Use of ANFIS based Filters For Reduction of Noise From Biomedical Signals

R. J. Gajbe Department of Electronics VidyaBharatiMahavidyalaya, Amravati-444602 (India) *e-mail: rjgajbe@gmail.com* Dr. Y. B. Gandole Department of Electronics Adarsha Science J.B.Arts and Birla Commerce, Mahavidyalaya, Dhamangaon Rly-444709 (India) *e-mail: ygandole@gmail.com*

Abstract—Biomedical signals are the collection of electrical signals acquired from any organ of human body. These signals acquire noise while traveling through different tissues or blood vessels.Similarly,these signals are affected by electrical noise and some other factors. Electrical noise included inherent noise in Electronic equipments, ambient noise, motion artifacts, power line interference, base line drift, electrosurgical noise and inherent instability of signal. By using conventional methods, it is very difficult to reduce noise from biomedical signal.Therefore different methodologies are used to remove noise and artifacts. This paper describes the adaptive filters and adaptive network based fuzzy inference system (ANFIS) filters which are used to reduce noise from biomedical signals.

Keywords- Adaptive filter, AI, ANFIS, LMS, SLMS, SSLMS, NLMS, NSLMS

I. INTRODUCTION

Biomedical signal means a collective electrical signal acquired from any organ that represents a physical variable of interest. This signal is normally a function of time and is described in terms of its amplitude, frequency, and phase.The analysis of these signals is very important for researchers and medical practitioners because careful medical diagnosis isvery essential for proper treatment. If the signals are not properly diagnosed and analyzed, it will lead to wrong diagnosis and can be dangerous for the lives.

The biomedical signals are noisy as well as artifacts due to electrical noise included inherent noise in Electronic quipments, ambient noise, motion artifacts, power line interference, base line drift, electrosurgical noise and inherent instability of signal. This reduces the performance of desired signal. Therefore for the proper treatment of a patient, it should be removed from the desired signal. Using an amplifier with high gain, high input impedance and differential input with good common mode rejection, various filter circuits could reduce the noise from biomedical signals. But using conventional method, it is difficult to reduce maximum noise from biomedical signal. Therefore there is a need of intelligent solution for this.

In fact, various mathematical techniques and Artificial Intelligence approaches are being used for noise reduction.Literature reviews show that in nonlinear system identification, a mathematical model includes Wavelet Transform, Time Frequency Approaches, Fourier Transforms, Wegner-Villie Distribution, Statistical Measures and Higher Order Statistics. AI includes artificial neural network, dynamic recurrent neural network, Fuzzy logic system and genetic algorithm.Accuracy of biomedical signal also depends on the properties of electrodes and their interaction with skin, amplifier design, the conversion and subsequent storage of the biomedical signal from analog to digital form.

In the recent years, biomedical applications using signal processing techniques are a major area of interest. The lot of bio-engineers and researchers from medical field are keenly interested for design of techniques to obtain noiseless biomedical signals. R. Sehamby andButa Singh (2016) [14] have designed the adaptive electrocardiogram filter to reduce noise caused by external systems & body artifacts.R. J.George (2015) [12] reveals in his study that the pipelined DLMS adaptive FIR filter is faster than non-pipelined LMS adaptive FIR filter.S. Silarbi, B. Abderrahmane and A. Benyettou (2014) [17] have proposed adaptive network fuzzy inference system for phonemes recognition.H. K. Gupta, R. Vijay and N. Gupta (2013) [5] have observed that the accuracy has been increased by increasing filter order as well as with increased in step size, convergence rate took place fast. B. Chandrakar, O. P. Yadav and V. K. Chandra (2013) [10] havestudied Finite Impulse Response (FIR) filter based on various windows and Infinite Impulse Response (IIR) filters for noise removal of ECG signal. The researcher D. C. Dhubkarya and A. Katara [13] have studied the comparison of MATLAB Simulation and DSP Processor implementation of an adaptive filter on Least Mean Squared (LMS) and Normalized Least Mean Squared (NLMS) Algorithms. They suggested NLMS algorithm is superior in hardware implementation.

