EEG Artifact Removal Using Supervised Learning based Neural Filter

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Abstract: During the acquisition time, electroencephalography (EEG) signals suffer from motion and eye blink artifacts. There is various unsupervised learning based artifact removal methods were designed in literature. But most of existing methods are unable to remove the high peaks of eye blink artifacts. The goal is to create a filter that suppresses all motion artifacts at the same time. Therefore this paper is proposed to design efficient supervised learning based adaptive neural Filter for eradication of motion artifacts. The performances of unsupervised approaches like canonical correlation analysis (CCA) and in combination to ensemble empirical mode decomposition (EEMD) are compared with the proposed adaptive neural filter. The multi perceptron neural network model is trained to design the optimum filter in this work. The learning rates are adapted and training is based on the filtered EEMD-CCA signal for improving the performance. The Qualitative evaluation is presented based on the reproduced signal and quantitate effectiveness is preseted using peak signal to noise ratio (dSNR), and estimation error along with accuracy of RIC curves.

Keywords: Electroencephalography (EEG), Canonical Correlation Analysis (CCA), Ensemble Empirical Mode Decomposition (EEMD), Artifact Removal, Neural Filter.

DOI: 10.48047/ecb/2023.12.8.704

1. Introduction

EEG signals, which may be utilised to immediately identify fluctuations in electrical activity in the brain across timescales of milliseconds, are frequently employed for studying human brain activity therefore are favoured over alternative physiological signals. Biomedical signals for Electroencephalography (EEG) are impacted when there are artefacts from muscular movements. The occurrence of these artefacts causes errors in the visual processing of the EEG signal, which leads to incorrect disease diagnosis. These are the person's muscular as well as ocular movements, which result in low-amplitude, low-frequency impulses of electricity that can pass through filters on sensors while recording EEG data [1]. Therefore when EEG signal evaluations are performed outside of the typical clinical setting, artefacts result. Filtering methods must be used primarily to minimise artefacts before processing the EEG data for subsequent analysis [2].

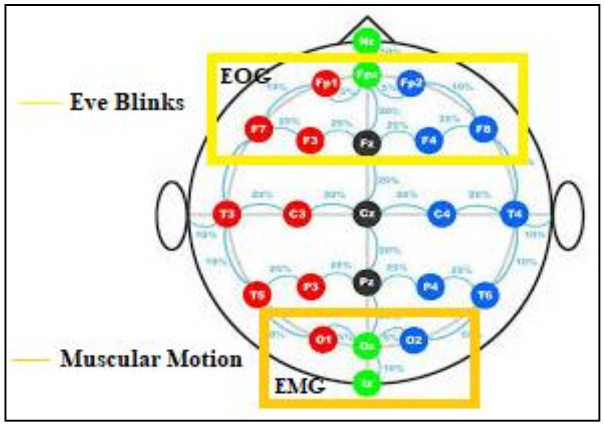

Fig. 1 (a) EEG signal scalp recording and responses

In addition to the sensors and surroundings, there are two primary types of artefacts in brain signals: eye blinks, which cause artefacts in electrooculograms (EOG), and muscular action, which causes artefacts in electromyograms (EMG). The most of unsupervised learning based filters were available in literature but are unable to simultaneously elimination of bot the motion artifacts. It is observed that EEMD and CCA based methods [1, 2, 3] were unable to completely remove the effect of eye blink artifacts.

The acquired EEG data is a multichannel data usually captured using the10-20 electrodes international standard. The process of EEG scalp data acquisition is illustrated in the Figure 1 (a). This EEG signals gives excellent results over other physiological signals. This EEG signals captured by the electrodes kept on scalps of human brain. There are two independent data bases of 16 and 24 respective channel or electrodes are considered in the preset study as shown in the Figure 1 (b).and (c) The 24 channels data is without motion artifact and 16 channels with EOG and EMG artifacts as shown in Figure 1 (c). Now the goal of paper is to eradicate the artifact signals.

