

Removal of Noise From ECG Signal Using Adaptive Filtering

Nitika Sharma and Jaspinder Singh Sidhu

Department of Electronics and Communication Engineering, Lovely Professional University, Phagwara – 144411, Punjab, India; niti.sharma.hsp@gmail.com, jaspinder.19601@gmail.com

Abstract

Noise removal from a non-stationary signal like Electrocardiogram (ECG) signal is a major problem. Moreover, nullifying different noises using different adaptive algorithms –Least Mean Square (LMS), Normalized Least Mean Square (NLMS) etc. from ECG signal is one of the advance studies in biomedical signal processing. In this paper, we will discuss how we can remove different type of noises like 50Hz Power-Line Interference, Base-line Wandering and Muscle Contraction noise from an ECG signal using an adaptive filter. Different performance parameters such as, Signal-to-Noise Ratio, Mean Square Error and Root Mean Square Error are also calculated to compare the results. Real time data has been collected from MIT-BIH arrhythmia database. At the end, results show the better performance of adaptive NLMS filter for removing different noises over adaptive LMS filter.

Keywords: Component, Formatting, Insert (Key Words), Style, Styling

1. Introduction

Electrocardiogram (ECG) is a method of measuring the electrical activities of the heart by placing different electrodes on the body surface. When the electrical abnormalities occur, then the heart cannot pump properly and not supply enough blood to body and brain. Therefore, ECG is very important for the diagnosis of cardiac patients. When ECG signal is recorded, it may be corrupted by different types of noises such as, power line interference, base line wandering, electrode contact noise, motion artifacts, muscle contraction, instrumentation noise which is generated by electronic devices etc. During diagnosis arrhythmia, the ECG wave is corrupted by a 50Hz noise (this 50Hz is frequency coming from the power supply in many countries) and other noises also¹. One of the simplest methods to remove the noise is to filter the signal using a notch filter at 50Hz. The exact frequency of the power supply hypothetically (might) wanders between 47Hz and 53Hz. This happens due to the slight variations in the power supply to the hospitals, so the static filters would require removing all the fre-

quencies between these ranges, which could excessively degrade the quality of the ECG signal². To avoid this loss of information different type of digital filters (FIR and IIR) have been used³⁻⁵. However, it is difficult to apply these filters because of fixed filter coefficients with non-stationary ECG signal to reduce different type of noises. To overcome these problems adaptive filters has become effective and popular method for analysis and processing of the ECG signal. In adaptive filters, input signal would be taken from both patient and power supply directly and it will track the actual fluctuating frequency of the noise². The most commonly used structure in case of implementation of adaptive filters is transversal structure. In this case, the adaptive filter has an input signal, $x(n)$ and an output signal $y(n)$, whereas $d(n)$ is the desired signal. The output $y(n)$ is generated by taking the convolution of filter weights at time n is given by vector $w(n)$ of length N and input sequence at time n is given by another vector $x(n)$ of N . We can write:

$$w(n) = [w(0), w(1), w(2), \dots, w(N-1)] \quad (1)$$

$$x(n) = [x(0), x(1), x(2), \dots, x(N-1)] \quad (2)$$

*Author for correspondence

The output filter:

$$y(n) = W^T x(n) \quad (3)$$

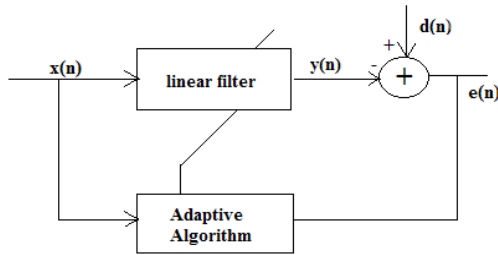


Figure 1. Basic structure of adaptive filter.

