IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

Minimization of Interferences in ECG Signal Using a Novel Adaptive Filtering Approach

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Abstract

Electrocardiogram is the one among very important biomedical signals. It is the recording of electrical potential of heart versus time. The ECG signals are often contaminated by noise from various sources. So it is essential to minimize the effect of various noises encountered in ECG during the recording process. In this paper an adaptive filter based upon a novel approach is presented for de-noising of ECG signal where any additional reference input is not required, the recorded ECG signal itself can be used as reference signal. Delayed version of signal is provided to another part of filter. NLMS algorithm is used to get the improved result as compared to LMS. Comparison is made on the basis of signal to noise ratio and men square error. Results show that the proposed approach gives better performance than conventional LMS algorithm without reference signal.

Keywords: ECG, LMS, NLMS algorithm, Adaptive filter, PLI.

Introduction

There are various biomedical signals present in the human body, by examining these biomedical signal one can check the health condition whether that person is clinically fit or not. Electrocardiogram is one of them. ECG signal is electric representation of the activity of human's heart. Various cardiac diseases can be recognized with the help of ECG signal. While recording process of ECG signal, several types of noises may encounter in it. The common type of noises are power line interference (PLI), electrode motion noise (EM), muscle artifacts, baseline wander etc. It is essential to remove or minimize these interferences prior to further diagnosis for any medical application. The QRS segment is very important and it is predominantly used for clinical observation. So if the noise changes the amplitude or time duration of the segment then recognizing the true condition of patient is very difficult task. Therefore the primary concern is to preprocess the ECG signal. The objective is to separate the valid signal component from the undesired noises so that the accurate interpretation of ECG could be done.

There are various filtering techniques available for removing the unwanted noise components from ECG signal. Huhta and Webster [1] have studied the sources of 60-Hz interference in ECG and also proposed some of remedial actions. Performance of different adaptive filters have been studied [2], [5]. Lin et. al. [3] proposed a PLI detector that employs an optimal linear discriminant analysis (LDA) algorithm to make a decision for the PLI presence. An efficient recursive least-squares (RLS) adaptive notch filter is also developed to serve the purpose of PLI suppression. RLS algorithm has advantage of higher convergence rate than LMS but it possesses computer complexity problem. Thakor et. al. [4] presented an LMS based adaptive filter which takes the impulse response of QRS complex and then applied it for arrhythmia detection process.

The variable step size NLMS algorithm was studied [6], [7], and it was found that the convergence rate is greater than LMS algorithm. In [8], steady state MSE convergence analysis for deterministic reference input have been shown, the filter weight in steady state condition is biased and the adaptive filter does not approach to Wiener solution. The solution of this is to group the filter weights in form of blocks, namely the block LMS [9]. Also several modifications have been done in step-size parameter to increase the convergence rate, SNR or to decrease the value of MSE, e.g. [10] proposed a new variable sep-size NLMS algorithm in which they included exponential decay impulse responses, Costa et. al. in [11] proposed a noise resilient variable step size LMS algorithm.

Several less computational complex adaptive algorithms in time domain were also presented by [12], but these algorithms exhibits slower convergence rate. Reddy et. al. [13] proposed a novel algorithm namely constrained stability least mean square (CSLMS) algorithm based on differential inputs and errors to eliminate base line wander and power line interference. Additionally

Sowmya I. et. al. in [14] have given optimum step size least mean square (OSSLMS) algorithm for respiration wander removal from cardiac signal. These methods give good convergence rate. The necessary condition for above mention algorithm is the requirement of reference input which is correlated with either desired signal or the noise present in ECG. If this condition failed, the output would not be of correct form. Chang et. al. [15] proposed a solution to this problem by introducing single input adaptive noise canceller. When there is limited availability of reference input, the primary input itself can be used as reference input with certain modification in filter structure.

Problem Identification

The prime requirement of any adaptive filter is the selection of proper reference input signal. The reference input must be either well correlated with the signal component or the noise present in signal. The two basic structures are shown below [16].

