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# Analysing the Inclusion of Soft Computing Techniques in Denoising EEG Signal

**Ashish Raj, Akanksha Deo, Mangesh S. Tomar, Manoj Kumar Bandil**

***Abstract— The electrical nature of the human nervous system has been innovated for more than a century. It is prominent that the variation of the surface potential distribution on the scalp reflects function and activities emerging from the underlying brain. This variation of the surface potential can be recorded by placing an array of electrodes to the scalp, and measuring the voltage between pairs of these electrodes. These measured voltages are then filtered, amplified, and recorded. The resulting data is called the EEG. As per the usefulness, EEG has proved to be an important tool for diagnosis, monitoring and managing various nervous disorders. The electrical activity of brain changes in accordance with various parameters inside & outside environment. A number of severe disorders in human body which were impossible to be traced in early stages are easily being signal processing stages are being predicted with help of EEG. But there are certain artifacts which are present in raw EEG recording. These raw signals are firstly processed with help of mathematical tools in order to make them more and more informative. The informative signal thus calculated from recording is known as ERP (event related potential). These ERP data are very specific and changes with every physiological & biological change in human body. Thus the analysis of ERP has got numerous clinical importance.But there are certain artifacts which are present in raw EEG recording. These artifacts make the ERP contaminated and it introduces inconsistency in the output. These artifacts in EEG signals arise due to two types of factors; Biological factors and External factors. The Biological factors are caused by EOG (Elecro-oculogram), ECG (Electrocardiogram), EMG (Electromyogram) and Respiratory (PNG).The external factors are caused due to line-interference, leads and electrodes. These noises have an adverse effect on EEG signals and act as a contamination to obtain clear cut information from EEG signals .Thus it is perquisite to eliminate these artifacts from the EEG. The ERP generated from artifacts free EEG are most suitable for versatile researches and efficient diagnosis. The clinical information thus obtained is of considerable importance in identifying different pathologies. Thus artifact rejection is most important preliminary stage before ERP analysis. This is a paper scrutinizing different soft computing methods for removing artifacts with illustrating characteristics of a good informative EEG signal. In this paper we have discussed about inclusion of several soft computing techniques with the conventional artifact removal approaches.***

***Index Terms— EEG; EMG; ECG; ocular artifacts; muscular artifacts; spike detection; Wavelet transform; Neural network., Fuzzy logic; Genetic Algorithm***

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**Ashish Raj,** Assistant.Prof**,** Department of Electrical Engineering, IITM, Gwalior India.

**Akanksha Deo**, Assistant.Prof**,** Department Of Electrical Engineering, IITM, Gwalior India.

**Mangesh Tomar,** Assistant.Prof**,** Department Of Electrical Engineering, IITM, Gwalior India.

**Manoj Kumar Bandil**, Associate Prof**,** Department Of Electrical Engineering, IITM, Gwalior India.

## I. INTRODUCTION

Signal averaging is most common method of extracting the signal. EEG is sampled for ~1 second after each stimulus presentation & averaged together across like stimuli. The time-locked signal emerges in which noise averages to zero.[1] We have to extract time locked activity by averaging these raw data.EEG signals are basically stimulus related processing whereas the noise are tonic background activity related to ongoing process(level of arousal..etc).There is a severe problem of signal to noise in EEG data .Since EEG is of the order of ± 50 micro volts. But ERP are on order of 2- 20 micro volts. We often want to detect difference of 1-2 microvolt thus precision is the important prerequisite in analysis of ERP. When these brain potentials are synchronised, it indicates the normal state of brain but when there is some abnormality in brain electrical potential, it indicates mental disorder. Event-related potentials are patterned voltage changes embedded in the ongoing EEG that reflect a process in response to a particular event (e.g., visual or auditory stimuli).ERPs are measured from the same "raw data" (i.e., scalp electrical activity over time and space) as EEG. ERP reflects sensory, motor, and/or cognitive events in the brain. It reflects synchronous post-synaptic potentials of large neuronal populations engaged in information processing.

