Artifact Removal from EEG using ANFIS-GA

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***Abstract*— Electroencephalogram (EEG) is the measurement of the electrical activity of the brain from the scalp. EEG is corrupted with various artifacts such as Electrooculogram(EOG) and Electromyogram (EMG) which originate from different sites other than the brain. In this paper we propose an Adaptive Noise Cancellation method(ANC) called Adaptive Neuro–Fuzzy Inference System(ANFIS), where a global optimization technique specifically Genetic Algorithm(ANFIS–GA) has been used to optimize the parameters of the ANFIS structure. This paper shows that the proposed method, ANFIS-GA eliminates the EOG artifact from the EEG and surpasses the performance as compared to the Hybrid Learning Algorithm that has been employed generally to tune the parameters of the ANFIS structure. A comparative study has been done on ANC implemented using ANFIS and ANFIS – GA.**

***Index Terms*—Adaptive Neuro–Fuzzy Inference System(ANFIS); Artifact removal; Genetic Algorithm(GA); Electroencephalogram(EEG); Electrooculogram(EOG); Optimization; Adaptive Noise Cancellation(ANC)**

I. INTRODUCTION

An electroencephalogram (EEG) measures the electrical impulses generated by neurons firing in the brain by positioning several electrodes over the scalp. EEG records carry information on how a human brain responds to certain stimuli. The EEG records are in the range of 200μV and are generally classified according to their frequency, and amplitude as well as the sites on the scalp at which they are recorded. The various frequency rhythms associated with EEG are alpha, beta, gamma, delta and mu rhythms.

Although EEG is intended to record cerebral activity at each location on the scalp, it also records electrical activities stemming from locations other than the brain. The recorded EEG activity that doesn't stem from the brain is termed as artifacts. The major artifacts that significantly corrupt EEG are electrooculogram (EOG), electrocardiogram (ECG), electromyogram (EMG) and power line interference (50 or 60 Hz).

Presence of artifacts in the EEG records make the analysis complicated, due to the introduction of spikes which can be misperceived as neurological rhythms. Hence these artifacts must be eradicated or attenuated from the EEG to ensure a correct analysis and diagnosis. Detection and elimination of these artifacts in EEG recordings is a complex task, but crucial to the development of practical systems [1].

Many techniques have been proposed to eliminate the artifacts from EEG signals. Some of the popular methods are linear filtering [2], linear combination and regression [3], independent component analysis [4] and wavelet transform [5] [6]. However these proposed methods require complex manual calculations and depends on visual analysis.

Another prominent technique for artifact removal in real time EEG is Adaptive Noise Cancellation (ANC) based on Adaptive Neuro–Fuzzy Inference System (ANFIS) [7][8]. However there is a possibility that this system may get trapped in the local minima and not give optimum results as generally a Hybrid Learning Algorithm (HLA) is used to determine the parameters of the ANFIS structure.

In this work, we propose a global optimization technique specifically Genetic Algorithm (GA) to optimize and fine–tune the parameters of the ANFIS structure thereby giving better performance compared to the existing approaches. A comparative analysis has been done between the applications of ANFIS which has been optimized using HLA and the proposed method, ANFIS–GA for removal of artifacts from EEG.

The rest of the paper has been ordered as follows. Section II briefly presents the concept of Adaptive Noise Cancellation, Adaptive Neuro–Fuzzy Inference System, and the application of Genetic Algorithm to tweak the parameters of the ANFIS structure. Section III presents the mechanism on how the simulated signals have been obtained as well as results of ANFIS and ANFIS–GA in denoising the EEG signal. Section IV is dedicated to conclusions.

II. METHODOLOGY

A. Adaptive Noise cancellation

An adaptive noise canceller shown in fig. 1[8], requires two inputs, a primary signal contaminated with noise and a reference signal containing noise correlated to the noise present in the primary signal. It models and eliminates the measurable interference of the reference noise signal in the primary signal. It is assumed that the noise in the primary signal is not correlated to clean signal present in the primary and there exists some degree of correlation between the noise in the reference signal and the noise in the primary signal. The adaptive filter adaptively filters and subtracts the reference input from the primary input and the output is assumed to be a clean denoised signal.

