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Novel Approach of Stationary & Non Stationary Implementation of NLMS & RLMS Algorithms for Suppression of Noise in Cardiac Signals

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ABSTRACT
Adaptive filter is an efficient method to filter ECG signal, because it does not need the signal statistical characteristics. In this paper we present a Gaussian & novel adaptive filter for removing the Baseline wander & power line interference from ECG signals based on recursive least mean square (RLMS) algorithm & Normalized least mean square (NLMS) algorithm. These algorithms are derived based on the minimization of mean square error, average power, power spectral density (PSD). The adaptive filter essentially minimizes the mean square error between a primary input, which is a noisy ECG, and a reference input which is either noise that is correlated in some way with the noise in the primary input. Finally, we have applied RLMS algorithm on ECG signals from the MIT-BIH database and compared its performance with the NLMS algorithm. The simulation result shows that the performance of the RLMS algorithm is superior to that of the NLMS based algorithm in noise reduction.
Keywords – adaptive noise cancelation, artifacts, Baseline Wander (BW), ECG signals, Noise cancelation, NLMS and RLMS algorithms, power line interference (PLI)

I. INTRODUCTION

A normal ECG contains waves, intervals, segments, and one complex as shown in Fig.1. The aim of the ECG simulator is to produce the typical ECG waveforms of different leads and as many arrhythmias as possible. My ECG simulation is a matlab based simulation and is able to produce normal lead II ECG waveform. The use of a simulation has many advantages in the ECG. First one is saving of time and another one is removing the difficulties of taking real ECG signals with invasive and noninvasive methods. The ECG simulator enables us to analyze and study normal and abnormal ECG waveforms without actually using the ECG machine. One can simulate any given ECG waveform using the ECG simulator.

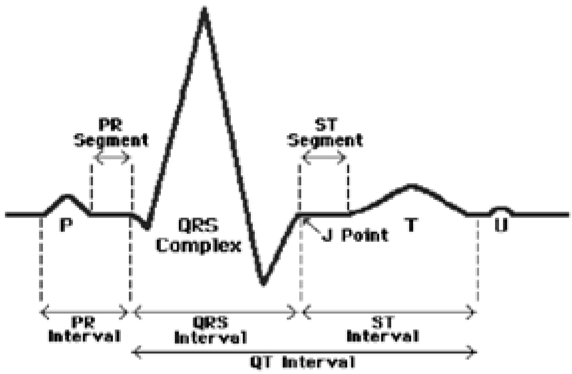

Fig.1.Typical E.C.G Waveform

Baseline wanders (BW) and power line interference (PLI) reduction is the first step in all electrocardiographic (ECG) signal processing. The baseline wander is caused by varying electrode-skin impedance, patient's movements and breath. This kind of disturbances is especially present in exercise electrocardiography, as well as during ambulatory and Holter monitoring. The ECG signal is also degraded by additive 50 or 60 Hz power line interference. This kind of disturbance can be modeled by a sinusoid with respective frequency and random phase. These two artifacts are the dominant artifacts and strongly affect the ST segment, degrade the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST waveforms and masks tiny features that are important for clinical monitoring and diagnosis. Cancelation of these artifacts in ECG signals is an important task for better diagnosis. Hence the extraction of high-resolution ECG signals from recordings which are contaminated with background noise is an important issue to investigate. The goal of ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement using both adaptive and non adaptive techniques [1]-[9], The Proposed recursive least mean squares (RLMS) algorithm has generally faster convergence than NLMS but it have less computational complexity. In this paper we have proposed a normalized sign vector variable step size RLMS algorithm that has both the faster convergence rate as well as less computational complexity. The performances of the RLMS algorithm and the proposed normalized sign vector variable step size NLMS algorithms are compared. We have shown that the proposed RLMS algorithm overcomes the limitations of NLMS algorithm.

II. PROPOSED IMPLEMENTATION

Consider a length L, NLMS based adaptive filter, depicted in Fig.2 that makes an input sequence $x(n)$ and updates the weights as

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

Where $w(n) = [w_0(n)w_1(n)\ldots w_{L-1}(n)]^t$ (2)

Error signal $e(n) = d(n) - w^t(n)x(n)$ (3)

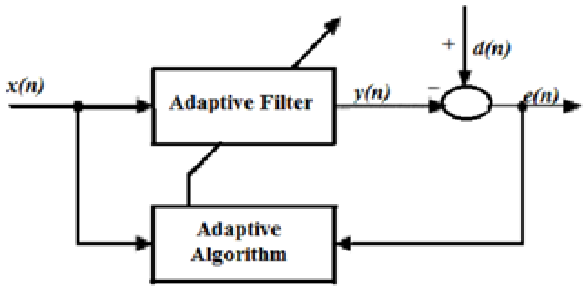

Fig.2. Adaptive filter structure

In order to remove the noise from the ECG signal, the ECG signal $s_1(n)$ corrupted with noise signal $p_1(n)$ is applied as the desired response $d(n)$ to the adaptive filter shown in Fig 2.

