.5039	0.00116	0.9929	16.0614	0.00200	0.9878
X	1.4887	23.9266	0.00042	0.9980	22.3791	0.00061	0.9971	22.6741	0.00057	0.9972	20.7281	0.00082	0.9958
Mean		24.14501	0.000462	0.9979	23.38469	0.000561	0.99733	23.05234	0.00052	0.99673	19.00308	0.001553	0.9931

Note: OSNR: output signal to noise ratio; MSE: mean square error; CC: correlation co-efficient.

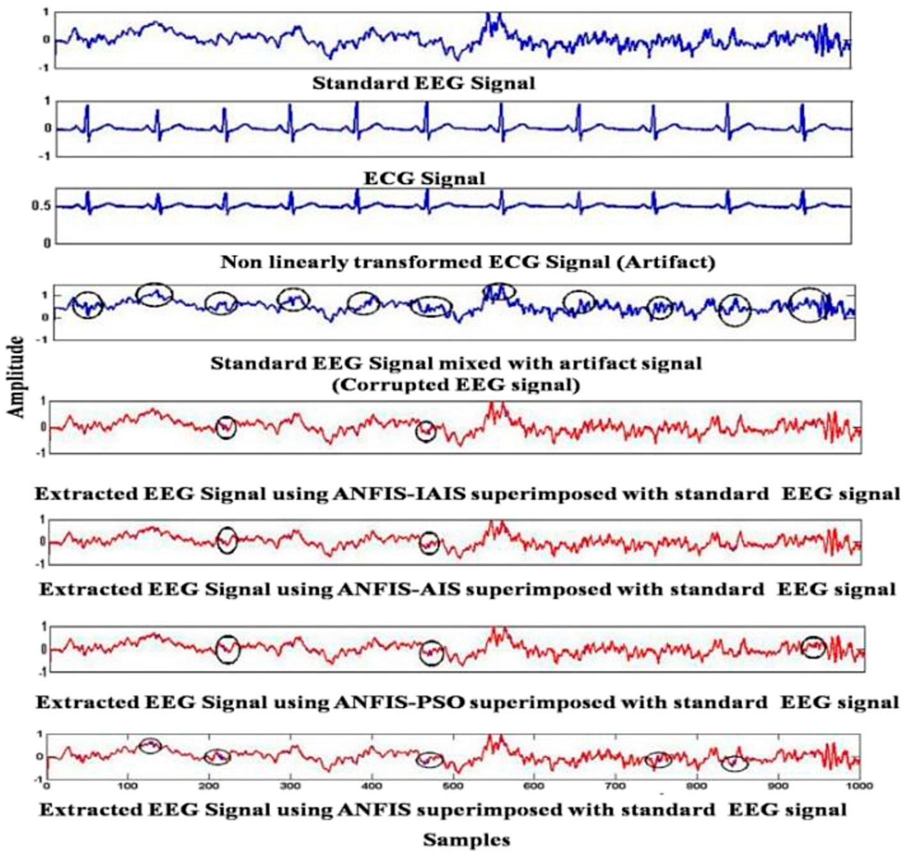

Figure 1. Comparison of various swarm intelligence incorporated techniques with ANFIS applied to remove the ECG artefact from the corrupted EEG signal of the data set I [Extracted EEG signals (blue), standard EEG signal (red)] (color online).

