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Implementation of Efficient Artifacts Removal Technique for Electroencephalogram Signal Using Neuro-Fuzzy Filtering and Multiwavelet Transformation

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ABSTRACT

Mind is the most unpredictable organ in the human body. The mind makes a scope of electric potential for each activity done by the human. For brain diagnosis the Electroenchaphalogram (EEG) is the signal of interest. But EEG which should read the scalp electrical activity of the human body also reads its physiological and extra physiological activities which are collectively called as ‘artifacts’. These artifacts which are the interference to EEG should be eliminated for proper diagnosis. In this paper, two efficient methods are implemented for the removal of artifacts. The first method proposes principle behind the neuro-fuzzy system clearly. In this work the neuro-fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdanimodel; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model. The Second method presents the details behind the multiwavelet transform. They are defined using several wavelets with several scaling functions. Multiwavelet has several advantages in comparison with scalar wavelet. The features such as compact support, orthogonally, symmetry, and higher order approximation are known to be important in signal processing. In this method thresholding technique is used for signal de-noising. The de-noising of EEG signal is carried out by using different combinations of threshold limit, thresholding function and window sizes. Choice of threshold limit and thresholding function is a crucial step in the denoising procedure, as it should not remove the original signal coefficients leading to loss of critical information in the analyzed data. It can be seen that the Multiwavelet transform is more efficient in removal of artifacts than Neuro fuzzy filter. The efficiency is measured in terms of SNR and Correlation factor.

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INTRODUCTION

The human cerebrum, separated from being the inside of human sensory system, plays an extraordinarily a momentous part in controlling all the physical and mental exercises and considered as the most unpredictable organ in individuals. Teplan.M (2002) early proves that, the recordings of the Electrical Movement o0f the cerebrum give learning with respect to those elements utilarian conditions of the brain. The human mind persistently gets tangible data through the neurons, breaks down the information and afterward reacts immediately. Consequently, the human cerebrum assumes a critical part in managing and observing the body's activities and responses. Hillyard (1970) early prove that, EEG is an estimation of the nonstop mind wave designs or electrical movement of the cerebrum, as recorded with the arrangement of little metal circles called anodes situated in an institutionalized example on the scalp. The ensuing following reflects the summation of the movement of a large number of individual neurons. The voltage and recurrence are deciphered and it is valuable for surveying cerebrum demise, seizure movement, and for deciding phases of sleep.EEG is a mind wave imaging system used to quantify the spontaneous electrical action of the cerebrum over a brief time of time by means of the metal anodes set on the scalp and the conductive media. EEG assumes an imperative part in distinguishing the irregularities identified with the electrical exercises of the mind, for example,

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epilepsy, slumber issue and cerebrum tumors. The real disadvantage in the evacuation of ancient rarities is the precision in the order of antiques. To defeat this issue, the use of vital systems, for example, Neuro fluffy channel and multiwavelet change has enhanced the exactness in the order of curios.

Literature review:

Cichoki.A & Vorobyov.S (2000) , Lagerlund.T.D *et al*(2009) stated that, Principal Component Analysis (PCA) to expel the antiquities from EEG. It outflanked the relapse based routines. In any case, PCA can't totally separate visual relics from EEG, when both the waveforms have comparative voltage magnitudes PCA deteriorates the parts into uncorrelated, yet not so much free segments that are spatially orthogonal and therefore it can't manage higher-request measurable conditions. Canonical Correlation Analysis is utilized as a Blind Source Separation method (BSS) for curios expulsion from EEG signal. Jungt.P. &Humphries (2000) reported that, it quantifies the straight relationship between two multi-dimensional variables, by discovering two bases and bases are ideal concerning correlation. CCA technique has significant measure of otherworldly blunder and subsequently it can't be actualized continuously.

o Relapse Method is focused around unpredictable relapse examination. Paulchamy.B. &Ilavennila (2012) reported that, it is suitable for taking care of exchange of EOG movement to EEG which can have diverse recurrence and stage qualities, in light of the fact that the relapse equation is utilized as a part of recurrence domain. This procedure is requesting in light of the fact that it requires quantitative information identifying with a few thousand people. Executing the information gathering can be drawn out and extravagant.

o Visually impaired Source Separation methods separate the EEG signals into segments that "assemble" the EEG signals. They distinguish the segments that are credited to antiques and reproduce the EEG signal without these parts. Carrie Joyce. A (2009) *et al* stated that it has been broadly connected to expel visual ancient rarities from EEG signals. The real limit in all these strategies is that either the separated EEG sign may contain clamour or the disposed of commotion sign may contain alluring EEG signal. In this paper, an endeavour is made to enhance the signal to commotion proportion of the extricated EEG sign, furthermore to guarantee that the uprooted clamour signal does not contain the EEG part.

Proposed methodalogy:

Neuro-fuzzy filter:

Neuro-Fuzzy framework is the mix of neural system and fluffy rationale thus called cross breed. Neural systems, utilized alone have instability however the blend of Neuro-Fuzzy has great expressiveness and vulnerability is decreased adjusting as per the progressions in the situations.

