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

**R.Karthika**
Vijay Rural Engineering College,
Nizamabad.

**K.Narender, M.Tech**
Vijay Rural Engineering College,
Nizamabad.

**Dr.B.R.Vikram**
M.E, Ph.D, MIEEE, LMISTE,
Vijay Rural Engineering College,
Nizamabad.

## Abstract:

Electrocardiogram (ECG) is a method of measuringthe electrical activities of heart. Every portion of ECG is veryessential for the diagnosis of different cardiac problems. But theamplitude and duration of ECG signal is usually corrupted bydifferent noises. In this paper we have done a broader study fordenoising every types of noise involved with real ECG signal.Two adaptive filters, such as, least-mean-square (LMS) andnormalized-least-mean-square (NLMS) are applied to remove thenoises. For better clarification simulation results are compared interms of different performance parameters such as, powerspectral density (PSD), spectrogram, frequency spectrum andconvergence. SNR, %PRD and MSE performance parameter arealso estimated. Signal Processing Toolbox built in MATLAB® isused for simulation, and, the simulation result clarifies thatadaptive NLMS filter is an excellent method for denoising theECG signal.

## I. INTRODUCTION:

ECG is generated by the heart muscle and measured on theskin surface of the body. When the electrical abnormalities ofthe heart occur, the heart cannot pump and supply enoughblood to the body and brain. As ECG is a graphical recordingof electrical impulses generated by heart, it is needed to bedone when chest pain occurred such as heart attack, shortnessof breath, faster heartbeats, high blood pressure, highcholesterol and to check the heart's electrical activity. AnECG is very sensitive, different types of noise and interferencecan corrupt the ECG signal as the real amplitude and durationof 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 andpower line interference.

These noise and interference makesthe incorrect diagnosis of the ECG signal [1-3]. So, theremoval of these noise and interference from the ECG signalhas become very crucial. Different types of digital filters (FIRand IIR) have been used to solve the problem [3-5]. However,it is difficult to apply these filters with fixed coefficients toreduce different types of noises, because the ECG signal isknown as a non-stationary signal. Recently, adaptive filteringhas Become effective and popular methods for processing andanalysis of the ECG signal [6-8]. It is well known thatadaptive filters with least mean square (LMS) algorithm showgood performance for processing and analysis of signal whichare non-stationary [1]. And in this study, we have usedadaptive LMS and normalized least mean square (NLMS)filter to denoise the ECG signal. We also have evaluated theirperformance. But it is shown that NLMS filter removes allspecified noise (mentioned above) more significantly.

## II. MATERIALS AND METHODS:

The original ECG signal is taken from the MIT-BIHarrhythmia database [9]. The different types of noise signal aregenerated by using MATLAB®. The noise signal is then addedwith the real ECG signal. To remove the different types ofnoises, the noisy ECG signal is then pass through two adaptivefilter algorithms (e.g., LMS and NLMS). However, the basicblock diagram for understanding the overall adaptive filteringprocess is depicted in Fig. 1.

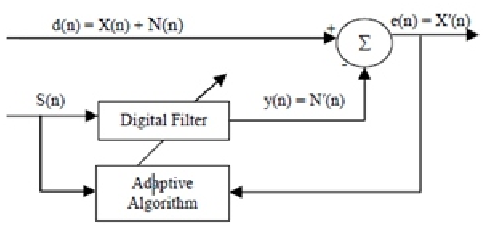


Figure1. Principle of adaptive filter[7].

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The block diagram indicates that, if the value of N(n) isknown, then after subtracting this from the mixed signal d(n),the original signal X(n) is obtained. But it is difficult due tothe harmonics of noise signal. For this reason an estimatednoise signal N´(n) is calculated through some filters andmeasureable 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

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

(b)

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 affectthe signal energy. Therefore the minimum error energy is

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

(c)

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

The LMS algorithm produces the least mean square of theerror signal by changing the filter tap weight, whosecoefficient updating equation is

