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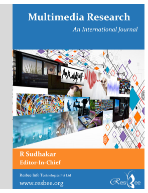

Artifacts Removal in EEG Signal using a NARX Model based CS Learning Algorithm

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Abstract: An Electroencephalogram (EEG) signal is essential clinical tool for monitoring the neurological disorders. The electrical activity of the EEG signal is obtained by placing several electrodes on the brain scalp. However, the recorded signals are easily affected by various artifacts which reduce its clinical convenience. In order to remove the artifacts signal such as EOG, EMG and ECG, we have proposed, a new nonlinear autoregressive with exogenous input (NARX) filter in this paper. Then, the efficient learning algorithm of cuckoo search (CS) algorithm is proposed for the elimination of various artifacts from the reordered EEG signal. Here, the performance of the proposed model is analysed using signal to noise ratio (SNR) and root mean square error (RMSE) value. Finally, results shows the effectiveness of the proposed model by extracting the artifcats signal from the recorded signals based on the maximum signal to noise ratio and minimum root mean square error value. From the results, we can conclude that the proposed model obtained the maximum SNR rate as 47.54db compared to various existing artifacts removal models such as independent component analysis (ICA), Fast independent component analysis (FICA), neural network model (NN).

Keywords: NARX filter, artifacts, learning algorithm, signal to noise ratio, EEG signal.

1. Introduction

Due to the presence of nerve firings, brain generates the electrical impulses that are diffused through the head. The non-invasive measurement of the electrical activity of the brain is obtained by various electrodes placed on the scalp called electroencephalogram. The EEG is used to record the abnormal behaviour of the human brain. While recording the EEG signal, various contaminations of signals called artifacts are added with the original EEG signal [9]. The artifacts present in the EEG signal are classified based on two groups such as physiological artifacts and technical arifcats. Basically, the artifacts generated by various factors such as electromyogram (EMG), electrocardiogram (ECG) and electrooculogram called biological artifacts [21,22]. Then, the technical arifcats are like static electricity discharges, movements of electrode leads and line noise. In order to obtain the original EEG signal, the artifacts are removed from the recorded signals using various artifacts removal methods such as independent component analysis (ICA) [6], principal component analysis (PCA) [7], linear combination and regression[1], adaptive filters, neural networks [8], non-liniear PCA [9], wavelet de-noising [1,6], Adaptive Neuro Fuzzy Inference System[6] , autoregressive (AR) [10], etc.

Basically, the eye blink artifacts are eliminated by adaptive filter techniques, which are used to subtract the EEG source signal from the interference signal [19]. The adaptive filter used artifacts removal produces the less computation complexity. However, we cannot undertake that the reference signal is a perfect signal. Moreover, the Stationary Wavelet Transform is used to remove the artifacts based on the frequency domain. Here, the low frequency artifacts signals are not considered in the Stationary Wavelet Transform arifacts removal process [12-18]. In addition, independent component analysis is one of the powerful techniques used by various researchers for artifacts removal process. However, the source separation of ICA algorithm is very difficult compared to other artifacts removal algorithms. In addition, many regression based techniques are used to perform the artifacts removal process, in which the coefficients are transferred between the EOG, EMG or EEG channels are

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determined using the calibration trail method. Then, theses coefficients are used to subtract the atifacts from the EEG signals. However, the true coefficient values obtained from the regression method is inedible from the adjusted value and also the true coefficient cannot calibrate again automatically [11].

In this paper, we have proposed, Artifacts removal in EEG signal using a new neural network enhanced adaptive filter based on the cuckoo search optimisation algorithm. Here, we have considered three most serious artifacts such as ocular, muscular and cardiac artifacts from EEG signal. Here, the proposed cuckoo search optimisation algorithm is used find the optimal weights for the NARX neural network for effective analysis. In this paper, we have considered three kinds of artifacts signal with EEG such as EOG, ECG and EMG. The rest of this paper is organised as follows: Section 2 reviews several existing approaches for various artifacts removal algorithms. Section 3 presents the problem and challenges based on the existing approaches. Then, the proposed methodology of Artifacts removal in EEG signal using a new neural network enhanced adaptive filter based on the cuckoo search optimisation algorithm is described in section 4. Extensive experimental results based on the analysis of proposed algorithm is given in Section 5. Finally, section 6 concludes this paper.

