

Removal of Structured Noise and Base Line Wander From ECG Signals Via LMS Adaptive and Fixed Notch Filter

Kawser Ahammed

Abstract—This research clearly demonstrates the comparative performance study of least mean square (LMS) adaptive and fixed notch filter in terms of simulation results and different performance parameters (mean square error, signal to noise ratio and percentage root mean square difference) for removing structured noise (50 Hz line interference and its harmonics) and baseline wandering from electrocardiogram (ECG) signals. The ECG samples collected from the PhysioNet ECG-ID database are corrupted by adding structured noise and base line wandering noise. The simulation results and numerical performance analysis of this research clearly show that LMS adaptive filter can remove noise efficiently from ECG signals rather than fixed notch filter.

Index Terms—LMS Filter, Fixed Notch Filter, Structured Noise, Base line Wander, ECG, Mean Square Error (MSE), Signal to Noise Ratio (SNR), Percentage Root Mean Square Difference (PRD).

I. INTRODUCTION

Electrocardiogram (ECG) is a medical diagnostic tool used for diagnosis of heart abnormalities and also a graphical representation of hearts functionality. Abnormalities of the heart can cause unconsciousness within second and death within minutes. Therefore, ECG is very necessary for the diagnosis of various cardiac pathologies such as arrhythmia, tachy/bradycardia and hypertrophy [1]–[3]. The ECG signal collected from human being is very weak because it is corrupted by various types of noises such as power line interference, various harmonics of power line interference, baseline wandering, motion artifacts, muscle contraction noise and instrumentation noise etc. [4]. Among these noises, power line interference (PLI) and baseline wander (BW) are considered the predominant artifacts. These two artifacts strongly degrade the signal quality, produce large amplitude signals in ECG and prevent tiny features that are important for clinical monitoring and diagnosis to be noticed. During recording of ECG signal, it is corrupted by power line interference coming from the power supply. This power line interference is assumed to occur at 50 Hz. During recording of ECG signal if a patient moves his or her body, additional low frequency components might appear in the recorded ECG signal. This low frequency interference is called baseline wander. Baseline wander causes the ECG base line to fluctuate slowly and contains frequencies in a range below 0.5 Hz. Due to these interferences it will be

impossible to obtain the ideal ECG signal. As a result, it is highly desirable to cancel such noises with a view to enhancing the quality of ECG signal. To filter out these noises, various adaptive filters had been studied in the literature [5]–[11]. But in this study, LMS adaptive filter and fixed notch filter have been employed to understand how well the adaptive LMS filter performs in removing these noises rather than the non-adaptive notch filter. To do this, ECG signal is corrupted with specific noises and this corrupted ECG signal is filtered with both LMS adaptive filter and fixed notch filter. Afterwards, the filtered ECG signals are compared in terms of signal to noise ratio (SNR) at the output, mean square error (MSE) and percentage root mean square difference (PRD) [12].

II. THE LMS ADAPTIVE NOISE CANCELLER

An LMS adaptive noise canceller used in this research can be considered as a circuit configuration system that removes the structured noise and base line wandering from ECG signal and ensures signal quality. Fig. 1 shows a basic LMS adaptive noise canceller system.

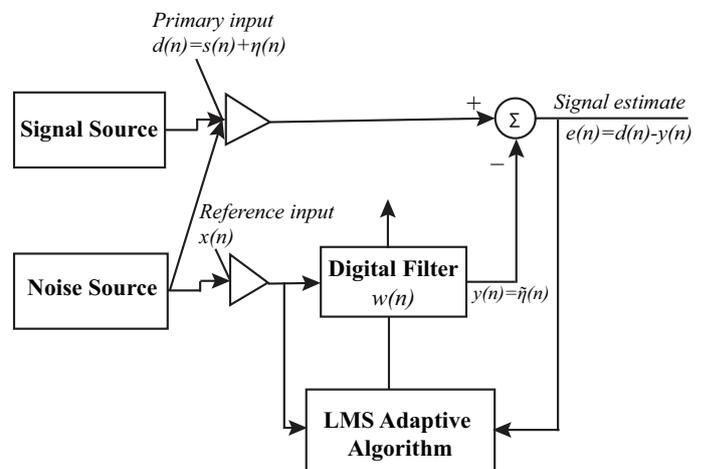


Fig. 1: Block diagram of LMS adaptive noise canceller system

Consider an LMS based adaptive filter of length M as shown in fig. 1 which takes dual input $d(n)$, $x(n)$ and gives a feedback as $e(n)$. In order to remove the noise from the ECG signal, the primary input receives ECG signal $s(n)$ corrupted with noise signal $\eta(n)$ as the desired signal $d(n) = s(n) + \eta(n)$. The signals $s(n)$ and $\eta(n)$ are uncorrelated with each other. Another noise signal $x(n)$ uncorrelated with $s(n)$ but correlated with $\eta(n)$ is applied at the reference input. This reference noise is filtered by the LMS adaptive filter to produce