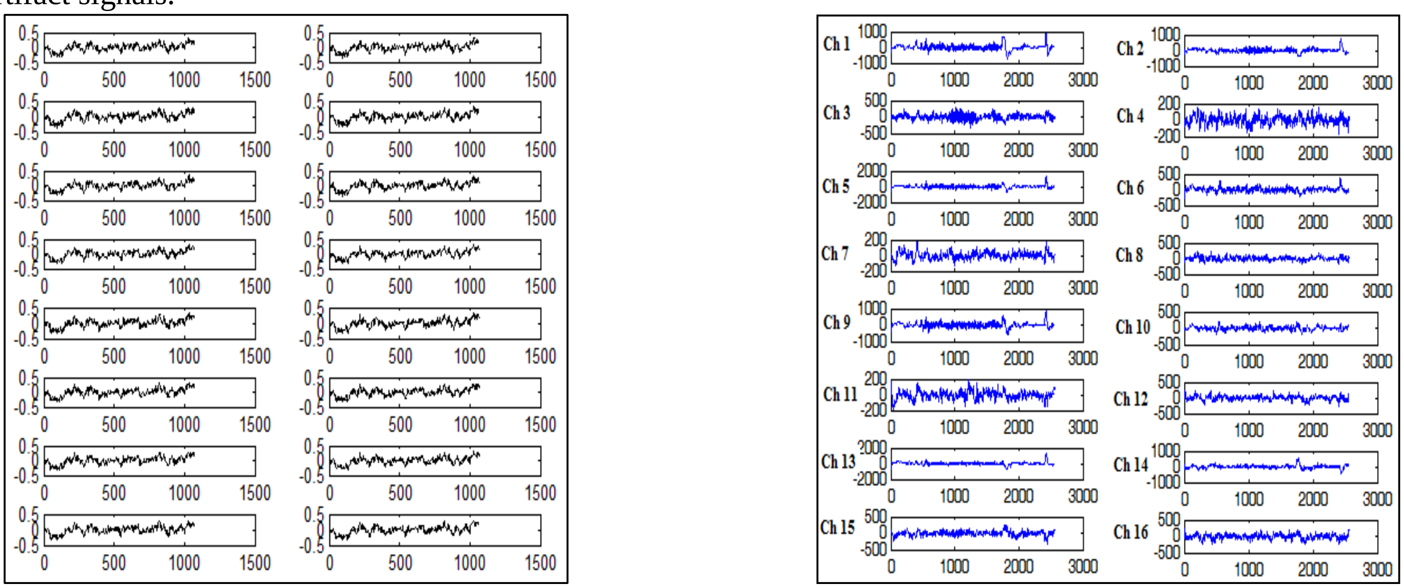

Fig. 1 (b) 16 MIT scalp channel without artifacts (in black) Fig. 1 (c) 16 channels with artifacts (blue)
Figure 1 the EEG signal data base used for the validation and study

The types of artifacts are plotted in the Figure 2 for the clear representation. It can be observed from Figure 2 that raw EEG data may suffer from either muscular motion artifact (shown under green rectangle), or eye blink artifact (shown under yellow rectangle) or both of them.

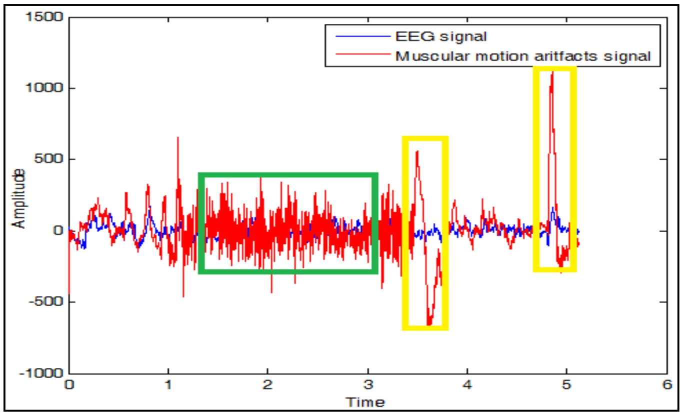

Fig. 2 Artifacts and clean EEG signal representation, the referenced artifact Channel 7 (in blue) and artifacts Channel 5 (in red) are shown for first 10 seconds recording

1.1 Contribution of work

This research paper focuses to design the supervised learning based adaptive neural filter for the removal of nose and EEG motion artifacts. These artifacts are generated due to movement in patient's body part and also due to electrode movement during EEG signal capturing. Thus, the elimination of these artifacts from the original EEG signal is a challenging process. The paper contributed to train the BPNN based adaptive neural network based multi perceptron filter for simultaneously eliminating the muscular and eye blink artifacts. The performance of unsupervised EEMD-CCA based filter is validated and compared with the proposed neural filter model.

2. Multi Perceptron NN

In this paper it is propped to design the adaptive NN filter for artifacts removal case. The core of the NN filter is the efficient use of the multi perceptron layer model. The input and output modelling is achieved for adaptive filter based on the NN are adapting the multi perceptron architecture as shown in the Figure 2, The artefact EEG signal (net input xn)) is multiplied by the connections' associated weights (Wij) administering stimulation to the net input results in the output signal y(n).

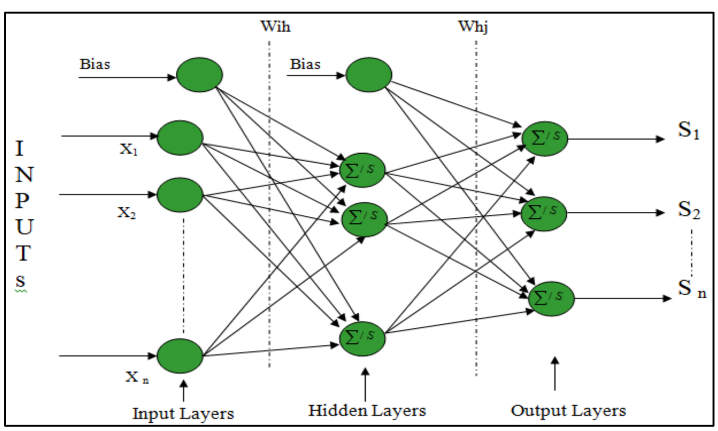

Fig. 3 the multi perceptron Feed Forward NN architecture

The basic architecture of the adaptive filter design is shown in the Figure 4. It can be observed that in order to update the adaptive weights proposed method uses the steepest decent search based BPNN adaptive filter models. The proposed filter uses the minimum mean square error (MMSE) updating concept as shown n Figure

4.

