A Noval approach for EEG signal artefact removal using Deep convolutional Algorithm

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Abstract: Brain activity is analyzed with the help of EEG signals. It has small amplitude, thus it is influenced by the various artefacts. It is highly needed that the artefacts should get eliminated from the EEG signals by efficacious processing. This paper explores the technicality of deep learning in order to remove the artefacts. For which Pre-processing and feature extraction is to be carried out initially for the EEG signals. Here the wavelet transform is applied to extract the wavelet features, which are scattered to the projected classifier which is called killer whale fractional calculus optimization (KWFCO). The technique is carried out with experimentation for removing artefacts like EMG, EOG, ECG and random noise on the EEG signal. The proposed technique's simulation results have been presented, and they have been found to perform well with improvement in MSE and SNR.

Introduction: Humans neurological disorders can be analyzed by using EEG signals. For this purpose, high quality EEG signals are required. It is an important task to sweep out all the artefacts present in EEG signals to enhance the quality which is suitable for any application. EEG signals are extensively used in the fields of Medical diagnosis such as Anesthetic level, Epilepsy, Brain injury, Tumor location, Alertness monitor, monitoring during surgery, efficacy of yoga etc [1] , Brain-computer interface (BCI) research and Neuro marketing.

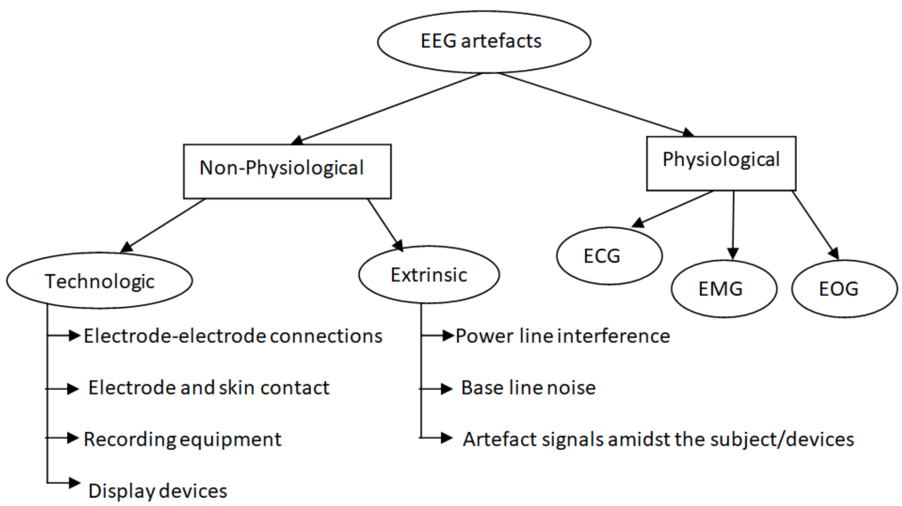


Figure1.Different types of artefacts present in EEG signal

In the long drawn out process, EEG signals are impacted by non-physiological and physiological artefacts [2]. Artefacts of EEG signals are shown in the figure1. EEG plays a vital role in diagnosing sleep disorders. The combination of support vector machine and principal component analysis is used to identify the sleep stages classification [3].

Singular spectrum analyzer is used to remove EOG artefacts from EEG signal, but its disadvantage is that it requires EOG signal as reference signal. The accuracy of this method depends upon the quality of reference signal. Adaptive Noise Canceller (ANC) and Singular Spectrum Analysis (SSA) are used to analyze brain activities from EEG. In this method ANC plays an important role to remove artefacts present in the EEG signal [4].

In multi-channel EEG, various artefacts are removed efficiently by the combination of WICA and SVM. In this method SVM is trained by features like Variance, range of amplitude, Shannon's entropy and kurtosis [5]. ANC with Nature inspired techniques are more powerful, accurate and its output preserves the good shape as input signals. Depending on the application, a particular algorithm is selected [6]. Motion artefacts from EEG signals are removed by using multi resolution schemes. In this method the EEG signals are transmitted through the discrete wavelet transform, total variation and filter respectively for sub banding, approximation and artefact removal from sub bands [7]. Empirical Mode Decomposition (EMD), wavelet transform based methods and regressive models are frequently used for single channel EEG signals denoising, whereas Blind source separation methods are used for multichannel [8].