The output $y(n)$ of digital FIR filter can be obtained from:

$$y(n) = \sum_{j=0}^{N-1} w_j(n)x(n-j) \quad (4)$$

where N is the length of the filter, $w_j(n)$ are the filter coefficients that vary with time and are adaptation algorithm controlled this variation, $x(n)_j$ are the tap inputs for $j=0,1,\dots,N-1$, where ' j ' is refer as input samples. The error signal is calculated as:

$$e(n) = d(n) - y(n) \quad (5)$$

1.1 Least Mean Square (LMS) Algorithm

This algorithm is an approximation of the steepest decent algorithm. The idea behind LMS filters to use steepest decent algorithm to minimize a cost function by finding the filter weights $w(n)$. Cost function is the mean square error which is minimized by LMS algorithm¹. Cost function which is denoted by $C(n)$ can be written as:

$$C(n) = E\{|e(n)|^2\} \quad C(n) = E\{|e(n)|^2\} \quad (6)$$

The ECG signal, s is the original uncontaminated input signal. The desired output signal x is the contaminated ECG signal. Adaptive filter will do its best to reproduce this contaminated signal only if the original 50Hz noise source v is known. Therefore, it can only reproduce the part of x which is known as t , that is linearly correlated with v . The adaptive filter will also attempt to mimic the noise source, so that the output of the adaptive filter y will be close to the contaminated noise t . Therefore, by this way the error signal e will be

close to the original uncontaminated signal ECG signal s . Now $(s+t)$ is the primary input signal and v be the reference signal.

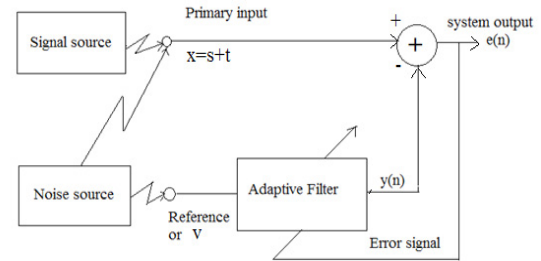


Figure 2. Noise canceller.

The output of the adaptive filter is y and the error is e , the mean square error (MSE) is given as [2]:

$$e = s+t-y \quad (7)$$

$$e^2 = ((s+t)-y)^2 = (s+t)^2 + y^2 - 2(s+t)y = (t-y)^2 + s^2 + 2st - 2sy \quad (8)$$

Signal and noise are uncorrelated, so their product will be zero. Therefore MSE is:

$$[e^2]_{\min} = E[(t-y)^2]_{\min} + E[s^2] \quad (9)$$

Adapting the filter to minimize the error energy will not affect the signal energy which we obtained after squaring the equation (7) and minimum error energy is obtained from equation (9). $E(e-s)$ $E(e-s)^2$ are also minimized since $(e-s) = (t-y)(e-s) = (t-y)s$ so, we can say that minimizing the total output energy is same as minimize the noise energy. Minimizing the MSE in a filter, error is the best least square estimate of the signal s or in other words adaptive filter extract the signal from noised signal by minimizing the MSE between the reference and primary inputs².

The filter weight update equation of LMS algorithm which helps in minimizing the error is:

$$w(n+1) = w(n) + 2\mu e(n)v(n) \quad (10)$$

Where, $w(n)$ is the current weight value vector, μ is an appropriate step size or convergence factor which is $0 < \mu < 0.2$ for the convergence speed and overall behavior. If the step size is large then the coefficients fluctuates widely and the LMS algorithm experience a gradient noise amplification problem. In case of LMS, step size should be less but because of less μ the rate of

convergence is slow. To increase the rate of convergence normalization of step size is required. Therefore the variants of LMS algorithm with normalization of step size are called as Normalized LMS (NLMS) algorithm. In practical applications, fixed step size algorithm or LMS algorithm is required because of easier implementation and single adjustable parameter μ for controlling the convergence rate. The main drawback of this algorithm is the selection of step size parameter μ and also it is sensitive to the scaling of its input signal which makes very hard to choose a μ that guarantees the stability of the algorithm.