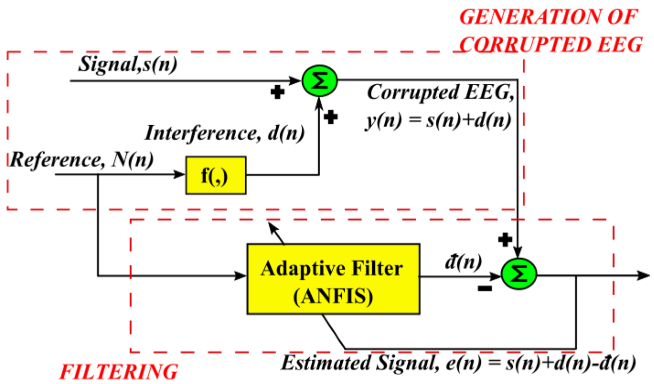

Fig. 1. Schematic of Adaptive Noise Canceller (ANC) Using ANFIS

The reference noise signal *N(n)* containing the artifacts is given as an input to the adaptive noise canceller. In order to simulate the human body, the reference noise signal passes through the unknown non-linear dynamics of the human body *f(.)* in order to yield a distorted noise signal *d(n).* A delayed version of the distorted noise signal (in order to account for the time taken for the signal to travel from the artifact generating source to the scalp) is then added to the clean EEG signal *s(n)* producing a corrupted signal expressed as,

$$y(n) = s(n) + d(n) = s(n) + f(N(n) + N(n-1) + N(n-2)..) \quad (1)$$

where *y(n)* represents the EEG measured at the electrodes. This measured EEG signal *y(n)* is given as the second input to the ANC.

The objective of the ANC is to retrieve the clean EEG signal *s(n)*. The ANC does so by modifying its coefficients in such a way that the "error" signal produced becomes a close approximation of *s(n)*. The "error" signal is given as,

$$\hat{e}(n) = s(n) + d(n) - đ(n), \quad (2)$$

Since the non – linear dynamics of the human body *f(.)* can't be determined , *d(*n) can't be determined directly and hence an ANFIS structure has been proposed [8], in order to replicate the delayed version of interference noise signal, *đ(n).*

B. *ANFIS Structure*

ANC using linear filters has been widely employed to remove ECG from EEG, maternal ECG cancellation to extract the fetal ECG from the abdominal signal, echo elimination on long distance telephone transmission lines and antenna side lobe interference removal [9]. The concept of linear adaptive filtering can be extended to the realms of non – linear adaptive filtering. Adaptive Neuro–Fuzzy Inference System (ANFIS), is one such non – linear adaptive filtering technique which has been employed here to remove artifacts from the EEG signal.

The ANFIS structure was originally presented by Jang [11]. It combines the linguistic capability of the Fuzzy Inference System (FIS) along with the learning capability of the Neural Network. Hence the rules and the parameters of membership functions of the ANFIS system are estimated using the Back Propagation (BP) algorithm of Neural Networks (NN).

The ANFIS structure is constructed out of zero or first order sugeno fuzzy model. A first order sugeno fuzzy model with two rules is shown in fig. 2. The rules of a first order sugeno model with x and y as inputs are defined,

$$\text{IF } x \text{ is } A_1 \text{ AND } y \text{ is } B_1, \text{ THEN } f1 = p_1(x) + q_1(y) + r_1 \quad (3)$$
$$\text{IF } x \text{ is } A_2 \text{ AND } y \text{ is } B_2, \text{ THEN } f2 = p_2(x) + q_2(y) + r_2 \quad (4)$$

The part of the rule before *THEN* is called as the antecedent (non-linear) and the part of the rule follows *THEN* is called as consequent (linear). The ANFIS system learns about the input-target pairs by tweaking two sets of parameters, one being the consequent parameters represented by the symbols p_1, p_2, q_1, q_2, r_1, r_2 in the above set of rules and the other being the premise parameters which define the input and output membership functions.

ANFIS is a five layered structure as illustrated in fig. 3, is fundamentally composed of membership function layer (layer 1), rule layer (layer 2), normalized layer (layer 3), defuzzification layer (layer 4) and total output layer (layer5). Circular nodes represent fixed nodes and square nodes represent adaptive nodes that have parameters to be trained.