Firefly and Levenberg Marquardt algorithm are integrated to Optimize the weights of adaptive filter is effectively eliminate the artefacts from EEG signals [9].EEG signal with artefacts are classified as artefacts by independent component analysis (ICA), then the artefacts are eliminated by linear discriminant analysis (LDA)[10]. Least mean squares (LMS) based cascade adaptive filters eliminate EOG spikes, ECG artefacts and line interference using FIR filters by adjusting their coefficients similar to EEG artefacts[11].

The remaining portion of the paper is structured as follows: Section 1 stipulates EEG introduction and literature survey. Section 2 represents the Killer whale Fractional calculus optimization algorithm for the removal of artefacts using deep-ConvLSTM network. Deep conv-LSTM structure is described in Section 3. Section 4 presents Killer whale Fractional Calculus Optimization (KWFCO) Algorithm description Section 5 implies results. Section6 provides conclusion remarks.

II. Killer whale Fractional calculus optimization algorithm for the removal of artefacts using deep-ConvLSTM network:

This part illustrates the specific exploitation of the projected framework in order to eliminate the artefacts from EEG signals. The diagram of the scheme related to removal of artefact proposed is depicted in figure2. It can be understood through the figure that the feature extraction is made susceptible through the pre-processed signals of EEG. Since the signals consist of sensitive information the wavelet features of the signals are obtained by applying the wavelet transform to the EEG signals. The training is maintained through deep learning with productivity received by projected algorithm, as a novas development out of joining FC and Killer whale algorithm.

Pre-Processing: The purpose of removing unwanted noise like power line noise of EEG signal is accomplished by pre-processing. When the EEG signals occupy the projected system which makes use of the notch filter, it is used to sweep out the 50/60 Hz frequencies from EEG signals.

Feature Extraction: In continuation to pre-processing feature extraction are subjected by EEG signals. For any application it is quite important to get the accurate information from the contaminated EEG signals. This process observes apt-able data from EEG signals through executing the needy transition and produces the extracted feature for training. The wavelet features

