ECG Signal Denoising by Using Least-Mean-Square and Normalised-Least-Mean-Square Algorithm Based Adaptive Filter

Conference Paper · May 2014

DOI: 10.1109/ICIEV.2014.6850857

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Abstract— **Electrocardiogram (ECG) is a method of measuring the electrical activities of heart. Every portion of ECG is very essential for the diagnosis of different cardiac problems. But the amplitude and duration of ECG signal is usually corrupted by different noises. In this paper we have done a broader study for denoising every types of noise involved with real ECG signal. Two adaptive filters, such as, least-mean-square (LMS) and normalized-least-mean-square (NLMS) are applied to remove the noises. For better clarification simulation results are compared in terms of different performance parameters such as, power spectral density (PSD), spectrogram, frequency spectrum and convergence. SNR, %PRD and MSE performance parameter are also estimated. Signal Processing Toolbox built in MATLAB® is used for simulation, and, the simulation result clarifies that adaptive NLMS filter is an excellent method for denoising the ECG signal.**

Keywords- Noises; ECG signal; Adaptive filter; SNR; %PRD; PSD; Spectrogram.

I. INTRODUCTION

ECG is generated by the heart muscle and measured on the skin surface of the body. When the electrical abnormalities of the heart occur, the heart cannot pump and supply enough blood to the body and brain. As ECG is a graphical recording of electrical impulses generated by heart, it is needed to be done when chest pain occurred such as heart attack, shortness of breath, faster heartbeats, high blood pressure, high cholesterol and to check the heart's electrical activity. An ECG is very sensitive, different types of noise and interference can corrupt the ECG signal as the real amplitude and duration of the signal can be changed. ECG signals are mostly affected by white noise, colored noise, electrode movement noise, muscle artifact noise, baseline wander, composite noise and power line interference. These noise and interference makes the incorrect diagnosis of the ECG signal [1-3]. So, the removal of these noise and interference from the ECG signal has become very crucial. Different types of digital filters (FIR and IIR) have been used to solve the problem [3-5]. However, it is difficult to apply these filters with fixed coefficients to reduce different types of noises, because the ECG signal is known as a non-stationary signal. Recently, adaptive filtering has become effective and popular methods for processing and analysis of the ECG signal [6-8]. It is well known that adaptive filters with least mean square (LMS) algorithm show good performance for processing and analysis of signal which are non stationary [1]. And in this study, we have used adaptive LMS and normalized least mean square (NLMS) filter to denoise the ECG signal. We also have evaluated their performance. But it is shown that NLMS filter removes all specified noise (mentioned above) more significantly.

II. MATERIALS AND METHODS

The original ECG signal is taken from the MIT-BIH arrhythmia database [9]. The different types of noise signal are generated by using MATLAB®. The noise signal is then added with the real ECG signal. To remove the different types of noises, the noisy ECG signal is then pass through two adaptive filter algorithms (e.g., LMS and NLMS). However, the basic block diagram for understanding the overall adaptive filtering process is depicted in Fig. 1.

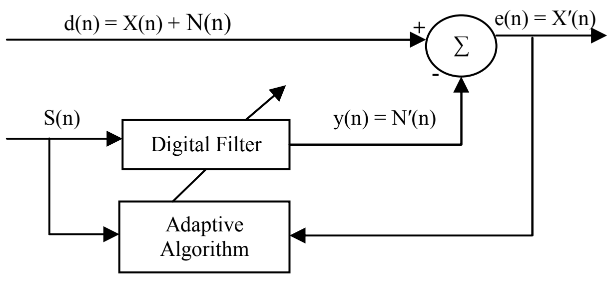


Figure 1. Principle of adaptive filter[7].

The block diagram indicates that, if the value of N(n) is known, then after subtracting this from the mixed signal d(n), the original signal X(n) is obtained. But it is difficult due to the harmonics of noise signal. For this reason an estimated noise signal N′(n) is calculated through some filters and measureable noise source S(n). If N′(n) is more close to N(n), then the estimated desired signal is X′(n) more close to the original signal X(n).