Signal and noise (in each epoch) sum linearly together to produce the recorded waveform for each epoch (not some peculiar interaction). The evoked signal wave shape attributable solely to the stimulus is the same for each presentation. The noise contributions can be considered to constitute statistically independent samples of a random process. [1]

***1.1 Artifacts in EEG***- Artifacts are the unwanted noises, and disambiguates in the EEG signal which arise due to relative biological and external factors. The biological artifacts are caused by EOG (Elecro-oculogram), ECG (Electrocardiogram), EMG (Electromyogram) and Respiratory (PNG).Figure 1 shows various types of artifacts present in EEG signals. Figure 1(a) shows a clean EEG whereas various artifacts such as eye blink, eye movement, muscular movements, pulse etc are shown along with the clean EEG signal.

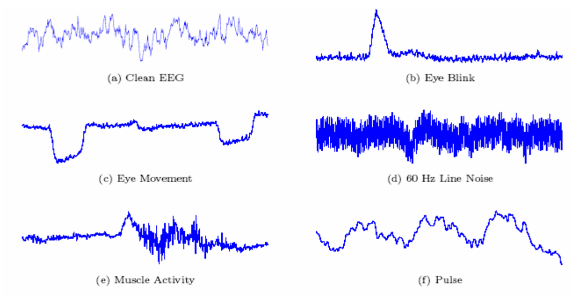


**Figure 1 (Various artifacts present in EEG signals)**

The external factors are caused due to line-interference, leads and electrodes. A large number of researches present a wide variety of algorithms for identifying and removing artifacts in the EEG. These methods may operate in either a fully automatic or semi-automatic manner. It can be applied either for specific artifact or for several types of artifacts. There are various parameters like time series topology, spectral template, and other statistical properties of EEG which are used to classify EEG signal. In clinical valuation, artifacts are eliminated by visual inspection of recording. For example, artifact removal methods could be evaluated by looking at the change in the EEG cleanliness metric before and after use of the method. Thresholds are trained on the data to optimally identify clean epochs via differential evolution (DE). Finally, the optimal thresholds are presented and an algorithm is discussed for identifying clean EEG epochs. [2]

There are simple criteria for artifact recognition, which serves as a base for designing algorithms of several artifact removing techniques. These criteria, for a corrupted EEG signal includes high amplitude of delta wave (0.5-4 Hz) in channels Fp1 and Fp2, similarity of signals in channels Fp1 and Fp2 and rapid decline of delta wave posterior .

## II. PARADIGM OF METHODOLOGIES

There are a number of conventional techniques for removing artifacts in EEG signal. These techniques are characterized as subtraction method, linear regression method and blind source separation method. In this section we have discussed theory and methodology of these conventional artifact removing techniques.

***2.1 Wavelet Transform –*** Wavelet Transform is a mathematical compression technique. Unlike Fourier Transform it is applied on time varying signals (Fourier Transform is applied on stationary signals). [3]

$$\Psi_{j,k}(t) = 2^{j/2}\Psi(2^j - k) \qquad \text{(i)}$$

The Discrete Wavelet Transform (DWT) means, choosing subsets of the scales j and positions k of the mother wavelet ψ (t). Choosing scales and positions are based on powers of two, which are called dyadic scales and positions (j and k are integers). Equation  shows that, it is possible to build a wavelet for any function by dilating a function on ψ (t) with a coefficient 2j, and translating the resulting function on a grid whose interval is proportional to 2–j. Contracted (compressed) versions of the wavelet function match the high-frequency components, while dilated (stretched) versions match the low frequency components. By correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. Many researchers developed real-valued extensions to the standard DWT such as SWT (Stationary Wavelet Transform). The key point is that it gives a better approximation than the discrete wavelet transforms (DWT) since, it is redundant, linear and shift invariant [4].These properties provide the SWT to be realized using a recursive algorithm. [4]

