International Journal of Recent Research and Review, Vol. VII, Issue 2, June 2014

ISSN 2277 – 8322

Noise Reduction Technique for ECG Signals Using Adaptive Filters

Arpit Sharma[1], Sandeep Toshniwal[2], Richa Sharma[3]

[1]*Research Scholar, Dept. of Electronics & Communication, KITE, Jaipur, India*

[2]*Reader, Dept. of Electronics & Communication, KITE, Jaipur, India*

[3] *Asst. Professor, Dept. of Electrical Engineering, ACEIT, Jaipur, India*

Email Id: kingarpit24@gmail.com, toshniwal.sandeep@gmail.com,sharma.r0707@gmail.com

***Abstract* - The ECG finds its importance in the detection of cardiac abnormalities. Noise reduction in ECG signal is an important task of biomedical science. ECG signals are very low frequency signals of about 0.5Hz-100Hz and digital filters are very efficient for noise removal of such low frequency signals. In this Paper an adaptive filter for high resolution ECG Signal is presented which estimate the deterministic component of the ECG Signal and remove the noise. The filter needs two input: the signal (primary input) and an impulse correlated with the deterministic component (reference input). Several signals to noise ratio were considered and the effect of shape variation was also studied. The adaptive filters essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Different filter structures are presented to eliminate the diverse forms of noise: 60Hz power line interference, baseline wander, muscle noise and the motion artifact. Finally, we have applied these algorithms on real ECG signals obtained from the MIT-BIH data base. Simulation results are also shown. Performance of filters is analyzed based on SNR and MSE.**

***Keywords* - ECG, Adaptive filter Algorithms, LMS, NLMS, SDLMS, SELMS, SSLMS.**

I. INTRODUCTION

One of the main problems in biomedical data processing like electrocardiography is the separation of the wanted signal from noises caused by power line interference, high frequency interference, extern electromagnetic fields and random body movements and respiration [1]. Different types of digital filters are used to remove signal components from unwanted frequency ranges. It is difficult to apply filters with fixed coefficients to reduce random noises, because hum behaviour is not exact known depending on the time. Adaptive filter technique is required to overcome this problem. Electrocardiogram (ECG) is one of the most important parameters for heart activity monitoring. A doctor can detect different types of deflections by the full form analysis of the ECG signal. Fig. 1 shows the standard ECG Signal.

In many applications for biomedical signal processing the useful signals are superposed by different components. Interference may have technical sources, for example, power supply harmonic 50 Hz, high frequency noises and electromagnetic fields from other electronics devices, and biological sources, such as muscular reaction, respiratory movements and changing parameters of the direct contact between electrodes and the skin [1]. So, extraction and analysis of the information-bearing signal are complicated, caused by distortions from interference. Using advanced digital signal processing this task can be shifted from the analogue to the digital domain [2].

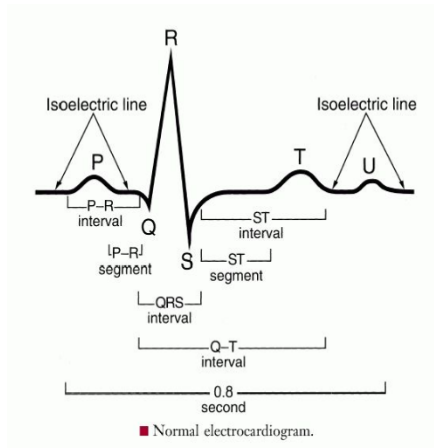

Fig. 1 Standard ECG waveform

Usually two types of digital filters are used for data processing: frequency-selective filters with fixed coefficients and filters with variable coefficients. Various adaptive and non-adaptive methods are there for ECG signals enhancement [3-7]. The first type is normally applied to suppress an unnecessary frequency range of a signal, such as power supply harmonic and high-frequency waves. These interference components have a fixed frequency; therefore it is possible to calculate filter coefficients depending on the sampling frequency, the cutoff frequency, passband ripple and stopband attenuation. The greater problem is to reduce random noise, generated by respiratory and moving effects. The frequency spectrum of those noise sources is time dependent and not exactly known. So, a filter with fixed coefficients can't deal with this kind of noise signals and valuable information may be lost. These difficulties can be solved using an adaptive filter, a system with variable coefficients. Frequency response of an adaptive filter is adjusted automatically according to the specified criterion to improve the output signal quality depending on the behaviour of the input signal during the measurement[8]. In this paper different types of adaptive filters are described and compared. Performance of filters is analyzed based on SNR and MSE.