Jyh-Shing Roger Jang (1993) [18] suggested that the role of neural networks in signal processing have similar applications in Adaptive network based fuzzy inference system (ANFIS). The nonlinear and structured knowledge representation of ANFIS are the primary advantages over classical linear approaches in adaptive filtering and adaptive signal processing such as identification, inverse modeling, predictive coding, adaptive channel equalization, adaptive inference (noise or echo)cancelling, etc.

II. SOFTWARE SPECIFICATION REQUIREMENT ANDIMPLEMENTATION DETAILS

In real life situations, the accuracy of the measurement is required. As we know that biomedical signals are error prone due to complicated situations. ANFIS can be used to obtain reasonably good accuracy and intelligently reduce the noise. In this section, we have simulated the MATLAB codes for the data conversion, adaptive filter algorithm, artificial intelligent [ANFIS] training and its testing.

Database collection:

To design ANFIS Model, a sufficiently large amount of data is required for training and testing. We have collected standard data bases for biomedical signal from the following websites.

https://physionet.org

http://www.emglab.net

https://drive.google.com/file/d/0B3NaVR72FYQcaHAybXVC Z0ViVVk/view.

We have used 500 samples for the training and testing of Adaptive filters and ANFIS based filters.

Software specification:

MATLAB (Matrix Laboratory), 2014b is used for simulation. It is a numerical computing environment and fourth-generation programming language developed by Math-Works. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN.

Implementation details:

The GUI is constructed by using Matlab codes. Other set of codes have been used to run the various algorithms for noise removal in Matlab simulator.

The main GUI contains four parts-

1] File input and its conversion

2] Adaptive filter algorithm and its Input parameter section

3] Output parameters section

4] Artificial intelligent noise removal section.

File input and its conversion:

Most of the data bases are available in .dat or .xls format. To read this in Matlab, we have designed a code which will convert and save the .dat file or .xls file in .mat file format.

Biosignal.dat



Figure 1: Block diagram of conversion of .dat and .xls files into .m files.

Adaptive filter section and its Input parameter section: There are numerous Adaptive filter algorithms [22], out of which 5 algorithms were used.

These are

1] Adaptive Least Mean Square (LMS) Algorithm: If w(n) is the filter coefficient vector at step n (time), then its' updated value w(n+1) is given by

 $w (n + 1) = w (n) + 2 \mu e(n) x(n)$ Where, Filter output $y(n) = w^{T}(n) x (n)$ Errore(n) = d (n) - x (n)Filter taps at time n, $w(n) = [w_0(n) w_1(n) \dots w_{M-1}(n)]$ and Input data, $x (n) = [x(n) x(n-1) \dots x(n-(M+1))]^{T}$ 2] Adaptive Normalized LMS Algorithm: The updated value w (n + 1) is given by

$$w(n + 1) = w(n) + \frac{1}{x^{T}(n) \times (n)} e(n) \times (n)$$

with

$$\mu(n) = \frac{1}{2 x^{T}(n) x(n)}$$

3] Adaptive Sign LMS Algorithm:

The updated value w(n + 1) is given by

 $w (n + 1) = w (n) + 2 \mu e(n) Sign (x (n))$

4] Adaptive Sign Sign LMS Algorithm: The updated value w(n + 1) is given by

$$w(n + 1) = w(n) + 2 \mu Sign(e(n))Sign(x(n))$$

5] Adaptive Normalized Sign LMS Algorithm: The updated value w (n + 1) is

is given by

$$w (n + 1) = w (n) + 2 \mu - \frac{Sign (e(n) x(n))}{||x(n)||^2}$$

Output parameter section:

The performance of ANFIS is assessed on the basis of performance parameters Signal to Noise Ratio (SNR_out). The output SNR (SNR_out), is calculated from the power of input signal x (n) and noise signal e (n) and is given by,

$$SNR_out = 10 \ Log_{10} \ \boxed{\begin{array}{c} Signal \ Power}{Noise \ Power}}$$

Or SNR_out= P_{signal}/P_{noise} .