2. Literature Review

This section shows the literature survey of various research papers based on the artifacts removal in EEG signal. Wim De Clercq et al. [2] have proposed a subspace based method for modelling the common dynamics which have been applied to synthetic data and interictal and ictal activity contaminated with muscle artifact. However, the performance of the proposed model was used to remove the artifacts successfully when compared to other artifacts removal algorithms. They have compared the both synthetic data and the analyzed real life data with the h principal component analysis (PCA). Finally, they have concluded that, the proposed arifacts removal model successfully removed the artifacts from EEG signal than PCA.

Pavitra Krishnaswamy et al. [3] have developed Reference-Free Harmonic Regression Technique to Remove EEG-fMRI Ballistocardiogram Artifacts. Here, the proposed model was used to physically motivate parametric models of the BCG artifact and the true EEG signal. Then, the maximum likelihood approaches were incorporated to identify the model parameters in order to subtract the BCG from corrupted EEG measurements. Furthermore, the proposed model works fine for the short data segments. However, the main drawback of this method is mainly due to reiterate runs of the Kalman filter during the numerical optimization.

Qinglin Zhao et al. [4] have proposed an Improved Adaptive Predictor Filtering model for Automatic Identification and Removal of Ocular Artifacts in EEG. Here, they have developed a hybrid de-noising method by combining both Discrete Wavelet Transformation and an Adaptive Predictor Filter. Especially, the ocular artifact zones based signals are predicted by APF based model. Then, the proposed model as compared with various existing algorithms such as Independent Component Analysis (ICA), Discrete Wavelet Transform (DWT) and Adaptive Noise Cancellation (ANC).They have analysed the performance of the proposed artifacts removal model with other existing algorithms based on the computational speed.

Hossein Shahabi et al. [5] have proposed a novel method to remove eye blink artifacts from the electroencephalogram (EEG) signals. The developed artifacts removal model is based on three kinds of processing steps such as signal modelling, time variant covariance matrices and Kalman filter. Here, the proposed artifacts removal process was performed without considering the electro-oculogram (EOG) reference electrodes. Here, they have used toe models such as autoregressive model and output error model for predicting the activity of both EEG and eye blink respectively. Finally, the true EEG based signal is extracted using the kalman filter. Here, the performance of the proposed artifacts removal process was compared with the existing RLS algorithm.

3. Problem Definition

Basically, the mutual condition of the signal sources are minimised by the weight parameters. The weights are assigned between the fist and the hidden units and between the second input units and the hidden units respectively. Based on the values of weights, the neural networks are used for prediction purpose. However, fining the optimal weight is one of the major problems for the adaptive neutral network [7].

4. Proposed System

This section shows the detailed description of the opposed artifacts removal in EEG signal using NARX neural network based proposed optimisation algorithm.

4.1 NARX Model

This section presents the detailed description of the nonlinear autoregressive models with exogenous inputs (NARX) recurrent neural architectures. The main advantage of this neural network is based on the limited amount of feedback architectures. Because, the feedback architectures are generated from the output neuron instead of hidden neurons. In addition, the NARX neural network is commonly used in the time series modelling process. Figure 1 shows the block diagram representation of the NARX neural network. Here, three vectors of data is given as input such as vector of exogenous input, vector of delayed exogenous input and vector of delayed regressed input. NARX neural network operation is mainly used for time series non liner systems. Then, the mathematical representation of the NARX model can be represented as follows:

$$j(n+1) = f[i(n-g); i(n-g-1), \cdots, i(n-g-D_i+1); j(n), j(n-1) \cdots, j(n-D_j+1)]$$