Normalized LMS (NLMS) Algorithm

NLMS algorithm is derived from LMS algorithm. This algorithm needs to derive because the input signal power changes in time. Due to this change the step size between two adjacent coefficients of the filter will change which affect the convergence rate. In case of small signals rate of convergence will slow down but due to loud signals the convergence rate will increase and give an error. So to solve this problem, try to adjust the step size parameter with respect to input signal power and hence the step size parameter is normalized^{10,11}. The Normalized Least Mean Square (NLMS) algorithm can be known as a time varying step size algorithm with weight updating equation as:

$$w(n+1) = w(n) + 2\mu(n) \frac{e(n)}{\delta + x^T(n) \cdot x(n)} \quad (11)$$

$$\text{Where, } \mu(n) = \frac{\mu}{\delta + x^T(n) \cdot x(n)} \delta > 0$$

δ is a constant and it should be greater than zero. μ is normalized step size or NLMS adaption constant which optimize the convergence rate of the algorithm and should satisfy the condition $0 < \mu < 2$. This algorithm results in smaller step size values than the LMS algorithm. NLMS algorithm converges faster than the LMS algorithm, as convergence factor is variable which minimize the instantaneous output error¹¹.

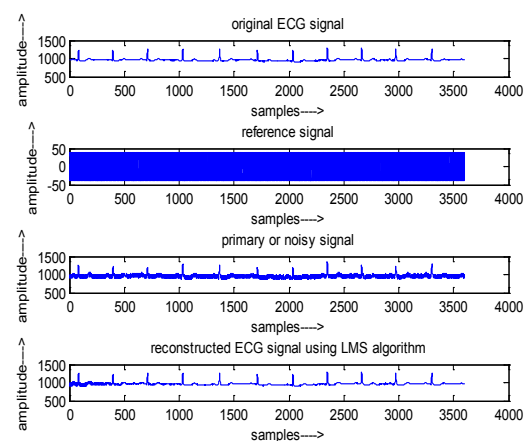
2. Results and Discussion

For implementation of adaptive algorithms and error minimization, data collected is raw ECG recorded data of different subjects like 100, 101, 108, 113, 114, 117, 118, 205 etc. from Physionet-bank, MIT-BIH arrhythmia database, with sampling frequency 360Hz over a period of just 10 second but we select one patient (record # 101)

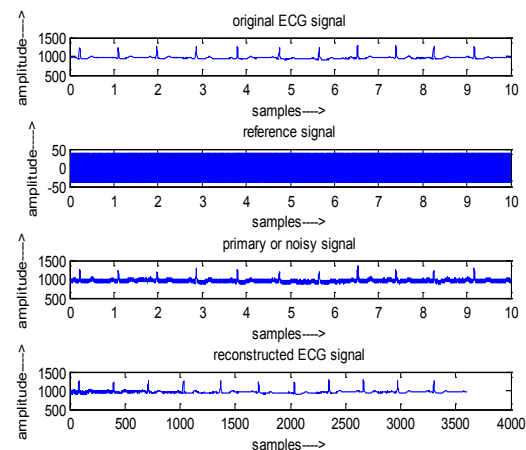
to analyze the data and to get required results. Similarly, it can also be done for other patients.

2.1 Power Line Interference

The 50Hz power-line interference is added to an original ECG signal collected from physionet and get the noisy signal. This corrupted/noisy signal is taken as a desired signal and signal coming from noise source is applied as a reference signal which is linearly correlated with noise signal but uncorrelated with original ECG signal. Finally, by subtracting reference signal from noise signal PLI is removed using LMS and NLMS Algorithms.



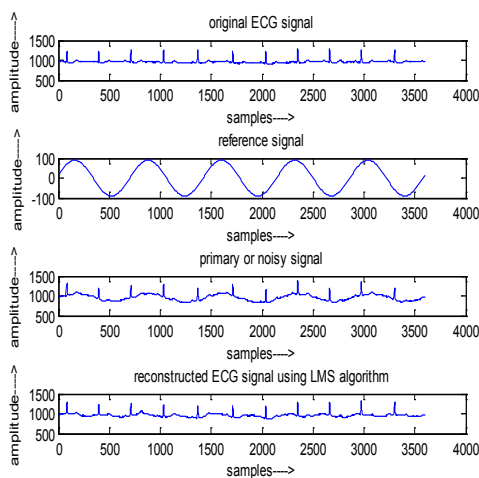
3(a)