Wherethe power is expressed in decibel.

Artificial intelligent noise removal algorithm:

We have designed an artificial intelligent model for removal of noise from biomedical signal by using Matlab coding. The fig. 2 shows the block diagram of proposed artificial intelligent model of adaptive network based fuzzy inferencesystem(ANFIS).



Figure 2: Block diagram of proposed ANFIS Model

ANFIS based Noise Removal Algorithm:

Proposed model havedesigned on the basis of Sugeno architecture. The basics of Sugeno inference architecture is discussed below.

Sugeno inference architecture [18]:

In TSK or Sugeno architecture, defuzzification block of Mamdani architectureis replaced by a normalization and weighted average. The TSK architecture does not require MAX operators, but a weighted average is applied directly to regions selected by MIN operators. The TSK system is really simple because of the output weights are directly proportional to the average function values at the selected regions by MIN operators.

Sugeno and Takagi used the following architecture which is graphically represented in Fig. 3.

R1: if x is A1 and y is B1 then z1 = p1x + q1y + r1R2: if x is A2 and y is B2 then z2 = p2x + q2y + r1Fact: x is x0 and y is y0

Consequence: z

The firing levels of the rules are computed by $wl = A1(x0) \wedge B1(y0), w2 = A2(x0) \wedge B2(y0)$ Then the crisp control action is expressed as

$$Z_0 = \frac{W_1 Z_1 + W_2 Z_2}{W_1 + W_2}$$

If we have n rules in our rule-base then the crisp control action is computed as

$$Z_{o} = \frac{\sum_{i=1}^{n} w_{i} z_{i}}{\sum_{i=1}^{n} w_{i}}$$

Where *wi*denotes the firing level of the *i*th rule, i = 1, ..., n



Figure 3 (a):Sugeno Fuzzy Model



Figure 3 (b): Equivalent ANFIS architecture

For the design of model, we have selected, Membership Functions per Input = 12Epoch numbers = 30

No. of taps= 02

However, an epoch corresponds to the entire training set going through the entire network once. It can be useful to limit the over fitting.

In addition to this, generalized Bell Type Membership Function (MF) has been used in the network.

A generalized bell MF is specified by three parameters (a, b, c):

1

$$f(\mathbf{x}; \mathbf{a}, \mathbf{b}, \mathbf{c}) = \frac{1}{1 + \left|\frac{\mathbf{x} - \mathbf{c}}{\mathbf{a}}\right|^2} \mathbf{b'}$$

where the parameter b is usually positive. If b is negative, the shape of this MF becomes an upside-down bell. However, each of these parameters has a physical meaning: c determines the centre of the corresponding membership function; a is the half width; and b (together with a) controls the slopes at the crossover points. Note that this MF is a direct generalization of the Cauchy distribution used in probability theory, so it is also referred to as the Cauchy MF. Because of their smoothness and concise notation, Gaussian and bell MFs are becoming increasingly popular for specifying fuzzy sets [58].

III. SIMULATION RESULTS

The major objective of this study was to investigate a noise removal filters. For this, simulations are carried out on ECG and EMG signals.The results are obtained on output parameter section of Matlab based GUI for removal of noise from biomedical signal. The Table 1 shows the signal to noise ratio of adaptive Filter using algorithms LMS, NLMS, NSLMS, SLMS and SSLMS for various step sizes on ECG signal 1.