Layer 1: Every node i in this layer is an adaptive node with a node function,

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1,2 \text{ or} \quad (5)$$
$$O_{1,I} = \mu_{B_{(i-2)}}(y) \text{ for } I = 3,4 \quad (6)$$

where x (or y) is the input to node i and A_i (or B_{i-2}) is a linguistic label associated with this node. The membership function chosen for each linguistic label is usually a Generalized Bell Membership Function (gbellmf) defined by,

$$\mu_A(x) = \frac{1}{1 + |(x - c_i)/a_i|^{2b_i}} \quad (7)$$

where $\{a_i, b_i, c_i\}$ is the parameter set called as premise parameters.

Layer 2: Every node in this layer is a fixed node labelled Π, whose output is the product of all the incoming signals and represents the firing strength of the rule,

$$O_{2,i} = w_i = \mu_{A_i}(x) * \mu_{B_i}(y) \text{ for } i = 1,2 \quad (8)$$

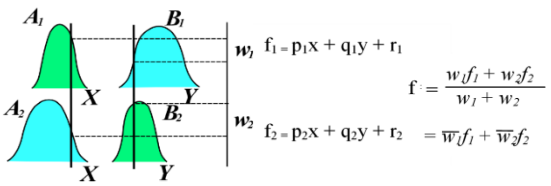

Fig. 2. First order sugeno fuzzy model with two rules

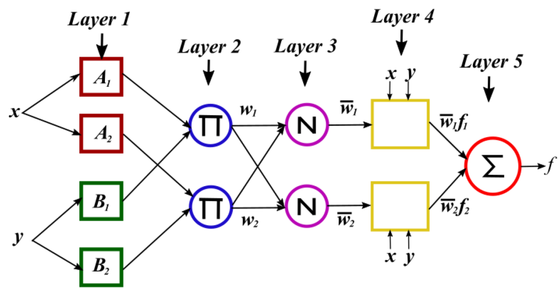

Fig. 3. ANFIS architecture

Layer 3: Every node in this layer fundamentally normalizes the firing strength of the rules,

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad ,for\ i = 1,2 \tag{9}$$

Layer 4: Every node i in this layer is an adaptive node having $\{p_i,\ q_i,\ r_i\}$ as the parameter set of this node (consequent parameters) with a node function:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i x + r_i) \tag{10}$$

Layer 5: This layer comprises of a single node which computes the overall output as the summation of all incoming signals:

$$Overall\ output = O_{5,i} = \Sigma_i \overline{w_i} f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \tag{11}$$

Commonly, a hybrid learning algorithm is employed in order to tune the parameters (rules, premise and consequent parameters) of the ANFIS structure. In the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by least squares method keeping the premise parameters fixed. In the backward pass, the signals that propagate backwards are the error signals and the premise parameters are updated by gradient descent method keeping the consequent parameters fixed.
The drawback of the hybrid learning algorithm is that the probability of the parameters getting trapped in the local optima is high, thereby resulting in the ANFIS structure not achieving global optimization.

C. *Artifact Removal Using ANFIS - GA*

In order to overcome the above drawback, a global optimization technique namely Genetic Algorithm has been utilized in order to obtain optimum values of parameters of the ANFIS structure [12].

The term genetic algorithm was proposed by Holland [13] in the year 1975 and further popularized in the late 1980's by Goldberg [14]. The gist of a genetic algorithm is summarized in the Pseudo-code given in fig. 4.

