Noise Cancellation in ECG Signals using Computationally Simplified Adaptive Filtering Techniques: Application to Biotelemetry

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Abstract

Several signed LMS based adaptive filters, which are computationally superior having multiplier free weight update loops are proposed for noise cancellation in the ECG signal. 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 and compared their performance with the conventional LMS algorithm. The results show that the performance of the signed regressor LMS algorithm is superior than conventional LMS algorithm, the performance of signed LMS and sign-sign LMS based realizations are comparable to that of the LMS based filtering techniques in terms of signal to noise ratio and computational complexity.

Keywords: Adaptive filtering, Artifact, ECG, LMS algorithm, Noise cancellation.

1. INTRODUCTION

The extraction of high-resolution ECG signals from recordings contaminated with back ground noise is an important issue to investigate. The goal for 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 [2]-[5]. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation.

Several papers have been presented in the area of biomedical signal processing where an adaptive solution based on the LMS algorithm is suggested [5]-[8]. The fundamental principles of adaptive filtering for noise cancelation were described by Widrow et al. [1]. Thakor and Zhu [5] proposed an adaptive recurrent filter to acquire the impulse response of normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG recordings. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. In these papers, the LMS algorithm operates on an "instantaneous" basis such that the estimate. In a recent study, however, a steady state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased, and thus, the adaptive estimate does not approach the Wiener solution. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [7], in which the coefficient vector is updated only once every occurrence based on a block gradient estimation. A major advantage of the block, or the transform domain LMS algorithm is that the input signals are approximately uncorrelated.

Complexity reduction of the noise cancellation system, particularly in applications such as wireless biotelemetry system has remained a topic of intense research. This is because of the fact that with increase in the ECG data transmission rate, the channel impulse response length increases and thus the order of the filter increases. Thus far, to the best of our knowledge, no effort has been made to reduce the computational complexity of the adaptive algorithm without affecting the signal quality. In order to achieve this, we considered the sign based adaptive algorithms. These algorithms enjoy less computational complexity because of the sign present in the algorithm. In the literature, there exist three versions of the signed LMS algorithm, namely, the signed regressor algorithm, the sign algorithm and the sign-sign algorithm. All these three require only half as many multiplications as in the LMS algorithm, thus making them attractive from practical implementation point of view [9]-[11]. In this paper, we considered the problem of noise cancellation and arrhythmia detection in ECG by effectively modifying and extending the framework of [5]. For that, we carried out simulations on MIT-BIH database. The simulation results shows that the performances of the sign based algorithms are comparable with LMS counterpart to eliminate the noise from ECG signals.

2. PROPOSED IMPLEMENTATION

When the doctors are examining the patient on-line and want to review the ECG of the patient in real-time, there is a good chance that the ECG signal has been contaminated by noise. The predominant artifacts present in the ECG includes: Power-line Interference (PLI), Baseline wander (BW), Muscle artifacts (MA) and Motion artifacts (EM), mainly caused by patient breathing, movement, power line interference, bad electrodes and improper electrode site preparation. The low frequency ST segments of ECG signals are strongly affected by these contaminations, which lead to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the noise in order to better obtain and interpret the ECG data.

2.1 Basic Adaptive Filtering Structure

Figure 1 shows an adaptive filter with a primary input that is an ECG signal s_1 with additive noise n_1. While the reference input is noise n_2, possibly recorded from another generator of noise n_2 that is correlated in some way with n_1. If the filter output is y and the filter error $e= (s_1+n_1)-y$, then

$$e^2 = (s_1 + n_1)^2 - 2y\,(s_1 + n_1) + y^2$$
$$= (n_1 - y)^2 + s_1^2 + 2\,s_1\,n_1 - 2y\,s_1. \qquad (1)$$

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$$E[e^2]=E[(n_1 - y)^2]+E[s_1^2] \qquad (2)$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_1. The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs.