Where, $i(n)$ and $j(n)$ denotes the discrete time setup with input model and output model respectively. Then, the input and output memory of the NARX model can be represented as D_i and D_j respectively. Here, the both input and output memory should be greater than one for all the time of the processing steps. However, the input memory should always be less than the output memory. Where, g is the delay parameter which is sued to process the dead time. Without lack of simplification, the NARX model is obtained by making the parameter value k is zero. After assigning the null delay parameter, the NARX model is obtained using the following formula:

$$j(n+1) = f[i(n); i(n-1), \cdots, i(n-D_i+1); j(n), j(n-1) \cdots, j(n-D_j+1)]$$

Then, the above equation can also be written in simplified form that can be shown below:

$$j(n+1) = f[i(n); j(n)]$$

Where, $i(n)$ and $j(n)$ denotes the input and output regressors respectively. During the training phase, the input selection of inputs to the feed forward network is should be more accurate. In order to improve the training process, the weight and bias values of the NARX neural network are selected using suitable optimisation algorithm. Basically, the NARX model is used to predict the feature values of a time series from the past values of that same time series and the pat values of the other time series. Here, the NARX neural network based operation is based on various factors such as number of hidden layers, number delay lines and weighing function.

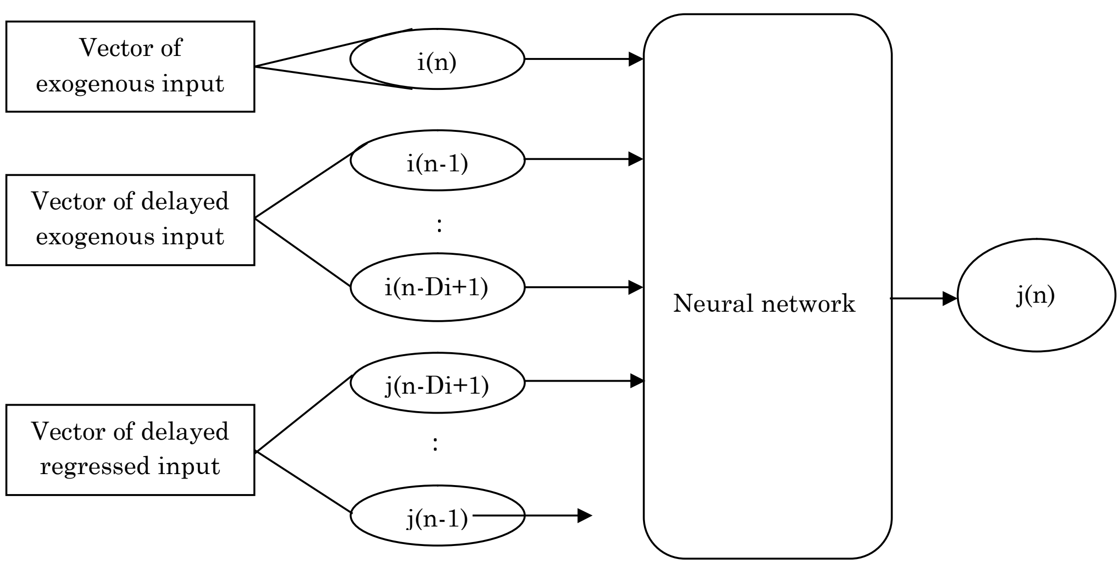


Fig. 1. *Block diagram representation of the NARX model*

4.2 Cuckoo Search Algorithm

Basically, the optimal selection process of an input subset orders plays one of the challenging task in NARX neural network. In order to find the optimal solution, lot of learning algorithms are used in NARX neural network. In this paper, we have proposed cuckoo search optimisation algorithm for learning process. The recently developed cuckoo search algorithm is one of nature inspired searching algorithm which express the social behaviour of cuckoos that is the aggressive reproduction of cuckoo species with of Levy flight behaviour. Initially, female cuckoo lays her eggs in the host bird's nest. Then, the host birds raise her brood without identifying the cuckoo's egg. When, the cuckoo's egg is detected by host bird, it has been vanished the cuckoo's egg by throwing it out. Basically, three rules are followed by the cuckoo search algorithm hat can be described as follows: i) initially, the host nests are chosen randomly for keeping the cuckoo's egg. ii) Then, the better nests are considered for the next generation based on the high quality eggs. iii) Then, the discovered probability of cuckoos egg by host bird is defined as $p_a \in (0,1)$. Based on the CS algorithm, the updating position of the solution vector can be represented using following formula:

$$U_i(t+1) = U_i(t) + r \quad S_i(t)$$

Where, the individual and current position iterations are denoted as i and t respectively. Then, the step size of the cuckoos' egg based on the random movement is represented as follows:

$$S_i(t) = rand\left(U_{i \in (1,n)} \quad U_{j \in (1,n)}\right)$$

Where, rand denotes the uniform random distribution function in the interval [0,1]. Then, random selection of positions from the whole population is denoted as

$$U_i(t+1) = U_i(t) + a \oplus levy(\beta)$$

$$levy \sim U = t^{1 \quad \beta}$$

Where, the symbol $\oplus$ denotes the entry-wise multiplications and the parameter equivalent to the step size of cuckoo is defined as α that can be determined using the levy distribution function. Then, the new nest generation based on the levy distribution function is defined as follows:

$$S_i(t) = a\left(U_i(t) \quad U_j(t) \oplus levy(\beta)\right)$$

Then, the update aw of cuckoo search algorithm is represented as follows:

$$U(t+1) = \begin{array}{ll} U_i(t) + r' & P > p_a \\ U_i(t) & otherwise \end{array}$$

Where, the discovery probability is defined as p_a that is used to create ne nest based on the update law. Then, P is the random number in interval [0,1]. Finally, the sleeted results are sorted by applying the ranking order and the current best solution is selected for further evaluation.

4.3 Artifact Removal in EEG Signal using NARX Model Based on the Proposed Optimisation Algorithm

This section shows the NARX model based on proposed cuckoo search algorithm for removing the artifacts from the EEG signal. Basically, many different sources contribute as artifacts to record EEG signal such as EOG generated by eye movement, EMG generated by the activity of muscle and ECG by heart beats. Figure 2 shows the artifacts removal process using the proposed model. Here, EEG data signals are collected from 10 scalp electrodes that can be denoted as number of channels. Then, the collected EEG signals are added with various artifacts such as EOG, ECG and EMG. In order to remove these artifacts, we have applied to NARX model. Basically, the future values of the original time series functions are predicted by the weights of NARX neural network model. In order to find the optimal weights, the NARX model is trained by cuckoo search algorithm. Finally, the original EEG signals are extracted using the proposed NARX model.