Genetic algorithm initially starts with a random population of chromosomes. Each chromosome comprises of a set of real values defining the premise parameters of the ANFIS structure namely the center parameters (c_i), width parameters (a_i), the steepness at the crossover points (b_i) of the generalized bell membership function and the consequent parameters of the ANFIS structure $\{(p_i)\ (q_i)\ (r_i)\}$. Initially the population is generated with the chromosomes having random values. The structure of the chromosome is given by, $\{(a_i)\ (b_i)\ (c_i)(p_i)\ (q_i)\ (r_i)\}$.

```
START
    Initialize an initial population of solutions randomly
    Compute fitness of initial population
    Repeat
        Choose a pair of parents depending on their fitness value
        Generate off-springs using cross-over operator
        Apply mutation operator to the offsprings
        Compute fitness of generated off-springs
        All generated off-springs comprise of a new population,
        previous population dies
    Until a stop criterion has been achieved
END
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Fig. 4. Summary of Genetic Algorithm

The viability of a chromosome being the best solution to the defined problem is given by fitness function,

$$Fitness = \frac{1}{1 + MSE} \tag{12}$$

where, *MSE* is the mean square error between the desired/target output and the actual output obtained from the ANFIS structure. In order to breed chromosomes for the next generation, chromosomes of the previous generation having the best fitness value are crossed over with other chromosomes by roulette wheel method and are also mutated using mutation operators. A new generation is created when the above process is complete.

As each generation progresses, the chromosomes evolve so as to maximize the value of the fitness function. Genetic algorithm is terminated when the stopping criteria has been achieved (number of generations, best fitness value etc.).

III. RESULTS AND DISCUSSION

A. *Simulated Signals*

In order to evaluate the performance of ANFIS and ANFIS–GA on artifact removal from the EEG signal, we simulated clean EEG, EOG artifacts and by combining the above two signals, we obtain a corrupted EEG signal that has been used for the simulation study. These simulated signals are shown in fig. 5. For comparative analysis between the two systems, Signal to Noise Ratio (SNR), and Mean Square Error (MSE) are used as performance indexes.

In order to simulate a clean EEG signal an auto regressive function [8] is used,

$$s(t) = 1.0084s(t-1) - 0.1887s(t-2) - 0.3109s(t-3) - 0.0510s(t-4) + w(t) \tag{13}$$

where $w(t)$ is a random white noise sequence with Gaussian distribution.

