

An Efficient Noise Removal Technique to Remove Noise from the ECG Signal Using Adaptive Filter

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ABSTRACT: Electrocardiogram (ECG) is a diagnosis tool that recorded the electrical activity of the heart by using several electrodes attached to the body surface. But the amplitude and duration of ECG signals are usually corrupted by different noises therefore in this study different noises like power line interference (PLI), baseline wander (BW), and random noise are analyzed. Random noise is also called as electromyographic (EMG) noise. These noises misguide the diagnosis of the heart which is not desired. To avoid this problem caused by different noises, removal of these noises has become essential. The adaptive filter has been proposed to filter these noises from the ECG signal. There are various adaptive filtering algorithms are used to filter ECG signals. The three basic adaptive filtering algorithms are Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Constrained Stability Least Mean Square (CSLMS) algorithms are applied to remove these noises. In this paper, we have applied these algorithms on ECG signals corrupted with various noises and compared its performance with the LMS, NLMS and CSLMS algorithms. For output performance measurement different output parameters are used such as signal to noise ratio (SNR), percent root mean square difference (PRD) and mean square error (MSE).

KEYWORDS: Electrocardiogram (ECG), Adaptive Filter, Least mean square (LMS), Normalized least mean square (NLMS), CSLMS algorithm, SNR, MSE.

I. INTRODUCTION

The human heart is an organ that gives a continuous blood flow through the cardiac cycle and is one of the most important organs in the human body. A human body is a good electrical conductor, hence the electrical movement of the heart can be measured by utilizing surface electrodes. The ECG is a diagnosis tool that graphically recorded the electrical activity of the heart by using several electrodes.

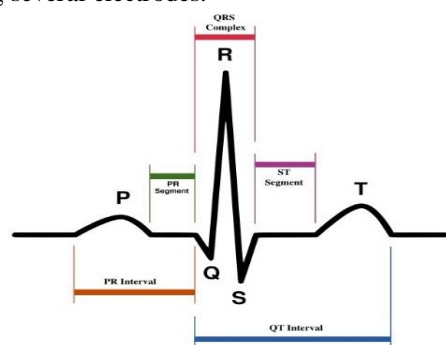


Figure 1 Typical waveforms of an ECG signal

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It is used as a test to collect information about surgical procedures, heart diseases, etc. The ECG is a representation of heart electrical action in time, which is very used to identify heart issues. According to the most recent statistics, revealed by the World Health organization, cardiovascular diseases remaining the main specific reason for mortality in any area of the world. The ECG signal measured from the patient results in a periodic waveform known as PQRST complex waveform. Figure 1 shows a PQRST-complex waveform. The PQRST- complex waveform is labelled with P, Q, R, S and T, which are generally used in medical Electrocardiogram terminology. PQRST complex waveform consists of a complete cardiac cycle. In a cardiac cycle consists of P wave, QRS Complex, and T wave. ECG signal is a low amplitude voltage signal, and because of noise sources that can destroy it, the ECG signal recording should consider this issue. electrocardiographic signals are usually corrupted by different noises. These noises are power line interference, baseline wander, random noise and electrode movement. The heart is Organic systems, and they are always affected by other organic systems. Hence, therefore, heart signals usually contain signals of different parts of the human body e.g. Electromyography signals. Removing undesirable signal components from ECG signal can underlie better interpretation of the signal. A basic method for noise cancellation analyzes the signal and suppresses undesired frequency components. The main issue is that noise can overlap the whole signal, and in these cases the established methods for signal denoising are not adequate to overcome this difficulty it should be taken into account new methods based on advanced signal processing techniques such as Adaptive Signal Processing. Adaptive signal processing methods can perform some tuning in their filtering parameters in such way that will enhance their performance. These filters are called Adaptive filter and denoising of the ECG signal is done by utilizing Adaptive filter. The adaptive filter is a type of a linear filter which updates the weights of the filter by utilizing an Adaptive algorithm.