Mathematically the output is given by

$$e = X + N - y \qquad (1)$$

The power or energy of this signal is computed by squaring it

$$e^2 = X^2 + (N - y)^2 + 2X(N - y) \qquad (2)$$

Taking expectations of both sides results

$$E(e^2) = E(X^2) + E(N - Y)^2 + 2EX(N - y) \qquad (3)$$

$$E(e^2) = E(X^2) + E(N - y)^2 \qquad (4)$$

Adapting the filter to minimize the error energy will not affect the signal energy. Therefore the minimum error energy is

$$E(e^2)_{min} = E(X^2) + E(N - y)^2{}_{min} \qquad (5)$$

$E(e - X)^2$is also minimized since, (e – X) = (n – y). Therefore, minimizing the total output energy is the same as minimizing the noise energy.

The LMS algorithm produces the least mean square of the error signal by changing the filter tap weight, whose coefficient updating equation is

$$W_{k+1} = W_k + 2\mu e_k X_k \qquad (6)$$

Where, μ is an appropriate step size to be chosen as 0 < μ < 0.2 for the convergence. The larger steps sizes make the coefficients to fluctuate widely and the LMS algorithm experiences a problem with gradient noise amplification, which can be solved by the normalization of the step size. This variant of the LMS algorithm, with normalization of the step size, is called Normalized LMS (NLMS) algorithm, whose coefficient updating equation is

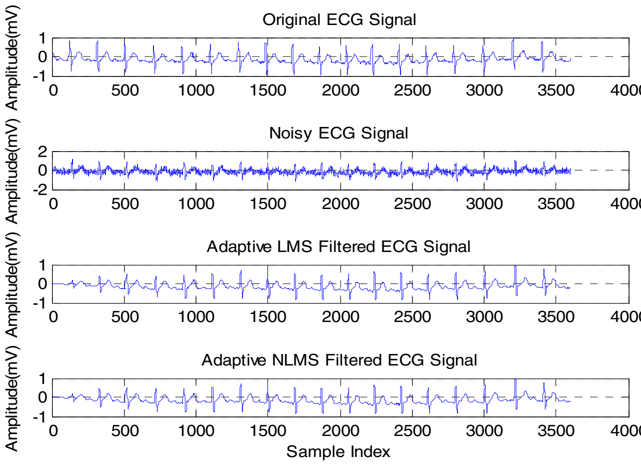
$$W_{k+1} = W_k + \beta \frac{x_k^*}{\alpha + \|X_k\|^2} e_k \qquad (7)$$

Where β is normalized step size for 0<β<2.

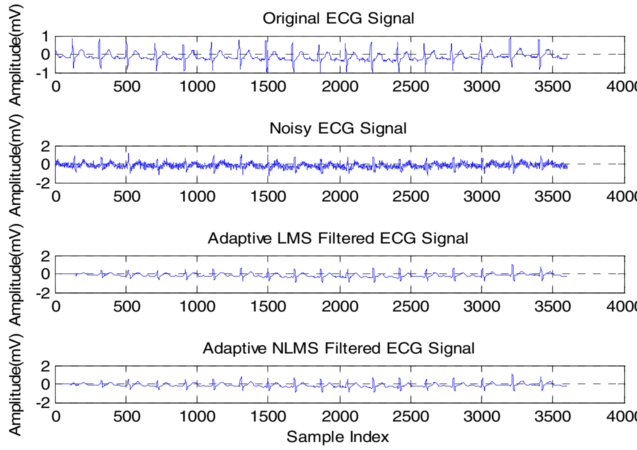
III. Results and Discussion

The 13 beat real ECG signal is taken from the MIT-BIH arrhythmia database [9] whose sampling number is 4000 and amplitude is 1 mV. The different types of noises such as white noise, colored noise, muscle artifact, base line wander, electrode movement noise, composite noise and power line interference are generated by using MATLAB®. These noises are then added to the real ECG signal to get the desired mixed signal. Finally, the noise is removed using two different adaptive filters based on LMS and NLMS algorithm. The results are shown in Fig. 2. If the amplitude of the reconstructed signal increases,

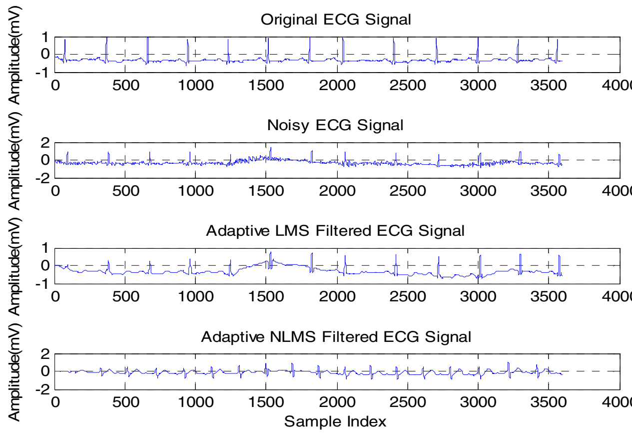
(a)