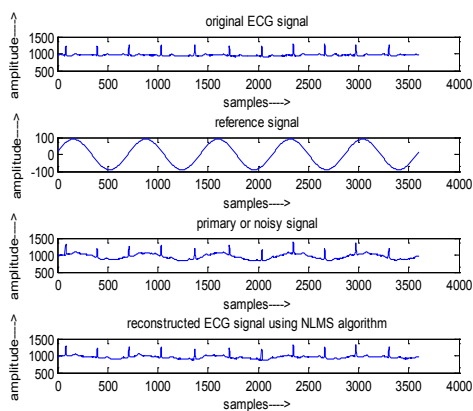
3(b)

Figure 3. (a) Time domain representation of 50 Hz PLI noise using LMS algorithm (b) Time domain representation of 50 Hz PLI noise using NLMS algorithm (record #101).

It can be seen that, for step size $\mu=0.0000001$, the convergence rate of LMS algorithm is very small which makes convergence slower than NLMS algorithm for $\mu = 0.0001$ which is larger than LMS step size. Amplitude of reconstructed signal is same as original signal. If reconstructed signal's amplitude increases then the signal will be highly distorted. On the other hand, if amplitude of the recovered signal decreases then the SNR and other parameters decreases but distortion will be lesser. Therefore we can say that if step size is not chosen correctly then the recovered signal will suffer with some distortion in the signal. So, we observe that for PLI noise NLMS is better than LMS algorithm.



3(c)



3(d)

Figure 4. (a) Time domain representation of BW noise using LMS algorithm (b) Time domain representation of BW noise using NLMS algorithm (record #101).

2.2 Baseline Wander

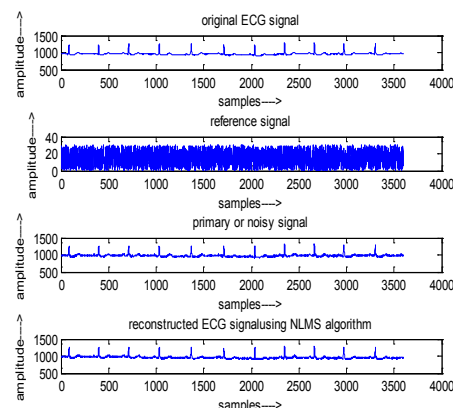
BW noise is a low frequency noise which occurs because of respiration. The frequency taken for this signal is 0.5Hz. Because of this noise the original ECG signal drifts from its base line and the noise is added in the original as a sinusoidal signal with 0.5 Hz frequency.

From above figures it can be seen that, the results shown by LMS and NLMS are looking same so it is not possible to analyze by only seeing that which algorithm converge faster. But in Baseline Wandering noise convergence take place only if the step size is $\mu=0.000000001$ for LMS algorithm and $\mu = 0.000001$ for NLMS algorithm otherwise it keep on diverging. So, NLMS algorithm is better for BW noise because only in this case convergence is obtained.

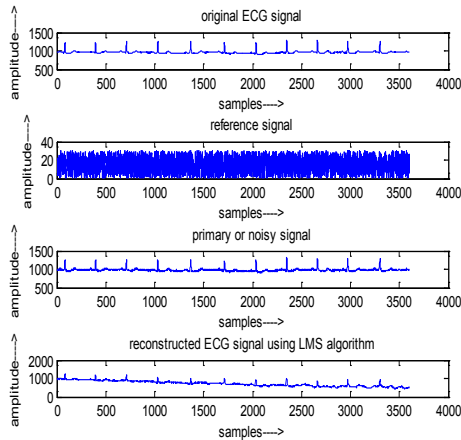
2.3 Muscle Contraction Noise

Muscle contraction noise occurs due to contraction of muscles beside the heart muscles. In other words, this noise occurs due to the generation of artificial mili-volt level potential. This noise is insignificant usually, because it induced in patient's body randomly. This noise is a very small or negligible noise with very small range. To obtain the simulation results by adding this noise to ECG signal, random signal is used. The maximum level of noise is formed if the amplitude of random signal added to original ECG is $\pm 50\%$ of uncorrupted ECG signal.