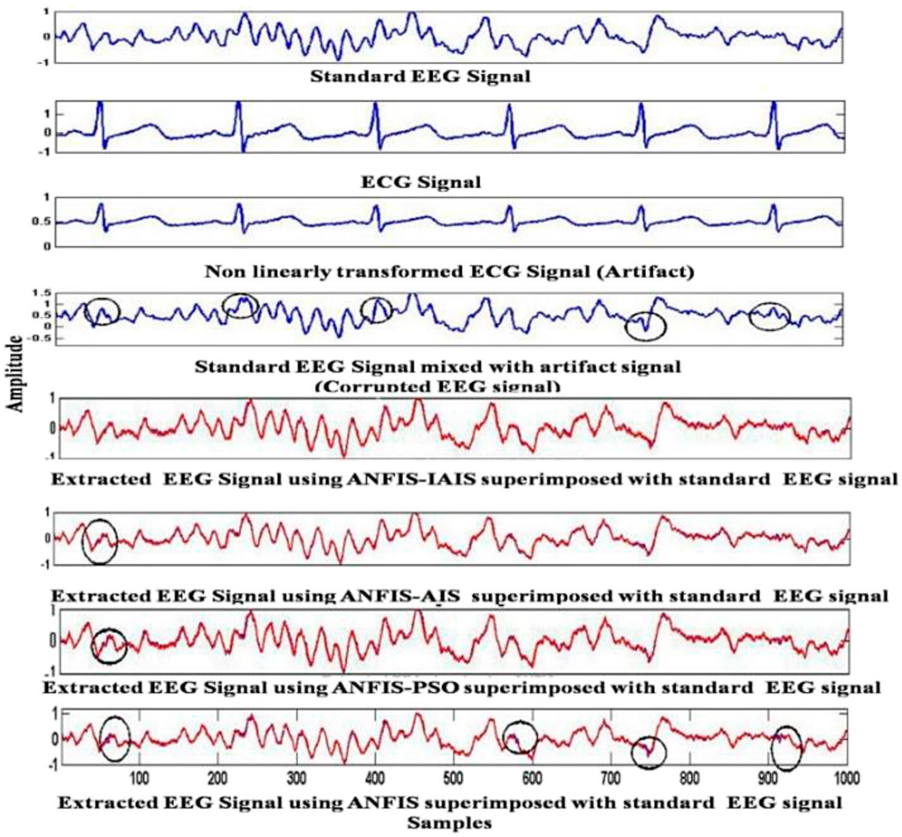

Figure 2. Comparison of various swarm intelligence incorporated techniques with ANFIS applied to remove the ECG artefact from the corrupted EEG signal of the data set X [Extracted EEG signals (blue), standard EEG signal (red)] (color online).

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.

	ANFIS-IAIS				ANFIS-AIS				ANFIS-PSO				ANFIS			
Data set	TP	FN	FP	TN	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	7	4	1	59
II	10	0	0	60	10	0	0	60	10	0	0	60	7	3	0	60
III	12	0	0	64	12	0	0	64	12	0	0	64	8	4	0	64
IV	10	2	0	48	10	2	0	48	9	3	0	48	7	5	4	44
V	13	0	0	41	13	0	0	41	12	1	0	41	10	3	0	41
VI	11	0	0	47	10	1	0	47	9	2	0	47	6	5	3	44
VII	13	0	0	68	13	0	0	68	13	0	0	68	9	4	0	68
VIII	5	0	0	55	5	0	0	55	5	0	0	55	1	4	0	55
IX	5	1	0	46	4	2	0	46	4	2	0	46	3	3	0	46
X	6	0	0	40	5	1	0	40	5	1	0	40	2	4	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	6.0	3.9	0.8	52.1
Sensitivity	94.9				91.9				87.9				60.6			
Specificity	100.0				100.0				100.0				98.5			
Accuracy	99.2				98.7				98.1				92.5			

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\%, \quad (12)$$

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

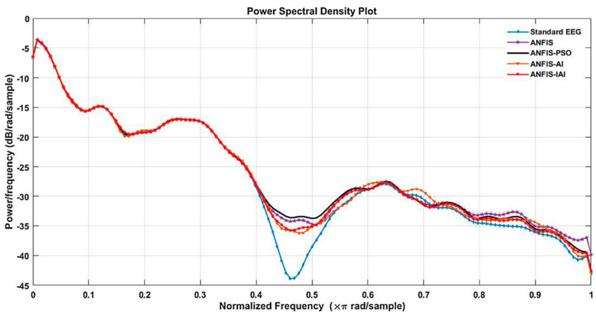

Figure 3. PSD plot of dataset I.