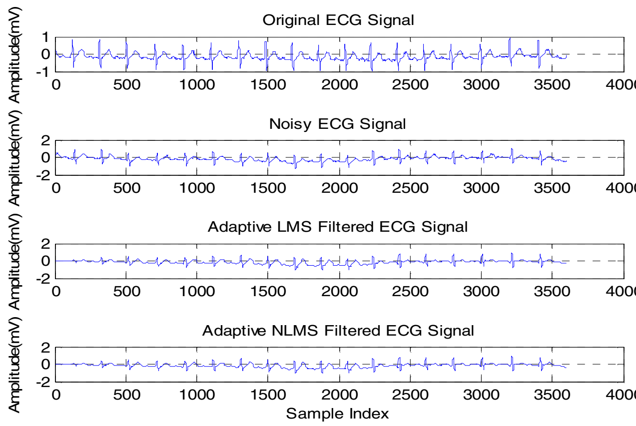
(b)



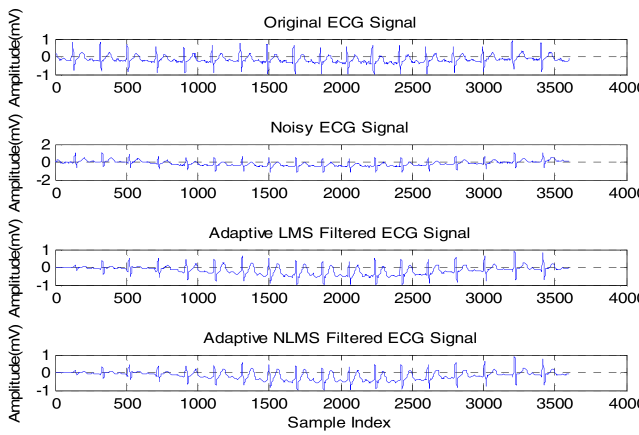
(c)



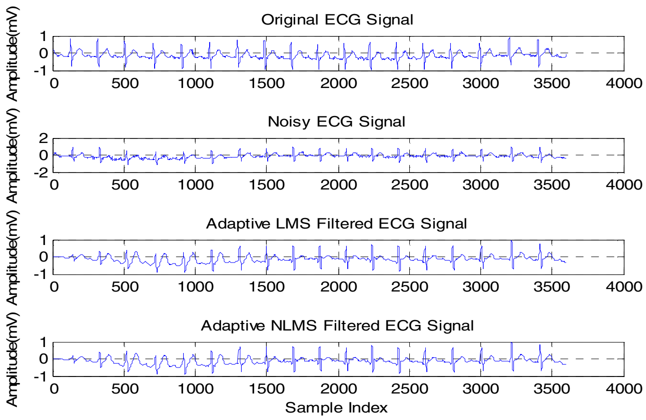
(d)



(e)



(f)



(g)

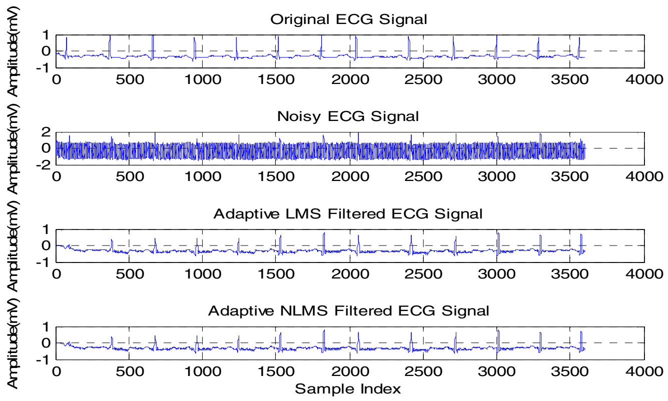


Figure 2. Graphical representation of LMS filtering signal for μ=0.007 and NLMS filtering signal for μ=1 after removing (a) White Gaussian noise, (b) Colored noise, (c) Real muscle artifact noise, (d) Real electrode movement noise, (e) Real baseline wander noise, (f) Composite noise, and (g) Power line interferrence.

then there will be high distortion and vice versa. When the value of μ equal to 0.007, then we see that some noise also appear on the signal peak compared with the value of μ equal to 0.001.But when the value of μ is 0.001, then the reconstructed signal amplitude is less than the original signal as well as all other measuring values, such as, the SNR, %PRD decreases with low distortion. So we can say that the SNR for step size μ of 0.007 is better but exhibits some distortion.