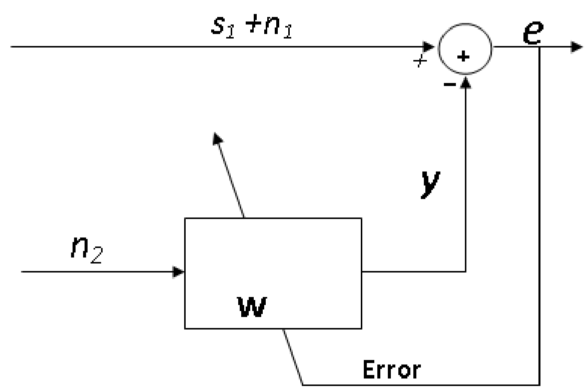

FIGURE 1: Adaptive Filter Structure.

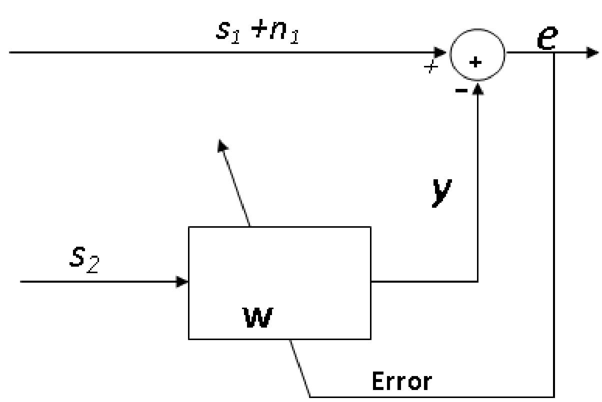

FIGURE 2: Alternate Adaptive Filter Structure.

Figure 2 illustrates another situation where the ECG is recorded from several electrode leads. The primary input $s_1 + n_1$ is a signal from one the leads. A reference signal s_2 is obtained from a second lead that is noise free. The signal s_1 can be extracted by minimizing the MSE between the primary and the reference inputs. Generally in biomedical signal processing the filter structure shown in figure 1 is used, since it is difficult to obtain a noise free signal. Using the same procedure similar to (1) we can show that

$$E[e^2]=E[(s_1 - y)^2]+E[n_1^2] \qquad (3)$$

Minimizing the MSE results in a filter error output y that is the best least-squares estimate of the signal s_1.

2.2 Simplified Adaptive Algorithms

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e(n) is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate.
The error estimation e(n) is

$$e(n) = \mathbf{d}(n) - \mathbf{w}(n)\, \mathbf{\Phi}(n) \qquad (4)$$

Coefficient updating equation is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathbf{\Phi}(n)\, e(n), \qquad (5)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < (2 / \text{tr } R)$ for the convergence of the algorithm.

The most important members of simplified LMS algorithms are:

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

$$y(n) = \mathbf{w}^t(n)x(n), \qquad (6)$$

where, $\mathbf{w}(n) = [\, w_0(n),\ w_1(n),\ \ldots\ ,\ w_{L-1}(n)\,]^t$ is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, sgn\{\mathbf{\Phi}(n)\}e(n), \qquad (7)$$

Because of the replacement of $\mathbf{\Phi}(n)$ by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

The Sign Algorithm (SLMS): This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathbf{\Phi}(n)\, sgn\{e(n)\}, \qquad (8)$$

The Sign – Sign Algorithm (SSLMS): This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, sgn\{\mathbf{\Phi}(n)\}\, sgn\{e(n)\}, \qquad (9)$$

where $sgn\{\,.\,\}$ is well known signum function,

$e(n) = d(n) - y(n)$ is the error signal.