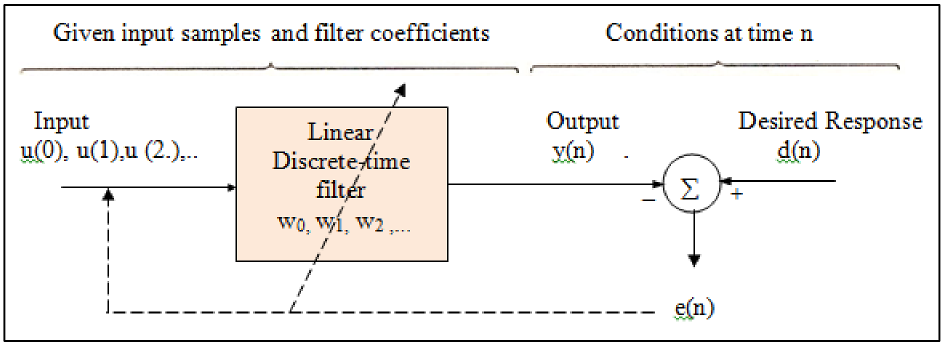

Fig. 4 the block repetition of the adaptive filter process

There is a natural inaccuracy in estimating$d(n)$, which is represented by the difference as;

$$e(n) = \ desired\ responce — output \qquad (1)$$

Let y_0(n) represent the outcome of the MSE-optimized filter, and let e(n) represent the equivalent estimation error,

$$e_0(n) = \ d(n) — y_0(n) \qquad (2)$$

Paper proposed NN filter which works on the concept of supervised learning. A sequence of sample inputs are given to the network during supervised learning and the output is then compared to the anticipated answers. Up until the network has the capacity to deliver the anticipated response, the learning continues.

2.1 BPNN Filter Model

BPNN is essentially a gradient descent method for minimizing an error criteria e(n). The gradient of the entire learning set is used as the basis for the descent in the batches mode variant:

$$Wij\ (n) \ = \ -\eta \ \ d\,E \ \ + \ \alpha\, \Delta Wij\ (n-1) \qquad (3)$$

Where learning rate (η) as well as momentum (α) are two key nonnegative steady parameters. Weight changes in gradient-descending learning are proportional to the inverse of the error gradients. The output to the hidden layer is given by;

$$\frac{\partial \varepsilon_k}{\partial w^k_{hj}} = \frac{\partial \varepsilon_k}{\partial \delta\left(y^k_j\right)} \frac{\partial \delta\left(y^k_j\right)}{\partial y^k_j} \frac{\partial y^k_j}{\partial w^k_{hj}} \qquad (4)$$

Similarly the hidden layer inputs are defined as

$$\frac{\partial \varepsilon_k}{\partial w^k_{ih}} = \frac{\partial \varepsilon_k}{\partial \delta\left(z^k_{ih}\right)} \frac{\partial \delta\left(z^k_h\right)}{\partial z^k_h} \frac{\partial z^k_h}{\partial w^k_{ih}} \qquad (5)$$

The desired signal and error signal are continuously updated till the medium criterion is not satisfied so as to reach to the optimal solution by the system. .

3. EEG Artifact Removal Methodologies

Numerous unsupervised techniques are employed for the removal of EEG artefacts. These techniques include various fusions of EEMD [7], EEMD-CCA [2], and EEMD-ICA. Basic modeling for various decomposition techniques is defined in this section.

3.1 The Empirical Mode Decomposition (EEMD)

The EEMD breaks down a signal into numerous intrinsic mode functions (IMFs) through an iterative process known as sifting. The IMF1 is the mean of the upper and lower envelops of the first-level EEG signal X(t). To obtain the residual signal, IMF1 is subtracted from X(t). After each iteration of this procedure, the remaining signal energy level is close to zero, which is the halting condition. The residual signal is still visible as;

$$P_n(t) = P_{n-1}(t) - IMF_n(t) \tag{6}$$

Where, $P_n(t) = EEG(t)$ input EEG data. Finally, the signal is reconstructed by adding all IMFs and residual signal a

$$EEG_{emd}(t) = P_n(t) + \sum_{i=1}^{N} IMF_i(t) \tag{7}$$

The submission of eq. (2) leads to the averaged IMF's component $EEG_{emd}(t)$ which can be used from the further processing stages.

3.2 CCA and Decomposition

The usual current CCA algorithm assumes X[n] and Y[n] are two sets of random variables (Ref. Roy et al [2]). Let X[n] be the $EEG_{emd}(t)$ matrix's input vector, and Y[n] may be defined as its temporal correlations determined by 2D convolution operations with X[n] vectors employing the linear convolution masking as [1 0 1] mathematically given as:

$$Y[n] = conv2(EEG_{emd}(t), [1\ 0\ 1]) \tag{8}$$

Let be the maximum canonical correlation, C_{xx} and C_{yy} are auto co-variances of vectors $X = EEG_{emd}(t)$ and temporal vector Y. in addition to this let C_{xy} and C_{yx} cross co-variances values of the X and Y respectively. The correlation matrices can be determined as;

$$C_{xx} = \mathrm{C}(1{:}sx, 1{:}sx) + \beta * I_{sx} \tag{9}$$

$$C_{yy} = \mathrm{C}(1{:}sy, 1{:}sy) + \beta * I_{sy} \tag{10}$$

Where, sx and sy are the size of $X = EEG_{emd}(t)$, and Y respectively

4. Related Works

There are huge amount of methodologies were proposed in the past for eliminating the motion artifacts from the raw EEG data. This section is aimed to sequentially review the existing work specifically on EEG artifact removal. The broad classification of the artifact removal methods are given in the Figure 5. Overall review is sub divided to two parts first part considering Canonical Correlation Analysis (CCA) and IIR filter based approaches and second is based on neural filter designs. The components provide the information's distinct nature, whilst artefacts mix into independent sources hence signal reconstructions done with no source's knowledge are marketed as providing artefact-free information.