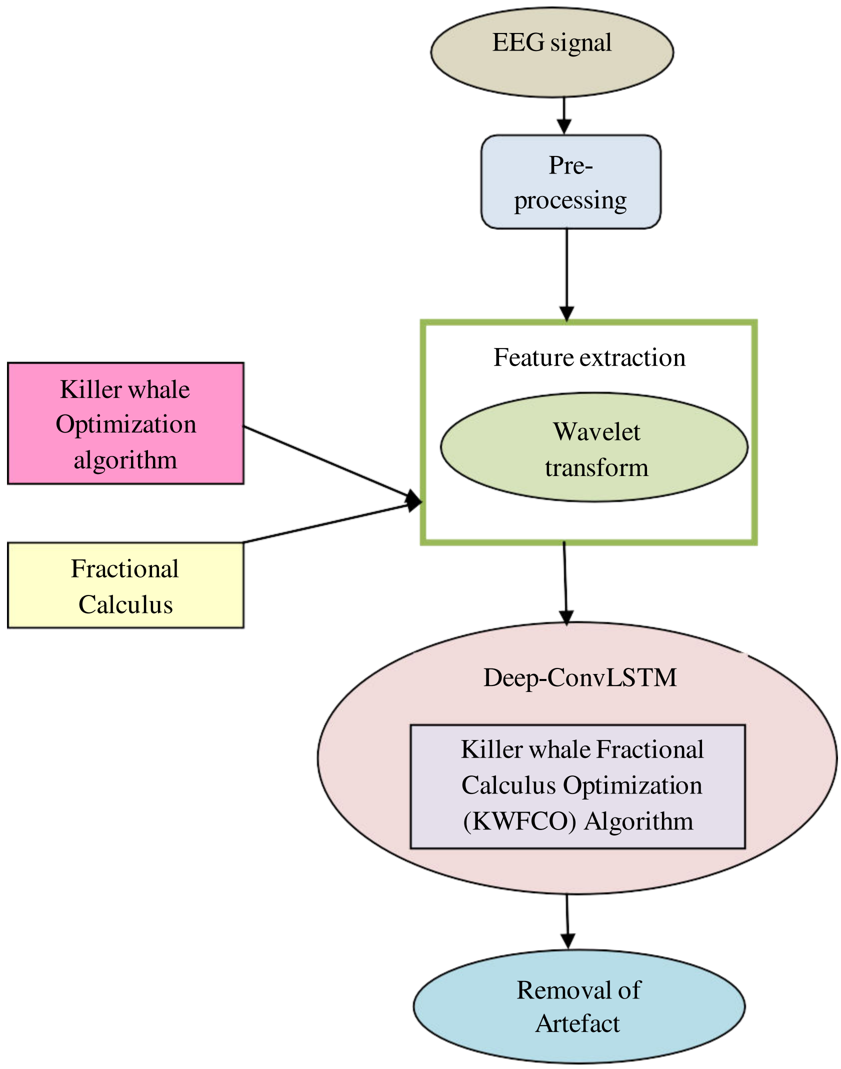


Figure2. Flow chart of killer whale Fractional calculus optimization algorithm for the removal of artefacts using deep-ConvLSTM network

Portrait EEG signal for removal of artefact and therefore this deed gains the valued features from EEG signals, for which the haar wavelet transform, the simplest possible is applied to the signal.

III. Deep conv-LSTM network construction for removing of artefacts from EEG signals:

This part explores the design of the projected deep conv-LSTM network which is shown in figure3. Features of EEG signals have been fed to the network training, as explored in the architecture [15]. The projected deep conv-LSTM has the layered interrelation, which is built as a stack. The outcomes from each network are concatenated as well as supplemented to the 1X1 convolutional network for the last prediction. The encoding structure represents the initial network and forecasting network represents the other. The output of the final prediction is interpreted as follows:

$$\begin{aligned} S_{t+1},\ldots S_{t+K} &= \underset{S_{t+1},\ldots S_{t+K}}{\arg\max}\; s\left(S_{t+1},\ldots S_{t+K} \,\middle|\, \hat{S}_{t-J+1},\ldots,\hat{S}_t \right) \\ &\approx \underset{S_{t+1},\ldots S_{t+K}}{\arg\max}\; s\left(S_{t+1},\ldots S_{t+K} \,\middle|\, f_{encoding}\left(\hat{S}_{t-J+1},\ldots \hat{S}_t \right) \right) \\ &\approx g_{forecasting}\left(f_{encoding}\left(\hat{S}_{t-J+1},\ldots \hat{S}_t \right) \right) \end{aligned} \tag{1}$$