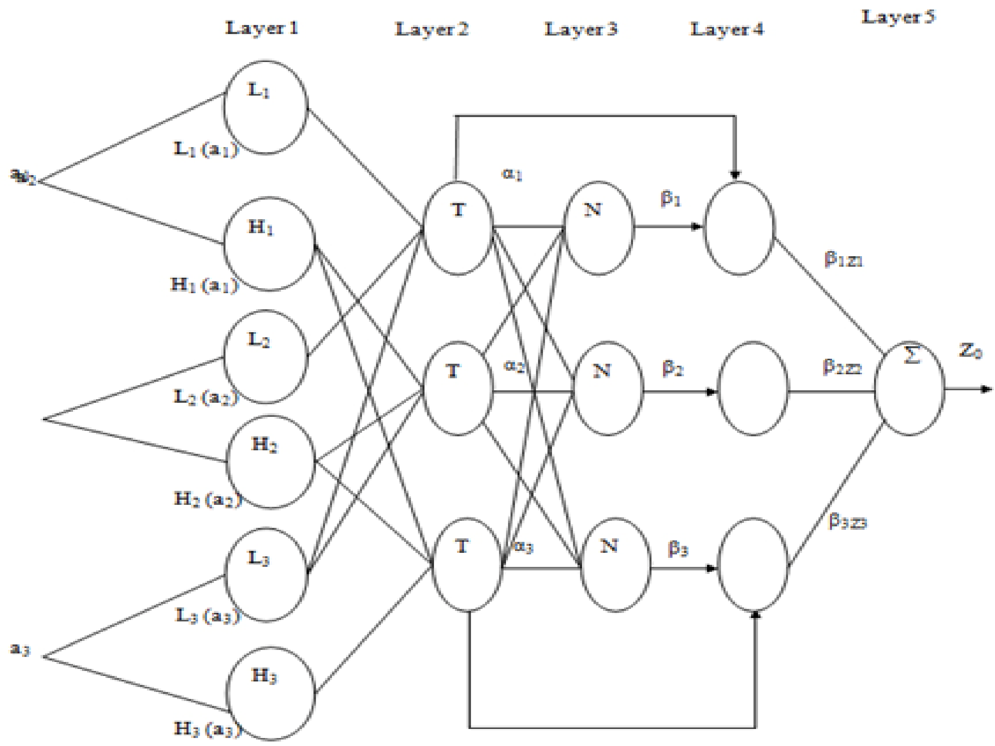

Fig 1: Structure of Neuro-Fuzzy Filter

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The neuro fluffy methodology is utilized to expel the clamor from EEG Signal. Abdulhamit Subasi & Ergun Ercelebi (2005), Linc.T (1995) prove that, the numerous measurements of EEG sign contain just void noises the preprocessing of the EEG sign is performed to upgrade the investigation on these signs. The evacuation of the relics and brief time high-plentifulness occasions empower one to highlight critical trademark offers in the EEG signals. The computational procedure of fluffy neural frameworks is indicated in Fig 1. The fluffy neural calculation take after the three steps, first improvement of fluffy neural models inspired by organic neurons, Second models of synaptic associations which fuses fluffiness into neural system, and third advancement of learning calculations that is the strategy for changing the synaptic weights

MATERIALS AND METHODS

The pictorial representation of the neuro-fluffy channel that incorporates subnet works is demonstrated in Figure.1.The circle means total methods. Ashish Raj (2012) *et al* stated that, it incorporates subsystems that experience fuzzy principles. Neuro-Fuzzy channel structure utilized a summed up ringer sort as enrollment capacity for tuning the parameters.

Layer 1: The yield of the hub is the extent to which the given data fulfills the etymological name connected with this hub.

Layer 2: Every hub figures the terminating quality of the related principle. The hubs of this layer are called guideline hubs.

The yield of top neuron is given in Equation (1).

$$\alpha_1 = L_1(a_1) \wedge L_2(a_2) \wedge L_3(a_3) \tag{1}$$

The yield of the center neuron is given in Equation 1.

$$\alpha_2 = H_1(a_1) \wedge H_2(a_2) \wedge L_3(a_3) \tag{2}$$

$$\alpha_3 = H_1(a_1) \wedge H_2(a_2) \wedge H_3(a_3) \tag{3}$$

The yield of the base neuron is given in Equation (3).

Layer 3 : This layer is marked as N to show the standardization of the terminating levels. The yield of the top, center and base neuron is the standardized terminating level of the comparing standard. It is given in Equation (4), Equation (5) and Equation (6).

$$\beta_1 = \frac{\alpha_1}{\alpha_1 - \alpha_2 + \alpha_3} \tag{4}$$

$$\beta_2 = \frac{\alpha_2}{\alpha_1 + \alpha_2 + \alpha_3} \tag{5}$$

$$\beta_3 = \frac{\alpha_3}{\alpha_1 + \alpha_2 + \alpha_3} \tag{6}$$

Layer 4: The yield of the top, center and base neuron is the result of the standardized terminating Level. It is demonstrated in Equation (7), Equation (8) and Equation (9).

$$\beta_1 = \beta_1 VB^{-1}(\alpha_1) \tag{7}$$

$$\beta_2 z_2 = \beta_2 B^{-1}(\alpha_2) \tag{8}$$

$$\beta_3 z_3 = \beta_3 S^{-1}(\alpha_3) \tag{9}$$

Layer 5: The single hub in this layer processes the general framework yield as the aggregate of all approaching signs. The yield is given in Equation (10).

$$z_0 = \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 \tag{10}$$

Rule 1: If x is A_1 and y is B_1, it denoted as in Equation (11).

$$f_1 = p_1 x + q_1 y + r_1 \tag{11}$$

Rule 2: If x is A_2 and y is B_2, it denoted as in Equation (12).

$$f_2 = p_2 x + q_2 y + r_2 \tag{12}$$

p, q and r represent consequent parameters. A and B are linguistic labels.

The mixture neural nets can't utilize specifically the standard mistake back spread calculation for learning, they can be prepared by steepest plummet strategies to take in the parameters of the participation capacities speaking to the etymological terms in the rules.Maan Shaker.M (2005) , Paulchamy Balaiah & Ilavennila(2012) reported that, the immediate fuzzification of customary neural systems is to expand association weights and/or inputs and/or fuzzy coveted yields (or focuses) to fuzzy numbers.