The sequence $d(n)$ is the so-called desired response available during initial training period. The performance of these algorithms compared from the convergence characteristics shown in figure 3. From the convergence curves it is clear that the performance of the signed-regressor algorithm is only slightly worse than the conventional LMS algorithm. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behavior is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

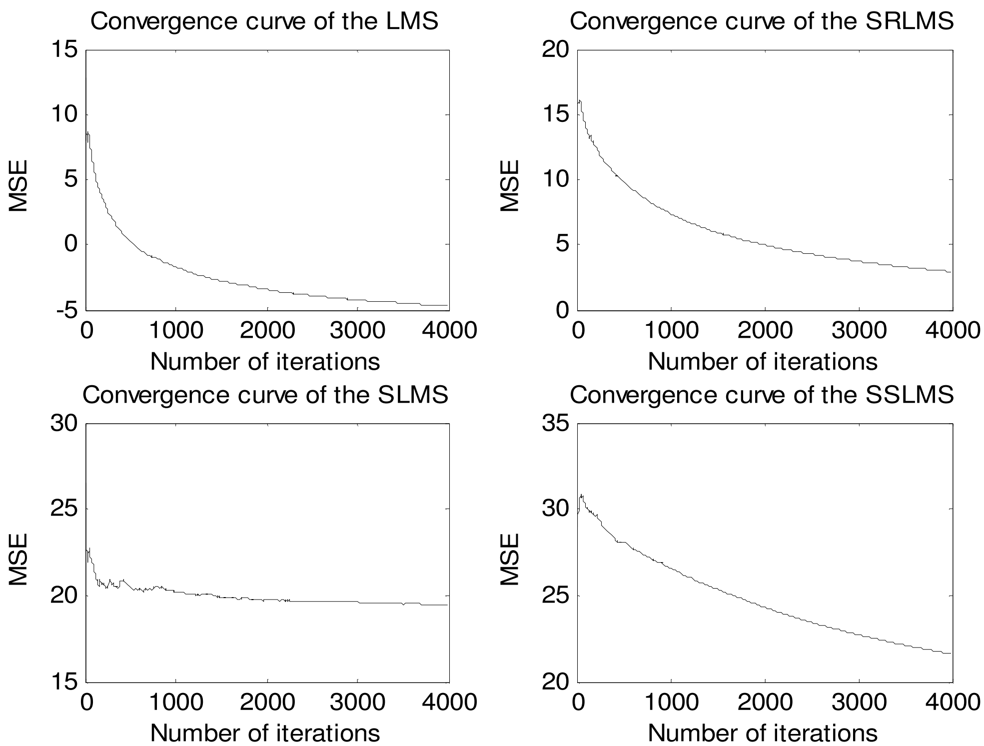

FIGURE 3: Convergence Characteristics of various algorithms

2.3 Noise Generator

The reference signal n_2 shown in figure 1 is taken from noise generator. A synthetic PLI with 1mv amplitude is simulated for PLI cancellation. No harmonics are synthesized. In order to test the filtering capability in non-stationary environment we have considered real BW, MA and EM noises. These are taken from MIT-BIH Normal Sinus Rhythm Database (NSTDB). This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrhythmias. A random noise with variance of 0.001 is added to the ECG signals to evaluate the performance of the algorithm. The input SNR for the above non-stationary noise is taken as 1.25dB. In these three simplified algorithms because of the sign present in the recursion some tiny noise remains along the ST segment of the ECG signal. In order to extract the residual noise a tiny PLI is added to the noise reference signal. This improvers the performance of the filter.

2.4 Computational Complexity Issues

The computational complexity figures required to compute all the three versions of sign LMS, as proposed above are summarized in Table 1, offers significant reduction in the number of operations required for LMS algorithm. Further, as these sign based algorithms are largely free from multiplication operation, these algorithms provides elegant means for removing the noise from the ECG signals. For LMS algorithm L+1 multiplications and L+1 additions are required to compute the weight update equation (5). In case of signed regressor algorithm only one multiplication is required to compute $\mu e(n)$. Where as other two signed LMS algorithms does not require multiplication if we choose μ value a power of 2. In these cases multiplication becomes shift operation which is less complex in practical realizations.

Algorithm	Multiplications	Additions	Shifts
LMS	L+1	L+1	Nil
SRLMS	1	L+1	Nil
SLMS	Nil	L+1	L
SSLMS	Nil	L+1	Nil

TABLE 1: A Computational Complexity Comparison Table.