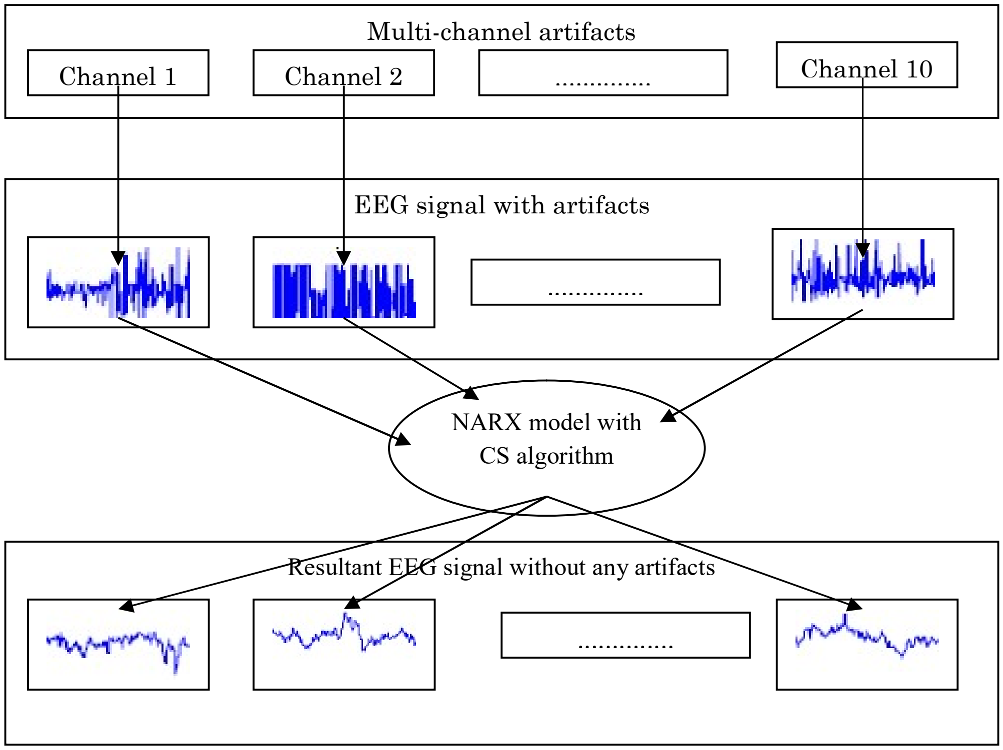


Fig. 2. *Block diagram representation of the artifacts removal model*

5. Results and Discussion

In this paper, we have proposed a new method for modelling the multichannel recording. We showed that, the proposed method can be used to remove artifacts signal from EEG signal with a low spatial correlation. The performance analysis of the proposed NARX model is discussed in this section.

5.1 Evaluation Metrics

The proposed artifacts removal model is compared with the existing models based on two kinds of evaluation metrics such as root mean square error and signal to noise ratio.

Root mean square error: Here, the evaluation metrics of root mean square error is used to measure the difference between predicted value and observed value. The results of RMSE value is used to measure the accuracy of the resultant signal.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(E_p - E_o\right)^2}$$

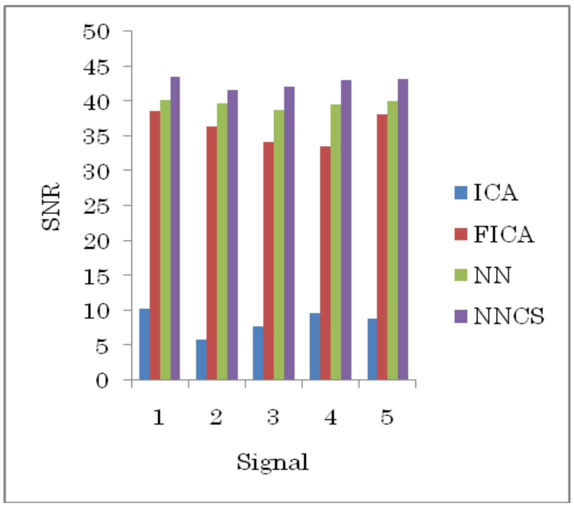
Where, N is the total number of iteration time and the predicted value error is defined as E_p. Then, the observed signal error value is defined as E_o.

Signal to noise ratio: signal to noise ratio is defined as the ration of the signal power to the noise power. Here, signal power is denotes the power of clean EEG signal and the noise power is defined as the artifacts signals such as EMG, EOG and ECG. Then, the standard formula for signal noise ratio is represented as follows:

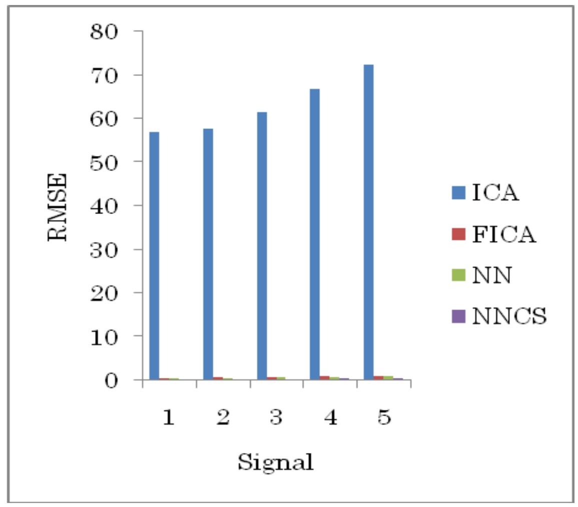
$$SNR = \frac{Signal\,Power}{Noise\,Power}$$