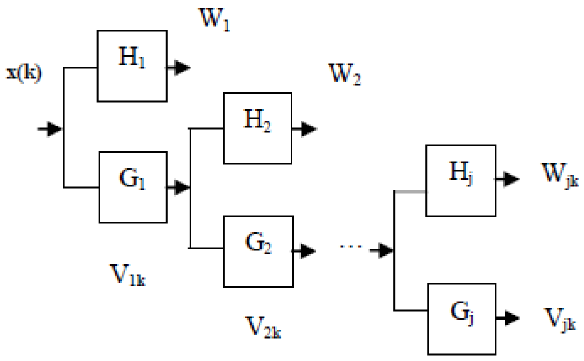


**Figure 2.Computation of the SWT of a signal x (k)**

In given figure 2. $W_{j,k}$ and $V_{j,k}$ are called the detail and the approximation coefficients of the SWT. The filters $H_j$ and $G_j$ are the standard low pass and high pass wavelet filters, respectively.

***2.2 Blind Source Separation Method*** - Blind source separation method involves two methods such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA). After deleting the artifacts from the original EEG by BSS method, the clean EEG can be reconstructed without artifacts. Blind source separation (BSS) is the technique used to separate independent signals from a set of mixed signals without any prior knowledge of the signals. The source signals $s(t)=[s1(t),s2(t),\ldots,s_m(t)]^T$ are to be estimated from the observed signals $x(t)=[x_1(t),x_2(t),\ldots,x_m(t)]^T$. The system is modelled as x(t) = As(t), where the mixing matrix, A, represents unknown observations. The most simple and widely used assumption in EEG processing is the linear instantaneous mixing: source signals reach the sensors simultaneous. [5] .The noisy mixture in this case is written as.

$$X = AS + N \qquad \text{(ii)}$$

Where X is the matrix of the mixed signals ($x_i$) corresponds to a row of X, *i.e.*, a sensor signal), A is the unknown non-singular mixing matrix, S is the matrix of independent sources ($s_i$ corresponds to a source), N is an additive noise matrix. The motive of BSS is to calculate a linear transformation B of the sensor signals X that makes the outputs as independent as possible.

***2.2.1 Principal Component Analysis***- The mathematical technique in PCA is Eigen analysis. We solve for the Eigen values and Eigen vectors of a square symmetric matrix with sums of squares and cross products. The eigenvector related with the largest Eigen value has the same direction as the first principal component. The eigenvector associated with the second largest Eigen value determines the direction of the second principal component. The sum of the Eigen values equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of this matrix.


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***2.2.2 Independent Component Analysis –*** An EEG signal contaminated with artifacts consist of true signal S(t) along with artifacts ε(t) and can be represented by the relation as

$$C\ (t) = S\ (t) + \varepsilon\ (t) \qquad \text{(iii)}$$

Independent component analysis has been successfully employed to eliminate e(t) from the true EEG signals. Blind Source separation had given a method principal component analysis and independent component analysis is just advancement to it. Important criteria to be fulfilled for successful implementation of ICA is as follows-

i. The number of sources should be equal to number of sensors applied;
ii. The mixing medium should be linear with negligible propagation delay;
iii. The source should be independent.

ICA starts assuming that $K$ simultaneously recorded EEG signals $X\ (t) = \{x_1(t) \ldots x_K(t)\}$ are linear mixtures of $N$ ($N \leq K$) a priori unknown independent components (sources) $S(t) = \{s_1(t), \ldots, s_N(t)\}$ including artifactual and of the neural origin.[6]

$$X\ (t) = MS\ (t), \qquad \text{(iv)}$$

Where $M$ is the unknown mixing matrix defining weights at which each source is present in the EEG signals recorded at the scalp. Topography scalp maps of the components provide additional information on the localization of the sources. The aim of ICA is to estimate both $S(t)$ and $M$ from $X(t)$. Once the algorithm has been applied we analyze the temporal structure and topography of the components $S(t)$ (e.g. the ocular artifacts mainly project to frontal sites) and identify among them those components that account for artifacts. Then we set the identified artifactual components to zero, $S_{artf}(t) = 0$, obtaining a new component matrix $\hat{}S(t)$ where the artifactual sources have been rejected. Finally, we reconstruct ICA-corrected EEG signals.

$$\hat{}X\ (t) = M\hat{}S\ (t). \qquad \text{(v)}$$

Obtained this way the new data set $\hat{}X(t)$ represents the ICA estimation of the original, artifact free data.