Both LMS and NLMS algorithms working on muscle contraction noise but only NLMS algorithm shows convergence and remove the noise. In LMS algorithm, it does not show any convergence and also distort the original signal and decreases signal to noise ratio.



3(e)



3(f)

Figure 5. (a) Time domain representation of MC noise using LMS algorithm (b) Time domain representation of MC noise using NLMS algorithm (record #101).

Table 1. Values of performance parameters of different adaptive filters for PLI noise

Adaptive filter	Database record	Performance parameters		
		MSE	SNR	RMSE
LMS	100	0.0235	0.9423	0.1533
	101	0.0234	0.9243	0.1531
	108	0.0234	0.9507	0.1531
	113	0.0235	0.9841	0.1532
	114	0.0235	0.9047	0.1533
	117	0.0242	0.9702	0.1522
	118	0.0231	0.9819	0.1519
	205	0.0234	0.9588	0.1530
	average	0.02338	0.9521	0.15289
NLMS	100	0.0247	0.9530	0.1573
	101	0.0223	0.9577	0.1494
	108	0.0233	0.9493	0.1522
	113	0.0188	0.9630	0.1370
	114	0.0255	0.9373	0.1596
	117	0.0213	0.9576	0.1460
	118	0.0192	0.9626	0.1386
	205	0.0227	0.9527	0.1506
	average	0.02223	0.9629	0.1489

The different parameters calculated for more efficiency and clarity are SNR of LMS 0.9243 and NLMS is

0.9577 which is more than LMS. Other parameters are MSE and RMSE. The value of MSR, RMSE in case of LMS algorithm is 0.0234 and 0.1531 but for NLMS these values are 0.0223 and 0.1494 which are lesser than LMS. From these values it is clear that for PLI noise NLMS algorithm is the better option.

Table 2. Values of performance parameters of different adaptive filters for BW noise

Adaptive filters	Database record	Performance parameters		
		MSE	SNR	RMSE
LMS	100	0.0234	0.9588	0.1530
	101	0.0201	0.5407	0.1419
	108	0.0204	0.4051	0.1429
	113	0.0199	0.8751	0.1410
	114	0.0205	0.2455	0.1432
	117	0.0187	0.7300	0.1366
	118	0.0174	0.8327	0.1319
	205	0.0203	0.5078	0.1424
	average	0.02088	0.636963	0.1416
NLMS	100	0.0240	0.1219	0.1549
	101	0.0174	0.6528	0.1319
	108	0.0198	0.4304	0.1408
	113	0.0186	0.7028	0.1363
	114	0.0255	0.0524	0.1597
	117	0.0195	0.6938	0.1397
	118	0.0193	0.6317	0.1388
	205	0.0124	0.6202	0.1116
	average	0.01997	0.48826	0.1392

Table 3. Values of performance parameters of different adaptive filter for MC noise

Adaptive filters	Database record	Performance parameters		
		MSE	SNR	RMSE
LMS	100	0.0330	0.0307	0.1817
	101	0.0329	0.0761	0.1814
	108	0.0329	0.0523	0.1814
	113	0.0330	0.2595	0.1816
	114	0.0330	0.0230	0.1817
	117	0.0327	0.1255	0.1807
	118	0.0326	0.2458	0.1805
	205	0.0329	0.0735	0.1814
	average	0.03288	0.1108	0.1813

NLMS	100	0.0282	0.3643	0.1678
	101	0.0173	0.8318	0.1316
	108	0.0250	0.6561	0.1582
	113	0.0264	0.9801	0.1624
	114	0.0292	0.2327	0.1708
	117	0.0245	0.9274	0.1565
	118	0.0262	0.9706	0.1620
	205	0.0215	0.9011	0.1465
	average	0.024788	0.733013	0.156975

To analyze which algorithm is better another parameters compared. For LMS algorithm (record#101) MSE, RMSE, SNR are 0.0201, 0.1419, 0.5407 and NLMS algorithm MSE is 0.0174, RMSE is 0.1319 and SNR is 0.6528. From these parameters it is clear that NLMS algorithm is better for this type of noise.