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

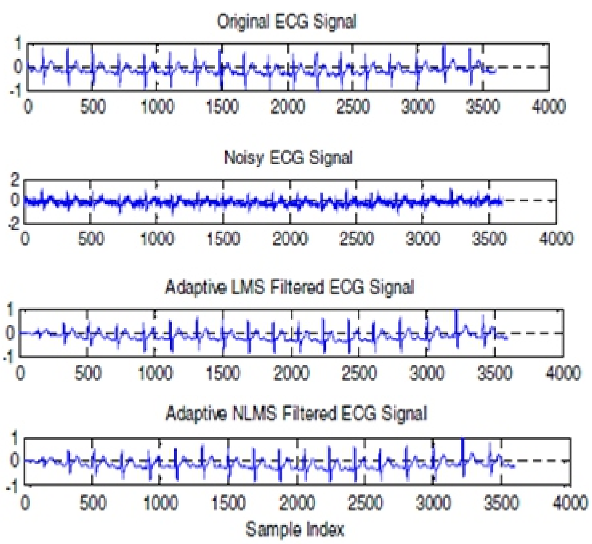
Where, μ is an appropriate step size to be chosen as 0 < μ <0.2 for the convergence. The larger steps sizes make thecoefficients to fluctuate widely and the LMS algorithmexperiences a problem with gradient noise amplification,which can be solved by the normalization of the step size. Thisvariant of the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

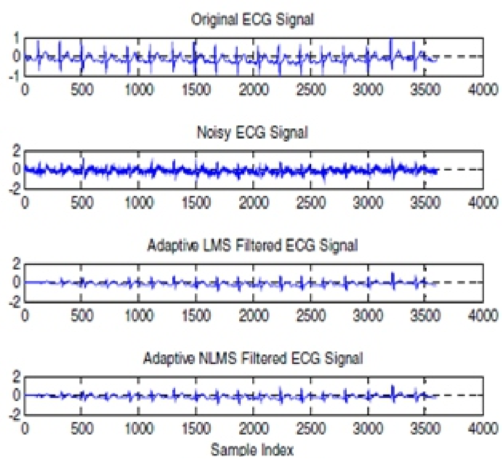
$$W_{k+1} = W_k + \beta \frac{x_k^*}{\alpha + \|X_k\|^2} e_k \qquad (7)$$

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-BIHarrhythmia database [9] whose sampling number is 4000 andamplitude is 1 mV. The different types of noises such as whitenoise, colored noise, muscle artifact, base line wander,electrode movement noise, composite noise and power lineinterference are generated by using MATLAB®. These noisesare then added to the real ECG signal to get the desired mixedsignal. Finally, the noise is removed using two differentadaptive filters based on LMS and NLMS algorithm. Theresults are shown in Fig. 2. If the amplitude of thereconstructed signal increases,(e)



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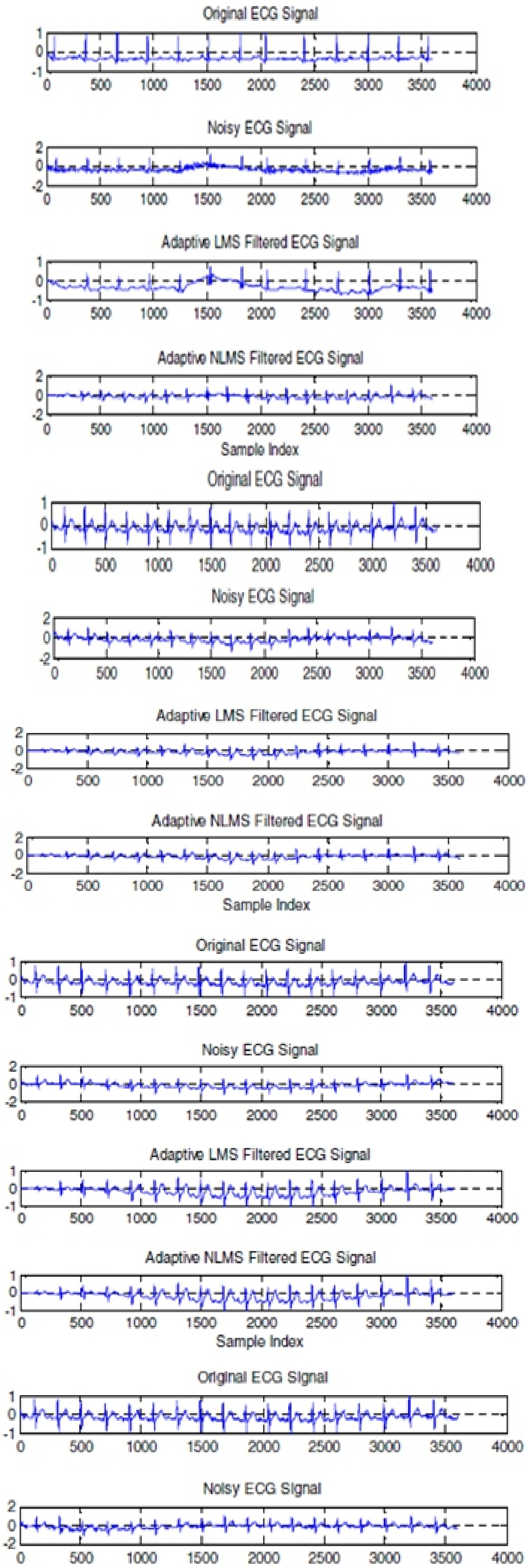