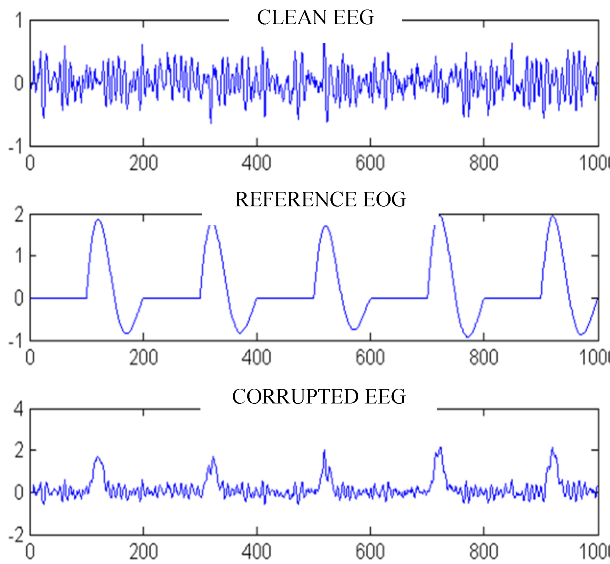

Fig. 5. Simulated signals for a length of 1000 samples

The EOG artifacts employed are sinusoids which are exponentially damped having random amplitudes and shapes,

$$N_j(k) = K a_j e^{-4k/\tau_j} \sin(2\pi k/N), \text{ for } k = 0, 1, \ldots, N-1 \quad (14)$$

where,

N determines the length of the artifact waveform and is set to 100 samples,
parameters a_j and τ_j determines the amplitude and shape of the j^{th} artifact,
K is an amplitude scaling constant.

To simulate the deviations in amplitude and shape of the artifacts, both parameters were set to new random values at the start of each artifact. These generated artifacts were scaled and added to the simulated clean EEG to generate the corrupted EEG signal.

In order to simulate non – linear dynamics of the human body, a non – linear function is utilized in order to combine the simulated EOG artifacts with the clean EEG signal [8],

$$x(t) = EEG(t) + \alpha\xi(EOG(t)) \quad (15)$$

where α is a scaling factor, and ξ is the nonlinear transfer, which was chosen to be of the form [8],

$$\xi(EOG(t)) = EOG(t) + EOG^2(t) + EOG^3(t) \quad (16)$$

in which the scaling factor α is selected as 0.75 [8].

A. Performance Indexes

In order to demonstrate the superiority of ANFIS – GA over ANFIS, the simulated signals was given to both the systems, ANFIS and ANFIS-GA. The reference EOG and a delayed version of the same was given as inputs. The output obtained from both the systems was analyzed against the clean EEG signal and various performance indexes such as SNR and MSE were evaluated [8]. SNR is defined as,

$$SNR = 10\log_{10}\left\{\frac{\Sigma(E_{eeg})^2}{\Sigma(S_{eeg} - E_{eeg})^2}\right\} \quad (17)$$

where

E_{eeg} is the denoised EEG signal
S_{eeg} is the standard clean EEG signal.

The MSE is calculated using the following formula,

$$error = S_{eeg} - E_{eeg} \quad (18)$$

$$MSE = \frac{\Sigma(error)^2}{length(error)} \quad (19)$$

B. Performance Analysis

Performance of ANFIS for denoising the EEG signal has been tabulated in Table I.

TABLE I. PERFORMANCE ANALYSIS OF ANFIS

ANFIS Setup		Performance Indices	
No of inputs	MF	SNR(dB)	MSE
2	3 gbellmfs	12.1179	0.0029
2	4 gbellmfs	10.5094	0.0040

Fig. 7 shows the denoised EEG signal along with the original clean EEG signal. The absolute error is in the range –0.1 to 0.1.

The ANFIS structure considered for optimization [15] has two inputs and three membership functions for each input as shown in fig. 6. Increase in the number of membership functions deteriorates the performance of the ANFIS structure as shown in Table I. Hence we have considered the ANFIS structure where each input has three membership functions and have optimized this structure using Genetic Algorithm.