A. Power Line Interference (PLI)

The ECG signal can be affected by power line interference due to 50 Hz or 60 Hz power supply to which ECG machine is connected. Power line interference contains 50 Hz pickup in India and 60 Hz pickup in the United States. It is indicated as spike or impulse at 60Hz/50Hz harmonics, and it will appear as spikes at integral multiples of the fundamental frequency. Its frequency content is 60Hz/50Hz and amplitude is up to 50 percent of peak to peak ECG signal amplitude. It means that For a high-quality analysis of the electrocardiogram (ECG) signal, the amplitude of the power line interference (PLI) should be smaller than 0.5% of the peak-to-peak QRS wave amplitude.

B. Baseline Wander (BW)

Baseline wander is usually caused by respiration at a very low frequency which is in the range of 0.1 - 0.3 Hz [2]. It means that ECG signals affected by baseline wander noise of relatively small amplitude where the frequency of the baseline wander 0.1 - 0.3 Hz. The adaptive filter would be able to separate the noise from the ECG signal. The expansion and contraction of the lungs electrode skin impedance to vary, which causes the baseline of the ECG to change. Baseline wander may be also caused by coughing or breathing with large movement of the chest, or leg moves in the case of limb lead ECG acquisition. During exercise, the breathing rate increase and causes the frequency of the baseline wandering to increase.

C. Random Noise

Random noise is also called as electromyographic (EMG) noise and this noise cause due to the contraction of other muscles besides the heart. When other muscles in the vicinity of the electrode contract, they generate a depolarization wave and repolarisation waves that can also pick up by the ECG. The amplitude of the electromyographic signal is random in nature and can be modelled by the Gaussian distribution function. The mean of this noise can be assumed to be zero and the variance dependent on the environmental variables. The standard deviation of the noise is generally 10% of the peak to peak ECG amplitude. It should be noted that the electrical activity of muscles during a period of contraction can generate surface potential comparable to those from the heart. In other words he EMG is caused by

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Vol. 6, Issue 6, June 2017

muscular contraction, which generates a microvolt-range electrical signal. It is typically low in amplitude, high in frequency and variable duration.

II. RELATED WORK

The noises which commonly disturb the basic electrocardiogram (ECG) are power line interference (PLI), Baseline wander (BW) and Random noise. During the past few years, various contributions have been made in literature regarding noise removal from electrocardiogram signal. Different researchers have worked on power line interference, Baseline wander and Random noise in ECG signal.

In the paper [1], “ECG Signal Denoising by Using Least-Mean-Square and Normalized- Least-Mean-Square Algorithm Based Adaptive Filter”, Uzzal Biswas, Anup Das, Saurov Debnath and Isabela Oishee have implemented LMS and NLMS algorithm based adaptive filter for noise reduction in the electrocardiogram. They have analyzed the performance by comparing output parameters such as signal to noise ratio (SNR), percentage root mean square difference (PRD) and mean square error (MSE) power spectral density (PSD), spectrogram, frequency spectrum and convergence. Signal Processing Toolbox built in MATLAB® is used for simulation. According to their paper, the NLMS algorithm based adaptive filter has better performance in comparison to LMS based adaptive filter.

In the paper [6], “Adaptive Filtering for Respiration Influence Reduction on Heart Rate Variability”, Raymundo Cassani, Patricia Mejia, Jose Antonio Tavares, Juan Carlos Sanchez and Raul Martinez described the adaptive noise cancelling method of estimating signals which are corrupted by various noises by employing LMS algorithm. This method uses a primary input also called desired input signal containing the corrupted signal and secondary input also called a reference input containing noise correlated in some unknown way with the primary noise. The secondary input is adaptively filtered signal and subtracted from the primary input to obtain the signal estimate. In this paper focused on the applications of the adaptive noise cancellation technique.

In 2010, “Performance Evaluation of Different Adaptive Filters for ECG Signal Processing”, Sachin Singh and Dr. K.L. Yadav [9] introduced a new adaptive algorithm. In this paper, the proposed method RLS algorithm reduces the computation time without degrading the accuracy of the system. The LMS algorithms are simple and easy to implement, but the convergence speed is slow for small values of step size Sachin Singh and Dr. K.L. Yadav introduced an efficient Recursive least square (RLS) algorithm for noise cancellation in ECG signal. The performance of the proposed algorithm was compared with other adaptive algorithms for denoise ECG signal. It was shown that the proposed algorithm has a good overall performance.