3. SIMULATION RESULTS

To show that signed LMS algorithms are appropriate for ECG denoising we have used real ECG signals. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work. The 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 11-bit resolution over a 10 mV range. In our simulation, first we collected 4000 samples of ECG signal. In this simulation μ for all the filters is chosen as 0.001 and the filter length as 5. For all the figures in this section *number of samples* is taken on x-axis and *amplitude* on y-axis, unless stated. Figure 4 shows the clean ECG signal (data105) and its frequency spectrum. In our experiments we have considered a dataset of five ECG records: data100, data105, data108, data203 and data228 to ensure the consistency of the results

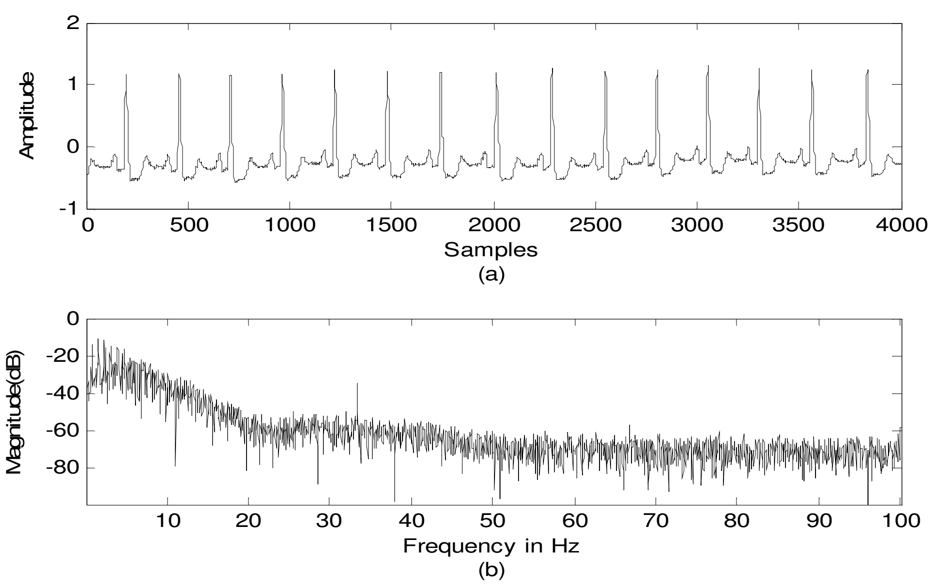

FIGURE 4: Clean ECG signal (data105) and its Spectrum.

3.1 Adaptive Power-line Interference (PLI) Cancellation

In this experiment, first we collected 4000 samples of ECG signal and corrupted with synthetic PLI with frequency 60Hz, sampled at 200Hz. This signal is applied as primary input to the adaptive filter shown in figure 1. The experiment is performed over the dataset average SNR improvement is considered to compare the performance of the algorithms. The reference signal is a synthesized PLI, the output of the filter is recovered signal. These results for data105 are shown in figure 5. Table 2 shows the SNR improvement for the dataset. In SNR measurements it is found that signed-regressor LMS algorithm gets average SNR improvement 29.5441dB, sign LMS gets 22.5405dB, sign-sign LMS improves 20.5345dB and conventional LMS algorithm improves 31.0146dB. Figure 4 shows the power spectrum of the noisy signal before and after filtering with sign regressor LMS algorithm. The spectrum clears that the sign regressor LMS algorithm filters the PLI efficiently comparable to LMS filter with reduced number of computations.