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an output $y(n)$ that is as close a replica of $\eta(n)$. As a result, the estimate of noise $y(n)$ can be calculated from the following equation [13]–[15]:

$$y(n) = \sum_{l=0}^{M-1} w_l(n)x(n-l) \quad (1)$$

Here, $w_l(n) = [w_0(n), w_1(n), \dots, w_{M-1}(n)]$ is the adjustable tap weights or filter coefficients at the n th index and updated in each iteration by using previous filter coefficient and error signal $e(n) = d(n) - y(n) = s(n) + \eta(n) - y(n)$. The updated filter coefficient for LMS algorithm is defined as [13]–[15]:

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

where μ is the step size parameter. Due to uncorrelated behavior of signal and noise with each other, the mean squared error (MSE) becomes [16]:

$$E[e^2(n)] = E[s^2(n)] + E[\{\eta(n) - y(n)\}^2] \quad (3)$$

The LMS based adaptive filter removes noise from the ECG signal by iteratively minimizing this MSE between primary and reference input. This minimization of MSE results in a filter error output that is the best least square estimate of the signal $s(n)$ results from the minimization of MSE.

III. NOTCH FILTER

A filter that highly removes a particular frequency component from the input signal spectrum is called notch filter. After filtering, the amplitude of input signal spectrum will remain relatively unchanged for all of the frequencies except at notch frequency. Alternatively, a notch filter is a band rejection filter with very narrow stopband and two passbands. Instrumentation and recording system signals corrupted by power line interference are two application areas of notch filter. The basic block diagram for realizing the notch filtering is depicted in Fig. 2.

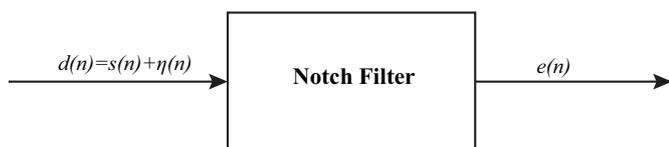


Fig. 2: Block Diagram of Notch Filtering Process

IV. DATA COLLECTION

The database used in this research has been collected from PhysioNet dataset, available online [17], [18]. This is ECG-ID database. The database contains 310 ECG recordings and the recordings were obtained from 90 persons (44 men and 46 women aged from 13 to 75 years). Each ECG signal is digitized at 500 Hz over a nominal 10 mV range. The duration of each ECG signal is 10 seconds. The length of the signal has been represented by 5000 samples.

V. SIMULATION RESULTS

A. Removal of Baseline Wander Using Adaptive LMS Filter and Notch Filter

In this research, baseline wander has been simulated with the help of MATLAB. This simulated noise is mixed with the clean ECG signal to produce the corresponding corrupted ECG signal. Finally, the contaminated ECG signal is filtered using both adaptive LMS filter and notch filter, shown in Fig. 3, to produce enhanced ECG signal. For plotting the time domain waveforms shown in fig.3, optimum step size of LMS adaptive filter and -3 dB bandwidth of notch filter have been used. The plots of fig.3 demonstrate that LMS adaptive filter is more efficient for removing base line wander rather than the notch filter. To clearly comprehend the performance measure of these two filters in removing base line wander noise, numerical performance measures of these filters have been shown in this research in terms of SNR, MSE and PRD.