5.2 Performance Analysis of SNR and RMSE using ECG Artifacts

This section shows the performance analysis of proposed NARX model based on two evaluation metrics such as signal to noise ratio and root mean square error by removing the ECG artifacts signals. The electrical activity of the heart signal is named as ECG, which has been act as artifact signal while recording the EEG. In order to remove theses ECG artifact, various models are used such as Independent component analysis (ICA), Fast Independent component analysis (FICA), Neural Network (NN) and proposed NARX network based CS algorithm (NNCS). Figure 3 (a) shows the performance analysis of proposed model based on SNR analysis. Here, we have considered five signal soucer for analysing te signal performance. While analysing the third signal source, the value of SNAR obtained by various methods such as ICA, FICA, NN and NNCS are 7.8db, 34.21db, 38.76db and 42.12db respectively. From the figure 3(a), we can understand at the maximum SNAR value obtained by the proposed neural network model. Figure 3(b) shows the performance analysis of proposed model based on RMSE value. Basically the RMSE value is very small for better performance. While considering the second signal source, the maximum RMSE value is obtained by ICA model. Then, the RMSE value of 0.78 and 0.57 is obtained by both FICA and NN model. However, the proposed NNCS model obtained the minimum RMSE value of 0.29 when compared to other network models.



(a) SNR analysis

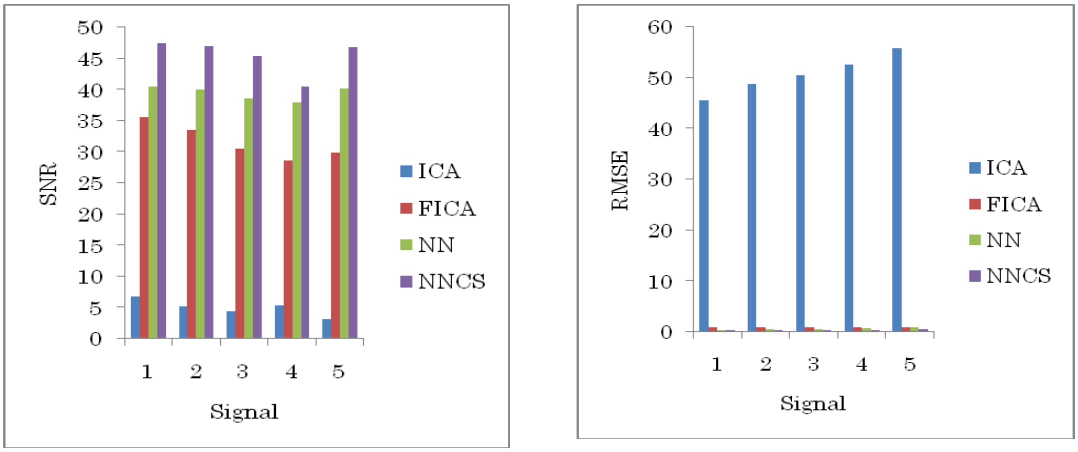


(b) RMSE analysis

Fig. 3. *Performance analysis of SNR and RMSE using ECG artifacts*

5.3 Performance Analysis of SNR and RMSE using EMG Artifacts

This section shows the performance analysis of artifacts removal models based on SNR and RMSE. Here, we have considered EMG signal as artifact, which is generated based on the activity of muscle. While recording the EEG signal, EMG signal is act as an artifact that can be removed by various models such as ICA, FICA, NN and the proposed NNCS. Figure 4(a) shows the SNR analysis of the EEG signal recording by removing the EMG artifacts. Here, we have considered five signal sources for analysis the performance of the SNR and RSE value. While taking the fifth signal source, 3.23db of SNR value is obtained by ICA model. Meanwhile, FICA and NN model obtained the SNAR value as 29.95db and 40.23db respectively. Then, the maximum SNR value is obtained by the proposed model is 46.78db. Figure 4 (b) shows the RMSE analysis of the proposed model based on the EMG artifacts signal. By analysis the above figure, we can say, the proposed model obtained the minimum RMSE value of 0.5 compared to other models such as ICA, FICA and NN. Then, the maximum RMSE value is obtained by the ICA model as 55.78, which shows the least performance.