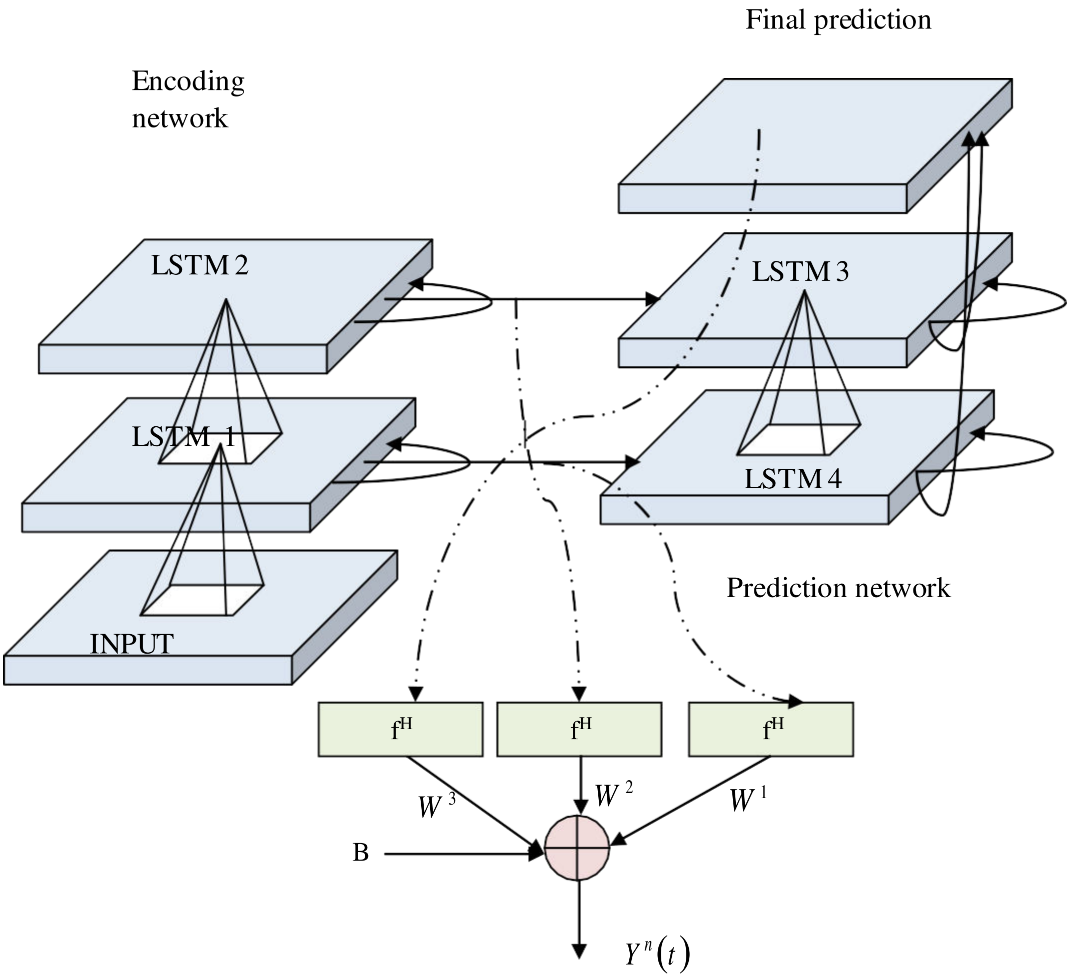


Figure3. Deep convolution Long Short Term Memory architecture

The conv-LSTM layered network is joined to the network fed forward via the possible hidden layer weighted. The input layer has the wavelet features and hidden neurons containing the weights as well as the bias B for the outcome computation which is represented as $Y^n(t)$.

In the elimination of artefacts from EEG signals Deep-ConvLSTM network weights play a significant role. In this proposed method Deep-ConvLSTM weights are generated through Killer whale Fractional Calculus Optimization (KWEPCFCO) Algorithm.

IV. Killer whale Fractional Calculus Optimization (KWFCO) Algorithm description: The proposed KWFCO is implemented incorporating the properties of the FC into the KWO approach. The KWO algorithm is used for solution updation, Whereas the FC technique attempts to incorporate past solutions by including the second order derivative. As a result, the suggested KWFCO algorithm approaches the best solution more quickly than the existing KWO method. The computational steps in the proposed KWFCO algorithm for determining optimal weights are outlined below.

Step 1: Initialize the population: The algorithm begins with Population initialisation, which is nothing but the Whale population. Let the solution space contains N number of solutions represented as:

$$X = \{X_1, X_2..., X_i, ...X_N\}; 1 \le i \le N \tag{2}$$

Where X_i the ith solution and N is the population size.

Step 2: Evaluation of fitness: The fitness evaluation is the next step. The optimisation approach here is to determine the suitable weight for the Deep ConvLSTM network, in such a way that the error is minimum in the fitness function. Fitness of all the N solutions are evaluated in this step by using the equation:

$$E = \frac{1}{N}\sum_{n=1}^{N}\left(D^n - Y^n\right) \tag{3}$$

Where D^n indicates the desired response and Y^n refers to the output of the Deep ConvLSTM network.