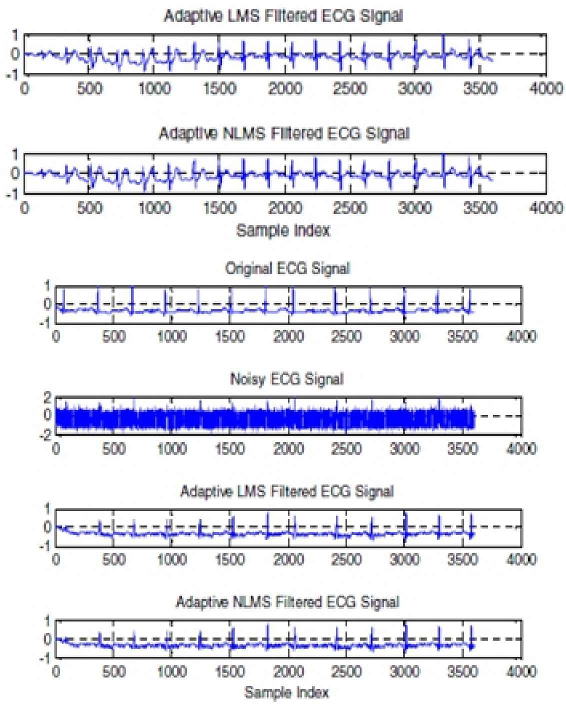


Figure2. Graphical representation of LMS filtering signal forμ=0.007 and NLMS filtering signal for μ=1 after removing (a)White Gaussian noise, (b) Colored noise, (c) Real muscle artifactnoise, (d) Real electrode movement noise, (e) Real baseline wandernoise, (f) Composite noise, and (g) Power line interference.

Then there will be high distortion and vice versa. When thevalue of μ equal to 0.007, then we see that some noise alsoappear on the signal peak compared with the value of μ equalto 0.001.But when the value of μ is 0.001, then thereconstructed signal amplitude is less than the original signalas 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 somedistortion.

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

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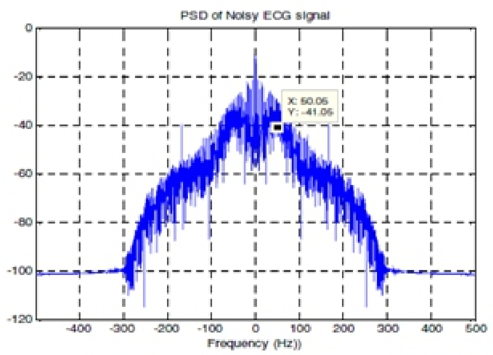
## TABLE I. VALUES OF PERFORMANCE PARAMETERS OF TWO ADAPTIVE FILTERS FOR DIFFERENT TYPES OF NOISE.

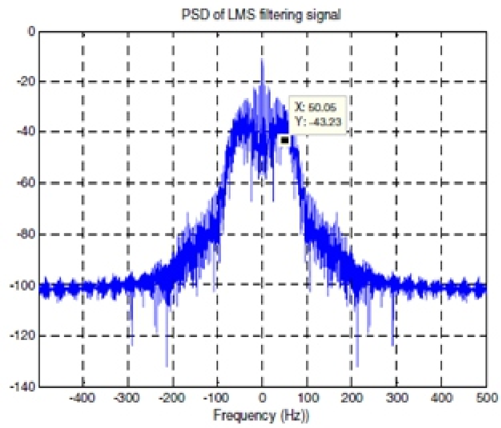
| Noises | Adaptive Filters | Reconstructed Signal's | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | SNR | | | | %PRD | | | | MSE | | | |
| | | Patient Data 100 | Patient Data 106 | Patient Data 215 | Average | Patient Data 100 | Patient Data 106 | Patient Data 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 adaptiveLMS and NLMS filter we use four visual parameters such asPSD, spectrogram, frequency spectrum and convergence forthe removal of power line interference.