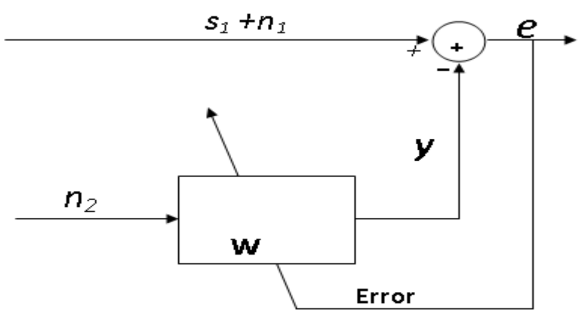

Figure 1. Adaptive Filter structure

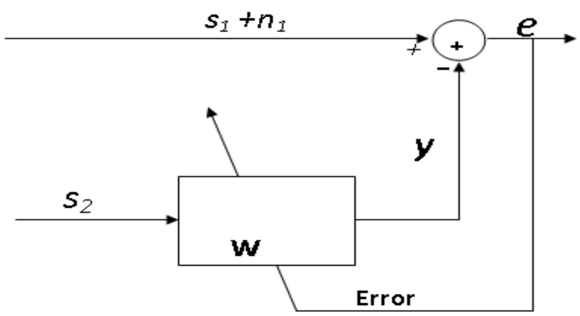

Figure 2. Alternate Adaptive Filter structure

In figure 1, S_1 is the signal component and n_1 is the noise present in the signal. The reference input n_2 is the noise signal generated with any other noise generator and it is well correlated with noise n1. If the filter output is y and the filter error e= (S_1+n_1) - y, then

$$E[e^2] = (S_1 + n_1)^2 - 2y(S_1 + n_1) + y^2 \quad (1)$$

$$= (n_1 - y)^2 + S_1^2 + 2S_1 n_1 - 2yS_1 \quad (2)$$

Since the signal and noise are uncorrelated, the mean squared error is [16]:

$$E[e^2] = E[(n_1 - y)^2] + E[S_1^2] \quad (3)$$

For figure 2.2, reference signal S_2 is another ECG signal having similar characteristics as desired ECG signal. The mean squared error in this case is

$$E[e^2] = E[(S_1 - y)^2] + E[n_1^2] \quad (4)$$

Generally in biomedical signal processing filter structure of figure 1 is used, since it is difficult to obtain a noise free signal [16].

Consider a situation when a proper reference input signal is not available, particularly in case of ambulatory medical diagnosis condition, the output of adaptive filter under limited availability of reference input is not good enough and a huge amount of noise is still present after filtration. The single input adaptive noise canceller has been presented to overcome this situation [15], [17]. In this process the adaptive filtering operation does not rely upon the availability of well correlated reference input but the delayed version of the input signal is itself acts as a reference input. The delayed signal either can be given in primary path or in reference path. MSE studies show that the delay in primary input gives good results as compared to delay in secondary [15]. The LMS algorithm is used as weight update equation in this case.

Although the problem of reference input has been sorted out but the use of LMS algorithm for the process of weight update results in poor response of MSE, since the LMS algorithm has lower convergence speed. The proposed implementation enhances the value of MSE as well as SNR by using normalized least mean square (NLMS) algorithm instead of traditional LMS algorithm for updating filter weights at every iteration.

Methodology

The following block diagram describes the whole process done in this thesis.

 ISSN: 2277-9655

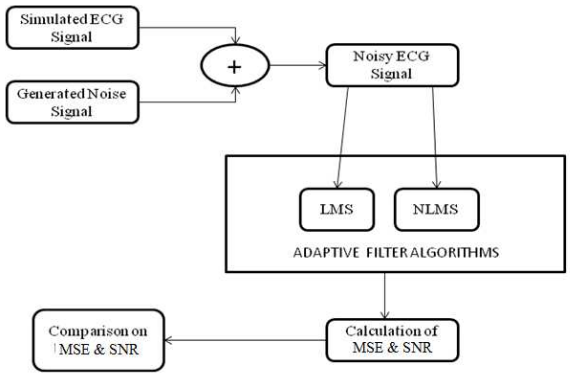

Figure 3. Block Diagram of Methodology

When there is limited availability of reference input, the single input adaptive noise canceller can be used for de-noising of ECG signal [3]. In this thesis, NLMS algorithm is proposed for updating the filter weights in place of LMS algorithm which has been implemented in [42]. The filter is shown below:

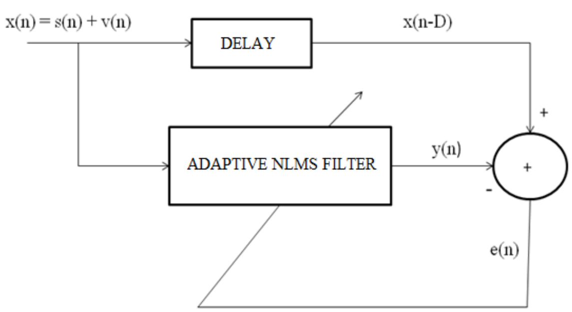

Figure 4. Adaptive NLMS Filter with Delay in Primary Path

The delay element can be used in reference path also but that does not show good value of MSE. While using the delay in primary path, it is necessary that filter length must be greater than the number of delay introduced i.e. M > D, where M is the filter length and D is number of delay [18]. The calculation of MSE is done by using following two equations [15], [17]:

When the proper reference input is available.

$$MSE = \frac{1}{m}\sum_{n=1}^{m}\{s(n) - e(n)\}^2 \qquad (5)$$

When there is limited availability of reference input.

$$MSE = \frac{1}{m}\sum_{n=1+D}^{m+D}\{s(n-D) - y(n)\}^2 \qquad (6)$$

Where m is the number of samples within the segment where adaptive filters converged.

The signal to noise ratio is calculated by following equation:

$$SNR\,(dB) = 10\,log_{10}\frac{\sum_{i=1}^{N}\{x(i)\}^2}{\sum_{i=1}^{N}\{x(i) - \bar{x}(i)\}^2} \qquad (7)$$

The result obtained by proposed algorithm is then compared with the existing algorithm to evaluate the performance of proposed method. The results show that the proposed method gives better value of MSE and SNR when compared with existing method.

Simulation Results

To show that the proposed novel approach of using NLMS algorithm is really effective than that of conventional LMS with delay [15] in ambulatory requirements, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). The arrhythmia data base consists of 48 half hour excerpts of two channel ambulatory ECG recordings, which were obtained from 47 subjects, including 25 men aged 32-89 years, and women aged 23-89 years. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. In our simulation we collected 5000 samples of ECG signal. For all the figures numbers of samples are taken on x-axis and amplitude on y-axis. In our experiments, we used data set of five records (records 100, 101, 103, 104 and 105) but due to space constraint simulation result of record 105 are shown in this paper. SNR and MSE are the evaluation parameters