Step 3: KWFCO algorithm position update: This algorithm is inspired by the social behaviour of Killer Whale. Matriline is the group of killer whale which consists of members and leader. The duty of the leader is to search the prey position and maximum velocity and minimum distance to catch the prey [12]. The global optimum is determined by comparing the outcomes of each member's actions. In this method, if the member's objective function value is greater than the leader, then the leader must discover another new potential prey [13].

In the chasing mode the whale moves from current location to prey location with some velocity, so the position and velocity updates are formulated as:

$$V_{ij}(t+1) = V_{ij}(t) + c_1\left[X_{best,j}(t) - X_{i,j}(t)\right] + c_2\left[X_{global,j}(t) - X_{i,j}(t)\right] + c_3 .X_{leader,j}(t) \tag{4}$$

$$X_{i,j}(t+1) = X_{i,j}(t) + V_{i,j}(t+1) \tag{5}$$

Where, $V_{ij}(t+1)$ is the velocity updation of whale(i) in j^{th} dimension, $X_{best,\,j}$ is the whales(i) best Position in j^{th} dimension, $X_{i,\,j}$ is whales(i) Position in j^{th} dimension, $X_{global,\,j}$ Global best Position, $X_{leader,\,j}$ is the leader whale position in j^{th} dimension, c_1, c_2, c_3 are the constants. If the global best cost function is less than the leader whale cost function then the leader whale will shift to another cluster therefore c_3=0, If global best cost function is greater than the leader whale cost function then c_2=0 [13].

In the position update, substitute the above expression (4)

$$X_{i,j}(t+1)=X_{i,j}(t)+V_{ij}(t)+c_1\left[X_{best,j}(t)-X_{i,j}(t)\right]+c_2\left[X_{global,j}(t)-X_{i,j}(t)\right]+c_3.X_{leader,j}(t)$$

(6)

Rearranging the preceding equation,

$$X_{i,j}(t+1)-X_{i,j}(t)=V_{ij}(t)+c_1\left[X_{best,j}(t)-X_{i,j}(t)\right]+c_2\left[X_{global,j}(t)-X_{i,j}(t)\right]+c_3.X_{leader,j}(t) \quad (7)$$

To include previous solutions in the position update, the fractional calculus is used [14]. Using fractional calculus to solve the preceding expression

$$D^{\alpha}\left[X_{i,j}(t+1)-X_{i,j}(t)\right]=V_{ij}(t)+c_1\left[X_{best,j}(t)-X_{i,j}(t)\right]+c_2\left[X_{global,j}(t)-X_{i,j}(t)\right]+c_3.X_{leader,j}(t)$$

(8)

$$X_{i,j}(t+1)-\alpha X_{i,j}(t)-\frac{1}{2}\alpha.X_{i,j}(t-1)-\frac{1}{6}\alpha.(1-\alpha).X_{i,j}(t-2)-\frac{1}{24}\alpha.(1-\alpha).(2-\alpha).X_{i,j}(t-3) \quad (9)$$
$$=V_{ij}(t)+c_1\left[X_{best,j}(t)-X_{i,j}(t)\right]+c_2\left[X_{global,j}(t)-X_{i,j}(t)\right]+c_3.X_{leader,j}(t)$$

The KW algorithm's final phrase for position update is as follows

$$X_{i,j}(t+1)=\alpha X_{i,j}(t)+\frac{1}{2}\alpha.X_{i,j}(t-1)+\frac{1}{6}\alpha.(1-\alpha).X_{i,j}(t-2)+\frac{1}{24}\alpha.(1-\alpha).(2-\alpha).X_{i,j}(t-3) \quad (10)$$
$$+V_{ij}(t)+c_1\left[X_{best,j}(t)-X_{i,j}(t)\right]+c_2\left[X_{global,j}(t)-X_{i,j}(t)\right]+c_3.X_{leader,j}(t)$$

Step 4: Best solution finding: By using position update equation of KWFCO algorithm, find the best solution $X_{global,\,j}(t)$,which is minimum fitness value.

Step 5: Finally, the algorithm terminates, when the number of iterations is complete and the optimal solution is nothing but the optimal weight of the Deep-ConvLSTM network.