Performance of ANFIS–GA for denoising the EEG signal has been tabulated in Table II.

TABLE II. PERFORMANCE ANALYSIS OF ANFIS - GA

ANFIS Setup		GA Setup	Performance Indices	
No. of inputs	MF	No. of generations	SNR(dB)	MSE
2	3 gbellmfs	200	15.5538	0.0014
2	3 gbellmfs	400	20.8129	4.0949 e-04

Fig. 8 shows the result of ANFIS–GA in denoising the EEG signal for 200 generations with population size of 100. The SNR obtained (15.5538 dB) from this system shows moderate improvement over the ANFIS structure (12.1179 dB) tuned using Hybrid Learning Algorithm.

Fig. 9 displays the result of ANFIS–GA performing the same denoising operation for 400 generations with population size of 100. This system shows considerable improvement with a SNR of 20.8129 dB.

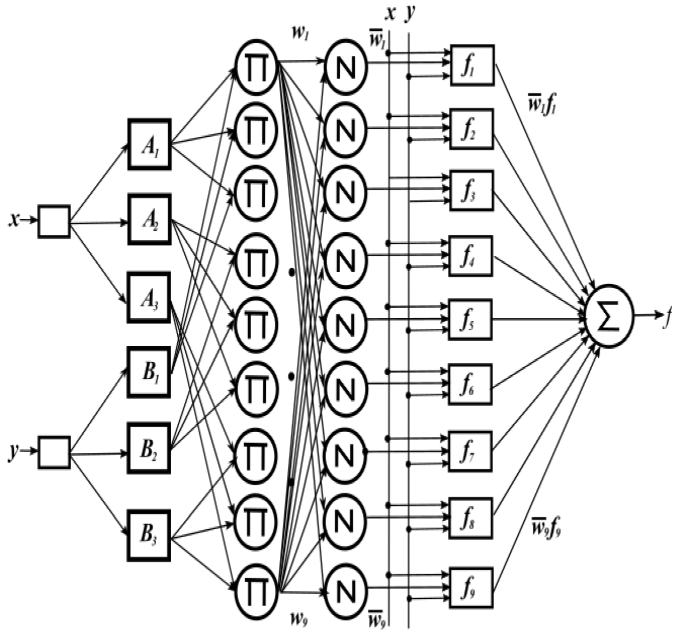

Fig. 6. ANFIS structure having two inputs and three membership functions

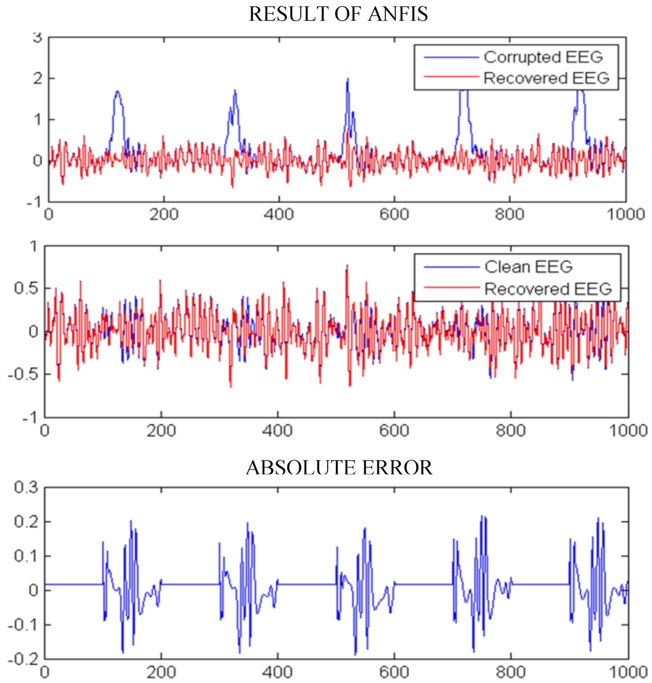

Fig. 7. Result of ANFIS, Inputs = 2, Membership Functions = 3. a) Corrupted EEG v/s recovered EEG, b) Original Clean EEG v/s recovered EEG, c) Absolute error of output

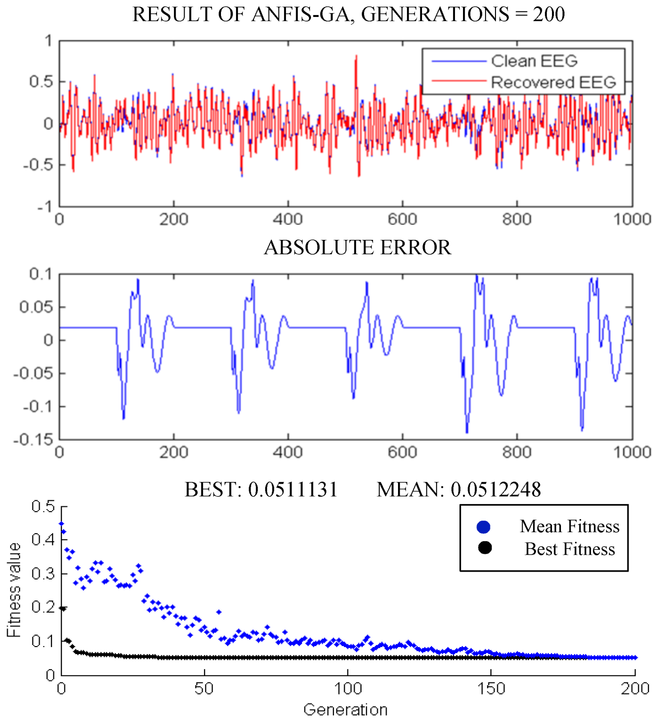

Fig. 8. Result of ANFIS-GA, Generations = 200, Population Size = 100 a)Original Clean EEG v/s recovered EEG, b) Absolute error of output, c) Error of ANFIS structure v/s generations

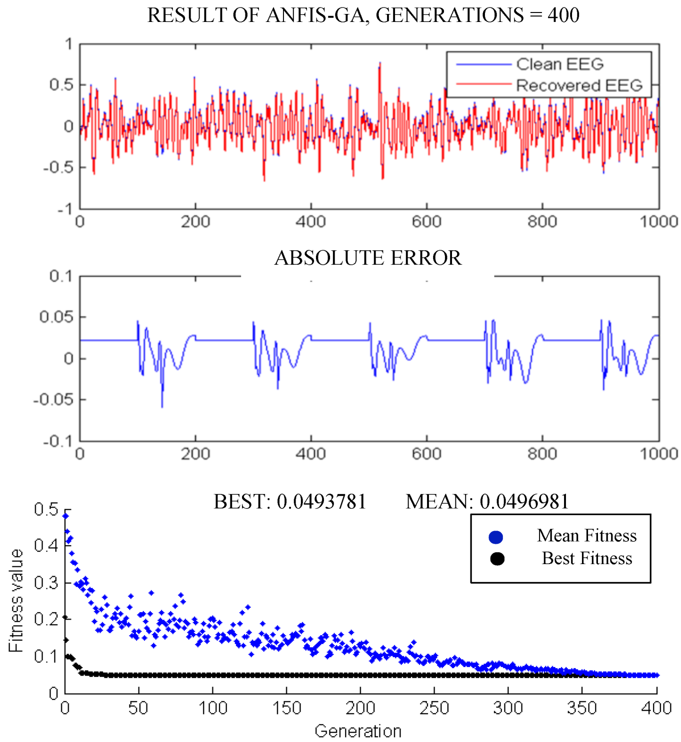

Fig. 9. Result of ANFIS-GA, Generations=400, Population Size=100 a) Original Clean EEG v/s recovered EEG, b) Absolute error of output, c) Error of ANFIS structure v/s generations

Hence ANFIS-GA outperforms the ANFIS structure optimized using the hybrid learning algorithm in denoising the EEG signal. With an increase in number of generations, ANFIS-GA provides a better SNR and MSE as compared to ANFIS. However increase in number of generations results in increased computational time. But the improved performance provided by the proposed method eclipses the increase in the computational time.

IV. CONCLUSION

The EEG signal is corrupted by various artifacts such as EOG and EMG. Commonly used filtering methods for the EEG signal such as linear filtering, linear combination and regression, wavelet transform and independent component analysis require complex manual calculations and depends on visual analysis. In order to denoise the corrupted EEG signal, an ANC method based on ANFIS is used. In this paper, a global optimization namely the Genetic Algorithm has been used to optimize the ANFIS structure(ANFIS–GA). It has been shown the ANFIS–GA system results in better performance with a SNR of 20.8129 dB(400 generations) and 15.5538 dB(200 generations) as compared to the ANFIS structure(12.1179 dB) tuned using the generally used Hybrid Learning Algorithm.