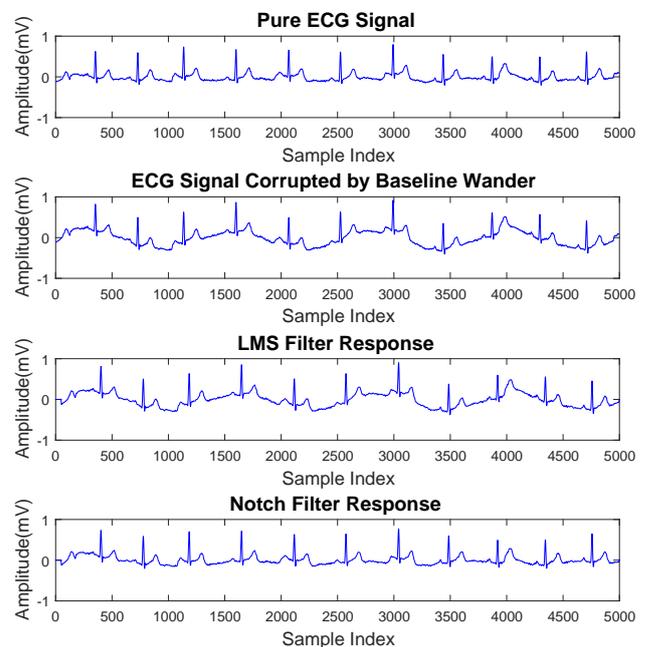


Fig. 3: Graphical representation of removing baseline wander from ECG signal using both LMS adaptive filter and notch filter

B. Removal of Power Line Interference Using LMS Adaptive Filter and Notch Filter

The power line interference of 50Hz simulated by MATLAB is added to a clean ECG signal. This corrupted ECG signal is filtered by both LMS adaptive filter and notch filter shown in fig.4. In this research, optimum step size of LMS adaptive and -3 dB bandwidth of notch filter have been used for plotting the time domain waveforms shown in fig.4. The plots of fig.4 demonstrate that LMS adaptive filter is more efficient for removing power line interference than the notch filter. To justify this result, numerical performance measures of these two filters have been determined in this research in terms of SNR, MSE and PRD.

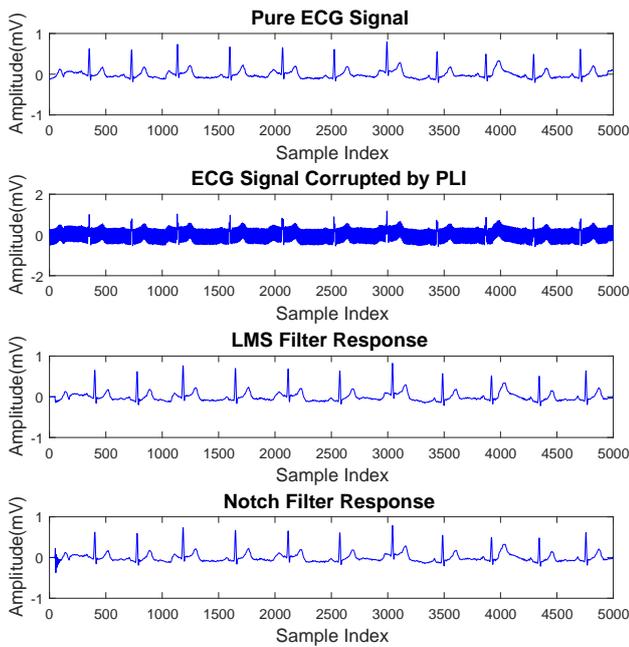


Fig. 4: Graphical representation of removing power line interference from ECG signal using both LMS adaptive filter and notch filter

C. Removal of Power Line Interference and its Harmonics Using LMS Adaptive Filter and Notch Filter

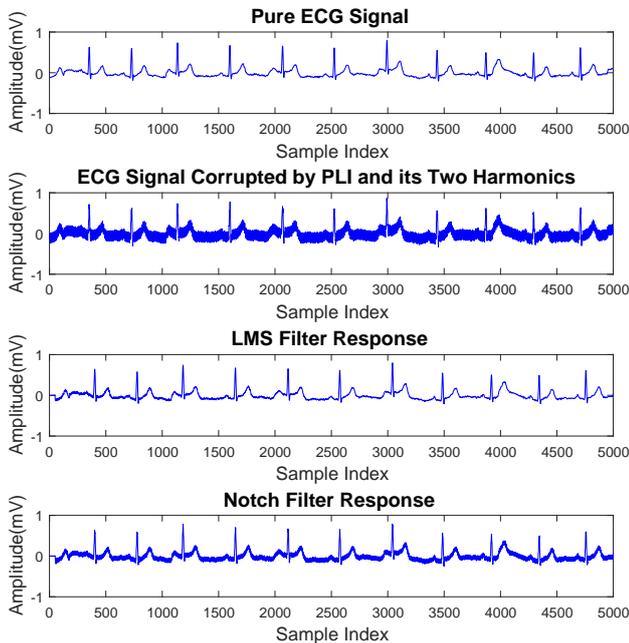


Fig. 5: Graphical representation of removing power line interference and its harmonics from ECG signal using both LMS adaptive filter and notch filter

The power line interference of 50Hz and its two harmonics (100Hz and 150Hz) are added to a clean ECG signal. In order to produce enhanced ECG signal, this corrupted ECG signal is filtered by both LMS adaptive filter and notch filter shown in fig.5. In this research, optimum step size of LMS

adaptive filter and -3 dB bandwidth of notch filter have also been used for plotting the time domain waveforms shown in fig.5. The plots of fig.5 demonstrate that LMS adaptive filter is more efficient for removing power line interference and its harmonics rather than the notch filter. Moreover, numerical performance measures of these two filters have also been analysed in this research in terms of SNR, MSE and PRD in removing this noise.