V. Results and Discussion

Evaluation metrics:

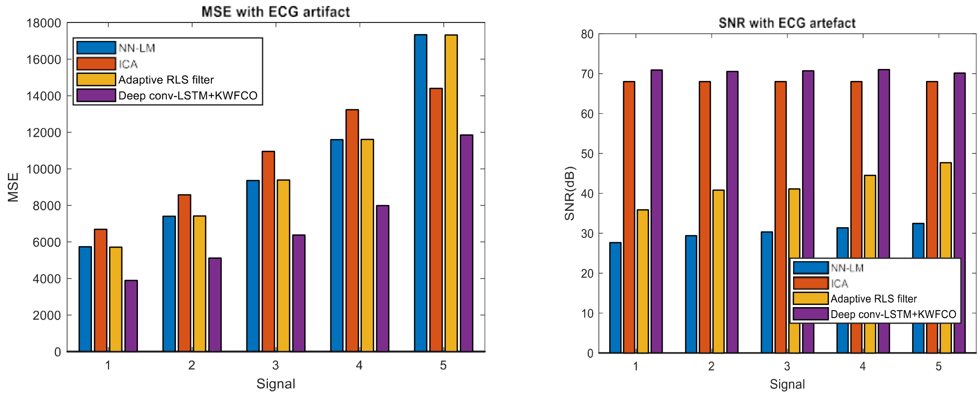
MSE: The MSE metric defines the deviation in actual response to desired response and it is expressed as,

$$MSE=\frac{1}{N}\sum_{n=1}^{N}\left(D^n-Y^n\right)^2 \quad (11)$$

SNR: The SNR measure is calculated as follows,

$$SNR=\frac{\sum_{n=1}^{N}\left(D^n\right)^2}{\sum_{n=1}^{N}\left(D^n-Y^n\right)^2} \quad (12)$$

ECG artefact analysis:



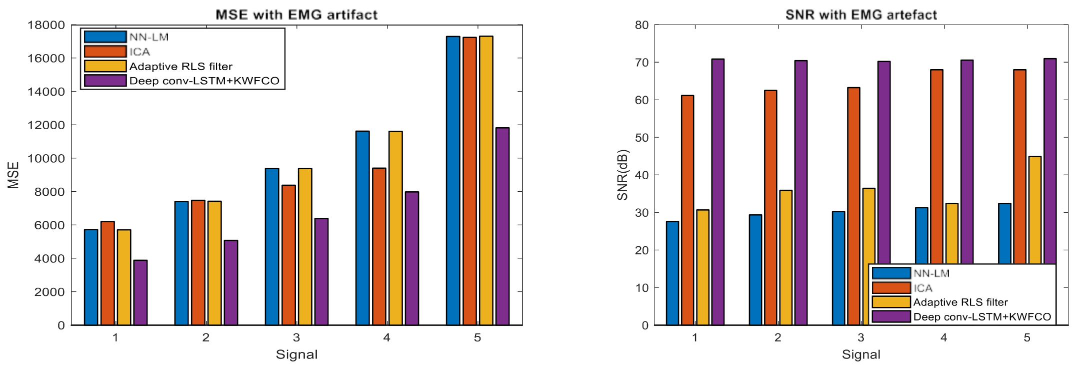
(a)

(b)

Figure4. EEG with ECG artefact analysis based on (a) MSE (b) SNR

Figure4 prostates the analysis of EEG signal in comparison with deep conv-LSTM based on projected KWFCO with the retaining schemes which all are influenced by ECG artefacts. The ECG signals are evaluated through MSE and SNR metrics for the five input signals of EEG. Figure4a explores the comparative analysis of the projected deep conv-LSTM with KWFCO algorithm in order to remove the ECG artefact on the basis of MSE metric. When the EEG signals which are contaminated with the ECG artefact are accomplished as input the models like NN-LM, ICA and Adaptive RLS filter gain the MSE values of 5727, 6684, 5718 respectively. Consequently the projected deep conv-LSTM with KWFCO algorithm performs better with lesser value of MSE that is 3894.Figure 4b describes the same proposal with algorithm to remove ECG artefact where the basis is SNR metric. When the EEG signals which are contaminated with the ECG artefact retaining NN-LM, ICA and Adaptive RLS filter models gained the SNR values of 27.62dB, 68dB, 35.87dB respectively. The same combination of deep conv-LSTM and KWFCO algorithm dominated other models with higher values of SNR that is 70.87 db