Table I shows the SNR, %PRD and MSE of LMS and NLMS filter for different types of noise in the case of record no. 100, record no 106 and record no. 215 respectively. The tabular analysis indicate that the reconstructed ECG signal obtained from the adaptive NLMS filter has high SNR, low %PRD and MSE than the LMS adaptive filter for all type of noises.

TABLE I. VALUES OF PERFORMANCE PARAMETERS OF TWO ADAPTIVE FILTER FOR DIFFERENT TYPES OF NOISE.

Noises	Adaptive Filters	Reconstructed Signal's											
		SNR				%PRD				MSE			
		Patient Data 100	Patient Data 106	Patient Data 215	Average	Patient Data 100	Patient Data 106	Patient Data 215	Average	Patient Data 100	Patient Data 106	Patient Data 215	Average
White	LMS	4.1988	3.4309	2.7827	3.4708	4.3718	6.5914	10.435	7.1328	0.0098	0.0521	0.0304	0.0308
	NLMS	4.5994	3.7449	3.2337	3.8593	2.7126	5.1899	8.9146	5.6057	0.0091	0.0520	0.0288	0.0300
Color	LMS	2.8301	3.4613	2.8301	3.0405	3.2286	5.8652	9.8299	6.3079	0.0097	0.0517	0.0305	0.0306
	NLMS	4.6847	3.7206	4.0082	4.1378	1.7977	4.7011	5.7894	4.0961	0.0095	0.0516	0.0303	0.0305
Muscle artifact	LMS	2.3405	1.9804	2.8204	2.3804	2.4575	2.6642	2.2378	2.4532	0.0303	0.0760	0.0483	0.0515
	NLMS	2.4160	2.0303	2.9380	2.4614	2.1411	2.4341	1.8119	2.1290	0.0300	0.0759	0.0482	0.0514
Material	LMS	6.4302	5.7663	6.2186	6.1383	0.2212	0.2160	0.1373	0.1915	0.0434	0.0955	0.0524	0.0638
	NLMS	6.4331	5.7775	6.3196	6.1767	0.2157	0.2107	0.1376	0.1880	0.0432	0.0943	0.0523	0.0633
Base line wander	LMS	8.4746	6.9457	8.1197	7.8466	0.1818	0.1639	0.2644	0.2034	0.0491	0.0954	0.0515	0.0653
	NLMS	8.4757	6.9466	8.1204	7.8475	0.1818	0.1639	0.2644	0.2034	0.0491	0.0951	0.0514	0.0652
Composite	LMS	4.7719	4.6630	5.2204	4.8851	6.3385	4.6630	5.2204	5.4073	0.0331	0.0834	0.0487	0.0551
	NLMS	4.1510	4.6037	5.1443	4.6330	6.2417	4.7037	5.1443	5.3632	0.0274	0.0834	0.0485	0.0531
Power line	LMS	-6.4651	-5.9427	-10.365	-7.5909	3.4789	6.3419	10.075	6.6319	0.0097	0.0531	0.0306	0.0311
Interference	NLMS	-5.8527	-5.3141	-9.9306	-7.0324	0.9092	3.5101	8.6050	4.3414	0.0096	0.0530	0.0305	0.0310

To visually observe the denoising performance of adaptive LMS and NLMS filter we use four visual parameters such as PSD, spectrogram, frequency spectrum and convergence for the removal of power line interference.

The PSD represents the amount of power per unit bandwidth and it helps to understand the performance of removing noise from ECG signal [6]. The PSD of mixed signal, LMS filtering signal and NLMS filtering signal is shown graphically in Fig. 3 and tabular form in Table II. From figure we can see that the PSD of noisy ECG signal at 50 Hz is -41.05 dB, but when the noisy signal is passed through LMS and NLMS filter the power of the filtering signal is reduced to -43.23 dB and -41.28 dB. So, NLMS filter removing the power line interference more clearly.