A. Minimization of Power Line Interference

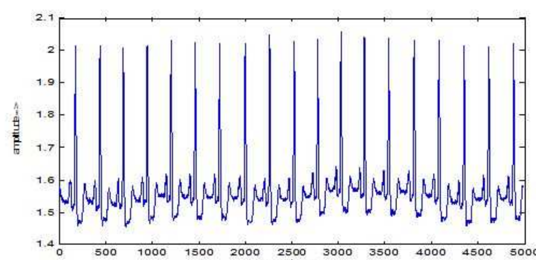

Figure 5. MIT-BIH Record No. 105

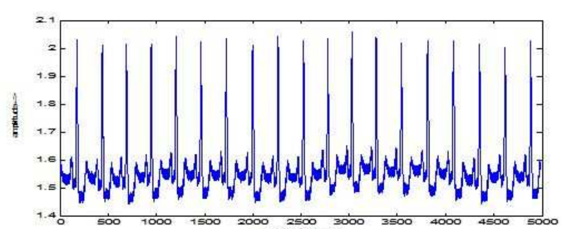

Figure 6. MIT-BIH Record No. 105 Corrupted with 50-Hz PLI

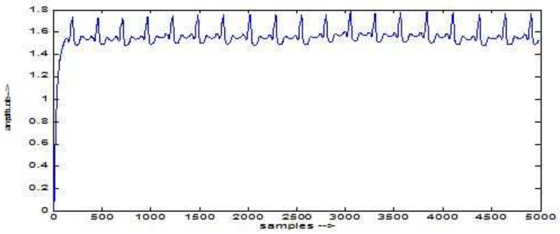

Figure 7. Filtered ECG signal 105 using LMS Algorithm

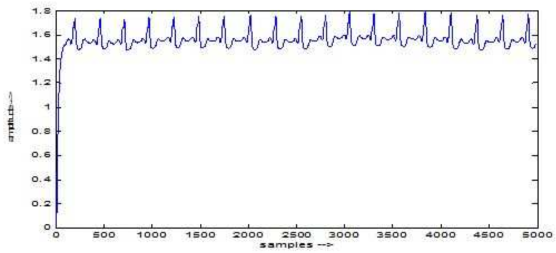

Figure 8. Filtered ECG signal 105 using NLMS Algorithm

Table 1. Comparison of SNR and MSE for ECG Record No. 105 corrupted with PLI

Filter Length (M)	LMS		NLMS	
	SNR(dB)	MSE	SNR(dB)	MSE
20	23.0222	0.0122	25.3296	0.0072
30	25.8051	0.0064	27.8661	0.0040
40	25.6352	0.0067	26.9672	0.0049
50	25.2272	0.0073	25.9406	0.0062
60	25.0620	0.0076	25.2572	0.0073
70	25.0956	0.0076	24.8301	0.0080
Average	**24.9745**	**0.0079**	**26.0318**	**0.0062**

B. Minimization of Real Muscle Artifacts

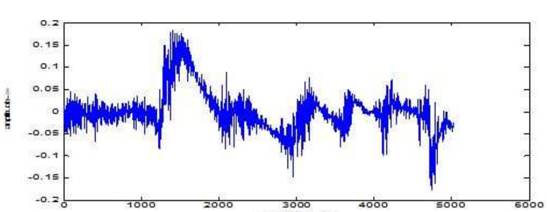

Figure 9. Real Muscle Artifacts

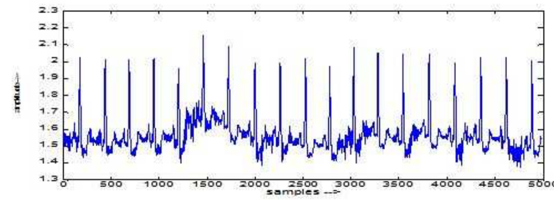

Figure 10. MIT-BIH Record No. 105 Corrupted with real MA

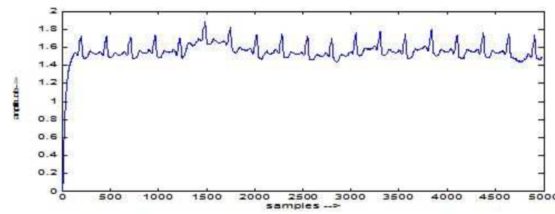

Figure 11. Filtered ECG signal using LMS Algorithm

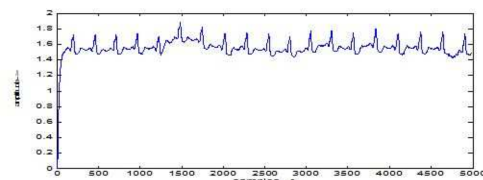

Figure 12. Filtered ECG signal using NLMS Algorithm

Table 2. Comparison of SNR and MSE for ECG Record No. 105 corrupted with real MA

Filter Length (M)	LMS		NLMS	
	SNR(dB)	MSE	SNR(dB)	MSE
20	22.3799	0.0141	24.3547	0.0090
30	24.6603	0.0084	26.2143	0.0058
40	24.5332	0.0086	25.5782	0.0064
50	24.2174	0.0093	24.8137	0.0084
60	24.0797	0.0096	24.2719	0.0091
70	24.1011	0.0095	23.9254	0.0099
Average	**23.9952**	**0.0099**	**24.8597**	**0.0081**

Conclusion

In this paper the problem of noise cancellation from ECG signals using novel adaptive filtering approach is proposed and tested on real ECG signals obtained from MIT-BIH data base. For this, the input is delayed and the reference signal is the input itself. Simulation results confirm that the novel NLMS approach based filter provides high signal to noise ratio and low mean square error when compared to conventional LMS based filter.

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