Multiwavelet transform:

The wavelet change is successfully executed in sign denoising. Wavelets can be successfully used in multi determination examination with scaling capacity φ(t) and wavelet capacity ψ(t). Vasily Strela early prove that, the wavelets permit the use of numerous scaling and wavelet functions. The name multiwavelet itself recommends that it can be executed utilizing a few wavelets having a few scaling functions. Multiwavelets offer a few preferences, for example, conservative help, orthogonality, symmetry, and higher request estimate contrasted with scalar wavelets. A scalar wavelet can never acquire all these properties at the same time. Further a multiwavelet framework gives flawless remaking while protecting length, great execution at the limits, and a high request of estimate fortuitously. Multiwavelets can have two or all the more scaling capacities and wavelet capacities. So as to give notational distinction to a multiwavelet framework, the set of scaling capacities can be composed

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utilizing the vector documentation is given in Equation (13)

$$\Phi(t) = [\phi_1(t), \phi_2(t), \ldots \phi_r(t)]^T \quad (13)$$

Where $\psi(t)$ is known as the multi-scaling capacity. The multiwavelet capacity is characterized from the situated of wavelet capacity is given in Equation (14).

$$\Psi(t) = [\psi_1(t), \psi_2(t), \ldots\ldots \psi_r(t)]^T \quad (14)$$

At the point when r=1, relates to a scalar wavelet. The multiwavelet framework obliges two or more include streams in the multiwavelet channel bank. The hypothesis of multiwavelet additionally has its premise in multi determination investigation (MRA) when contrasted with scalar wavelets. Then again, the multiwavelets have a few scaling capacities. For multiwavelets, the thought of MRA is the same aside from that now a premise for V0 and V1 is produced by deciphers of N scaling capacities given in Equation (15).

$$\phi_1(t-k), \phi_2(t-k), \ldots \phi_N(t-k) \quad (15)$$

The grid expansion is fulfilled by the multi scaling capacity and the multiwavelet capacities are utilizing Equation (16),(17).

$$\Phi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} H_k \phi(2t-k) \quad (16)$$

$$\psi(t)= \sqrt{2}\sum_{k=-\infty}^{\infty} G_k \phi(2t-k) \quad (17)$$

The channel coefficients Hk and Gk are N by N grids rather than scalar. Each of the multiwavelets includes a framework esteemed multi-rate channel bank. The multiwavelet channel bank is made out of "taps" that are N × N networks. A symmetric multiwavelet channel save money with 4-coefficients has a low pass channel which is meant by the four N × N networks and is named C. The high pass channel which is named as D, can't be acquired straightforwardly as an "exchanging flip" of the low pass channel as on account of scalar 2-band Para unitary channel bank. In multiwavelet channel bank, the wavelet channels D must be outlined. Venkata Ramanan (2009) *et al* , Tao Xia & Qingtang Jiang (1998) reported that, the result got is a N channel, N × N framework channel bank that works on N info data. These inputs are separated into 2n yield streams, each of which is down tested by an element of 2. This is demonstrated in Figure2.

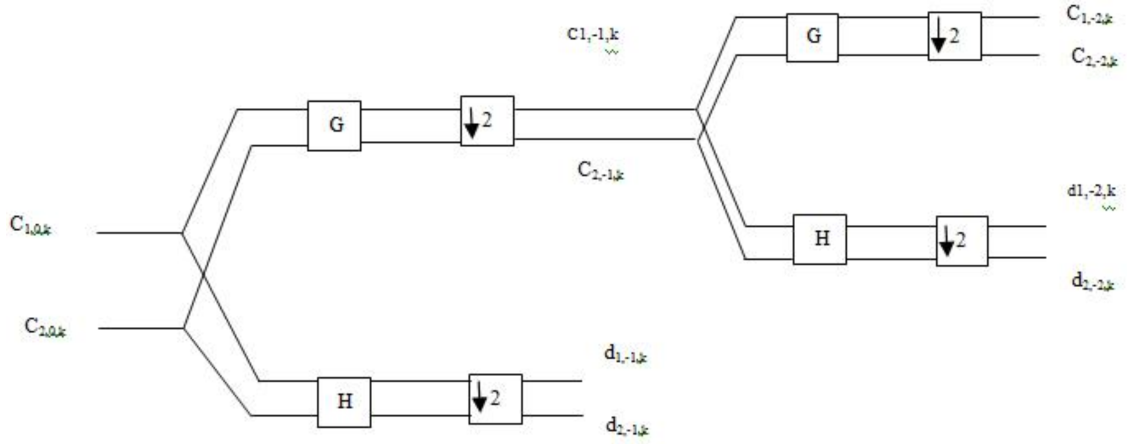

Fig 2: Decomposition of the Signal

Multiwavelet denoising technique:

EEG is a sign super forced on a boisterous sign. Let S(t) speak to the genuine sign and speak to the outer clamor. The measured sign is composed in the structure as Equation (18).

$$X(t) = S(t) + \varepsilon(t) \quad (18)$$

Expect that that S(t) and ε (t) are uncorrelated and are stationary forms. At the point when a sign is deteriorated utilizing wavelet change, a set of wavelet coefficients that connects to the high recurrence sub-groups are acquired. The subtle elements in the information set are introduced inside these high recurrence sub-groups. The points of interest may be dismissed influencing the principle peculiarities of the information set in the event that they are unimportant. Strela.V&Walden.A.T (1998), Strela.V (1998) early prove that, thresholding gives guaranteeing results in sign and picture de-noising. The best possible determination of limit farthest point, thresholding capacity and window sizes is thought to be much essential in denoising method on the grounds that the first flag coefficients which contain the discriminating data in the investigated information ought not be evacuated. In this work, the accompanying thresholding (Measurable Observational) recipe is utilized for ascertaining the thresholding limits. This equation creates better de-noised results than, which is connected to the whole length of the sign. Edge quality is given in Equation (19)