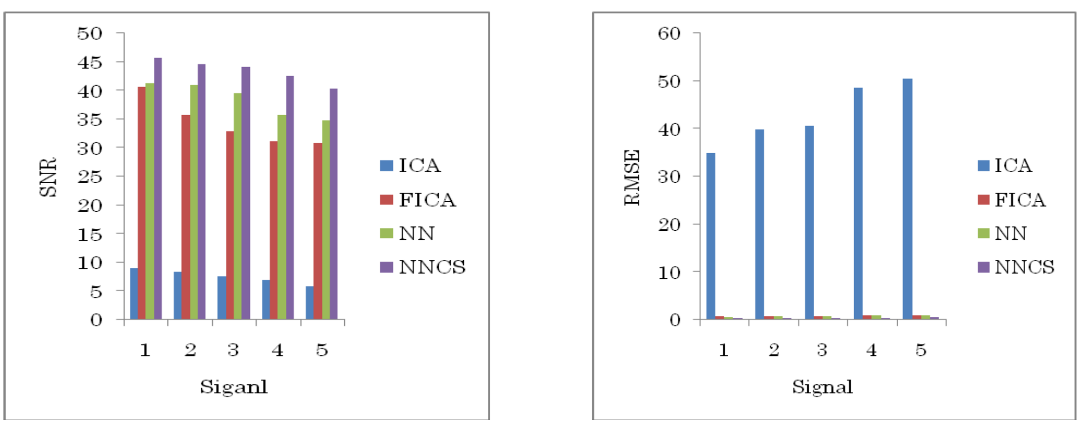


(a) SNR analysis (b) RMSE analysis

Fig. 4. *Performance analysis of SNR and RMSE using EMG artifacts*

5.4 Performance Analysis of SNR and RMSE using EOG Artifacts

In this section, the performance analysis of the proposed model is compared with various existing model by removing the EOG artifact signal while recording the signal of EEG. Here, the artifcats signal is generated from the eye movements called EOG. Figure 5 (a) shows the performance analysis of the SNR and RMSE using EOG artifacts. While analysing the first signal source, the ICA and FICA models obtained the SNAR value of 8.99db and 40.69db respectively. When compared to ICA, FICA model produced the better SNR value. Then, the SNR value of NN model is measured a s41.23 db which is higher than FICA. However, the maximum SNR value is obtained by the proposed NNCS model as 45.76 for removing artifacts effectively. Figure 5 (b) shows the RMSE analysis of the EEG recording by considering the EOG artifacts. By analysing the first signal source, the RMSE value is obtained by various models such as ICA, FICA, NN and NNCS are 34.87, 0.78, 0.65 and 0.29 respectively. From the results, we can conclude that that proposed model obtained the minimum RMSE value of 0.29 compares to other exiting artifacts removal models.



(a) SNR analysis (b) RMSE analysis

Fig. 5. *Performance analysis of SNR and RMSE using EOG artifacts*

6. Conclusion

In this paper, we have proposed Cuckoo Search learning algorithm for NARX model filtering by removing the artifacts signal from EEG. Here, the proposed cuckoo search algorithm is used to finds the optimal weights of the NARX filter for improving the artifacts removal performance. Here, the performance of the proposed NARX filter model in removing the artifacts from EEG signals has also been compared to ICA, FICA and NN model filter. Here, 10 signal sources are considered and the various artifacts like ECG, EOG and EMG signals are included for the analysis. The results conforms the superiority of the proposed filter by obtaining the maximum SNR value as 47.54db and minimum RMSE value as 0.24.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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