For independent component estimation can be used many different algorithms. One of the applied methods is the method of genetic algorithm estimation of independent component. The independent component estimation mentioned here are using fixed point iteration [7] optimized for the calculation of the components, [8]. This method is faster and it's called Fast ICA. Negentropy was used for determination of statistical component independence as a contrast function [8]. Negentropy use statistical moments of higher levels:

$$J(y) = 1/12\ E\ \{y^3\}^2 + 1/48\ kurtosis\ (y)^2 \qquad \text{(vi)}$$

Where kurtosis(y) is a fourth order cumulate.

## III. SOFT COMPUTING TECHNIQUES

***3.1 Artificial Neural Network –*** Use of artificial network for artifacts removal is one of the finest methods. The properties of ANN such as massive parallel structure, high degree of interconnection capabilities of high speed computations, non linear mapping and self organization makes it best candidate for prediction and compression problem. Basically for higher efficiency neural networks are accompanied with pre-processing of EEG signals on wavelet transform. The EEG signal is sampled and reconstructed on basis of wavelet transform and a neural network based predictor is introduced in them. Fig.3 shows the basic network for neural network based analysis and synthesis.

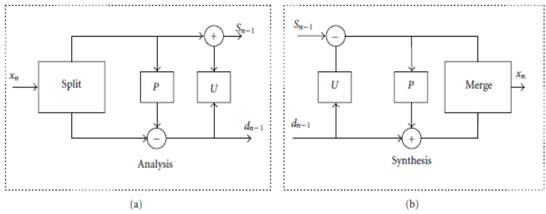


**Figure 3. (Neural network based analysis and synthesis)**

The introduction of ANN brought new possibilities in development of adaptive methods of structures recognition and solving complex classification problems which can be related to their ability to learn a certain mapping from the set of the realisation examples. However performance of ANNs depends heavily on input parameters. We will apply ANNs for artifact recognition testing their performance for different input parameter sets. The problem of artifact rejection using neural network can also be based on Group method of data handling (GMDH). GMDH algorithms generate a multilayer neural network step-by-step by growing up new layers of neurons. The network grows until a predefined criterion reaches a minimum located near to a global one. This criterion is based on a cross-validation error function assuming training and validation data subsets. The resultant classification model is described by a concise set of the neurons with a given transfer function, for example, a polynomial one. [9]

$$y = g\ (v;\ w) = w_0 + w_1 + w_1\, v_1 + w_2\, v_2 + w_3 v_1 v_2 \qquad \text{(vii)}$$

In the framework of our technique first we learn the GMDH-type neural network from the given training data. This network has a nearly minimal number of neurons and involves those features which make the most important contribution to classification of the patterns. Then using the selected features and the training examples that have been correctly classified, we induce an appropriate DT. As a result we derive a comprehensible classification rule whilst also attempting to keep its classification error down. Let us also initialize a decision tree, **T**, and define a procedure find_node that is invoked with the $\mathbf{X}_0$ and $\mathbf{X}_1$ as the parameters. This procedure searches for an input variable,$v_1$, and a threshold, $q_1$, which provide the best partition of the subsets $\mathbf{X}_0$ and $\mathbf{X}_1$. A new node $f(v_1, q_1)$ involving variable $v_1$ and threshold $q_1$ is added to the **T**. The procedure to find node calls itself while splitting nodes contain more than $p$ given training examples belonging to classes 0 and 1. [10]

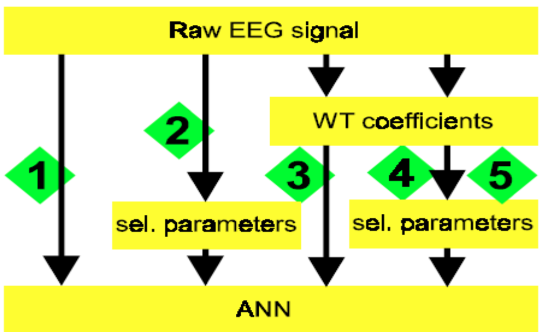


**Figure 4(Five ways of pre-processing of the input EEG signal)**

Figure 4 indicates the five different ways of pre processing EEG signals. This diagram clearly shows that neural network is a method to enhance our conventional artefact removing. Resultant model developed is highly specific and accurate. Neural network is also used to develop lossless data compression techniques in EEG signal processing.