In the paper [4], “Least-Mean-Square Algorithm Based Adaptive Filters for Removing Power Line Interference from ECG Signal”, Md. Maniruzzaman, Kazi Md. Shimul Billah and Bablu Gain have used adaptive filters for the cancellation of noise in electrocardiographic (ECG) signal. According to their paper, adaptive filtering has become one of the effective methods for the processing and analysis of the electrocardiogram signal and the LMS based adaptive filter remove noise from ECG signal more effectively.

In the paper [5], “ECG Noise Removal using GA tuned Sign-Data Least Mean Square Algorithm”, Baby Paul, P. Mythili proposed a new adaptive filtering technique for denoising the electrocardiogram (ECG) signal based on Genetic Algorithm (GA) tuned Sign-Data Least Mean Square (SD-LMS) algorithm. The proposed algorithm has a good overall performance. The proposed algorithm gave an average signal to noise ratio (SNR) improvement in ECG signal for power line interference and baseline wander noises.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

Table 1: Comparison of Adaptive filter Algorithm

Noise	Adaptive filter Algorithm	SNR	MSE	%PRD
Power Line Interference and Baseline Wander	LMS	Low	High	High
	NLMS	High	Low	Low
Reference paper		[1] [4]	[1]	[1] [4]

III. PROPOSED METHODOLOGY

(I) Adaptive Filter

Adaptive filter plays a very important role in the elimination of noise from the corrupted signals. A generalized basic adaptive filter structure is shown in the figure, where n denotes the iteration number, $x(n)$ denotes the filter input signal, $y(n)$ is the adaptive filter output signal, and $d(n)$ denotes the desired signal. The error signal $e(n)$ is calculated as $d(n) - y(n)$. The error signal $e(n)$ is required by the adaptive algorithm is used to find the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive filter output signal $y(n)$ is matching the desired signal $d(n)$ in some sense. At each sampling time, an adaptation algorithm adjusts the filter coefficients $w(n)=[w_0(n) w_1(n) \dots w_{N-1}(n)]$ to minimize the difference between the desired signal and filter output. The filter parameters are based on minimizing the mean squared error between the filter output and desired signal.

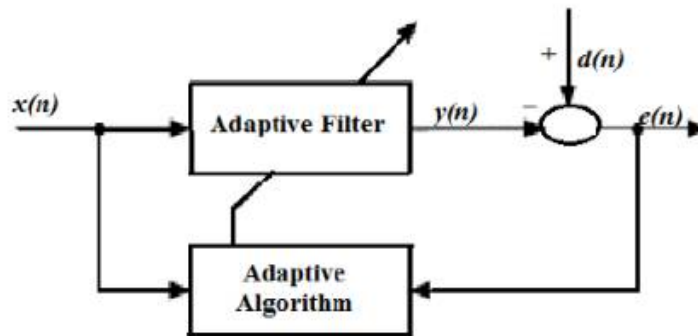


Figure 2 Adaptive filter structure

The adaptive filter can be implemented in various structures or realization. The choice of the structure can affect the computational complexity, i.e. amount of arithmetic operations per iteration of the process. There are two types of adaptive filter realization, distinguished by the form of the impulse response, namely the finite impulse response (FIR) filter and the infinite impulse response (IIR) filters. These two filters (finite impulse response (FIR) and infinite impulse response (IIR)) are digital filter FIR filters are used to implement non-recursive structures, whereas IIR filters are used to implement recursive realizations. But FIR filter structure is most widely used. For such structures, the impulse response is equal to the filter coefficients.