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$$T_k = N \quad x \quad \left(\frac{\bar{x}-\sigma}{\bar{x}+\sigma} \right) \qquad (19)$$

Window Length=10 Seconds

Where N is a Positive Integer, ranging from 100 to 150

x - Mean of all samples, σ - Standard deviation of all samples

RESULTS AND DISCUSSIONS

EEG information with antiquities are taken from the site http://www.scan.uscd.edu/ ~ arno/famzdata/publicy accessible EEG information html for testing the proposed systems. Krishnaveni.V *et al* (2011) ,Senthilkumar.P *et al* (2008) reported that, the impact of curios is overwhelming in the frontal and fronto-polar channels like Fp1, Fp2, F7, and F8. Thus it is sufficient to apply the strategy to these channels. On account of multiwavelet change the denoising of EEG signs is completed by utilizing limit, edge capacity and window Size. Decision of limit utmost and thresholding capacity is a urgent venture in the de nosing methodology, as it ought not uproot the first flag coefficients prompting loss of basic data in the dissected information. The Fig 3. Demonstrates the first EEG.

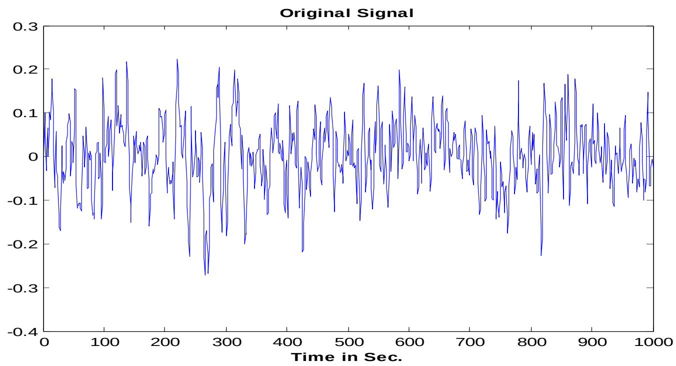


Fig. 3: Original EEG.

Let the EEG sign and the blended curios be viewed as (EOG+EMG+ECG). Neuro fluffy separating is performed till the EEG sign is free from the curios. The Fig 4. Demonstrates (a) Original EEG signal (b) Noised signal (c) Denoised signal.

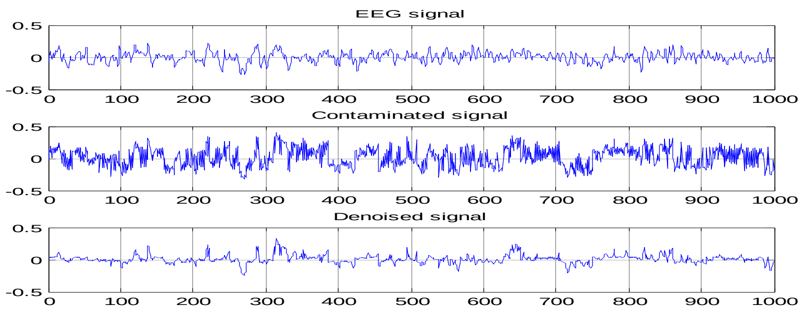
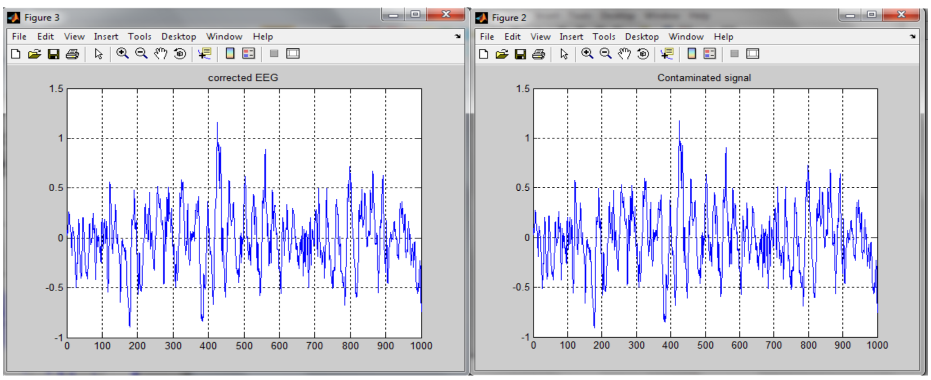


Fig. 4: Result of Neuro-Fuzzy filters (EEG+(EOG +EMG+ECG).



(a) Contaminated Signals (b) Corrected EEG

Fig. 5: Results of Multiwavelet Transform

Let the EEG sign and the blended antiquities be viewed as (EOG+EMG+ECG). Multiwavelet change is performed till the EEG sign is free from the antiques. The Figure 5.

Shows contaminated signal (i.e.) Combination of original signal and ocular artifacts taken from eye. The main task is to remove artifacts from the noisy signal. Corrected EEG signal using multiwavelet transform is illustrated in Figure(5)(b). This corrected signal gives original signal. Signal to noise ratio and cross correlation is the important technical evaluation parameter in signal. Table 1.Compares SNR values of Neuro fuzzy filter and multiwavelet filter.The SNR of five trial using Neuro fuzzy filter and multiwavelet transform is illustrated in Figure(6). From the figure, the SNR value of denoised signal is higher than the corrupted signal.