***3.2 Genetic Algorithm-*** Artifact rejection process has been highly assisted with the evolution of genetic algorithm. As the size of the normalization window has been tuned with help of hybrid genetic algorithm. Genetic algorithm is an approach to simulate all the possible solutions using three powerful A genetic algorithm (GA) is a method for solving optimization problems that are based on natural selection from the population members. The genetic algorithm repeatedly modifies a population of individual solutions. At each step the genetic algorithm tries to select the best individuals. From the current "parent" population genetic algorithm creates "children", who constitute next generation. Over successive generations the population evolves toward an optimal solution. The genetic algorithm uses three main rules at each step to create the next generation

- Selection rules select the individuals, called parents that contribute to the population at the next generation.
- Crossover rules combine two parents to form children for the next generation.
- Mutation rules apply random changes to individual parents to form children tools such as selection, mutation and crossover.

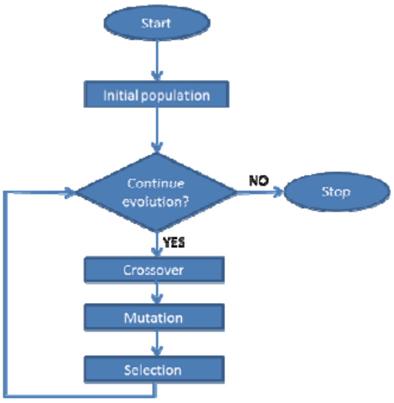


**Figure 5(Flowchart of Genetic Algorithm)**

***3.2.1 ICA based Genetic Algorithm-*** The step of proposed method as fallow: at first using ICA algorithm extract Independent components (ICs) of each trial then GA select the best and related ICs among the hole ICs this steps .

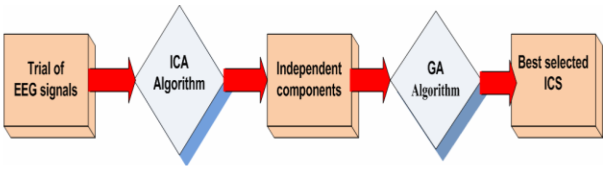


**Figure 6 (ICA based Genetic Algorithm for Artifact Removal)**

The proposed approach to the use of GAs for Artifact removal involves encoding a set of d, ICs as a binary string of the elements, in which a 0 in the string indicates that the corresponding IC is to be omitted, and a 1 that it is to be included. This coding scheme represents the presence or absence of a particular IC from the IC space which is illustrated in figure 7. The length of chromosome equal to IC space dimensions. Then the selected ICs used as input data for classifiers. This paper used the fitness function shown below to combine the two terms: [11]

$$\text{Fitness} = \text{classification error} + \alpha * (\text{No. of Active Gens})$$

Where error corresponds to the classification error that used elected ICs and active gens correspond to the number of ICs selected (i.e., ones in the chromosome). In this function α is considered between (0, 1) and the higher α results in less selected features.