The coefficients for FIR filter of order N are defined as

$$w(n)=[w_0(n), w_1(n), \dots, w_{N-1}(n)]^T \quad (1)$$

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

The output of the adaptive filter is $y(n)$ which is given by

$$y(n) = W(n)^T x(n) \quad (2)$$

The error signal $e(n)$ is the difference between the desired and the estimated signal

$$e(n) = d(n) - y(n) \quad (3)$$

The variable filter updates the filter coefficients $W(n+1)$ at every time instant

$$W(n+1) = W(n) + \Delta W(n) \quad (4)$$

Where, $\Delta W(n)$ is a correction factor for the FIR filter coefficients. The adaptive algorithm generates this correction factor based on the input signal and error signals and estimate of the desired filter.

(i) Least Mean Square (LMS) Algorithm

The LMS algorithm is a type of adaptive filter known as stochastic gradient-based algorithm as it utilizes the gradient vector of the adaptive filter tap weights to converge on the optimal wiener solution. It is widely used due to its computational simplicity. With every iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula:

The tap weights of the FIR vector are updated in preparation for the next iteration, by Eq. (5).

$$w(n+1) = w(n) + 2\mu x(n)e(n) \quad (5)$$

Where $x(n)$ is the input vector of time delayed input values and is given by

$$x(n) = [x(n), x(n-1), \dots, x(n-N+1)]^T \quad (6)$$

$w(n) = [w_0(n), w_1(n), \dots, w_{N-1}(n)]^T$ represents the coefficients of the adaptive FIR filter tap weight vector at time n and μ is known as the step size parameter and is a small positive constant. The step size parameter controls the updating factor. Selection of a suitable value for μ is compulsory to the performance of the LMS algorithm. For the small value of μ the adaptive filter takes the time to converge to the optimal solution will be too long and for the large value of μ the adaptive filter becomes unstable and its output diverges. The main reason for the popularity of LMS algorithms in adaptive filtering is its computational simplicity that makes its implementation easier than all other commonly used adaptive algorithms. The LMS algorithm requires $2N$ additions and $2N+1$ multiplications (N for calculating the output, $y(n)$, one for $2\mu e(n)$ and an additional N for the scalar by vector multiplication) for every iteration.

(ii) Normalized Least Mean Square (NLMS) Algorithm

In the standard LMS algorithm when the convergence factor μ is large, the algorithm experiences a gradient noise amplification problem. In order to solve this difficulty, we can use the NLMS algorithm [4]. We may view NLMS algorithm as a time-varying step-size algorithm, calculating the convergence factor μ as in Eq. (7)

For $i=0,1,2,\dots,N-1$

$$\mu_i(n) = \frac{\alpha}{c + \|x_i(n)\|^2} \quad (7)$$

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

Where α is the NLMS adaption constant, which optimize the convergence rate of the algorithm and should satisfy the condition $0 < \alpha < 2$, and c is the constant term for normalization and is always less than 1.

$$w(n+1) = w(n) + \mu_i(n)e(n)x_i(n) \quad (8)$$

$$w(n + 1) = w(n) + \left[\frac{\alpha}{c + \|x(n)\|^2} \right] x(n)e(n) \quad (9)$$

Where α is the NLMS adaption constant and c is the constant term for normalization. With $\alpha = 0.03$ and $c=0.08$, each iteration of the NLMS algorithm requires $3N+1$ multiplication operations. It is important to note that given an input data (at time n) represented by the input vector $x(n)$ and error signal $e(n)$ the NLMS algorithm updates the weight vector in such a way that the value $w(n+1)$ computed at time $n+1$ exhibits the minimum change with respect to known value $w(n)$ at time n . The normalized least mean square (NLMS) algorithm is a type of adaptive filter known as stochastic gradient-based algorithm as it utilizes the gradient vector of the adaptive filter tap weights to converge on the optimal solution. We may view the Normalized Least Mean Square (NLMS) algorithm as a time-varying step-size algorithm.

(iii) Constrained Stability Least Mean Square (CSLMS) Algorithm

A major drawback of adaptive noise canceller based on LMS and NLMS algorithm is the large value of mean square error which results in signal distortion in the noise-canceled signal. In this algorithm the step size that is μ inversely proportional to the squared norm of the difference between two consecutive input vectors rather than the input data vector as in the LMS and NLMS.