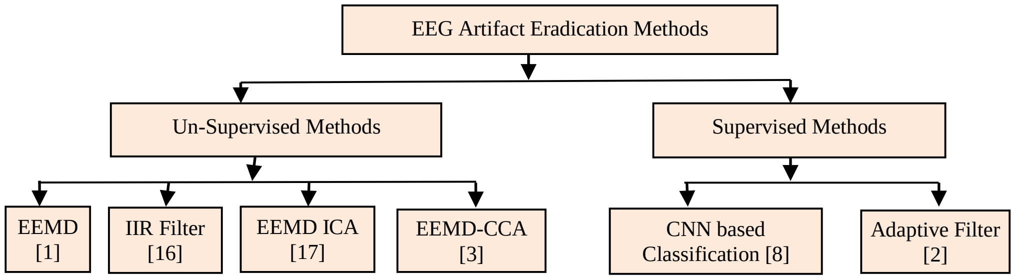

Fig. 5 Classifcation of Artifact eradication methods

H. Zeng et al [1] have used sub space based analysus in combination to EEMD for the EEG artifact eridication, A novel adaptve filter using the Dicision feedback is proposed by the Satyender, et al [2] for artifact removal. Effciecnt modified gaussian elimination basefd CCA approach was proposed by the Roy Vandana, et al. [3] the method was combination of EEMD_CCA_DWT approach. It has still slight eye blink amplitudes after elimination. But still method has good performance over previous approaches. Zhang, C., et al. [4] have used single ECG channel based artifact removal using automatic filtering concept. But for high amplitude EEG data it seems bit fuzzy to implement for.

For effectively eliminating EEG artefacts, an enhanced cascaded technique based on Gaussian elimination CCA (GECCA) and EEMD is used.by K.T. Sewwney [6].This research examines the physiological signals that are most likely to be recorded at home, identifying the artefacts that occur the most frequently and have the greatest deteriorating effect. Following that, a full examination of current artefact removal approaches will be presented. An assessment of the benefits and drawbacks of each of the proposed artefact identification and removal approaches is offered, with a focus on the personal healthcare arena. Mahmud, S. et al [7] have prpposed using CNN based EEG signal processomg. Frlich, L., et al. [8] examined 3 of the most regularly used ICA methods (extended Infomax, FastICA, and TDSEP) against two alternative linear decomposition approaches (Fourier-ICA and spatio-spectral decomposition) suited for oscillatory activity extraction. J. Geo et al. [9] had designed an innovative and robust technique for removing EMG artefacts from EEG signals in real-time is given. To separate EMG artefacts from EEG signals, the canonical correlation analysis (CCA) method is first applied to simulated EEG data contaminated by EMG and electrooculography (EOG) artefacts. An specific approach to eliminate the muscular EMG artifacts are preseted by the M. Anastasiadou, et al [10] but major concern is to eliminate the eye blinks peaks. .

Nalini singh et al [11] have proposed the combination of the EEMD with the CCA for the artifact removal butonly consider the few EEG channels for evaluationsof results. Recently Hemant Amhia et al [12] have designed the rduce order IIR filter for the artifact smootening from the ECG signals. The method works good enpough and belongs to unsupervised learning case. Prerna Kumari eta l [13] have used the IIR filter for denoising f dignita hearing aids applications an use of the BPNN based adptive filter for modulated signal denoising is preseted by the Vyas, P. K., et al [13]. Method is efficient enough and demonstrated the good use of sepesed gradient descent approach for modeling the BPNN neural filter. Some other singe EEG chanel artifact removal approaches are presented by the Maddirala, A. K et al [15] and Maddirala, A.K., et al [16]. In these methods they have adopted the k-meas based smoothening for the elimination of eye blinks, method performance was stochastic. L. Wang has used EEMD-ICA for artifact removal and is improved by the X. Chen eta l recent ly stated that EEDM-CCA is an efficient approach of the EEG artifact eradication. Thus EEDM-CCA is prefer in this research for improvement in performance. Seol HY, et a; [19] and the Gholami et al [20] have also designed valrious applictions of the NN based filter designs.

5. Proposed Methodology

In this paper a modified new methodology is proposed using the combination of the EEMD-CCA approach with the adaptive neural filter for elimination of EEG artifacts. The current study describes an adaptive artifact eradication technique-based filter design that uses NN technology. The EED-CCA filtered validated EEG data x(n) is used as the noisy signals input to the NN filter to train the filter. The basic FIR filter is used on the input data x(n) to produce the desired output d(n). The BACK PROPAGATION neutral network (BPNN) is then used to eliminate artifacts. The BPNN based training is applied for the adaptive learning based filtering process. The filter weights are adopted based on the learning model. The block diagram of the proposed method is shown in the Figure 6. It is clearly observed from Figure 6, that method condones the advantage of EEMD-CCA along with NN filter. Mostly filters are used in different commination systems [21-22].