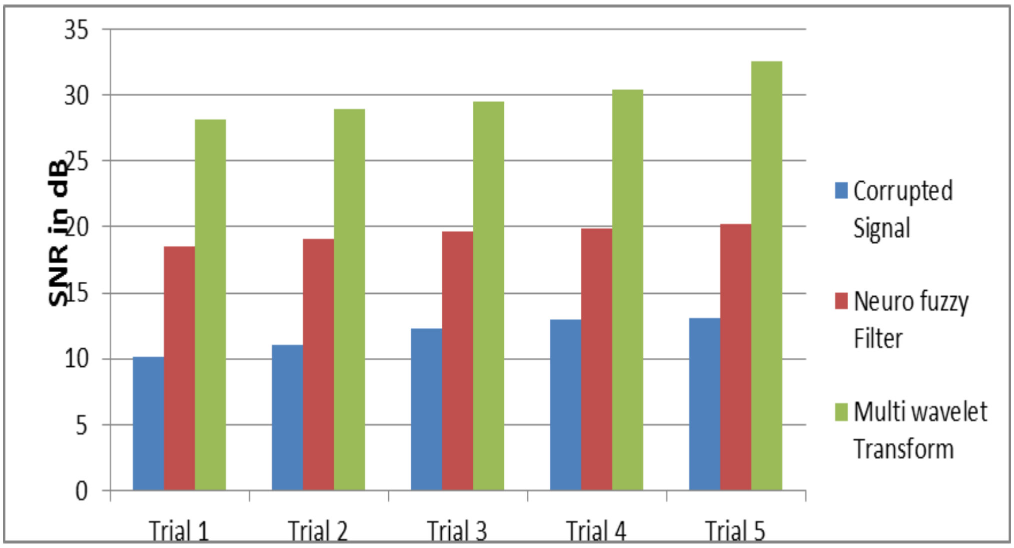


Fig. 6: SNR curve between Neuro fuzzy filter and Multiwavelet transform

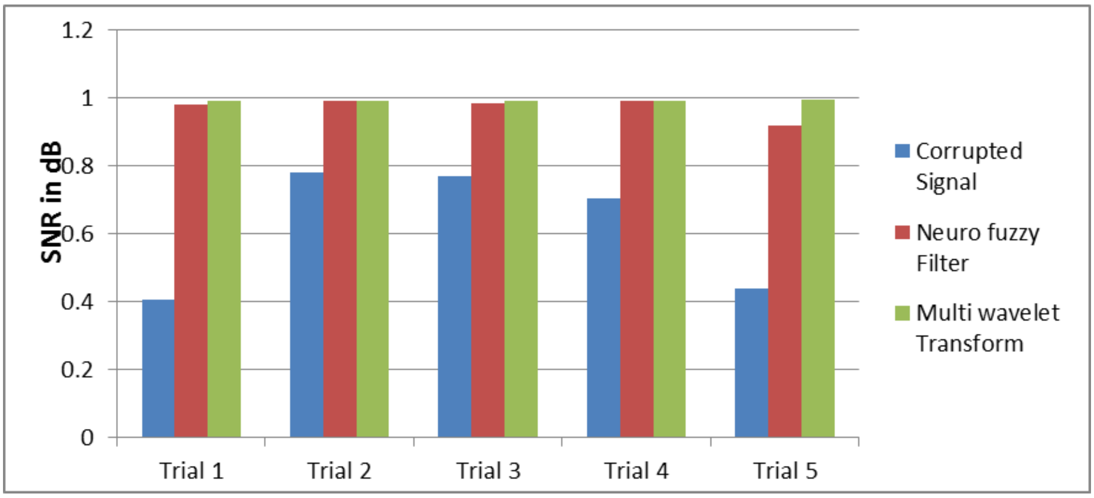


Fig. 7: Correlation Factor curve between Neuro fuzzy filter and Multiwavelet transform.

Table 1: SNR values for proposed methods.

Trials	Corrupted Signal SNR (dB)	SNR in dB for proposed Methods	
		Neuro fuzzy Filter	Multi wavelet Transform (SA4 Filter)
Trial 1	10.1040	18.5040	28.1010
Trial 2	11.1020	19.1020	28.9040
Trial 3	12.3010	19.7030	29.5040
Trial 4	12.9210	19.9040	30.4020
Trial 5	13.1020	20.2060	32.5010

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Table 2.specifies the correlation factor of denoised signal (Corrected EEG) using proposed methods Neuro-fuzzy filter and multiwavelet transform. Conclude that the Multiwavelet transform Correlation factor value is higher than Neuro fuzzy filter.

Table 2: Correlation factor values for proposed methods.

Trials	Corrupted Signal	Correlation factor for proposed methods	
		Neuro- fuzzy Filter	Multi wavelet Transform (SA4 Filter)
Trial 1	0.4050	0.9813	0.9913
Trial 2	0.7785	0.9912	0.9918
Trial 3	0.7696	0.9857	0.9927
Trial 4	0.7042	0.99102	0.9931
Trial 5	0.4365	0.9197	0.9948

The correlation factor plot for corrupted signal and denoised signal is described in Figure(7). This correlation plots gives the relation between noisy and de-noised signal

Results of Artifacts Removal from Real Time EEG Data Using Neuro Fuzzy Filter and Multi Wavelet Transform:

The results of real time EEG data with five trials of artifact removals using Neuo-fuzzy filter and multiwavelet transform (SA4 Filter) is discussed.

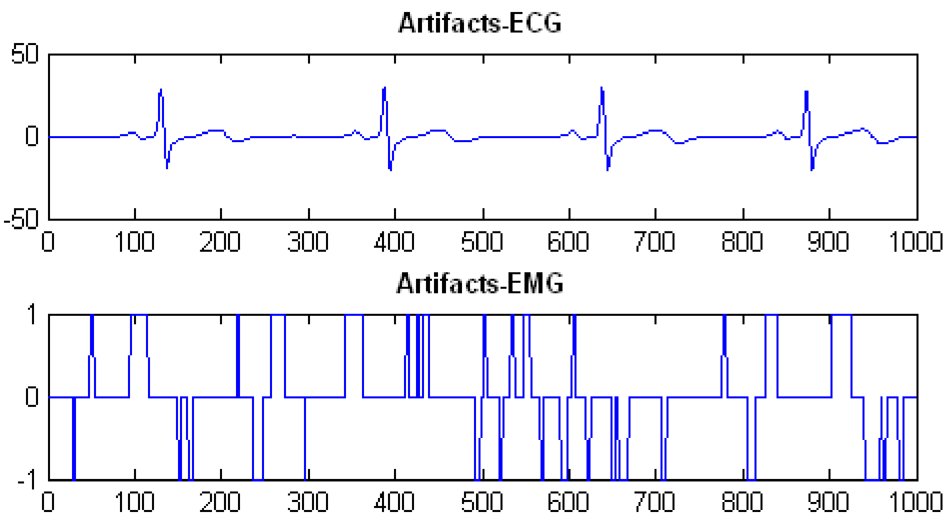

Fig. 8: Real Time artifacts ECG and EMG signal.