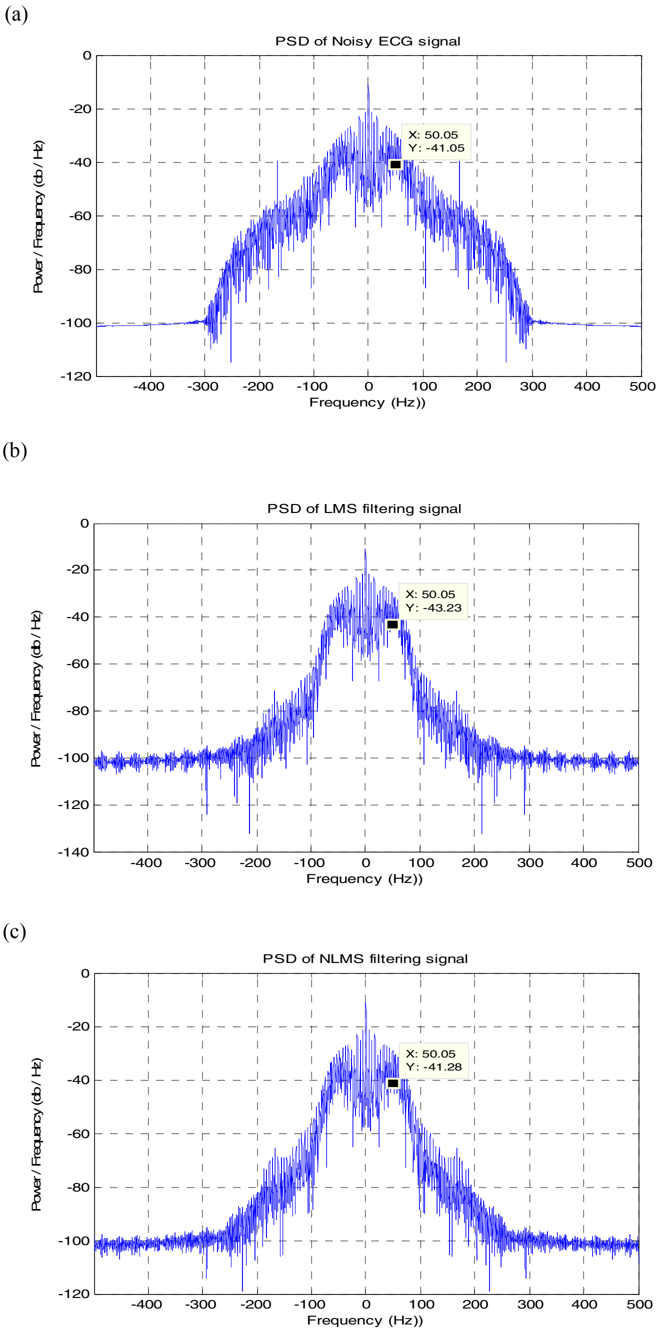


Figure 3. Graphical PSD of (a) Noisy ECG signal, (b) LMS filtering signal and (c) NLMS filtering signal.

TABLE II. VALUES OF PSD FOR TWO ADAPTIVE FILTER

Signal	PSD(dB)
Noisy ECG	-41.05
LMS Filtered ECG	-43.23
NLMS Filtered ECG	-41.28

Spectrogram shows how the spectral density of different signal changes with respect to time, so it is a time varying spectral analysis [6]. Fig. 4 shows the spectrogram of noisy ECG signal, LMS filtering signal and NLMS filtering signal. In spectrogram of noisy ECG signal has a black shade line in 50 Hz position. After applying LMS and NLMS filtering the shaded line is removed such that there is a noticeable change of spectral density of the filtering signal, where NLMS filter shows better performance than the LMS filter.