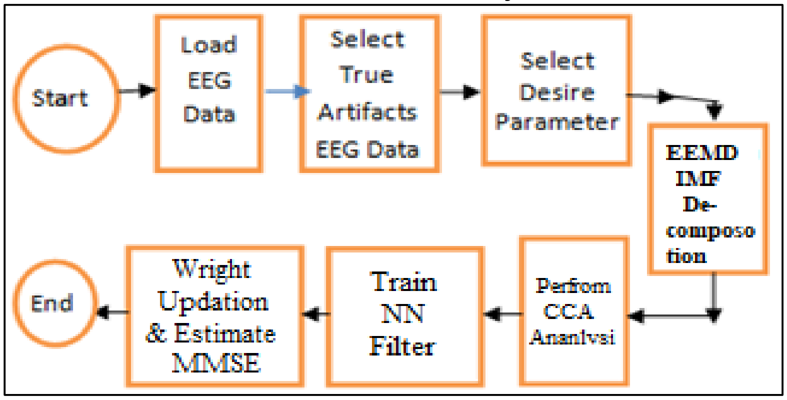

Fig. 6 sequential diagram of proposed NN based EEG artifact removal System

The proposed algorithm is sequentially written as follows;

Algorithm: 1 EEG artifact Removal using NN filter

1. Read true artifact EEG signals $\leftarrow EEG_i$, ← from EEG data base ← i is the channel no. in database
2. Exposed to the EEMD intrinsic mode functions (IMF's) and decomposes multi-channel data.using
$$X(t) = P_n(t) + \sum_{i=1}^{N} IMF_i(t)$$
3. Summed up IMFs is passed to the CCA mode decomposition
$Cxx = C(1{:}sx71{:}sx) + \beta * I_{(sx)}$
4. The summed up CCA modes are filtered using the conventional correlation filter model. Pearson's correlation coefficients are adopted for the suppression of artifacts and reconstruct artifact-free signal.
5. The neural filter parameter initialization is carried out.
6. Apply the neural filter in place of correlation filter to eliminate the further artifacts from the EEMD-CCA filter EEG data.
7. Train the neural filter for the optimum filtering of EEG artifacts.
8. Parametric evolution is carried out based on SNR and correlation improvement. And the qualitative performance comparison is carried out.

End algorithm

6. Results and Discussions

In this paper the novel approach of the EEG signal artifact removal is proposed. The adaptive Back propagation based neural filter is designed as the combination of the EEMD-CCA-NN approach. The adaptive filter is applied over the filtered EEMD-CCA signal data and the higher peaks of EOG signal eye blinks which are still available in EEG data are almost completely eliminated by the use of NN filter.

6.1 Results of EEMD-CCA Validation

The results of the applied EEMD and CCA mode decompositions are shown in the Figure 7 for the EEG input data 7 with motion artifacts. It is clear from the Figure 7 a) that EEMD decomposes from higher to lower frequencies while as in Figure 7 b) the CCA does the reverse operation.

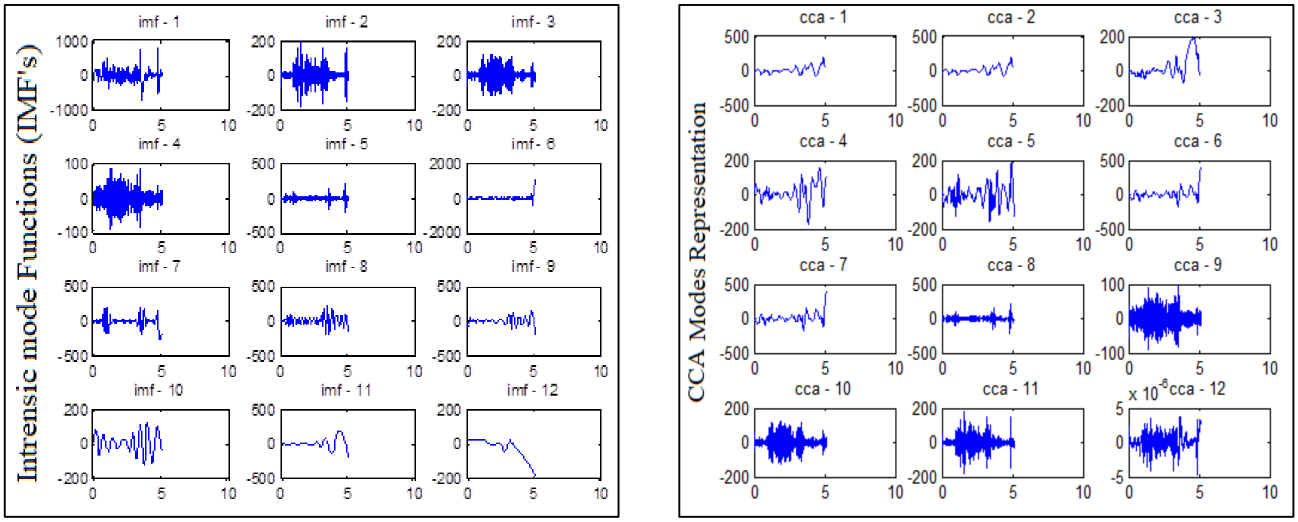

Fig. 7(a) EEMD mode IMF decomposition **Fig. 7(b) Exampple of CCA modes Decomposition.**

Fig. 7 Results of the multimode EEMD and CCA decomposition for EEG data.