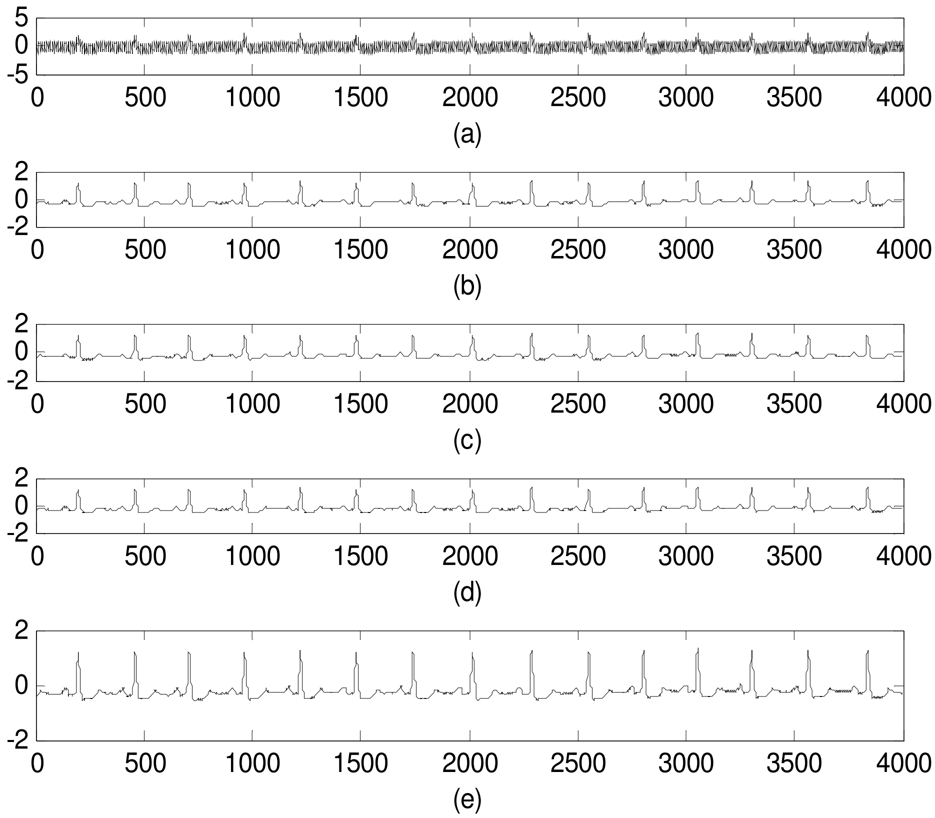

FIGURE 5: Typical filtering results of PLI Cancelation (a) MIT-BIH record 105 with 60Hz noise, (b) recovered signal using LMS algorithm, (c) recovered signal using signed regressor LMS algorithm, (d) recovered signal using sign LMS algorithm (e) recovered signal using sign sign LMS algorithm.

Rec. No	SNR Before Filtering	LMS		SRLMS		SLMS		SSLMS	
		SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp
100	-2.9191	28.7206	31.6397	26.6853	29.6044	17.8050	20.7241	14.1486	18.6195
105	-2.6949	28.5262	31.2211	26.9251	29.6200	20.3215	23.0164	18.0484	20.7433
108	-3.0647	28.4051	31.4698	26.4778	29.5425	22.4489	25.5136	19.3579	22.4226
203	-1.4531	27.3762	28.8293	26.8677	28.3208	18.5911	20.0442	17.1029	18.5560
228	-3.5242	28.3893	31.9135	27.1089	30.6331	19.8804	23.4046	18.8069	22.3311
Avg. (dBs)	-2.7312	28.2834	31.0146	26.8129	29.5441	19.8093	22.5405	17.4929	20.5345

