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Implementation of Constrained Stability Least Mean Square Algorithm for Suppression of Noise in Cardiac Signals

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***Abstract*— The baseline wander interference and power-line interference are the major disturbances in the cardiac signals. These interferences are suppressed using the adaptive filtering techniques. Different filter structures are presented to nullify the diverse form of noises. In this paper the constrained stability least mean square (CSLMS) algorithm is proposed which has the distinct feature of minimizing mean square error to effectively. Different adaptive filter methods are proposed and finally the CSLMS based adaptive filter algorithm is found to be the best in performance in terms of signal to noise ratio and mean square error without increasing the computational complexity.**

***Index Terms*—Cardiac signal, adaptive filters, ECG enhancement, constrained stability, step size parameter.**

I. Introduction

The cardiac signal is the electrical representation of the heart's activity over a period of time as detected by electrodes attached to the outer surface of the skin and recorded by a device external to the body. The external device is known as the electrocardiography. And the record obtained is called as electrocardiogram (ECG signal). The most common noises in ECG signal are:

1. Baseline wander interference
2. Power line interference
3. Muscle contraction noise
4. Electrosurgical noise
5. Motion artifacts

From various artifacts which contaminate electrocardiogram recording, the most common are power line and baseline drift. The power line interference occurs due to the stray currents which result because of the loops in the patient cables, loose contacts, dirty electrodes and also when the machine is not properly grounded. The power line interference is commonly known as 50Hz interference. The baseline wander is caused by varying electrode-skin impedance due to movement of patient. These two dominant artifacts masks the tiny features that are important for clinical monitoring and diagnosis of ECG signal. Although a fixed band rejection filter like notch filter can be implemented to reduce the noise power, it becomes non-optimal if either the amplitude or the frequency characteristics of the noise change.

Hence the need of filters that allow for the elimination of noise while maintaining an optimal signal to noise ratio for non-stationary processes are preferred. Conventional methods that include grounding are ineffective. Adaptive filtering is found to cancel these non-stationary interferences. Filtering is to process a signal in such a way that the signal-to-noise ratio is enhanced or noise of certain type is eliminated. It also means smoothing and prediction.

Many approaches have been proposed to address ECG enhancement using both adaptive and non-adaptive filtering techniques [1]-[4]. Adaptive filtering is the primary method used to filter the cardiac signal because it does not need the signal statistical characteristics. It also permits to detect some varying potentials and to track the dynamic variations of the signals. The LMS algorithm is the most common algorithm for adaptive signal processing. The popularity of this algorithm is due to its computational simplicity, quite simple to analyze and the algorithm appears to be very robust.

This paper presents filtering of cardiac signals in continuous stationary and non-stationary environment. The proposed CSLMS algorithm is based on the concept of different quantities and the constraint of equilibrium in the sequence of the estimation errors. Under certain conditions the adaptive noise cancellers based CSLMS algorithm shows the improved performance in terms of SNR and at the same time reducing the mean square error and the misadjustment compared to the conventional methods such as LMS and normalized LMS algorithms.

The simulation result shows that the performance of CSLMS algorithm is better than the LMS and NLMS algorithm.

II. Implementation Procedure

A. LMS algorithm

The LMS algorithm belongs to the class of stochastic gradient methods as this algorithm operates on stochastic inputs. Consider x(n) input vector of time delayed input values given as

$$x(n) = [x(n)\ x(n-1) \cdots x(n-L+1)]^t \qquad (1)$$

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And the tap weight vector at the *n*th index is

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

The steps in implementing the tap-weighting adaptation are

Step 1. Assume a value for $w(n)$ at time *n*

Step 2. Compute the filter output given by the equation

$$y(n)=w^t(n)x(n) \quad (3)$$

Step 3. Evaluate the estimation error given by the equation

$$e(n)=d(n)-w^t(n)x(n) \quad (4)$$

where d(n) is the desired response available initially

Step 4. Compute the next filter weight using the update Equation

$$w(n+1)=w(n)+\mu x(n)e(n) \quad (5)$$

Where μ is denotes the step-size parameter.