If the noise signal $y(n)$, possibly recorded from another generator of noise that is correlated in some way with $p_1(n)$ is applied at the input of the filter, i.e., $x(n) = p_2(n)$ the filter error becomes $e(n) = [p_1(n) + x(n)] - y(n)$. Where, $y(n)$ is the filter output and it is given by, $y(n) = w^t(n)x(n)$ since the signal and noise are uncorrelated, the mean-squared error (MSE) becomes.

$$E[e^2(n)] = E\{[s_1(n) - y(n)]^2\} + E[p_1^2(n)] \qquad (4)$$

III. SURVEY OF RELATED WORK

An adaptive recurrent filter structure is used for acquiring the impulse response of the normal Q, R, S waves. This method is applied to the detection of P-waves [1]. Normalized LMS (NLMS) algorithms takes into account a variation of the signal level at the filter output and select the normalized step size parameter that results in a stable as well as fast converging algorithm. RLMS algorithm is another class of adaptive algorithm. This algorithm is used in adaptive filters to find the filter coefficients that relates to producing least mean square of the error signal between the desired $d(n)$ and actual signal, $y(n)$ .the convergence characteristics of both the algorithms are shown in Fig. 3

3.1 RLMS ALGORITHM

The recursive algorithm is obtained from the conventional RLMS recursion by replacing the tap-input vector $x(n)$ with the vector $\operatorname{sgn}\{x(n)\}$. Consider a signed recursive RLMS based adaptive filter that processes an input signal $x(n)$ and generates the output y(n) as per the following:

$$y(n) = wt(n)x(n) \qquad (5)$$

Where, $w(n) = [w_0(n), w_1(n), \ldots w_{L-1}(n)]^t$ is an L^{th} order adaptive sfilter. The adaptive filter coefficients are updated by the recursive LMS algorithm (RLMS) as,

$$w(n+1) = w(n) + \mu \operatorname{sgn}\{x(n)\}e(n) \qquad (6)$$

3.2 NLMS ALGORITHM

The NLMS algorithm is a modified form of the standard LMS algorithm. The NLMS algorithm updates the coefficients of an adaptive filter by using the following equation 2

The NLMS algorithm becomes the same as the standard LMS algorithm except that the NLMS algorithm has a time-varying step size μ(n). This step size improves the convergence speed of the adaptive filter.

$$w(n+1) = w(n) + 2\mu \frac{x(n)}{\|x(n)\|^2} e(n) \qquad (7)$$

The aim of the ECG simulator is to produce the typical ECG waveforms of different leads and as many as possible. This ECG simulator is a MATLAB based simulations and is able to produce normal lead II ECG waveform. The use of a simulator has many advantages in the simulation of ECG waveforms. First one is saving of time and another one is removing the difficulties of taking real ECG signals with invasive and noninvasive methods. The ECG simulator enables us to analyze and study normal and abnormal ECG waveforms without actually using the ECG machine. One can simulate any given ECG waveform using the ECG simulation.

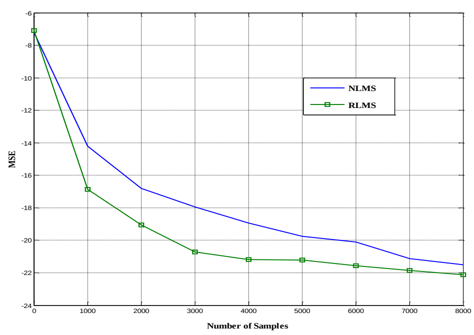

Fig3. Typical convergence curves of NLMS and RLMS for PLI cancellation.s

IV. SIMULATION RESULTS

To show that RLMS algorithm is really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). In our simulations we consider both stationary (PLI) and non-stationary (BW) noises. The arrhythmia data base consists of 48 half hour excerpts of two channel ambulatory ECG recordings, which were obtained from 47 subjects, including 25 men aged 32-89 years, and women aged 23-89 years. The recordings were digitized at 360 samples per second per channel with II-bit resolution over a 10 m V range. In our experiments we used a data set of five records (records 101, 102, 103, 104 and 105) but due to space constraint simulation results for record 105 are shown in this paper. In our simulation we collected 7200 samples of ECG signal, a random noise with variance (0") of 0.001, 0.01 and 0.1 is added to the ECG signals to evaluate the performance of the algorithm in terms of Mean square error (MSE), and power spectral density (PSD) signal to noise ratio. For all the figures number of samples is taken on x-axis and amplitude on y-axis, unless stated. Fig3. shows the comparison between RLMS and NLMS algorithms.

4.1 BASELINE WANDER REDUCTION

In this experiment, first we collected 7200 samples of the pure ECG signal from the MIT-BIH arrhythmia database(dataI05) and it is corrupted with real baseline wander (BW) taken from the MIT-BIH Noise Stress Test Database (NSTDB). This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrhythmias. The contaminated ECG signal is applied as primary input to the adaptive filter. Fig.4 The real Baseline Wander is given as reference signal. Different filter structures were implemented using the NLMS and RLMS algorithms. to study the relative performance and results are plotted in Fig.6. On average RLMS algorithm gets better improvement, than the NLMS algorithm.

