

Reduction of Noise from ECG Signal Using Adaptive Network Based Fuzzy Interface System Model

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Abstract:

ECG (Electrocardiogram) signal acquire noise while traveling through different tissues or blood vessels. The analysis of ECG signal is very important for researchers and careful medical diagnosis and proper treatment are also essential. For proper analysis of ECG signal noise as well as artifacts which have to be removed for proper treatment of a patient. Therefore different methodologies are used to remove noise and artifacts. This paper describes the adaptive network based fuzzy inference system which is used to reduce noise from ECG signal.

Keywords: adaptive network based fuzzy inference system, LMS, SLMS, SSLMS, NLMS, NSLMS.

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I. Introduction

ECG signal is normally a function of time and is describable in terms of its amplitude, frequency, and phase. The analysis of ECG signal is very important for researchers and careful medical diagnosis and proper treatment are also essential. If the signals are not properly diagnosed and analyzed, it will lead to wrong diagnosis and can be dangerous for the lives. Some noise as well as artifacts reduces the performance of ECG signal. During signal processing, the system picks up noise signal along with desired signal. Therefore for the proper treatment of a patient, it should be removed from the original 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 ECG signal. Now 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. Measuring and accurately of ECG signal depends on the properties of electrodes and their interaction with skin, amplifier design and the conversion and subsequent storage of the biomedical signal from analog to digital form.

ECG signal is affected by electrical noise and some other factors. Electrical noise included inherent noise in Electronic equipment's, ambient equipment's, ambient noise, motion artifacts, power line interference, base line drift, electrosurgical noise and inherent instability of signal. By using conventional method, it is difficult to reduce noise from biomedical signal.

Biomedical applications using signal processing techniques are a major area of interest and investigating various adaptive filters and artificial intelligent model. The lot of bio-engineers and researchers from medical field are keenly interested for design of techniques to obtain noiseless biomedical signals. Dhukarya D.C., Katara A. [1] have performed 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. Sehamby R. & Buta Singh (2016) [2] have been designed the adaptive electrocardiogram filter to reduce noise caused by external systems & body artifacts.

II. Software Specification Requirement And Implementation

Database Descriptions:

To design adaptive network based fuzzy inference system Model, We collect standard data bases for ECG signal from following web sites.

<https://physionet.org>

<http://www.emglab.net>

We used 400 samples for the training and testing of adaptive network based fuzzy inference system Model.

Software specification:

MATLAB (matrix laboratory), 2014b is used for simulation. 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 using MATLAB codes and run these codes 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.

Adaptive filter section and its Input parameter section:

There are numerous Adaptive filter algorithms [3], out of which 5 algorithms were used.

These are

- 1] Adaptive 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 $y(n) = w^T(n)x(n)$

$$\text{Error } e(n) = d(n) - x(n)$$

Filter taps at time n , $w(n) = [w_0(n) w_1(n) \dots \dots \dots w_{M-1}(n)]$ and

Input data, $x(n) = [x(n) x(n-1) \dots \dots \dots x(n-(M+1))]^T$

- 2] Adaptive Normalized LMS Algorithm:

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

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

with

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

- 3] Adaptive Sign LMS Algorithm:

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

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

- 4] Adaptive Sign Sign LMS Algorithm:

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

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

- 5] Normalized Sign LMS Algorithm:

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

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

Output parameter section:

The performance of ANFIS is assessed on the basis of performance parameters Signal To Noise Ratio (SNR_{out}).

SNR (Signal to Noise ratio):

The output SNR (SNR_{out}), is calculated from power of the input signal $x(n)$ and an noise signal $e(n)$ and is given by,

$$\text{SNR}_{\text{out}} = 10 \text{Log}_{10} \left(\frac{\text{Signal Power}}{\text{Noise Power}} \right)$$

Where SNR_{Out} is the ratio of the two powers expressed in decibels.

Artificial intelligent noise removal algorithm:

We have designed a artificial intelligent model for removal of noise from biomedical signal by using Matlab coding and run the programme which creates graphical user interface. The fig. 2 is the block diagram of proposed artificial intelligent model of adaptive network based fuzzy inference system.

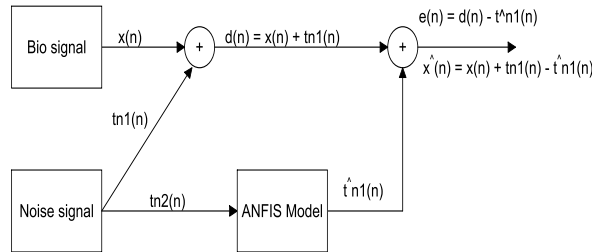


Figure 2: Block diagram of proposed ANFIS Model

ANFIS based Noise Removal Algorithm:

For the design of model, we choose,
 Membership Functions per Input = 12
 Epoch numbers = 30
 No. of taps= 2

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

Membership Function (MF) Type used in this network is Generalized bell MFs.