TABLE 2: SNR Improvement of various algorithms for PLI Cancellation

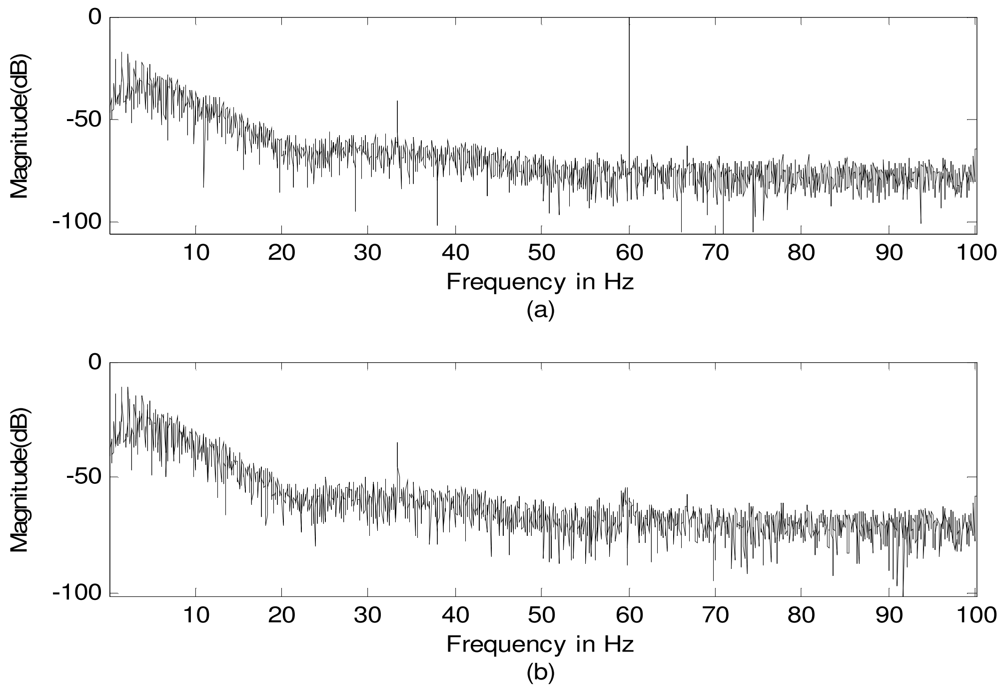

FIGURE 6: (a) Frequency spectrum of ECG with PLI, (b) Frequency spectrum after filtering with Sign regressor LMS algorithm.

3.2 Baseline Wander (BW) Reduction

In this experiment, first we collected 4000 samples of ECG signal (data105) and corrupted with real baseline wander (BW of MIT-BIH NSTDB), it is used as primary input to the adaptive filter of figure 1. The algorithms are applied on entire dataset. Simulation results for data105 are shown in figure 7. For the evaluating the performance of the proposed adaptive filter structures we have measured the average SNR improvement and compared with LMS algorithm. The sign-regressor LMS algorithm gets SNR improvement 10.1255dB, sign LMS gets 6.0443dB, sign-sign LMS improves 4.9937dB and conventional LMS algorithm improves 9.7282dB. Table 3 shows the SNR improvement for the dataset.

Rec. No	SNR Before Filtering	LMS		SRLMS		SLMS		SSLMS	
		SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp
100	1.2500	11.1571	9.9071	11.6220	10.3720	6.7036	5.4536	6.4829	5.2329
105	1.2500	12.3824	11.1324	13.1645	11.9561	8.0460	6.7960	6.4677	5.4177
108	1.2500	11.6224	10.3724	12.1420	10.8920	7.1091	5.8591	5.8679	4.6179
203	1.2500	6.8122	5.5622	6.6976	5.7260	6.4628	5.2128	5.0930	3.8430
228	1.2500	12.9172	11.6672	12.9314	11.6814	8.1500	6.9000	7.1053	5.8553
Avg. (dBs)	1.2500	10.9782	9.7282	11.3115	10.1255	7.2943	6.0443	6.2033	4.9937