The EEG signals filtering results are shown in the Figure 8 for the validation of the EEMD-CCA based filtering using correlation filter. It can be observed from the green color boxes in the Figure 6 that still certain amplitude of the eye blink peaks are available in the EEG data although signal is filtered significantly. In addition the muscular artifacts are filtered but still have magnitudes of the range of the around 200. The nature of the true EEG is still questionable. This in this paper additional level of adaptive neural (NN) filter is proposed to apply over EEMD-CCA filtered data.

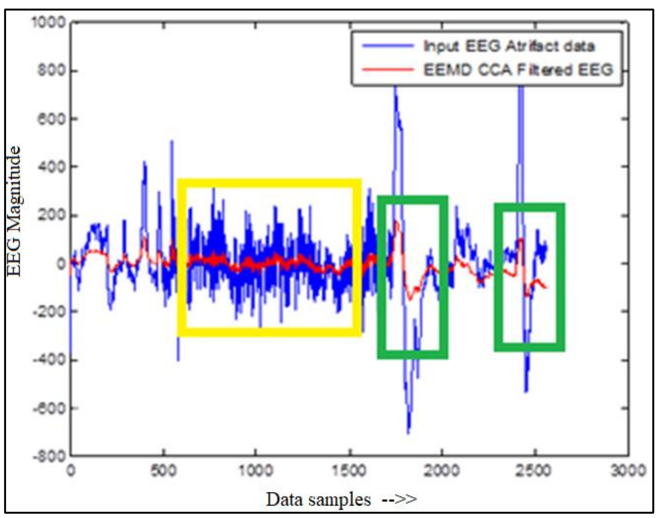

Fig. 8 Validated Results of EEMD-CCA filtered EEG signal data for motion artifacts

6.2 Modeling and Results of Adaptive neural Filter

In this paper it is proposed to design the adaptive neural filter model for the EEG signal smoothening. The sequential flow chart of the NN filter design is presented in the Figure 9. The basic system diagram of Figure 5 is sequentially presented in terms of NN filter design in the flow chart below. The 5 step of adaptive weight adaption based on the steepest decent gradient search algorithm is explained in Figure 9.

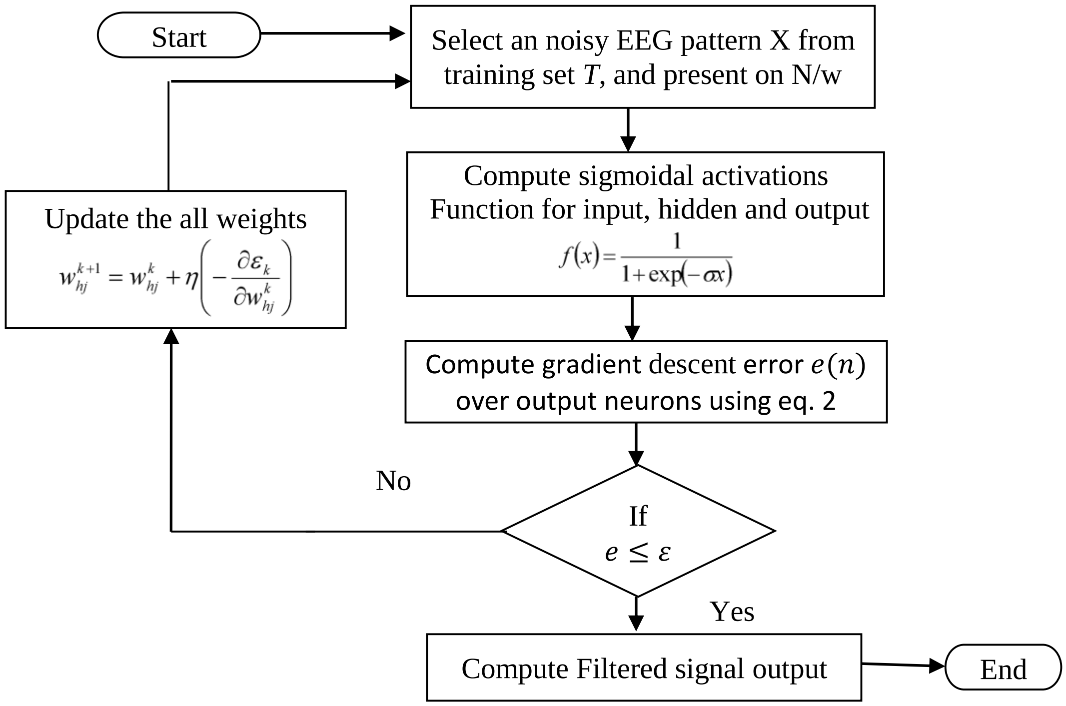

Fig. 9 flow chart of learning process of NN filter weight adaption

The first step of the neural filter is to add the random noise to the input EEG data an example of the random AWGN noisy signal over true EEG data is shown in the Figure 10. The noisy data is considered as the input to the NN filter loop.