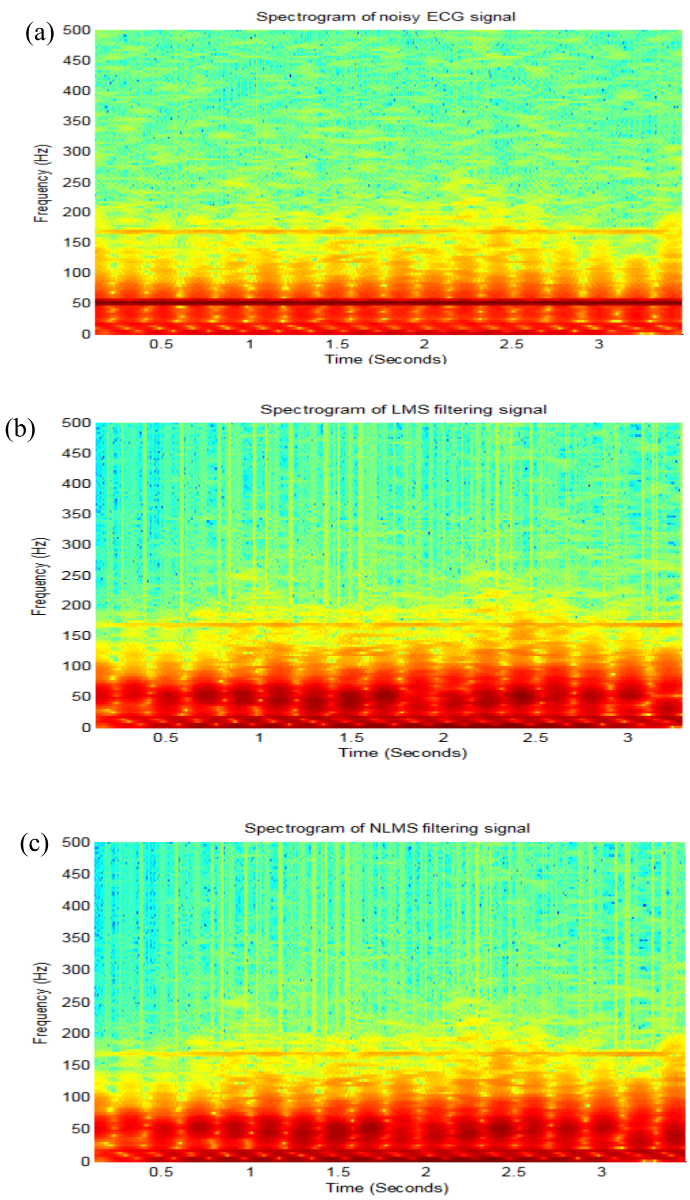


Figure 4. Spectrogram of (a) Noisy ECG signal, (b) LMS filtering signal and (c) NLMS filtering signal.

Frequency spectrum is a frequency domain spectral analysis [6]. The frequency spectrum of 50 Hz noisy ECG signal, LMS filtering signal and NLMS filtering signal is shown in Fig. 5. In noisy signal frequency spectrum, there is a spike at 50 Hz position. But the noise spike is disappeared after filtering by LMS and NLMS filter, where NLMS filter shows better performance than LMS filter for removing PLI.