TABLE 3: SNR Improvement of various algorithms for Baseline wander removal

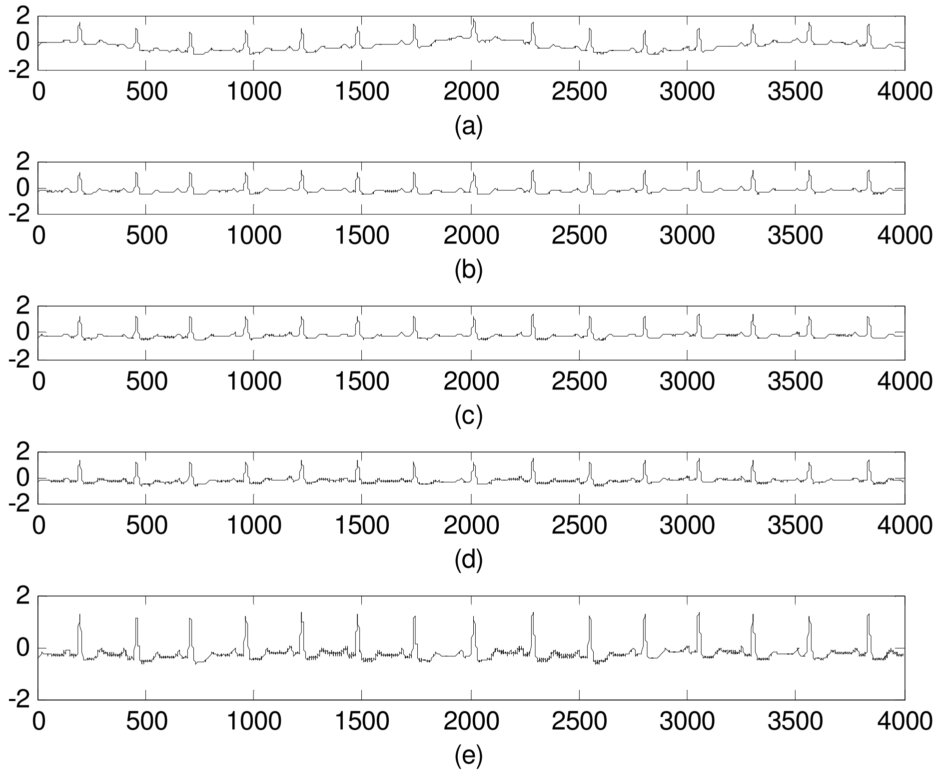

FIGURE 7: Typical filtering results of baseline wander reduction (a) MIT-BIH record 105 with real baseline wander, (b) recovered signal using LMS algorithm, (c) recovered signal using signed regressor LMS algorithm, (d) recovered signal using sign LMS algorithm, (e) recovered signal using sign sign LMS algorithm.

3.3 Muscle Artifacts (MA) Removal

The MA originally had a sampling frequency of 360Hz. The original ECG signal with MA is given as input to the adaptive filter. The results of data105 are shown in figure 8. The average SNR improvement of sign-regressor LMS algorithm is 12.2192dB, sign LMS gets 7.6995 dB, sign-sign LMS improves 6.9517dB and conventional LMS algorithm improves 11.4306dB. Table 4 shows the SNR improvement for the dataset.

Rec. No	SNR Before Filtering	LMS		SRLMS		SLMS		SSLMS	
		SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp
100	1.2500	11.4058	10.1558	12.3791	11.1291	7.8347	6.5847	7.0363	5.7863
105	1.2500	12.4265	11.1765	12.9827	11.7327	8.5680	7.3180	8.2148	6.9648
108	1.2500	12.3752	11.1252	13.4397	12.1897	8.0919	6.8414	7.4295	6.1795
203	1.2500	13.8786	12.6286	15.1749	13.9249	10.0800	8.8300	9.2585	8.0085
228	1.2500	13.3169	12.0669	13.3698	12.1198	10.1735	8.9235	9.0695	7.8195
Avg. (dBs)	1.2500	12.6806	11.4306	13.4692	12.2192	8.9496	7.6995	8.2017	6.9517

TABLE 4: SNR Improvement of various algorithms for adaptive cancellation of muscle artifacts