The output of the FIR filter $y(n)$ is calculated using Eq.(10)

$$y(n) = \sum_{i=0}^{N-1} w(n) x(n-i) = w^T(n)x(n) \quad (10)$$

The value of the error estimation is calculated using Eq. (11)

$$e(n) = d(n) - y(n) \quad (11)$$

The filter tap weight vectors are updated using the following equation (12)

$$w(n + 1) = w(n) + \mu \left[\frac{1}{p + \|\delta x(n)\|^2} \right] \delta x(n) \delta e(n) \quad (12)$$

Where $\delta x(n) = x(n) - x(n-1)$ is the difference between two consecutive input vectors. Also $\delta e(n) = e(n) - e(n-1)$ is the difference in the priori error sequence. The weight adaptation rule can be made more robust by introducing a small p and by multiplying the weight increment by a constant step size μ to control the speed of the adaptation. Where μ is the CSLMS adaption constant and p is the constant term for normalization. With $\mu = 0.0001$ and $p = 0.02$. This gives the weight update relation for CSLMS algorithm in its final form.

IV. EXPERIMENTAL RESULTS

To show that CSLMS algorithms are appropriate for ECG denoising, we have used real ECG signals. We used the benchmark MIT-BIH (Massachusetts Institute of Technology Beth Israel Hospital) arrhythmia database ECG recordings as the reference for our work.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

The MIT-BIH database consists of 48 half hour excerpts of two channels ambulatory ECG recordings, which were obtained from 47 subjects, including 25 men aged 23-89 years, and women aged 32-89 years.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mv range. In our simulation, first, we collected 3500 samples of electrocardiogram (ECG) signal. For all the figures in this section number of samples is taken on x-axis and amplitude on the y-axis, unless stated. In this experiment, we have considered a database of three ECG records: data100, data106, data215 to ensure the consistency of the results.

1. Power-line Interference (PLI) Cancellation

In this experiment, first, we collected 3500 samples of electrocardiogram (ECG) signal from MIT-BIH (Massachusetts Institute of Technology Beth Israel Hospital) arrhythmia database and corrupted with synthetic power line interference (PLI) with frequency 50Hz. This signal is applied as a primary input to the adaptive filter. The experiment is performed over the database signal to noise ratio (SNR), percent root mean square difference (PRD) and mean square error (MSE) improvement is considered to compare the performance of the algorithms. The reference signal is a synthesized PLI; the output of the filter is recovered signal. The results for data100, data106, and Data 215 are shown in the following table.

Table 2. Experimental results for Power-line Interference

Performance Parameter	Patient Data	Adaptive Filter		
		LMS	NLMS	CSLMS
SNR	100	1.4466	2.3079	2.6209
	106	1.4792	2.1286	2.5418
	215	1.3150	1.6895	2.5143
PRD	100	0.1892	0.0702	0.0489
	106	0.1821	0.0863	0.0536
	215	0.2200	0.1430	0.0553
MSE	100	0.0458	0.0214	0.0122
	106	0.0482	0.0219	0.0118
	215	0.0586	0.0318	0.0216

The above table shows the SNR, PRD, MSE improvement for the database. It is found that CSLMS (Constrained Stability Least Mean Square algorithm) algorithm improved SNR, PRD and MSE as compare to LMS and NLMS algorithms.

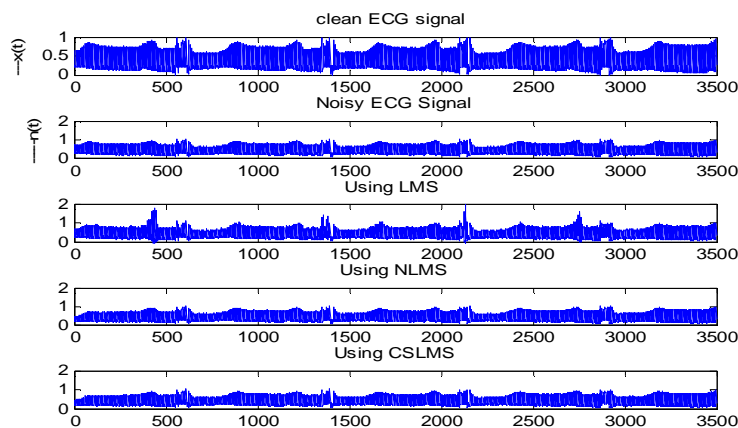


Figure 3 Typical filtering results of power line interference removal, (a) clean ECG signal (a) noisy ECG signal (c) recovered signal using LMS algorithm, (d) recovered signal using NLMS algorithm, (e) recovered signal using CSLMS algorithm.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