II. METHODOLOGY

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. It adapts to the change in signal characteristics in order to minimize the error. It finds its application in adaptive noise cancellation, system identification, frequency tracking and channel equalization. Fig.2 shows the general structure of an adaptive filter.

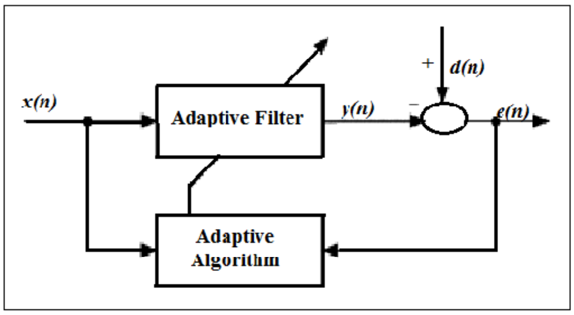

Fig. 2 General Structure of an Adaptive Filter

In Fig. 2, x(n) denotes the input signal. A digital filter is applied on the input signal x(n), produce output signal y(n). Adaptive algorithm adjusts the filter coefficient included in the vector w(n), in order to get the error signal e(n) be the smallest. The vector representation of x(n) is given in Eq(1). This input signal is corrupted with noises. In other words, it is the sum of desired signal d(n) and noise v(n), as mentioned in Eq(2). The input signal vector is x(n) which is given by

$$x(n)=[x(n),x(n-1),x(n-2),\ldots\ldots x(n-N-1)]^T \quad ..(1)$$

$$x(n)=d(n)+v(n) \quad ..(2)$$

The adaptive filter has a Finite Impulse Response (FIR) structure. For such structures, the impulse response is equal to the filter coefficients. The coefficients for a filter of order N are defined as

$$W(n)=[w_n(0),w_n(1),\ldots\ldots w_n(N-1)]^T \quad ..(3)$$

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

$$y(n)=W(n)^T x(n) \quad ..(4)$$

The error signal or cost function is the difference between the desired and the estimated signal

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

Moreover, the variable filter updates the filter coefficients at every time instant

$$W(n+1)=W(n)+\Delta W(n) \quad ..(6)$$

Where ΔW(n) is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity. RLS algorithm filter the convergence rate is faster than the LMS algorithm, the convergence is unrelated with the spectrum of input signal, its each iteration is much larger operation than LMS.

Consider a situation when a proper reference input signal is not available, particularly in case of ambulatory medical diagnosis condition, the output of adaptive filter under limited availability of reference input is not good enough and a huge amount of noise is still present after filtration. The single input adaptive noise canceller has been presented to overcome this situation [10]. In this process the adaptive filtering operation does not rely upon the availability of well correlated reference input but the delayed version of the input signal is itself acts as a reference input. The delayed signal either can be given in primary path or in reference path.

III. RESULTS

The ECG signals used are MIT BIH arrhythmia database ECG recording [9].In this paper, both base line wander (non-stationary noise) and power line interference (stationary noise) have been considered. This MIT BIH arrhythmia database consists of two channel ECG recording. The sampling rate of the recording is 360 samples per second. To demonstrate power line interference (PLI) cancellation we have chosen MIT-BIH record number 100. The input to the filter is ECG signal corresponds to the data 100 corrupted with synthetic PLI with frequency 60Hz. For analyzing the performance of different type of adaptive algorithm, MSE and SNR improvement are measured and compared. The corrupted ECG signal is the primary input to the adaptive filter and its delayed version ECG as desired response or reference signal. Different filter structure such as LMS(Least Mean Square), NLMS(Normalized Least Mean Square) , SELMS(Sign Error Least Mean Square), SDLMS (Sign Data Least Mean Square), SSLMS(Sign Sign Least Mean Square), and RLS(Recursive Least Square) has been implemented for removing different type of Noise.