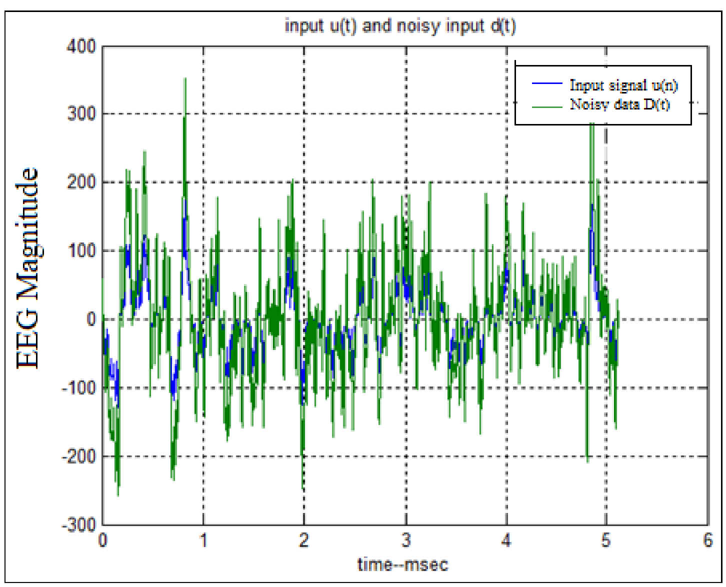

Fig. 10 Example of simulated input and random noisy EEG signal on true EEG data

The second step is to pass the noisy EEMD-CCA filtered EEG data with artifact considered as the input for training the NN filter. The results of the desired signal initial estimate d(n) and noisy data are presented in the as shown in the Figure 11. For the desired signal initial estimate d(n), the noisy EEMF-CCA signal is passed to the random finite impulse response (FIR) filter for considering the initial training data the respective results are presented in the Figure11 a). .

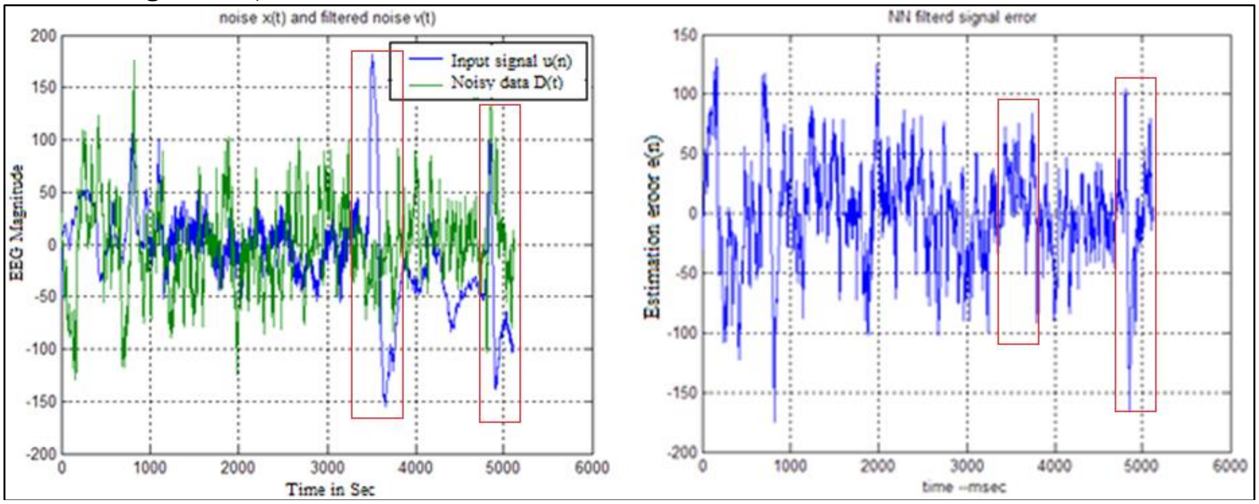

Fig. 11(a) Random FIR Filtered desired signal d(n) and noisy signal Xn(t) , Fig. 11(b) Estimation error
Figure 11 Results of the NN Filter for EEG artifact removal

The respective results of the calculation of the estimation error e(t) of the NN filter model for final titration counts is shown in the Figure 11 (b). It can be observed that significant reduction is offered in the estimation error as shown by the comparison of eye blink artifacts shown in red color boxes in the figure 11 a) and Figure 11 (b). Effectiveness of the NN based filter in combination to EEMD-CCA is clearly observed under first red box where the higher peak estimation error of nearly range of 300 mv (-150 to 150 mv) is reduced to the range of les then 100 mv after fingering. Another most important aspect of the filter design challenge is that true nature of t EEF data must not change after the smoothening. These results are very much clearly represented in the final filtering result of the proposed NN based filter design as shown in the Figure 12. It can be clearly observed that as the rue eeg data is considered as the desired input thus after the faltering and artifact removal the true nature of the data remains same although slght amplification is still there.

