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Reduction of Stationary and Non-Stationary Noise and Correction of Baseline Wander of ECG Signals Using a Constrained Stability Least Mean Square Algorithm

KEYWORDS adaptive noise cancellation, artifacts, ECG signals. LMS algorithm, noise cancelation

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ABSTRACT *Adaptive filter is a primary method to filter ECG signal, because it does not need the signal statistical characteristics. In this paper we present a novel adaptive filter for removing the artifacts from ECG signal based on Constrained Stability Least Mean Square (CSLMS) algorithm. This algorithm is derived based on the minimization of the square Euclidean norm of the difference weight vector under a stability constrained defined over the posteriori estimation error. The adaptive filter 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 the ECG in the primary input. Different filter structures are presented to eliminate the diverse forms of noise. Finally, we have applied this algorithm on ECG Signals from the MIT-BIH data base and compared its performance with the conventional LMS algorithm. The results show that the performance of the CSLMS based algorithm is superior to that of the LMS based algorithm in noise reduction*

INTRODUCTION

Baseline Wander and power line interference reduction is the first step in all electrocardiographic (ECG) Signal processing. The baseline wander is caused by varying electrode- skin impedance, patients movements and breath. The 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 (AC) 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 n 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 of address ECG enhancement using both adaptive and non-adaptive [1]-[6], adaptive filtering techniques permit to the detect time varying potentials and to track the dynamic variations of the signals. In [2], Thakor et al. proposed and LMS based adaptive recurrent filter to acquire the impulse response of normal QRS complexes and then applied it for arrhythmia detection in ambulatory ECG recordings part from these several adaptive signal processing techniques are also published, e.g. NLMS algorithm with decreasing step size, which converge to the global minimum [3], a variable step size NLMS algorithm with faster convergence rate [4],Costa et al. in [4] proposed a noise resilient variable step size, LMS which is specially indicated for biomedical application, also several modification are presented in literature to improve the performance of the LMS algorithm [5]- [8], recently in [9] Rahman et al. presented several less computational complex adaptive algorithms in time domain but these algorithms exhibits slower convergence rate. this paper presents novel adaptation for filtering cardiac signals in continuous stationary and non-stationary environments in biotelemetry systems, which are characterized by sudden changes of the signal statistics due to physiological, non-physiological reasons and noises due to free space propagation. The considered CLLMS algorithm is based o the concept of difference quantities and the constraint of equilibrium in the sequence of a posteriori estimation errors [10]. The method which applies nonlinearities to the error and input signal sequences, which can be derived using the Lagrange multiplier method as a generalization of the normalized LMS (NLMS) under certain conditions the adaptive noise cancellers (ANC) based on the CSLMS algorithm shows improved performance by decreasing the excess mean squared error and maladjustment compared to conventional algorithms like, LMS and NLMS algorithms. Thus far to the best of the authors knowledge, CSLMS algorithm is not used in the contest of ECG signal noise cancellation, in this paper various adaptive filter structures are presented to eliminate different kinds of noises form cardiac signals, finally to study the performance of the filter structures which effectively remove the artifacts from the ECH signals we carried out simulation o MIT0 BUN database, the simulation results shows that the performance of CLSMS based algorithms is better than LMS counterpart.

IMPLEMENTATION ANALYSIS

Consider a length L, LMS based adaptive filter, depicted in Fig 1 that takes and input sequence x (n) and updates the weights as

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

Where, $w(n) = [w_0(n), w_1(n)\ldots\ldots W_{L-1}(n)]^t$ is the tap weight vector at the nth index, $x(n) = [x(n)\ x(n-1)\ldots.x(n-L+1)]^t$ error signal $e(n) = d(n) - w^t(n)\, x(n)$, with d (n) being so called the desired response available during initial training period and μ denoting so-called step size parameter.