The PSD represents the amount of power per unitbandwidth and it helps to understand the performance ofremoving noise from ECG signal [6]. The PSD of mixedsignal, LMS filtering signal and NLMS filtering signal isshown graphically in Fig. 3 and tabular form in Table II. Fromfigure 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 LMSand NLMS filter the power of the filtering signal is reduced to -43.23 dB and -41.28 dB. So, NLMS filter removing the powerline interference more clearly. (a)




(b)




(c)

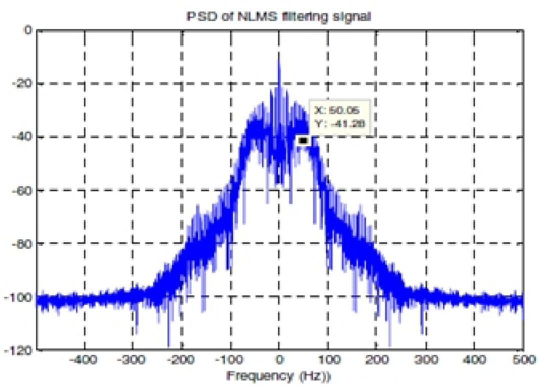



Figure 3. Graphical PSD of (a) Noisy ECG signal, (b) LMSfiltering signal and (c) NLMS filtering signal

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## TABL 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 differentsignal changes with respect to time, so it is a time varyingspectral analysis [6]. Fig. 4 shows the spectrogram of noisyECG signal, LMS filtering signal and NLMS filtering signal. Inspectrogram of noisy ECG signal has a black shade line in 50Hz position. After applying LMS and NLMS filtering theshaded line is removed such that there is a noticeable change ofspectral density of the filtering signal, where NLMS filtershows better performance than the LMS filter.

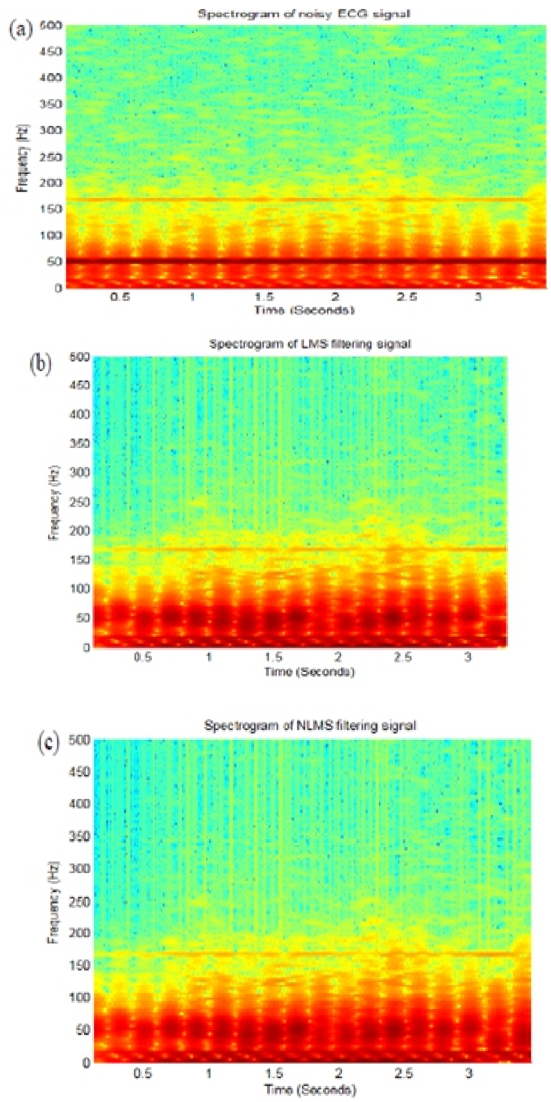


**Figure4. Spectrogram of (a) Noisy ECG signal, (b) LMS-filtering signal and (c) NLMS filtering signal.**

Frequency spectrum is a frequency domain spectral-analysis [6]. The frequency spectrum of 50 Hz noisy ECGsignal, LMS filtering signal and NLMS filtering signal isshown in Fig. 5. In noisy signal frequency spectrum, there is aspike at 50 Hz position. But the noise spike is disappearedafter filtering by LMS and NLMS filter, where NLMS filtershows better performance than LMS filter for removing PLI.