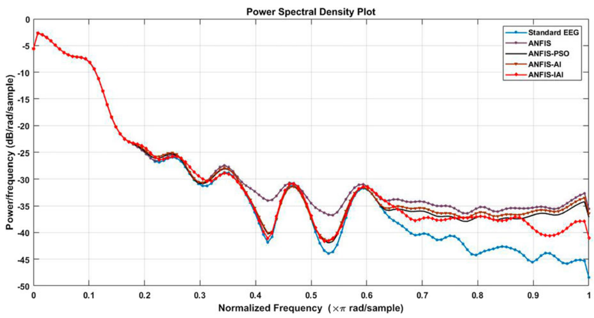

Figure 4. PSD plot of dataset X.

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.

	R^2 value			
Data sets	ANFIS-IAIS	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:

$$R^2 = \frac{\sum (\mathrm{EEG}_c(n) - \hat{\mathrm{E}}\mathrm{EG}(n))^2}{\sum \hat{\mathrm{E}}\mathrm{EG}(n)^2}. \quad (13)$$

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-IAIS, ANFIS-AIS, ANFIS-PSO and ANFIS along with reference ECG signal, corrupted EEG signal for the data set slp67xm and Ucddb028, respectively.

It is perceptible from the plot that ANFIS-IAIS, ANFIS-AIS and ANFIS-PSO are proficient at removing ECG artefact peaks from the corrupted EEG signals in real-time applications. Moreover, ANFS-IAIS 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.

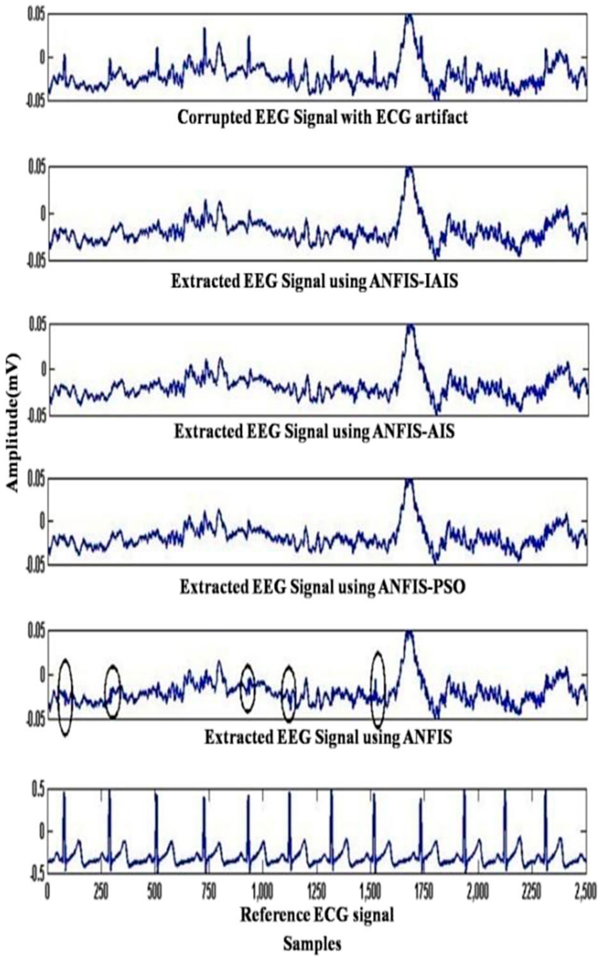

Figure 5. Comparison of various swarm intelligence incorporated techniques and ANFIS to remove the ECG artefacts from a polysomnograph EEG signal of Slp067x data set.