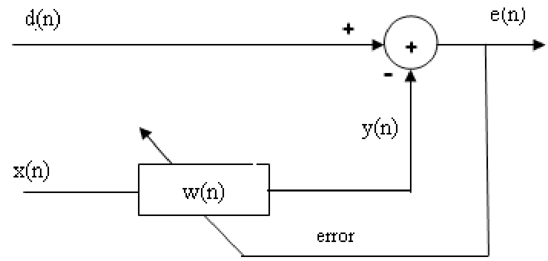

Fig.1 Adaptive Filter Structure

In order to remove the noise from the ECG signal, the ECG signal SI (n) corrupted with noise signal PI (n) is applied as the desired response d(n) to the adaptive filter shown in fig 1. If the noise signal P2 (n), possibly recorded from another generator of noise that is correlated in some way with PI (n) is applied at the input of the filter, i.e., x (n) = p_2 (n) the filter error becomes e (n)=[S_1(n) + P1 (n)]-y (n). Where y (n) is the filter output and it is given by,

y (n) = w(t n) x (n), (2)

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^2_1(n)] (3)

Minimizing the MSE results in a filter output which is the best least-squares estimate of the signal s_1(n).

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm takes into account variation in the signal level at the filter output and selecting the normalized step size parameter that results in a stable as well as fast converging algorithm. The weight update relation for NLMS algorithm is as follows

w (n+1) = {w (n) + [μ / (p + x^t(n) x(n)]} [x(n)e(n)] (4)

The variable step can be written as, μ (n) = {μ / [p + x^t(n) x (n)]} (5)

Here μ is fixed convergence factor to control maladjustment. A common major drawback of adaptive noise canceller based on LMS and NLMS algorithms is the large value of excess mean-square error which results in signal distortion in the noise-canceled signal. In the CSLMS algorithms the time-varying step size that is inversely proportional to the square norm of the difference between two consecutive input vectors rather than the input data vector as in the NLMS. This algorithm provides significant improvements in decreasing mean squared error (EMSE) and consequently minimizing signal distortion [22].

The weight update relation for CSLMS algorithm is as follows

w (n+1) = w (n) [δ x(n)δ e(n)/||δ x(n)||^2] (6)

Where δ x (n) = x (n) – x (n-1) is the difference between two consecutive input vectors. Also δ e (n) = e (n) – e(n-1) is the difference in the priori error sequence. The weight adaptation rule can be made more robust by introducing small P and by multiplying the weight increment by a constant step size μ to control the speed of the adaptation. The gives the weight update relation for CSLMS δ in its final form as follows, w (n+1) = w (n) + μ {δ x(n) δ e(n) / p + [||δ x(n)||]^2} (7)

The parameter P is set to avoid denominator being too small. Step size parameter too big and to prevent numerical instabilities in case of a vanishingly small squared norm. The convergence characteristics of both the algorithms are shown in fig. 2

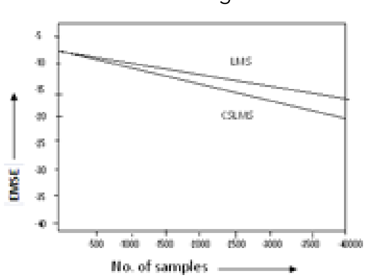

Fig.2 Typical convergence curves of LMS and CSLMS for PLI cancellation

SIMULATION ANALYSIS

To show that CSLMS 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.

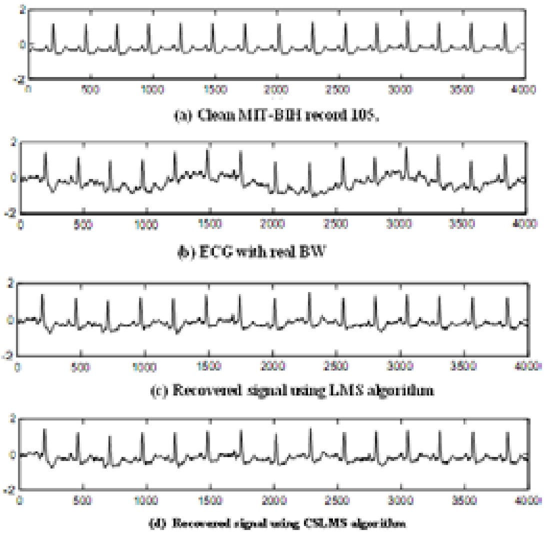

Fig.3 Typical filtering of Baseline wander Reduction

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 form 47 subjects, including 25men aged 32-9 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 my range. In our experiments we used a data ser 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 4000 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 minimum MSE (MMSE), MSE, excess MSE (EMSE) and maladjustment (M). For evaluating the performance of the proposed adaptive filter we have also measured the SNR improvement and compared with LMS algorithm. For all the figures number of samples is taken on x- axis and amplitude on y-axis, unless stated. Table I show the comparison of MMSE, MSE. EMSE and M for LMS, NLMS and CSLMS algorithms in terms of SNR improvement (SNRI).