VI. NUMERICAL PERFORMANCE ANALYSIS

Table I, Table II and Table III represent the numerical performance analysis of LMS adaptive filter and notch filter with respect to SNR at the output, MSE and PRD respectively. The values of performance parameters for LMS adaptive filter and Notch filter are calculated as follows [19]:

$$SNR_{dB} \text{ at the filter input} = 10 \log_{10} \frac{(ECG_{clean})^2}{(ECG_{corrupted} - ECG_{clean})^2}$$

$$SNR_{dB} \text{ at the filter output} = 10 \log_{10} \frac{(ECG_{clean})^2}{(ECG_{filtered} - ECG_{clean})^2}$$

$$\text{Mean square error} = \frac{1}{N} \sum_{i=1}^N (ECG_{filtered} - ECG_{clean})^2$$

Percentage root mean square difference,

$$= \sqrt{\frac{\frac{1}{N} \sum_{i=1}^N (ECG_{clean} - ECG_{filtered})^2}{\sum_{i=1}^N (ECG_{clean})^2}}$$

TABLE I: NUMERICAL PERFORMANCE ANALYSIS OF ADAPTIVE LMS AND FIXED NOTCH FILTER IN TERMS OF SNR

Interference type	Filter	Performance in terms of SNR at the output		
		ECG Record No.1	ECG Record No.2	Average
Baseline Wander	LMS	-2.3203	-2.7846	-2.55245
	NOTCH	-2.5326	-3.3493	-2.94095
PLI	LMS	-2.4698	-3.2498	-2.8598
	NOTCH	-2.4927	-3.2698	-2.88125
PLI and Its Harmonics	LMS	-2.5698	-3.3598	-2.9648
	NOTCH	-2.5998	-3.3898	-2.9948

TABLE II: NUMERICAL PERFORMANCE ANALYSIS OF ADAPTIVE LMS AND FIXED NOTCH FILTER IN TERMS OF MSE

Interference type	Filter	Performance in terms of MSE		
		ECG Record No.1	ECG Record No.2	Average
Baseline Wander	LMS	0.0241	0.0248	0.0489
	NOTCH	0.0263	0.0285	0.0548
PLI	LMS	0.0250	0.0276	0.0526
	NOTCH	0.0257	0.0277	0.0534
PLI and Its Harmonics	LMS	0.0277	0.0276	0.0553
	NOTCH	0.0322	0.0331	0.0653

TABLE III: NUMERICAL PERFORMANCE ANALYSIS OF ADAPTIVE LMS AND FIXED NOTCH FILTER IN TERMS OF PRD

Interference type	Filter	Performance in terms of PRD		
		ECG Record No.1	ECG Record No.2	Average
Baseline Wander	LMS	0.0185	0.0195	0.0190
	NOTCH	0.0315	0.0332	0.03235
PLI	LMS	0.0188	0.0206	0.0197
	NOTCH	0.0200	0.0218	0.0209
PLI and Its Harmonics	LMS	0.0209	0.0205	0.0207
	NOTCH	0.0211	0.0212	0.02115

To produce enhanced ECG signal, high values of SNR, low values of MSE and low values of PRD are required. From Table I it is observed that SNR at the filter output is lower for LMS filter rather than the notch filter. Table II demonstrates that MSE values for LMS filter are lower rather than the notch filter. Table III also shows that the values of PSD are lower for LMS filter rather than the notch filter.

VII. CONCLUSION

In this research, comparative performance study of LMS adaptive and fixed notch filter have been shown in order to determine how well an LMS adaptive filter performs in removing structured noise and base line wandering from ECG signals rather than the fixed notch filter. The analysis of this research has shown that both the LMS and fixed notch filter remove these noises successfully. But the simulation results, the values of SNR at the filter output, the values of MSE and PRD values demonstrate that LMS adaptive filter removes structured noise and base line wandering from ECG signals with more efficacy rather than the fixed notch filter.

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