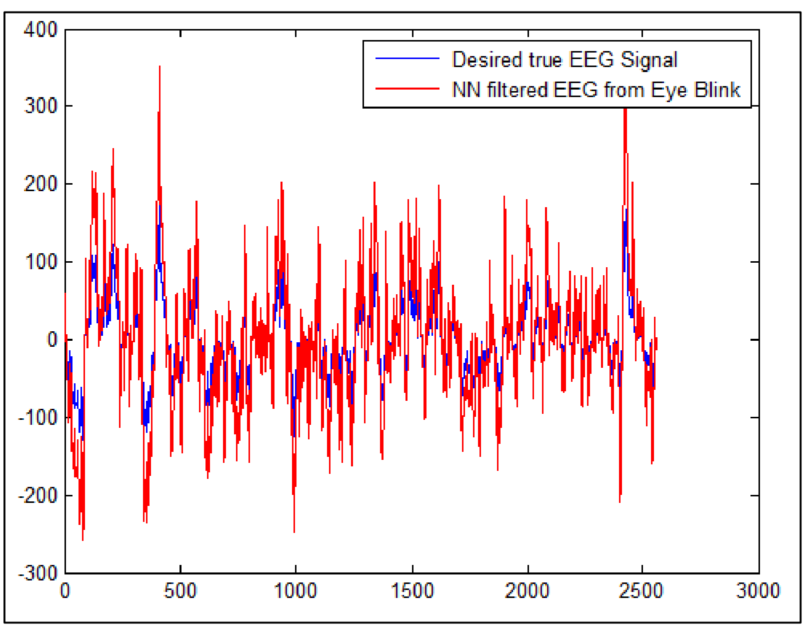

Fig. 12 Results of the applied proposed NN filtered EEG data

7. Parametric Evaluation

The parametric evaluation is done based on the power spectral density, DSNR calculation, and the Accuracy of ROC curves is plotted in the Figure 13 (a). The similarly the power spectral density is plotted in the Figure 13 (b) for two methods.

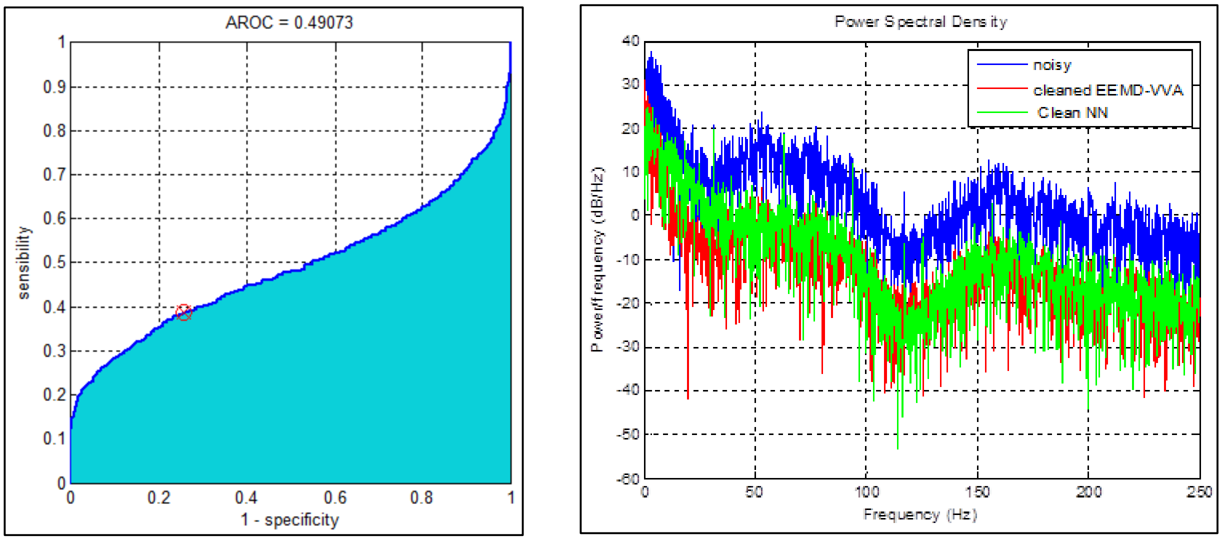

Fig. 13 quantitative results of the Filter design Fig. 13 (a) Extracted ROC curve accuracy for NN filter, Fig. 13 (b) The comparison of the Power spectra density

It can ne seem from the Figure 13 (b) that the smoothen PSD is achieved for the NN filter , although still there is significant efforts are required to carefully tune the filter for much better reproduction of EEG data.

8. Conclusions and Prospective

In this work we proposed to design the adaptive filter for removing the EEG artifact The supervised learning based neural filter is proposed to design for eliminating the ocular artifacts and minimizing macular artifacts. The neural filter design is a difficult problem in hand .It is required to tune the design parameters for improving the efficiency of EEG artifacts removal. In this study, it is suggested that an effective supervised learning-based adaptive neural filter be created to eliminate motion artifacts. When combined with EEMD-CCA the proposed adaptive neural filter outperform over the unsupervised methods like CCA and EEMD. The multi-perceptron neural network model is trained in this study to create the optimum filter. Training is based on the filtered EEMD-CCA signal, and learning rates are modified to enhance performance. Based on the parametric study it is concluded that NN filter is close approximation of true signal and MSE is minimized. In future the learning rates and filter parameters are to be tubed for the better performance of data filtering. Also independent NN filter can be applied directly on the true EEG data for filtering the data in future.

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