A. BASELINE WANDER REDUCTION

In this experiment, first we collected 4000 samples of the pure ECG signal from the MIT-BIH arrhythmia database (data 105) and it is corrupted with real baseline wander 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 of Fig I. the real baseline wander is given as reference signal. Different filter structures were implemented using the LMS and CSLMS algorithms to study the relative performance and results are plotted in Fig.3. On average LMS algorithm gets SNR improvement 3.1428dB, where as CSLMS gets 4.7613dB./

B. ADAPTIVE POWERLINE INTERFERENCE CANCELATION

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 1 mv and frequency 60Hz, sampled at 200Hz. The reference signal is synthesized PLI,

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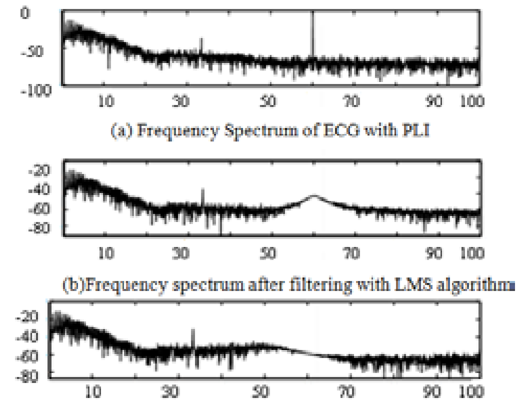
the output of the filter is recovered signal. These results are shown in Fig.4. In SNR measurements it is found that CSLMS algorithm improves 6.3702dB Fig.5 shows the power spectrum of the noisy signal before and after filtering with LMS and CSLMS algorithms.

CONCLUSION
In this paper the process of noise removal from ECG signal using CSLMS based adaptive filtering is presented.

μ	σ	Alg	Min. MSE	MSE	EXCE. MSE	MIS.AD
0.1	0.001	LMS	0.324	0.1586	-0.165	-0.510
		NLMS	0.324	0.1525	-0.171	-0.529
		CSLMS	0.324	0.1450	-0.179	-0.552
	0.01	LMS	0.322	0.1565	-0.165	-0.514
		NLMS	0.322	0.1502	-0.172	-0.533
		CSLMS	0.322	0.1429	-0.179	-0.556
	0.1	LMS	0.304	0.1371	-0.167	-0.550
		NLMS	0.304	0.1317	-0.173	-0.567
		CSLMS	0.304	0.1251	-0.179	-0.589
0.5	0.001	LMS	0.324	0.2404	-0.083	-0.258
		NLMS	0.324	0.1860	-0.138	-0.426
		CSLMS	0.324	0.1453	-0.178	-0.551
	0.01	LMS	0.322	0.2370	-0.085	-0.266
		NLMS	0.322	0.1833	V1389	-0.431
		CSLMS	0.322	0.1432	-0.178	-0.555
	0.1	LMS	0.302	0.2056	-0.097	-0.321
		NLMS	0.302	0.1592	-0.143	-0.474
		CSLMS	0.302	0.1260	-0.177	-0.585

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.



(c) Frequency spectrum after filtering with CSLMS algorithm

The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed over the respective LMS based realizations. Out simulation, however, confirm that the performance of the CSLMS is better than the LMS algorithm in terms of SNRI, MSE and maladjustment, this is shown in tables I and II. Hence CSLMS base adaptive noise canceller may be used in all practical applications.

Noise	Rec. No	SNRI after LMS	SNRI after ENLMS
Baseline wanders	101	2.2772	4.0204
	102	3.7013	4.9917
	103	3.3004	4.9690
	104	3.1798	4.9360
	105	3.2497	4.8894
	Average	3.1428	4.7613
Power line interference	101	6.1393	13.9129
	102	7.3513	14.0535
	103	5.7684	13.1728
	104	6.2568	13.3995
	105	5.9655	14.1440
	Average	6.3702	13.7365

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