Real Time EEG:

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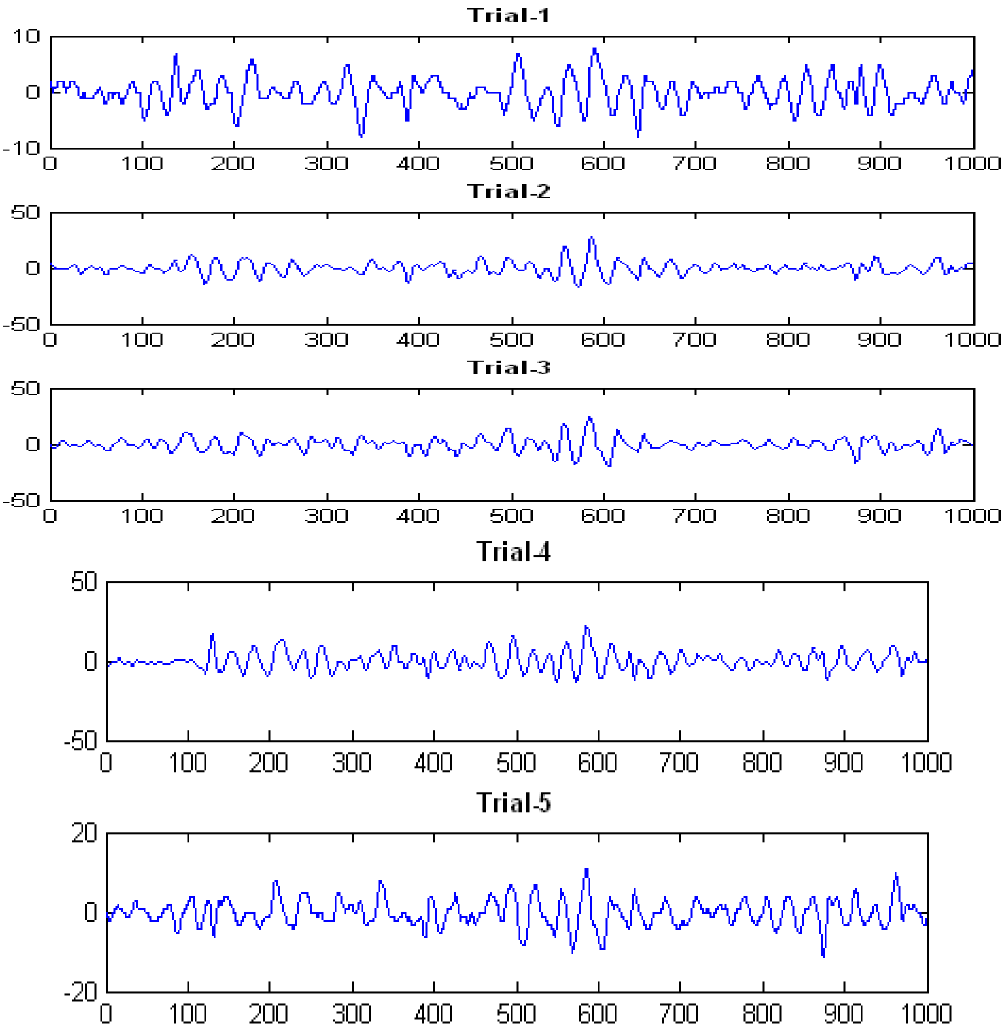
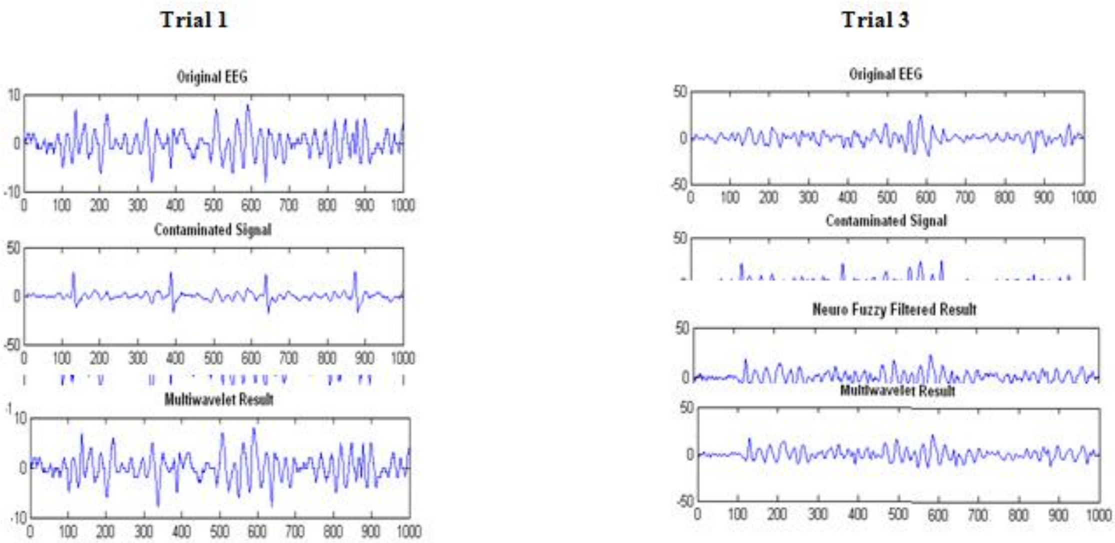


Fig. 9: Five trials of real EEG Signal.