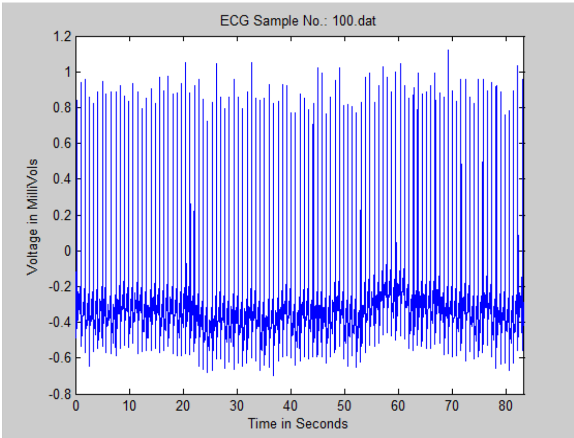

Fig. 3 Standard ECG Signal (MIT-BIH:100)

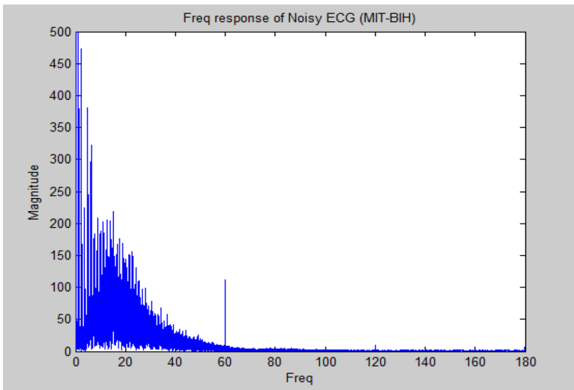

Fig. 4 Frequency Spectrum of Standard ECG Signal

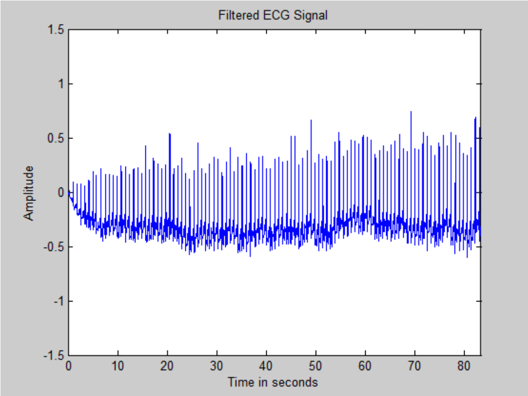

Fig. 5 Output of Adaptive Filter, Realized with NLMS Algorithm

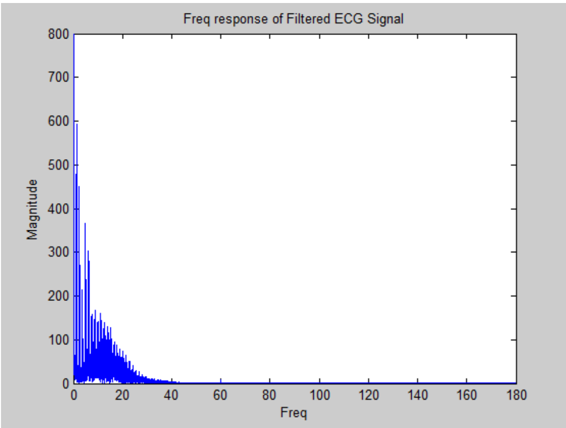

Fig. 6 Frequency Spectrum of Filtered Signal (NLMS adaptive Filter)