The above figure shows the typical filtering results of power line interference improvement for the database. It is found that CSLMS (Constrained Stability Least Mean Square) algorithm result improved as compared to LMS and NLMS.

2. Random Noise Cancellation

To demonstrate this we used MIT-BIH (Massachusetts Institute of Technology Beth Israel Hospital) arrhythmia database record number 100, 106, and 215 ECG data signal and corrupted with random noise. This signal is applied as a primary input to the adaptive filter. The experiment is performed over the dataset SNR, PRD and MSE improvement is considered to compare the performance of the algorithms. The reference signal is a random noise; the output of the filter is recovered signal. These results for data100, data106, and Data 215 are shown in the following table.

Table 3. Experimental Result for Random Noise

Performance Parameter	Patient Data	Adaptive Filter		
		LMS	NLMS	CSLMS
SNR	100	1.5801	2.4602	2.6249
	106	1.3318	2.1311	2.5424
	215	1.1426	2.1047	2.5035
PRD	100	0.1622	0.0589	0.0487
	106	0.2158	0.0880	0.0536
	215	0.2683	0.0886	0.0560
MSE	100	0.0426	0.0188	0.0124
	106	0.0510	0.0216	0.0119
	215	0.0668	0.0261	0.0219

The above table shows the SNR, PRD, MSE improvement for the database It is found that CSLMS (Constrained Stability Least Mean Square algorithm) improved SNR, percent root mean square difference (PRD) and MSE as compared to LMS (Least Mean Square) and NLMS (Normalized Least Mean Square).

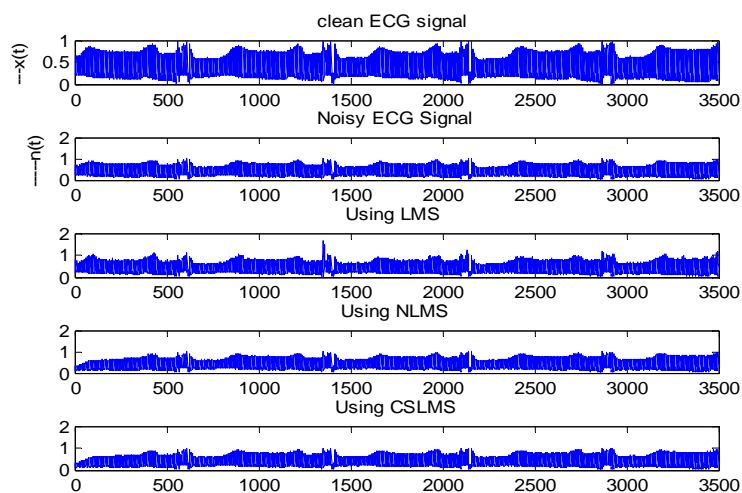


Figure 4 Typical filtering results of Random noise, (a) clean ECG signal (a) noisy ECG signal (c) recovered signal using LMS algorithm, (d) recovered signal using NLMS algorithm, (e) recovered signal using CSLMS algorithm.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

The above figure shows the typical filtering results of random noise improvement for the database. It is found that CSLMS (Constrained Stability Least Mean Square) algorithm result improved as compared to LMS and NLMS.

3. Baseline Wander (BW) Cancellation

In this experiment, first, we collected 3500 samples of electrocardiogram (ECG) signal for data100, data106, and data215 from MIT-BIH (Massachusetts Institute of Technology Beth Israel Hospital) arrhythmia database and corrupted with real baseline wander (BW). It is used as the primary input to the adaptive filter. The LMS, NLMS, and CSLMS algorithms are applied to the entire database. For evaluating the performance of the proposed adaptive filter structures we have measured the output performance parameter SNR, PRD and MSE improvement and compared with LMS, NLMS and CSLMS algorithm.