.EMG artefact analysis:

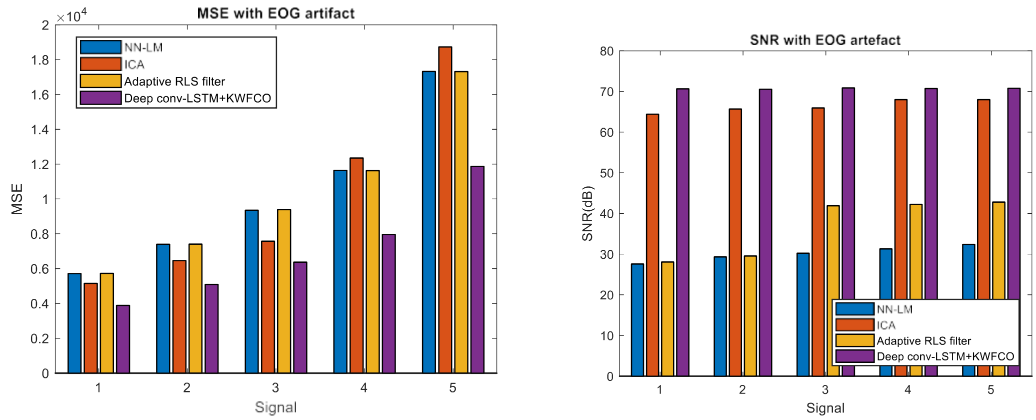


(a) (b)

Figure5. EEG with EMG artefact analysis based on (a) MSE (b) SNR

Figure5 prostrates the analysis of EEG signal in comparison with deep conv-LSTM based on projected KWFCO with the retaining schemes which all are influenced by EMG artefacts. The EMG signals are evaluated through MSE and SNR metrics for the five input signals of EEG. Figure5a explores the comparative analysis of the projected deep conv-LSTM with KWFCO algorithm in order to remove the EMG artefact on the basis of MSE metric. When the EEG signals which are contaminated with the EMG artefact are accomplished as input the models like NN-LM, ICA and Adaptive RLS filter gain the MSE values of 7406, 7475, 7427 respectively. Consequently the projected deep conv-LSTM with KWFCO algorithm performs better with lesser value of MSE that is 5079.Figure 5b describes the same proposal with algorithm to remove ECG artefact where the basis is SNR metric. When the EEG signals which are contaminated with the ECG artefact retaining NN-LM, ICA and Adaptive RLS filter models gained the SNR values of 31.31dB, 68dB, 32.43dB respectively. The same combination of deep conv-LSTM and KWFCO algorithm dominated other models with higher values of SNR that is 70.58db

EOG artefact analysis:

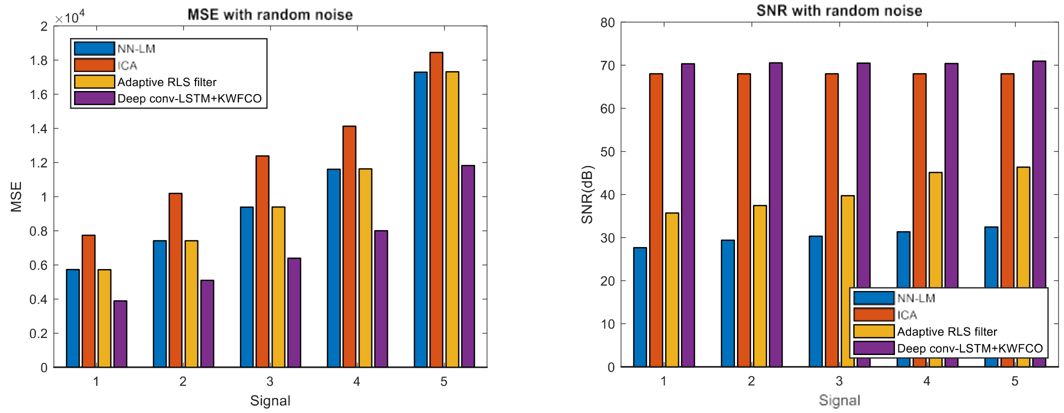


(a) (b)