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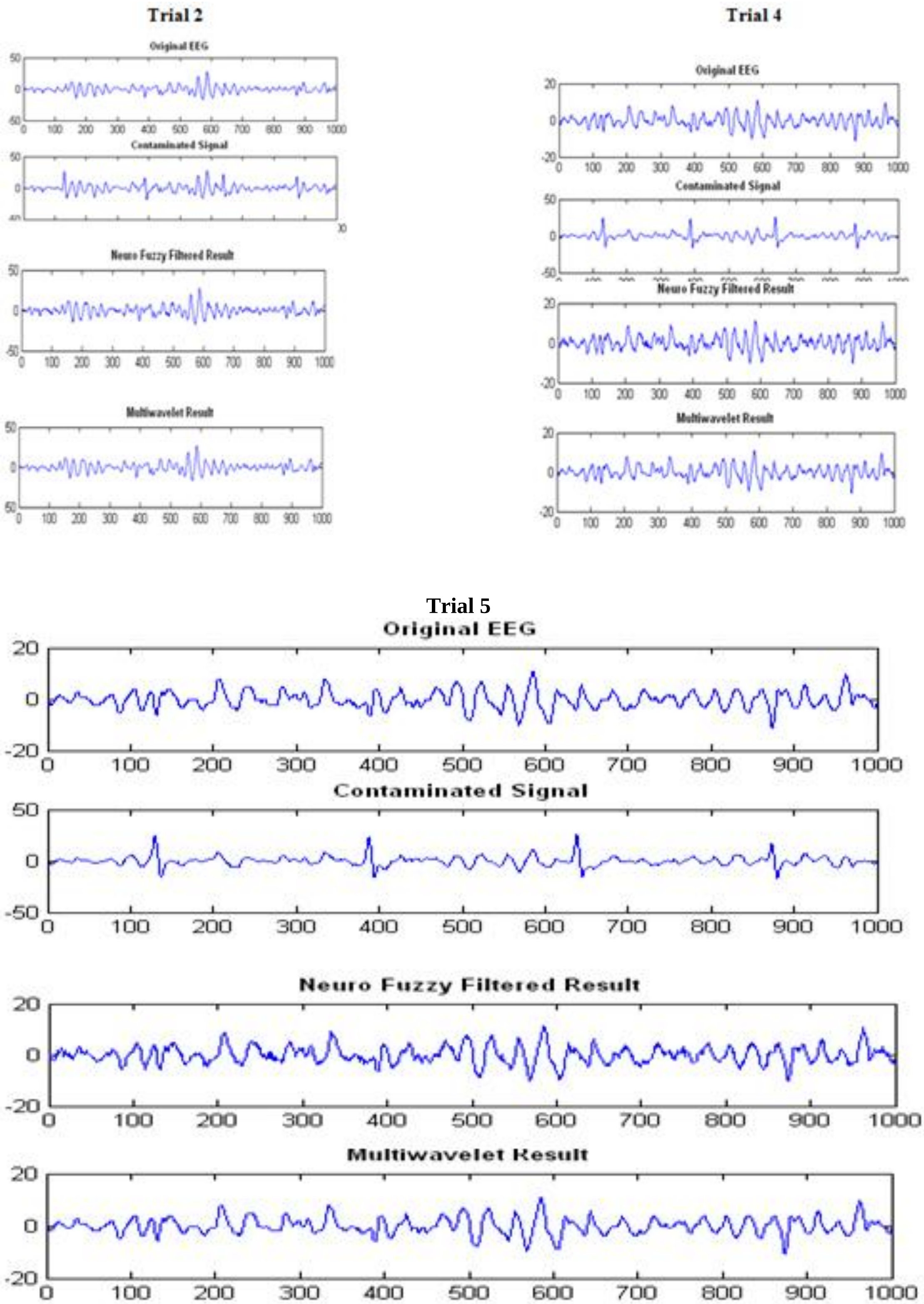

Fig. 10: Result of Neuro-Fuzzy filter and Multiwavelet transform for real EEG Signal.

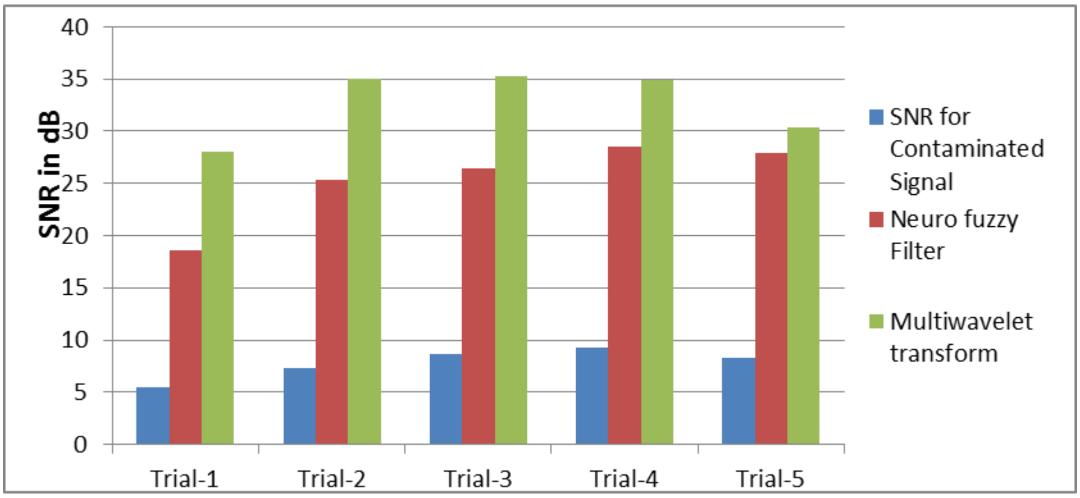

Fig. 11: SNR curve between Neuro fuzzy filter and Multiwavelet transform.