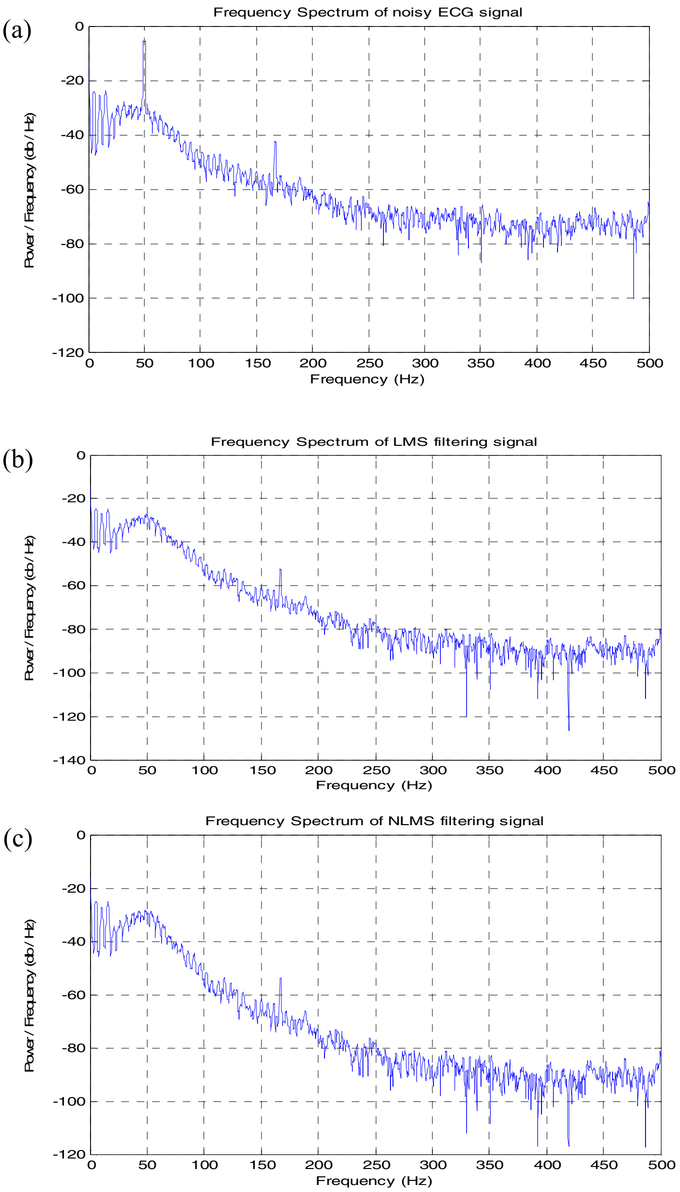


Figure 5. Frequency spectrum of (a) Noisy ECG signal, (b) LMS filtering signal and (c) NLMS filtering signal.

The convergence criterion shows that, the fast adaption of filtering signal with the original signal. The convergence of LMS and NLMS filtering reconstructed signal is depicted in Fig. 6. We can see that, the NLMS filtering signal adapts in far less iteration to original signal than the LMS filtering signal.

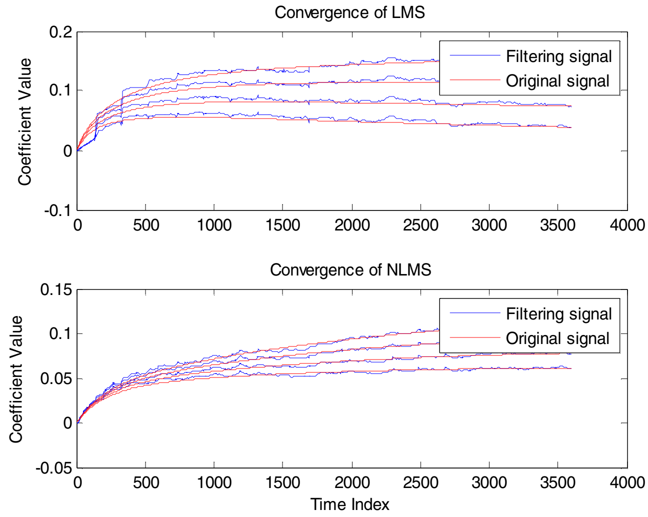


Figure 6. Convergence of LMS filtering signal and NLMS filtering signal.

In this study, we find that adaptive NLMS filter shows better performance compare to adaptive LMS filter. However, it is reported that adaptive LMS filter is better than adaptive signed regressor LMS (SRLMS), adaptive sign LMS (SLMS) and adaptive sign sign LMS (SSLMS) filter in terms of calculated SNR for denoising power line interference, baseline wander, muscle artifacts and motion artifacts [10]. Another paper reported that adaptive NLMS filter shows the better performance than the adaptive LMS and adaptive signed LMS (SLMS) filter in terms of SNR for removing the power line interference [11]. In one of our previous studies, we have shown that the adaptive NLMS filter denoises the power line interference from ECG signal exceptionally better than the other LMS algorithm based adaptive filter [12], in terms of SNR, PRD and MSE. For better clarification, we have done a broader study for denoising every types of noise involved with real ECG signal in this paper. From the simulation results, we also see that in terms of different performance parameters the adaptive NLMS filter shows the superior performance than adaptive LMS filter. So, NLMS based adaptive noise canceller may be used in all practical application.

IV. Conclusion

Analysis of ECG signal, both of noisy ECG signal and filtered signal reveals that adaptive NLMS and LMS filter both reduces the white noise, colored noise, muscle artifact noise, electrode movement noise, baseline wander noise, composite noise and power line interference properly. But the different performance parameters SNR, %PRD, MSE and also visual parameters PSD, frequency spectrum and convergence reveals that adaptive NLMS filter is more appreciable for removing various types of noises from ECG signal.

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