Fig. 1 shows the block diagram of the LMS algorithm, note that the error is feedback to effect weight adaptation, that will ultimately result in a better estimation of *x(n)*.

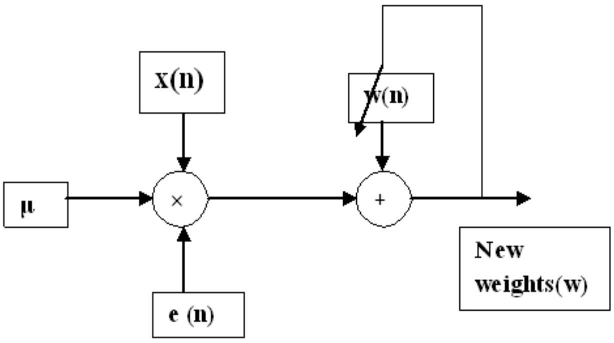

Fig. 1. LMS filter structure

Here for the ECG signal enhancement, the ECG signal s(n) is corrupted with the noise signal p(n) and is applied to the filter whose output is y(n). Since the signal and noise are uncorrelated, the mean square error (MSE) is,

$$E[e^2(n)]=E\{[s(n)-y(n)]^2\}+E[p^2(n)] \quad (6)$$

Minimizing the MSE results in the filter output which is the best least squares estimation of the signal s(n).

The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by selecting a different step size value μ for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector **x** (n).

This sum of the expected energies of the input samples is also equivalent to the dot product of the input vector with itself, and the trace of input vectors. The block diagram for NLMS is shown in fig. 2.

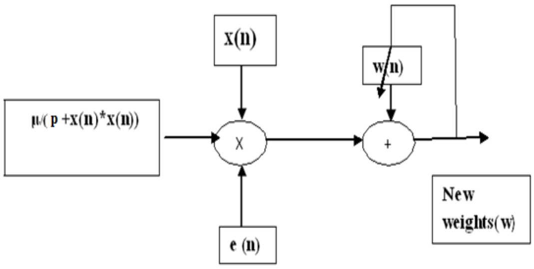

Fig.2. NLMS algorithm structure

The recursion formula for the NLMS algorithm is stated as

$$w(n+1)=w(n)+[\frac{\mu}{p+x^t(n)x(n)}]x(n)e(n) \quad (7)$$

The variable step is written as

$$\mu(n)=\frac{\mu}{p+x^t(n)x(n)} \quad (8)$$

The parameter μ is a constant step size value used to alter the convergence rate of the NLMS algorithm it is within the range of $0<\mu<1$, usually being equal to 1. The variable *p* is set to avoid the denominator of high value

The major drawback of the LMS and NLMS algorithms is the large value of mean square error which results in the distortion in the enhanced ECG signal. In the CSLMS algorithm the step size parameter is inversely proportional to the squared norm of the difference between the two consecutive inputs rather than the input vector as in NLMS algorithm.

The weight update relation of the CSLMS is as follows

$$w(n+1)=w(n)+[\frac{\delta x(n)\delta e(n)}{\|\delta x(n)\|^2}] \quad (9)$$

III. Simulation Results

The ECG waveform is the P, QRS and T waves which reflect the rhythmic electrical depolarization and repolarization of the myocardium association of the contractions of the atria and ventricles. For the diagnosis purpose the various time intervals, polarities and amplitude is studied. The amplitude and duration of the ECG parameter are as follows:

Amplitude	P wave	0.25mV
	Q wave	1.6mV
	R wave	25% of the P wave

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	T wave	0.1 to 0.5mV
Duration	P-R interval	0.12 to 0.2sec
	Q-T interval	0.35 to 0.44sec
	S-T interval	0.05 to 0.15sec
	P wave interval	0.11sec
	QRS interval	0.09sec

For the simulation purpose the 4000samples of the ECG waveform is considered based on the P, QRS, T amplitude values. And the ECG is corrupted with baseline wander interference taken from database of MIT-BIH noise stress(NSTDB). Now the noisy ECG is fed as an input to the adaptive filter and basewander interference noisy signal as the reference signal. Later different filtering techniques were implemented using LMS, NLMS and CLMS.