Let the real EEG signal and the mixed artifacts be considered (EEG+(ECG+EMG).Neuro fuzzy filter and Multiwavelet transform is performed till the EEG signal is free from the artifacts. The Figure (8) shows the real time artifacts ECG and EMG signal. Figure(9) shows the five trials of real time EEG signal. Figure (10) shows the five trials result of Neuro fuzzy filter and multiwavelet transform output.

5.2. Correlative SNR value:

Table.5.7 describes the signal to noise ratio of denoised signal using Neuro Fuzzy filter and multiwavelet transform for real time EEG Data. Conclude that the SNR of denoised signal using multiwavelet transform is higher than the denoised signal using Neuro fuzzy filter.

Table 3: Signal to Noise Ratio comparison between Neuro-fuzzy filter and Multiwavelet transform.

Trials	SNR for Contaminated Signal	SNR for De-noised Signal	
		Neuro fuzzy Filter	Multiwavelet transform
Trial-1	5.5243	18.6276	27.9943
Trial-2	7.2792	25.3578	34.9961
Trial-3	8.6072	26.4352	35.2639
Trial-4	9.3072	28.5073	34.8562
Trial-5	8.3030	27.9367	30.3810

The signal to noise ratio curve for multiwavelet transform and Neuro Fuzzy filter along with contaminated signal is illustrated in Figure11. This curve clearly shows that the multi wavelet transform proves better result than Neuro- Fuzzy filter.

5.3. Correlation factor comparison:

Brief summarization of the Correlation factor comparison between Neuro Fuzzy filter and multiwavelet transform of denoised signal along with contaminated signal for real time EEG data is given in Table4. Concluded that the CF of denoised signal using multiwavelet transform is higher than the denoised signal using Neuro Fuzzy filter.

Table 4: Correlation factor comparisons for proposed methods.

Trials	Correlation factor for contaminated signal	CF for De-noised Signal	
		Neuro Fuzzy filter	Multiwavelet transform
Trial-1	0.2060	0.9932	0.9992
Trial-2	0.6775	0.9986	0.9998
Trial-3	0.6956	0.9986	0.9999
Trial-4	0.8042	0.9986	0.9998
Trial-5	0.3395	0.9960	0.9995

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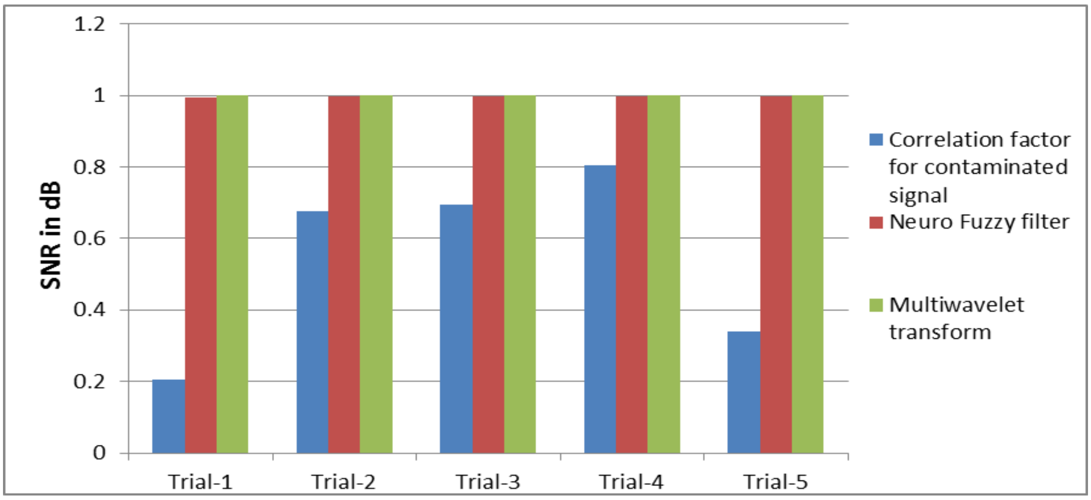

Fig. 12: Correlation factor for proposed methods.

The correlation factor curve for multiwavelet transform and Neuro Fuzzy filter along with contaminated signal is shown in Figure.12. This curve clearly shows that multiwavelet transform proves the better result than Neuro Fuzzy filter.

Conclusion:

An artifacts removal method should be able to remove the artifacts as well as keep related neurological phenomenon intact. In this paper two novel artifacts removal methods and its output performances are discussed. The major contributions of this work is, Improvement in power spectral density of de-noised signal, High signal to noise ratio value, Reduction in the time in removal process, Correlation achievement, Improvement of information content. The proposed methodology of Neuro-fuzzy filter, which are an integration of neural networks and fuzzy logic. The computational process envisioned for neuro-fuzzy systems is starts with the development of a "fuzzy neuron" based on the understanding of biological neuronal morphologies, followed by learning mechanisms.Another method of multiwavelet transform, it has several advantages in comparison with scalar wavelet. The features such as compact support, orthogonally, symmetry, and higher order approximation are known to be important in signal processing. In this method thresholding technique is used for signal de-noising. Because of using this transform the artifacts in the EEG signal could be removed without loss of information. Compare to Neuro fuzzy filter multiwavelet transform has outperformed as far as SNR, and correlation factor concerned

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