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REFERENCES

[1] H.K. Garg, P.G. Kohli and A.K. Kohli, "A Review of neural signal processing paradigms based on pyhsiological models for EEG," J. of AI, Volume 3, Issue 2, 2012, pp.56-73.

[2] Sadasivan, P.K.; Dutt, D.N., "Line interference cancellation from corrupted EEG signals using modified linear phase FIR digital filters".

[3] R. Croft and R. Barry, "EOG correction: which regression should we use?" Psychophysiology 37 (1), 2000, pp: 123-125.

[4] Guerrero-Mosquera, C. and Navia-Vázquez, A, "Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," Signal Processing, IET (Volume:6 , Issue: 2), 2012, pp. 99 – 106.

[5] V. Krishnaveni, S. Jayaraman, S. Aravind, V. Hariharasudhan, and K.Ramadoss, "Automatic identification and removal of ocular artifacts from EEG using wavelet transform," Meas. Sci. Rev. 6 (4), 2006, pp. 45-57.

[6] P. Senthil Kumar, R. Arumuganathan, K. Sivakumar, and C. Vimal, "Removal of ocular artifacts in the EEG through wavelet transform without using an EOG reference channel," Int. J. Open Probl. Comput. Sci. Math. 1 (3), 2008, pp. 188-200.

[7] Paulchamy Balaiah and Ilavennila, "Comparative Evaluation of Adaptive Filter and Neuro-Fuzzy Filter in Artifacts Removal from Electroencephalogram Signal," American J. of App. Sci. 9 (10), pp. 1583-1593, 2012

[8] Wei Chen, Ze Wang, Ka Fai Lao and Feng Wan, "Ocular Artifact Removal from EEG Using ANFIS," 2014 IEEE International Conference on Fuzzy Systems, pp. 2410-2417

[9] C.Kezi Selva vijila, P.Kanagasabapathy, and Stanley Johnson, "Fetal ECG Extraction using Soft computing Technique", Journal of Applied Sciences, 6: 251-256, 2006.

[10] C. Kezi Selva Vijila, P. Kanagasabapathy, S. Johnson, and V. Edwards, "Efficient cancellation of artifacts in EEG signal using ANFIS," Int. J. of Soft Comput. 2 (3), 2007, pp. 355-360.

[11] J. S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," IEEE Trans. Systems, Man, and Cybernetics, Vol. 23, 665-685, 1993.

[12] Shoorehdeli, M. Aliyari, M. Teshnehlab, and A. K. Sedigh. "A novel training algorithm in ANFIS structure." American Control Conference, 2006. IEEE, 2006.

[13] Holland, J. H., Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor, MI, (1975).

[14] Goldberg, David E., Genetic Algorithms in Search, Optimization and Machine Learning, Kluwer Academic Publishers, Boston, MA. (1989)

[15] Karaboga, Dervis, and Ebubekir Kaya. "Training ANFIS using artificial bee colony algorithm." Innovations in Intelligent Systems and Applications (INISTA), 2013 IEEE International Symposium on. IEEE, 2013.