Similarly for the removal of powerline interference the 4000 samples of the ECG amplitude values are considered as the input and is corrupted with synthetic PLI with amplitude of 1mV and the frequency of 50Hz, sampled at 200Hz. The reference signal is synthesized PLI and the output of the filter is recovered signal.

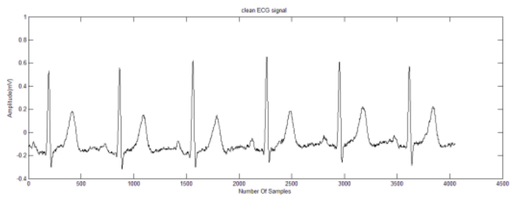

Fig. 1. Pure ECG signal

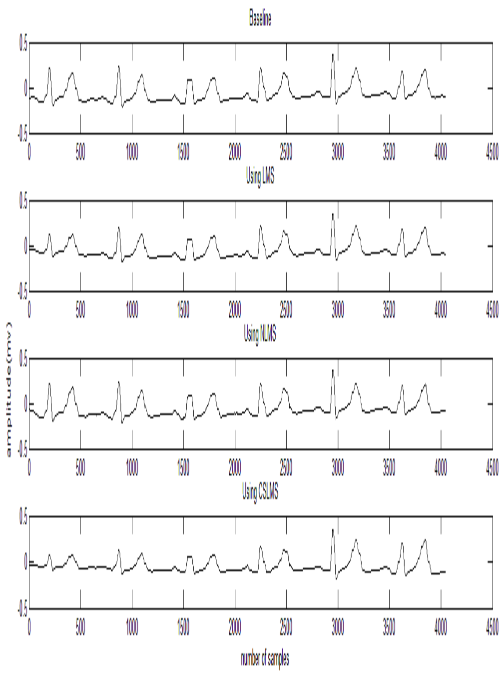

Fig.2. ECG basewander noisy signal and filtered signal using LMS, NLMS and CLMS algorithms

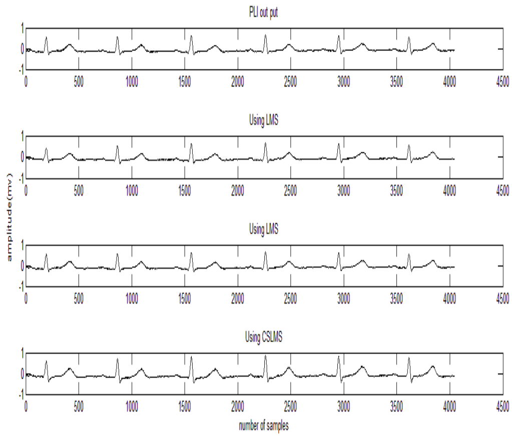

Fig.3. ECG powerline noisy signal and filtered signal using LMS, NLMS and CLMS algorithms

Table I shows the SNR value comparison using LMS, NLMS and CSLMS algorithms for the baseline wander interference for. It is clear that SNR is highly improved using CSLMS algorithm. And also Table II shows the SNR values for the three adaptive methods for powerline interference.

TABLE I
Comparison of SNR of the three examined algorithms after filtering baseline wander interference

μ	LMS	NLMS	CSLMS
0.01	1.3982	0.5473	1.5518
0.1	1.0546	0.2255	2.3218
0.5	0.2473	0.2042	7.3431

TABLE II
Comparison of SNR of the three examined algorithms after filtering powerline interference

μ	LMS	NLMS	CSLMS
0.01	7.6167	0.5674	7.8690
0.1	0.4951	0.1552	2.1256
0.5	0.2120	0.1274	4.5582

IV. CONCLUSION

The method of elimination of the power line interference present in the noisy ECG sample signal is presented. The ECG signal has been filtered using various digital adaptive filters and their performance is evaluated by finding the SNR ratio of the filtered signal.

Adaptive filtering with LMS, NLMS and CSLMS algorithms are simulated for noise cancellation in ECG signals and are compared with each other. Finally of all these algorithms, CSLMS algorithm reduces the noise and results in better SNR. This shows CSLMS algorithm, is effective in clinical situations.

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