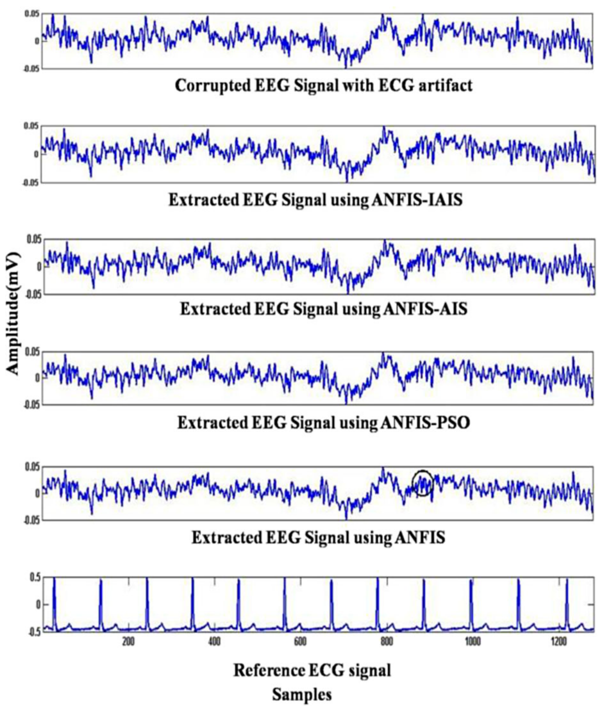

Figure 6. Comparison of various swarm intelligence incorporated techniques and ANFIS to remove the ECG artefacts from a polysomnograph EEG signal of Ucddb028 data set.

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.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

S. Suja Priyadharsini http://orcid.org/0000-0002-3926-5263

References

[1] Puthusserypady S, Ratnarajah T. Robust adaptive techniques for minimization of EOG artifacts from EEG signals. Sig Proc. 2006;86:2351–2363.
[2] Ghandeharion H, Erfanian A. A fully automatic ocular artifact suppression from EEG data using higher order statistics: improved performance by wavelet analysis. J Med Eng Phys. 2010;32:720–729.
[3] Jiang JA, Chao C-F, Chiu M-J, et al. An automatic analysis method for detecting and eliminating ECG artifacts in EEG. Comput Biol Med. 2007;37:1660–1671.
[4] Hemamalini S, Simon SP. Dynamic economic dispatch using artificial immune system for units with valve-point effect. Electr Power Energ Syst. 2011;33:868–874.
[5] Beheshti Z, Shamsuddin SMH. A review of population-based meta-heuristic algorithm. Int J Adv Soft Comput Appl. 2013;5:1–35.
[6] Sijbers J, Audekerke JV, Verhoye M, et al. Reduction of ECG and gradient related artifacts in simultaneously recorded human EEG/MRI data. Magn Reson Imaging. 2000;18:881–886.
[7] Lanquart JP, Dumont M, Linkowski P. QRS artifact elimination on full night sleep EEG. Med Eng Phys. 2006;28(2):156–165.
[8] Devuyst S, Dutoit T. Patricia Stenuit, Myriam Kerkhofs, and Etienne Stanus, cancelling ECG artifacts in EEG using a modified independent component analysis approach. EURASIP J Adv Signal Process. 2008;2008:1–13.
[9] Priyadharsini SS, Rajan SE. An efficient method for the removal of ECG artifact from measured EEG signal using PSO algorithm. Int J Adv Soft Comput Appl. 2014;6:1–19.
[10] Sadasivan PK, Dutt DN. A non-linear estimation model for adaptive minimization of EOG artifacts from EEG signals. Int J Biomed Comput. 1994;36:199–207.
[11] Castro LND, Jonathan T. Artificial immune systems: a new computational intelligence approach. Berlin: Springer-Verlag; 2002.
[12] Priyadharsini SS, Rajan SE, Sheniha SF. A novel approach for the elimination of artefacts from EEG signals employing an improved artificial immune system algorithm. J Exp Theor Artif Intell. 2015. doi:10.1080/0952813X.2015.1020571.
[13] Kumar PG, Victoire TAA, Renukadevi P, et al. Design of fuzzy expert system for microarray data classification using a novel genetic swarm algorithm. Expert Syst Appl. 2012;39:1811–1821.
[14] www.physionet.org.
[15] Goldberger AL, Amaral LAN, Glass L, et al. Physio bank, physio toolkit, and physio net: "components of a new research resource for complex physiologic signals". Circulation. 2000;101(23):e215–e220. Circulation Electronic Pages; http://circ.ahajournals.org/cgi/content/full/101/23/e215.