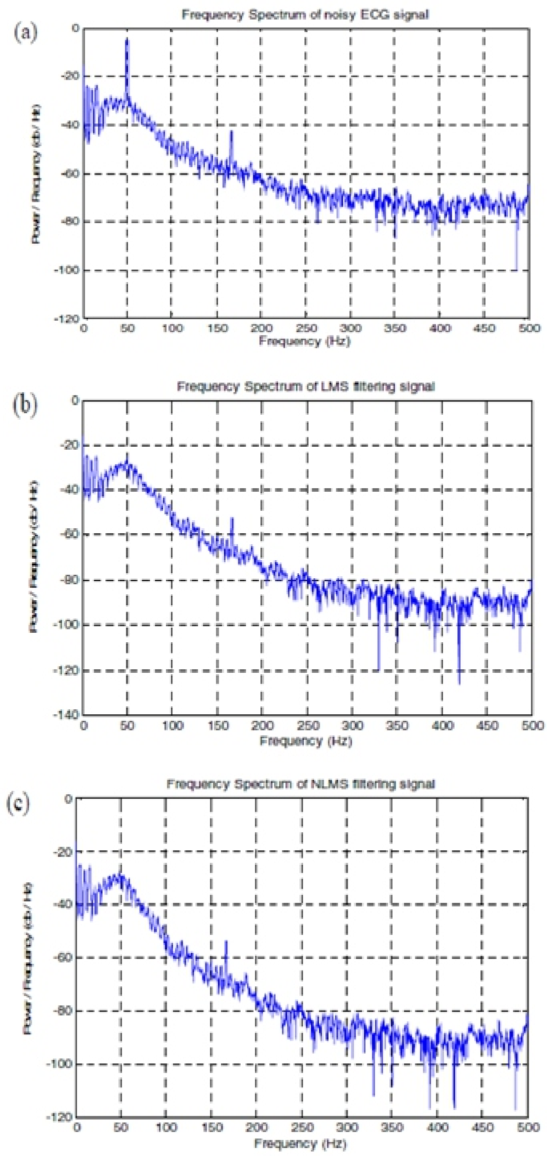


**Figure 5. Frequency spectrum of (a) Noisy ECGsignal, (b) LMSfiltering signal and (c) NLMS filtering signal.**

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The convergence criterion shows that, the fast adaption offiltering signal with the original signal. The convergence ofLMS and NLMS filtering reconstructed signal is depicted inFig. 6. We can see that, the NLMS filtering signal adapts in farless iteration to original signal than the LMS filtering signal.

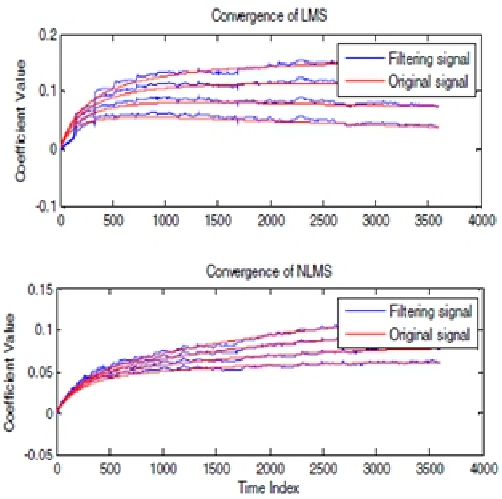


**Figure 6.Convergence of LMS filtering signal and NLMS filteringsignal.**

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 adaptivesigned regress or LMS (SRLMS), adaptive sign LMS (SLMS)and adaptive sign sign LMS (SSLMS) filter in terms ofcalculated SNR for denoising power line interference, baselinewander, muscle artifacts and motion artifacts [10]. Anotherpaper reported that adaptive NLMS filter shows the betterperformance than the adaptive LMS and adaptive signed LMS(SLMS) filter in terms of SNR for removing the power lineinterference [11].

In one of our previous studies, we haveshown that the adaptive NLMS filter denoises the power lineinterference from ECG signal exceptionally better than theother LMS algorithm based adaptive filter [12], in terms ofSNR, PRD and MSE. For better clarification, we have done abroader study for denoising every types of noise involved withreal ECG signal in this paper. From the simulation results, wealso see that in terms of different performance parameters theadaptive NLMS filter shows the superior performance thanadaptive LMS filter. So, NLMS based adaptive noise cancellermay be used in all practical application.

## IV. CONCLUSION:

Analysis of ECG signal, both of noisy ECG signal andfiltered signal reveals that adaptive NLMS and LMS filter bothreduces the white noise, colored noise, muscle artifact noise,electrode movement noise, baseline wander noise, compositenoise and power line interference properly. But the differentperformance parameters SNR, %PRD, MSE and also visualparameters PSD, frequency spectrum and convergence revealsthat adaptive NLMS filter is more appreciable for removingvarious types of noises from ECG signal.

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