Table 1: SNR_outVs Step size for adaptive filter using various algorithms

No. of taps= 2 and $SNR_i = 0$

Step	SNR_out					
Size	LMS	NLMS	NSLMS	SLMS	SSLMS	
1e-7	-0.19906	26.7339	26.7339	7.97304	26.7338	
1e-8	0.21109	26.7339	26.7339	24.324	26.7339	
1e-9	1.23573	26.7339	26.7339	26.7018	26.7339	
1e-10	10.2783	26.7339	26.7339	26.7336	26.7339	
1e-11	24.5255	26.7339	26.7339	26.7339	26.7339	
1e-12	26.7039	26.7339	26.7339	26.7339	26.7339	
1e-13	26.7336	26.7339	26.7339	26.7339	26.7339	
1e-14	26.7339	26.7339	26.7339	26.7339	26.7339	
1e-15	26.7339	26.7339	26.7339	26.7339	26.7339	

Table 1shows that Normalized LMS and Normalized Sign LMS algorithm performed better at a small step size also. But overall, all algorithms have good performance on step size 1e-

10, which governs the rate of convergence, speed of tracking ability.

However, use of small step size is to ensure a small steady state error. But a small step size decreases the convergence speed of the adaptive filter. However, increase in step size is to improve the convergence speed of the adaptive filter. But a large step size might cause the adaptive filter to become unstable. So we have to select optimum value of step size [57].

For this study, theANFIS based filters are examined on various biomedical signals(ECG and EMG). The SNR_outof ANFIS based filters are compared with the adaptive filters for the selected parameters;No. of Taps= 02, SNR_in= 0 and Step size= 1e-10. ANFIS based filters have tested on various ECGand EMG signals. For this, we used Generalized Bell Membership Function. The Table 2 shows the comparison of SNR_out of Adaptive and ANFIS based filters.

Table 2: Comparison of SNR_out of Adaptive and ANFIS based filters.

Algorithm	ANFIS bas	Adaptive		
	ECG1	ECG2	EMG	Filter SNR_out
LMS	19.5649	35.0811	22.6133	10.2783
NLMS	26.7339	35.1005	35.3044	26.7339
NSLMS	26.7339	35.1005	35.3044	26.7339
SLMS	26.7339	35.1005	35.3044	26.7336
SSLMS	26.7339	35.1005	35.3044	26.7339

From Table 2, it is inferred that SNR_out for all selected algorithms show excellent signal to noise ratio. Thus all algorithms are excellently filtered out the noise signal from the biomedical signal.

IV. DISCUSSION

The amplitude biomedical signals are obtained in mV or in μ V ranges. Thus the signals are easily affected by various noise sources result in degrading the signal. Even in the modern world of biomedical instrumentation, all possible filtering arrangements are carried out by the other researchers. But still due to randomness of noise signal, original signal get affected and this process is dynamic. So such problem demands the dynamic solution as well.

Therefore for the dynamic solution, we choose Artificial Intelligent based filtering algorithms. This has only two processes- training and testing. Training process based on subset outcomes of adaptive filtering algorithm in initial stages, which may not require in later time even on change of source input as well, called trained filter / smart filter. Such intelligent filters give the freedom of selection of signal with different SNR values; also not bother about number of parameter settings which lead one more step towards the auto filter concept.

For the simulation, we have used different ECG and EMG signals. The simulation results are carried out by measuring the performance parameters SNR_out and these results are summarized in tabular form in the Tables 1 and 2. The comparison of these two filters reveals that the ANFIS based algorithms give better results than the adaptive filter algorithms.

V. CONCLUSION

The main goal of the current study was to design artificial intelligent filters to reduce noise from the biomedical signals. The implementation of the biomedical signals on various adaptive algorithms (LMS, NLMS, NSLMS, SLMS and SSLMS) is successfully performed. The result of this study indicates that the AI (ANFIS) algorithms give better results than the adaptive filter algorithms. The AI algorithms are excellent systems to filter out the noise signal from the biomedical signal. The proposed algorithm plays an important role in noise reduction from any biomedical signals.

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