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

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

where the parameter b is usually positive. If b is negative, the shape of this MF becomes an upside-down bell. 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.

III. Simulation Results

The results are obtained on MATLAB based GUI for removal of noise from ECG signal and accordingly,. The Table 1 shows the signal to noise ratio of adaptive Filter using algorithms LMS, NLMS, NSLMS, SLMS, SSLMS for various step sizes.

Table 1: SNR_out Vs Step size for adaptive filter using various algorithms
 No. of taps= 2 and SNR_in = 0 dB

Step Size	LMS	NLMS	NSLMS	SLMS	SSLMS
	SNR_out	SNR_out	SNR_out	SNR_out	SNR_out
1e-7	-0.19907	26.7337	26.7337	7.97303	26.7337
1e-8	0.21109	26.7337	26.7337	24.3238	26.7338
1e-9	1.23573	26.7337	26.7337	26.7018	26.7338
1e-10	10.2783	26.7337	26.7337	26.7336	26.7338
1e-11	24.5255	26.7337	26.7337	26.7337	26.7338
1e-12	26.7039	26.7337	26.7337	26.7337	26.7338
1e-13	26.7336	26.7337	26.7337	26.7337	26.7338
1e-14	26.7339	26.7337	26.7337	26.7337	26.7338
1e-15	26.7339	26.7337	26.7337	26.7337	26.7338

Table 1 shows that Normalized LMS and Normalized Sign LMS gave better SNR_out for small step size of value 1e-7. But overall SNR_out for all algorithms are good on step size 1e-10.

ECG signal is examined using adaptive network based fuzzy inference system based filters on the performance parameter SNR_out. It compares the adaptive filters with adaptive network based fuzzy inference system based filters on the basis of SNR_out.

No. of Taps = 02, SNR_in = 0 dB and Step size = 1e-10 are selected as input parameters and adaptive network based fuzzy inference system based filters were tested on various ECG signals with MFs 15 per input

and epochs 30. For this, we used Generalized Bell Membership Function. The Table 2 shows comparison of SNR_out of Adaptive and ANFIS based filters.

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

Algorithm	ANFIS based Filter SNR_out		Adaptive Filter SNR_out
	ECG_Noise1	ECG_Noise2	
LMS	19.5647	35.0810	10.2781
NLMS	26.7337	35.1003	26.7337
NSLMS	26.7337	35.1003	26.7337
SLMS	26.7337	35.1003	26.7337
SSLMS	26.7337	35.1003	26.7337

From Table 2, it is inferred that SNR_out for all selected algorithms shows good result except Least mean square (LMS).

Figure 3 shows the Training data on adaptive network based fuzzy inference system Model

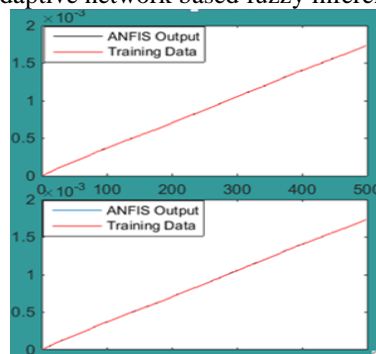


Figure 3: Training data on adaptive network based fuzzy inference system Model

Figure 4 shows the test of ECG signals on adaptive network based fuzzy inference system Model

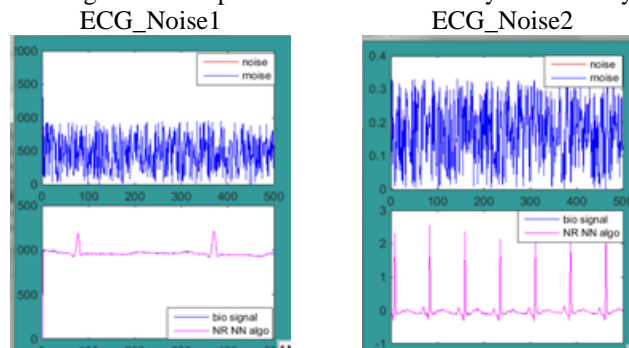


Figure 4 : Testing ECG signals on adaptive network based fuzzy inference system Model

IV. Discussion

As we know the ECG signals are observed in millivolts or in microvolts ranges. This can be easily affected by various noise sources result in degrading the signal. Even in the modern world of biomedical instrumentation, all possible filtering arrangements are done. But still due to randomness of noise signal get affected and this process is dynamic. So such problem demands the dynamic solution as well.

Artificial Intelligent based filtering algorithms, which has only two process 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 simulation, we used two different ECG signals. Simulation results are summarized in tabular form in the Tables 1 and 2. The simulation results are carried out by measurement of the performance parameters SNR_out. From these results, we found that the AI algorithms give better results than the adaptive filter algorithms.

V. Conclusion

From these results, we found that the adaptive network based fuzzy inference system algorithms give better results than the adaptive filter algorithms. The AI algorithms are excellent systems to filter out the noise signal from ECG signal.

References

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