4.2 POWER LINE INTERFERENCE CANCELLER

To demonstrate power line interference (PLI) cancelation we have chosen MIT-BIH record number 105. The input to the filter is ECG signal corresponds to the data 105 corrupted with synthetic PLI with amplitude 1mv and frequency 50Hz, sampled at 200Hz. The reference signal is synthesized PLI, the output of the filter is recovered signal. These results are shown in Fig.5. The power spectrum of the noisy signal before and after filtering with NLMS and RLMS algorithms

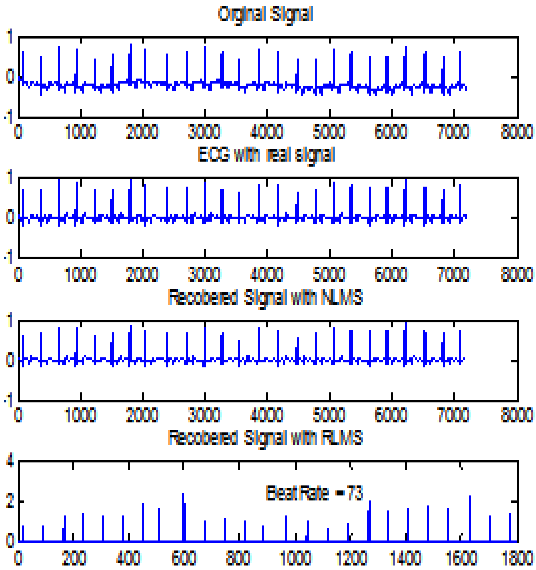

Fig. 4. Typical filtering results of baseline wander reduction (a) clean ECG signal, (b) ECG with real BW, (c) recovered signal using NLMS algorithm, (d) recovered signal using RLMS algorithm

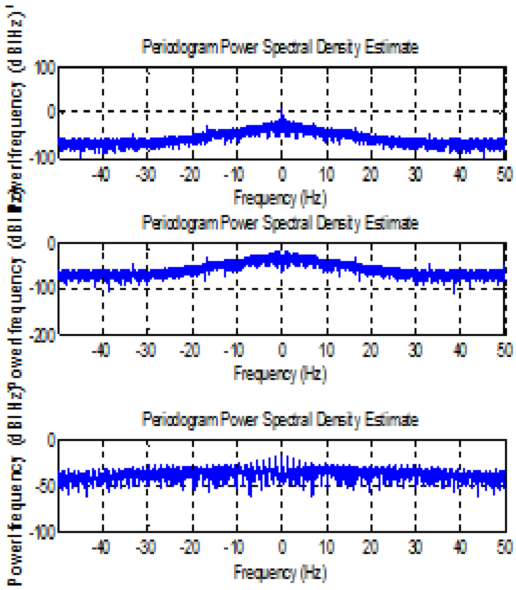

Fig 5. (a) Frequency spectrum of ECG with PLI, (b) Frequency spectrum after filtering with NLMS algorithm, (c) Frequency spectrum after filtering with RLMS algorithm.

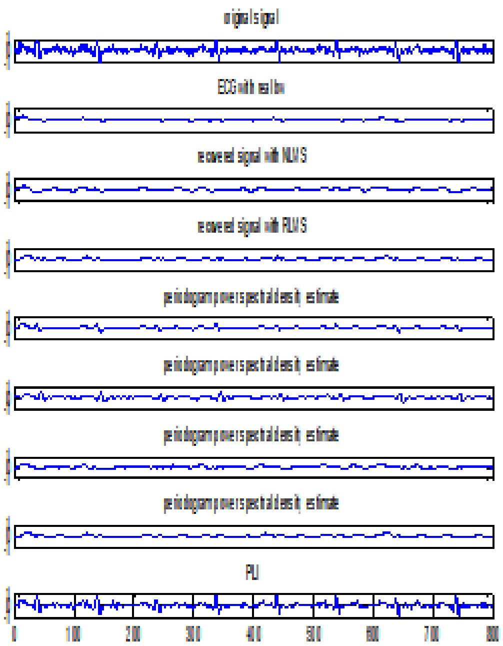

Fig6.The base line wander, power line interference cancellation by using NLMS and RLMS algorithms.

V. CONCLUSION

In this paper the process of noise removal from ECG signal using NLMS based adaptive filtering is presented. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. In this paper the problem of noise cancellation from ECG signals using novel adaptive filtering approach is proposed and tested on real ECG signals obtained from MIT-BIH data base. For this, the input is delayed and the reference signal is the input itself. The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed over the respective NLMS and RLMS based realizations. Our simulations, however, confirm that the performance of the RLMS is better than the NLMS algorithm in terms of SNR and MSE.

VI. FUTURE WORK

In the Future work, the window based FIR and MLMS algorithm based adaptive filters remove the high frequency power line interference and low frequency noises. In wavelet filter bank based denoising, only high frequency noise and power line interference are removed. The future developments to this work can be made as follows:

- Implementation of wavelet based denoising for the removal of base line wander.
- Use of other adaptive methods like FT-RLS, QRD-RLS algorithms for ECG denoising.
- Application of blind adaptive filtering for ECG enhancement.
- Real time application of implemented algorithms.

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