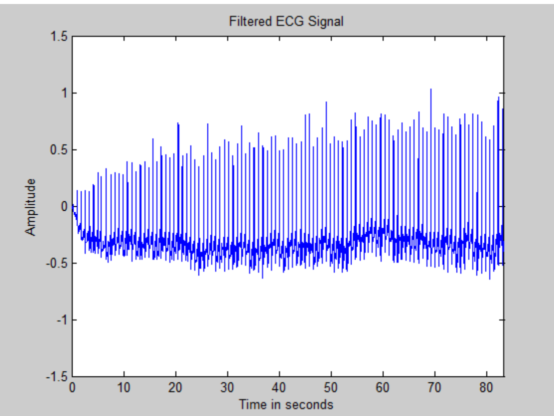

Fig. 7 Output of Adaptive Filter, Realized with LMS Algorithm

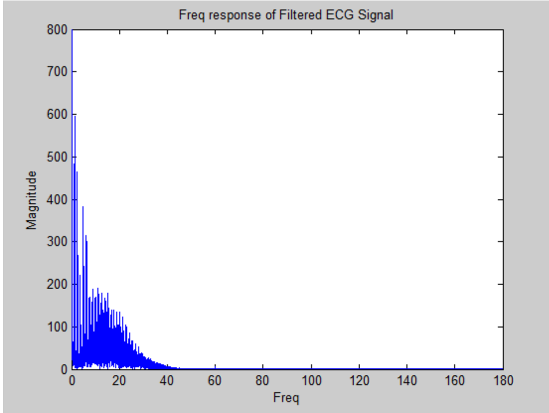

Fig. 8 Frequency Spectrum of Filtered Signal (LMS adaptive Filter)

For LMS based adaptive filters filter length is 15 and step size (mu) is 0.001.Whereas in RLS, filter length is 32.TABLE I shows the performance analysis of various adaptive filters.

TABLE I
Performance of Various Adaptive Algorithms

TYPE OF ADAPTIVE ALGORITHM	PSNR (In db)	SNR (In db)	MSE
LMS	16.1806	6.3250	0.0302
NLMS	16.6273	6.4575	0.0273
SELMS	15.2034	5.5651	0.0379
SDLMS	15.9161	6.1817	0.0321
SSLMS	15.1694	5.5546	0.0382
RLS	14.9363	5.3839	0.0403

IV. CONCLUSION

In this paper, different types of adaptive filtering have been used for removing artifacts from cardiac signals. The obtained results indicate that LMS and NLMS algorithm based adaptive filters have estimated the respective signals from the noisy environment accurately. From the simulation results it is shown that the output SNR values for the algorithms are obtained and compared with each other, with reference to Power-line Interference Noise and we can see that the approach of using adaptive filter algorithms for ECG signal enhancement provide a better realization than non-adaptive structures. As LMS have four other different types but we get the most efficient results with NLMS (Normalized Least Mean Square). This algorithm has an ability to remove both stationary and non-stationary noise in an ECG signal at a time. Hence NLMS based filter for noise cancellation is more efficient for medical applications.

V. FUTURE ENHANCEMENT

The future developments to this work can be made as follows:

- Implementation of efficient wavelet based de-noising for the removal of base line wander.
- Real time application of implemented algorithms.

VII. REFERENCES

[1] Anonymous, ANSI/AAMI EC11-1991, "American National Standard for Diagnostic Electrocardiographic Devices".

[2] Emmanual C. Ifeachor, Barrie W. Jervis: "Digital signal processing, a practical approach, second edition", Moscow: Yillyams (2004).

[3] Y.Der Lin and Y.Hen Hu "Power line interference detection and suppression in ECG signal processing", *IEEE Transactions and Biomedical engineering,*,vol.55, pp. 354- 357, January 2008.

[4] N.V Thakor and Y.S.Zhu, "Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection", *IEEE Transactions and Biomedical engineering,* vol.38, no.8, pp.785-794, August, 1991.

[5] J.M Leski and N.Henzel, "ECG baseline wander and power line interference reduction using nonlinear filter bank", *Signal processing*, vol.85, pp.781-793, 2005.

[6] S.Olmos and P.Laguna, "Steady state MSE convergence analysis in LMS adaptive filter with deterministic reference inputs for biomedical signals", *IEEE Transaction on Signal Processing,* vol.48, pp.2229-2241, August 2000.

[7] C.Mihov and I Dotsinsky, "Power line Interference elimination from ECG in case of non-multiplicity between the sampling rate and power line frequency", *Biomedical Signal processing and control,* vol.3, pp.334-340, June 2008.

[8] Widrow, B., and Stem, D., Adaptive signal processing, Prentice Hall, 1986.

[9] www.physionet.org/physiobank/database/#ecg.

[10] C.H. Chang, K. M. Chang, Hsien Ju-Ko, "Removal of Random Noises from ECG signal without external reference input", *International Journal of the Physical Sciences*, Vol. 6 (24), pp. 5699-5705, 16 October 2010.