In case of LMS algorithm, amplitude of the signal increases and decrease in SNR i.e. 0.0761(record#101) with step size $\mu=0.00000001$ with order of the filter is 40 and also MSE and RMSE is 0.0329 and 0.1814. But in NLMS algorithm with $\mu=0.000001$ and filter order 40 show convergence and eliminate noise. For this signal MSE is 0.0173, RMSE is 0.1316 are calculated which are lesser than LMS and SNR is 0.8318 is larger which shows that NLMS algorithm is better for Muscle contraction noise cancellation.

3. Conclusion

The time domain analysis shows that NLMS algorithm eliminates 50Hz power-line interference, base-line wandering and muscle contraction noise properly. The value of MSE obtained from NLMS algorithm is better than that of LMS filter. The NLMS filter also show the high SNR and less RMSE and MSE than LMS filter which confirms the superiority of NLMS filter. Thus, the results obtained after implementation conclude that adaptive NLMS algorithm which is based on noise cancellation is an effective technique to get the optimum filtering by removing 50Hz PLI, BW and MC than LMS filtering technique.

4. References

1. Adaptive filter [Internet]. 2009 [updated 2016 Mar 21; cited 2009]. Available from: wikipedia.org/wiki/Adaptive_filter.

2. Islam SZ, Islam SZ, Jidin R, Ali MAM. Performance study of adaptive filtering algorithms for noise cancellation of ECG signal. 7th International Conference on Information, Communications and Signal Processing (ICICS), Institute of Electrical and Electronics Engineers (IEEE); 2009 Dec 8–10. p. 1–5.
3. Kaur M, Singh B. Power line interference reduction in ECG using combination of MA method and IIR notch filter. International Journal of recent trends in Engineering. 2009 Nov; 2(6):125–9.
4. Kumar Y, Malik GK. Performance analysis of different filters for power line interface reduction in ECG signal. International Journal of Computer Applications. 2010 Jun; 3(7):1–6.
5. Chauvin MS, Agarwala R, Uplane MD, Gaikwad MS. Design of ECG instrumentation and implementation of digital filter for noise reduction. Proceedings of the 9th WSEAS International Conference on Signal Processing, Computational Geometry and Artificial Vision. 2004 Jan; 1(157–474):47–50.
6. Reddy DVRK, Rahman MZU, Sangeetha Y, Sudha NS. Base line wander and power line interference elimination from cardiac signals using a novel LMS algorithm based on differential inputs and errors. In the Proceedings of International Journal of Advanced Engineering and Applications; 2011 Jan. p. 187–91.
7. Sankar AB, Kumar D, Seethalakshmi K. Performance study of various adaptive filter algorithms for noise cancellation in respiratory signals. Signal Processing: An International Journal (SPIJ). 2010 Dec; 4(5):267–78.
8. Sornmo L. Time-varying filtering for removal of baseline wander in exercise ECGs. In the Proceedings of Computers in Cardiology, Institute of Electrical and Electronics Engineers (IEEE); 1991 Sep 23–26. p. 145–8.
9. Zhang N, Askildsen B, Hemmelmman BT. Investigation of adaptive filtering for noisy ECG signals. Institute of Electrical and Electronics Engineers (IEEE) Mountain Workshop on Adaptive and Learning Systems; 2006 Jul 24–26. p. 30–5.
10. Martens SM, Mischi M, Oei SG, Bergmans JW. An improved adaptive power line interference canceller for electrocardiography. Institute of Electrical and Electronics Engineers (IEEE) Transactions on Biomedical Engineering. 2006 Nov; 53(11):2220–31.
11. Gupta HK, Vijay R, Gupta N. Designing and implementation of algorithms on MATLAB for adaptive noise cancellation from ECG signal. International Journal of Computer Applications. 2013 May; 71(5):1–8.