Figure6. EEG with EOG artefact analysis based on (a) MSE (b) SNR

Figure6 prostrates the analysis of EEG signal in comparison with deep conv-LSTM based on projected KWFCO with the retaining schemes which all are influenced by EOG artefacts. The EOG signals are evaluated through MSE and SNR metrics for the five input signals of EEG. Figure6a explores the comparative analysis of the projected deep conv-LSTM with KWFCO algorithm in order to remove the EOG artefact on the basis of MSE metric. When the EEG signals which are contaminated with the EOG artefact are accomplished as input the models like NN-LM, ICA and Adaptive RLS filter gain the MSE values of 9364, 7578, 9388 respectively. Consequently the projected deep conv-LSTM with KWFCO algorithm performs better with lesser value of MSE that is 6381.Figure 6b describes the same proposal with algorithm to remove EOG artefact where the basis is SNR metric. When the EEG signals which are contaminated with the EOG artefact retaining NN-LM, ICA and Adaptive RLS filter models gained the SNR values of 30.28dB, 65.96dB, 41.88dB respectively. The same combination of deep conv-LSTM and KWFCO algorithm dominated other models with higher values of SNR that is 70.88db

Random noise analysis:



(a) (b)

Figure7. EEG with random noise analysis based on (a) MSE (b) SNR

Figure7 prostrates the analysis of EEG signal in comparison with deep conv-LSTM based on projected KWFCO with the retaining schemes which all are influenced by random noise artefacts. The random noise signals evaluated through MSE and SNR metrics for the five input signals of EEG. Figure7a explores the comparative analysis of the projected deep conv-LSTM with KWFCO algorithm in order to remove the random noise artefact on the basis of MSE metric. When the EEG signals which are contaminated with the random noise artefact are accomplished as input the models like NN-LM, ICA and Adaptive RLS filter gain the MSE values of 17286, 18445, 17315respectively. Consequently the projected deep conv-LSTM with KWFCO algorithm performs better with lesser value of MSE that is 11815.Figure 7b describes the same proposal with algorithm to remove random noise artefact where the basis is SNR metric. When the EEG signals which are contaminated with the random noise artefact retaining NN-LM, ICA and Adaptive RLS filter models gained the SNR values of 32.43dB, 68dB, 46.34dB respectively. The same combination of deep conv-LSTM and KWFCO algorithm dominated other models with higher values of SNR that is 70.95d

VI. Conclusion remarks: EEG signals having little amplitude and influenced by artefacts are used to analyze brain activity. The detection process is affected by the artefacts present in the EEG signal, which makes it relevant to eradicate the artefacts from EEG signals. This experiment has initialized the framework for the removal of artefacts. Here the modification of conv-LSTM network through the development of deep conv-LSTM is accomplished where the capacities for the projected network are selected from the KWFCO algorithm proposed. In this deed the algorithm is improved by modifying KW with fractional calculus. Firstly, different channels produce EEG signals which are processed beforehand and related to the extraction of features. EEG signals yielded wavelet features, which were then fed into the proposed deep conv-LSTM network, which removed artefacts from the signal while producing the original EEG signal.. For this experiment four distinctive artefacts i.e. EOG, ECG, EMG and random noise are promoted in EEG signals. The results of this scheme are contrasted with that of retained techniques as well as calculated with metrics of MSE and SNR. From simulation outcomes it is interpreted that the proposed deep conv-LSTM with KWFCO algorithm has achieved the values i.e. 3891 and 70.98dB for MSE and SNR respectively.

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