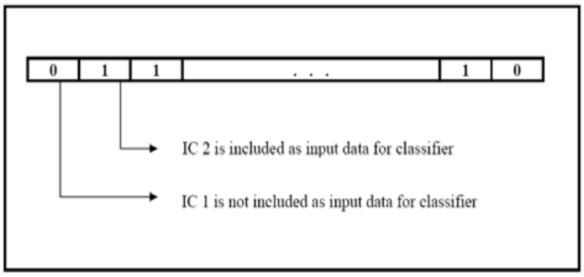


**Figure 7 (Genetic Algorithm Based IC selection model)**

***3.3 Hybrid Neuro- Fuzzy System –*** Neuro-fuzzy combines the feature of artificial neural network & fuzzy logic. These evolutionary techniques combine the learning feature of neural network leasing logic of fuzzy. The strength of neuro-fuzzy system involves the contradictory requirement in fuzzy modeling, that means interpretability v/s accuracy .Neural networks when used individually proves itself best in pattern recognition but they are not able to specify the logic behind their decisions. But in case of fuzzy logic the decisions are explained very logically but they are not able to be trained so that they can attain their rules according to the problem.

***3.3.1 Hybrid Neuro-Fuzzy System in Artifacts Removal-*** Application of neuro-fuzzy technique in the artifact removal of EEG can be explained by the given flowchart. Figure 8 shows the scenario of artifact removal system involving neuro fuzzy filter scheme.

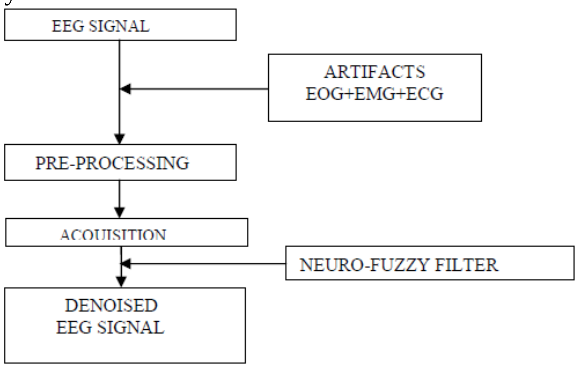


**Figure 8 (Overview of Neuro-Fuzzy Artifact Removal System)**

In the given fig. we see that at first the EEG signals are taken as primary input and artifacts are considered as reference input. In this system artifacts are removed efficiently by applying the techniques of neuro-fuzzy using neuro-fuzzy filter. Before applying neuro-fuzzy filter, some pre-processing of EEG signals is required these pre-processing involves tools such as sampling, feature transformation, normalization & feature extraction. This pre-processed data is then sent to neuro-fuzzy filter which produces the denoised EEG signal as per desire.

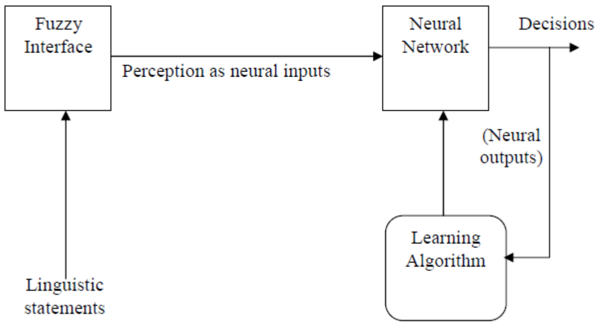


**Figure 9 (a)**

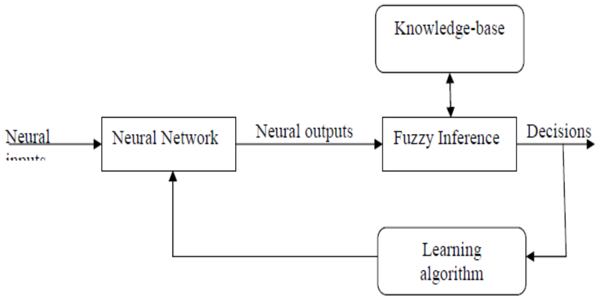


**Figure 9 (b)**

Figure 9 shows two different models of neuro-fuzzy system. In figure 9(a) linguistic statements are defined by fuzzy interface which along with perception as a neural signal is used to design a neural network trained learning algorithm. In figure 9(b) the neural outputs is fed to fuzzy interface which is knowledge based and hence a decision making system is designed.