Table 4. Experimental Results for Baseline Wander

Performance Parameter	Patient Data	Adaptive Filter		
		LMS	NLMS	CSLMS
SNR	100	1.8705	2.0555	2.6237
	106	0.8331	2.4147	2.5361
	215	1.2866	2.1044	2.5155
PRD	100	0.1161	0.0938	0.0488
	106	0.3832	0.0620	0.0539
	215	0.2274	0.0887	0.0552
MSE	100	0.0351	0.0244	0.0124
	106	0.0776	0.0177	0.0118
	215	0.0576	0.0258	0.0215

The above table shows the SNR, PRD, MSE improvement for the database. It is found that CSLMS (Constrained Stability Least Mean Square) algorithm improved signal to noise ratio (SNR), percent root mean square difference (PRD) and mean square error (MSE) as compared to Least Mean Square (LMS) and Normalized Least Mean Square (NLMS).

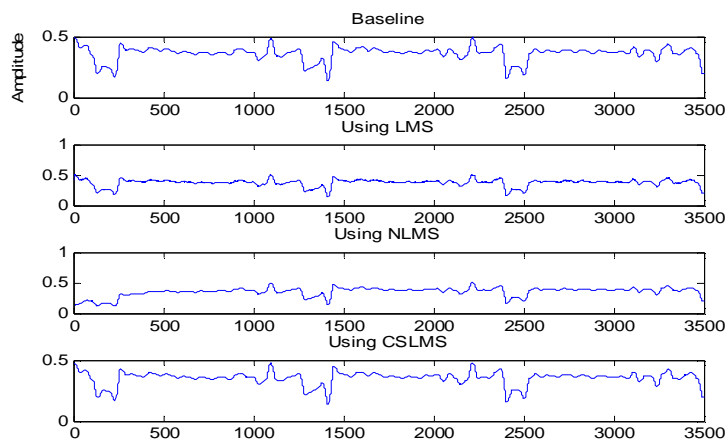


Figure 5 Typical filtering results of Baseline Wander, (a) Baseline Wander signal (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using CSLMS algorithm.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 6, June 2017

The above figure shows the typical filtering results of baseline wander improvement for the database. It is found that CSLMS (Constrained Stability Least Mean Square) algorithm gets improvement as compare to LMS and NLMS. The above simulation and implementation results are presented for Adaptive filter algorithm design to denoise the power line interference, random noise and baseline wander from electrocardiogram (ECG) signal. The simulation results also show that the LMS algorithm has low SNR but the NLMS algorithm has high SNR as compare to LMS. In a case of CSLMS algorithm, the SNR is high as compare to LMS and NLMS algorithm. The simulation results also show that the LMS algorithm has high MSE and PRD but it is simple to implement and gives good results if the step size is chosen correctly. The NLMS algorithm has a less MSE and PRD as compared to the LMS algorithm. In a case of CSLMS algorithm, the MSE and PRD is low as compare to LMS and NLMS algorithm, hence its performance results better than LMS and NLMS algorithms.

V. CONCLUSION

This paper begins with the review of some popular work in the field of ECG signal processing. In this the electrocardiogram signal and adaptive filter discussed. Various types of noises that affect the ECG signal and their origins are also described. For the simulations, the ECG signals are taken from the MIT-BIH database. In the analysis of electrocardiogram (ECG) signal, both of the noisy ECG signal and filtered signal reveals that LMS, NLMS and CSLMS algorithms based adaptive filter reduces the power line interference (PLI), baseline wander (BW), and random noise properly. But the different performance parameter signal to noise ratio (SNR), percent root mean square difference (PRD) and mean square error (MSE) reveals that the adaptive CSLMS (Constrained Stability Least Mean Square) filter is more appreciable than Least Mean Square (LMS) and Normalized Least Mean Square (NLMS) for removing various types of noises from ECG signal.

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