The model of hybrid neuro-fuzzy system is successfully used in designing various hybrid artifact rejection systems such as ANC (Adaptive Noise Cancelation) & ANFIS. [12]

## IV. Conclusions

The efficiency of EEG is directly related to the extent of accuracy of artifact removal system. In this paper we have reviewed the comprehensive artifact removal methods along with the soft computing techniques which can be further interfaced with them.The wavelet analysis for artifact removal in EEG is applied for online application but the section of critical threshold function is most important task for its accuracy. Similarly denoising of EEG signals with linear filters is applied when the frequency of noise do not overlap with each other. But selection of optimal parameters for the filter is again most critical factor for efficiency of filtering.

Artificial Neural Networks (ANNs) is an emerging and adaptive method of structure recognition and solving complex artifact removal problems and predictive systems with help of different learning and training algorithms. We can conclude that for ANNs application in the time series classification pre-processing should include frequency information about the signal. In many other applications power spectra calculated from Fourier transform are applied. Group method data handling is advanced application of neural network. The discovered rule is easily interpreted as decision tree testing the power of a high frequency band. An analogous feature is tested for recognizing muscle artifacts in sleep EEG by using the threshold technique additionally this technique evaluates the background neural activity at 3 minute window adjusted for adult EEG. Combining polynomial neural networks and decision tree techniques allows reducing classification error. [10]

ICA method is used when large number of noises needs to be distinguished but it lags for the real time applications.ICA performance is best for correcting image artifacts. Thus for higher performance ICA is interfaced with soft computing techniques such as neural network, genetic algorithm and neuro-fuzzy algorithms. When genetic algorithm was applied to get at feature selection stage. The overall performance was 98.44% ± 0.41% for non artifact EEG and 80.93%± 11.33% for EEG with artifacts. The rejection error were 0.01. [13] The time of execution in GA can be shortened by modifying the selected probabilities of mutation and crossover operations. However, the time required by GA for feature selection is fairly long in practice, so GA is rather suitable for the analysis of data in off-line mode.

In case of neuro-fuzzy the filtered signal has high signal to noise ratio. Also the power spectral density of signal is improved .Further various automatic artifact rejection techniques are developed based on neuro-fuzzy algorithm like ANC (adaptive noise cancellation) along with ANFIS which uses neuro-fuzzy algorithm for automatic denoising of EEG signals.[12]

Thus based on the reviews of recent results we conclude that soft computing techniques have increased the efficiency of EEG signal processing .It helps in overcoming the drawbacks of conventional rejection methods. Various self predictive systems are being designed and analysis of EEG signal has become possible with high precision. So based on the objective of research we can apply these soft computing techniques along with conventional method to develop highly efficient artifact rejection system.ANN is used to reduce classification error. It helps in removing muscular artifacts and developing lossless compression techniques for EEG signals with neural network predictors. Genetic algorithm increases the efficiency of LCA by shortening time of execution. It also assists off line artifact removal systems, whereas neural network combined with fuzzy logic (neuro-fuzzy) is used for designing automatic artifact removal system with help of Adaptive noise cancelation and ANFIS. [12]

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## AUTHORS PROFILE


**Mr. Ashish Raj** is working as Assistant.Prof. In Department of Electrical Engineering at Institute Of Information Technology and Management (ITM-GOI), Gwalior, India. His field of interest & research includes Biomedical Signal Processing.

**Ms. Akanksha Deo** is working as Assistant.Prof. In Department of Electrical Engineering at Institute Of Information Technology and Management (ITM-GOI), Gwalior, India. Her field of interest & research includes wavelet analysis, and signal processing.

**Mr. Mangesh Tomar** is working as Assistant.Prof. In Department of Electrical Engineering at Institute Of Information Technology and Management (ITM-GOI), Gwalior, India. Her field of interest & research includes wavelet analysis, and ecg signal processing.

**Mr. Manoj Kumar Bandil** is working as Associate .Prof. In Department of Electrical Engineering at Institute Of Information Technology and Management (ITM-GOI), Gwalior, India. His field of interest & research includes Biomedical Instrumentation System, EEG and inclusion of soft computing techniques in biomedical signal processing.