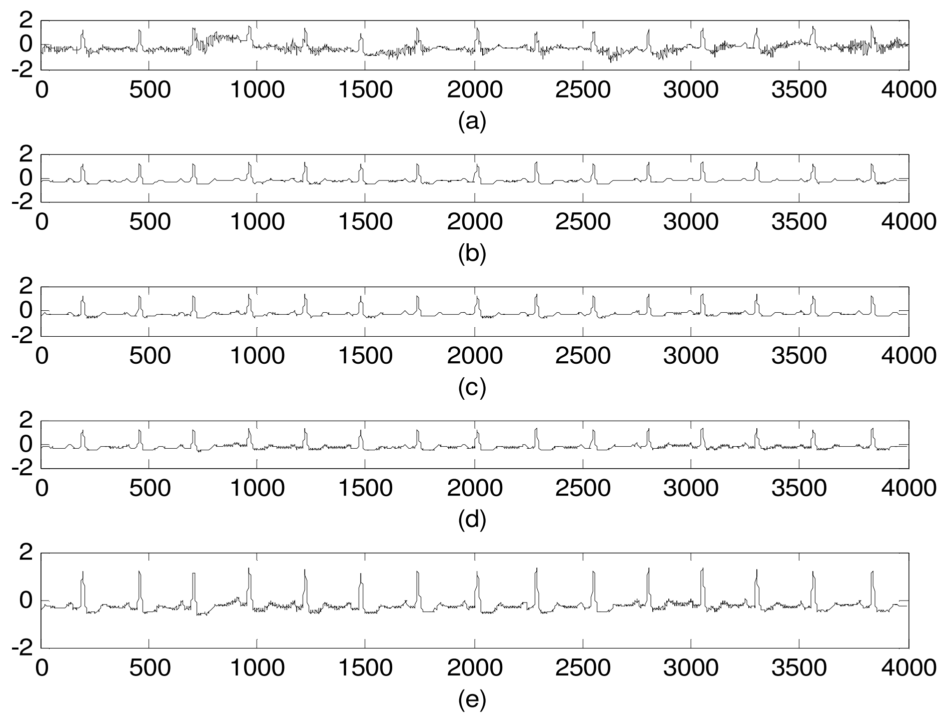

FIGURE 8: Typical filtering results of muscle artifacts removal (a) MIT-BIH record 105 with real muscle artifacts (b) recovered signal using LMS algorithm, (c) recovered signal using signed regressor LMS algorithm, (d) recovered signal using sign LMS algorithm, (e) recovered signal using sign sign LMS algorithm.

3.4 Motion Artifacts (EM) Removal

To demonstrate this we used MIT-BIH record number 105 ECG data with real electrode motion artifact (EM) added. The ECG signal corresponds to record 105 is corrupted with EM is given as input to the adaptive filter. The reference signal is taken from noise generator. The algorithms are tested for dataset. Figure 9 shows the results correspond to data105. The average SNR improvements for various algorithms are 11.8950dB, 7.2525dB, 5.7464dB and 10.3374dB for signed regressor, sign, sign-sign and LMS algorithms respectively. Table 5 shows the SNR improvement for the dataset.

Rec. No	SNR Before Filtering	LMS		SRLMS		SLMS		SSLMS	
		SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp	SNR After Filtering	SNR Imp
100	1.2500	11.5749	10.3249	13.3180	12.0680	7.6309	6.3809	6.4164	5.1664
105	1.2500	12.5709	11.3209	14.4069	13.1569	8.2145	6.9645	6.7265	5.4765
108	1.2500	12.4709	11.1809	14.9770	13.7270	9.0952	7.8455	7.0101	5.7601
203	1.2500	8.9543	7.7043	10.4778	9.2278	8.6879	7.4379	7.0210	5.7710
228	1.2500	12.4062	11.1562	12.5457	11.2957	8.8840	7.6340	7.8080	6.5580
Avg. (dBs)	1.2500	11.5954	10.3374	13.1450	11.8950	8.5025	7.2525	6.9964	5.7464

TABLE 5: SNR Improvement of various algorithms for motion artifacts Cancellation.

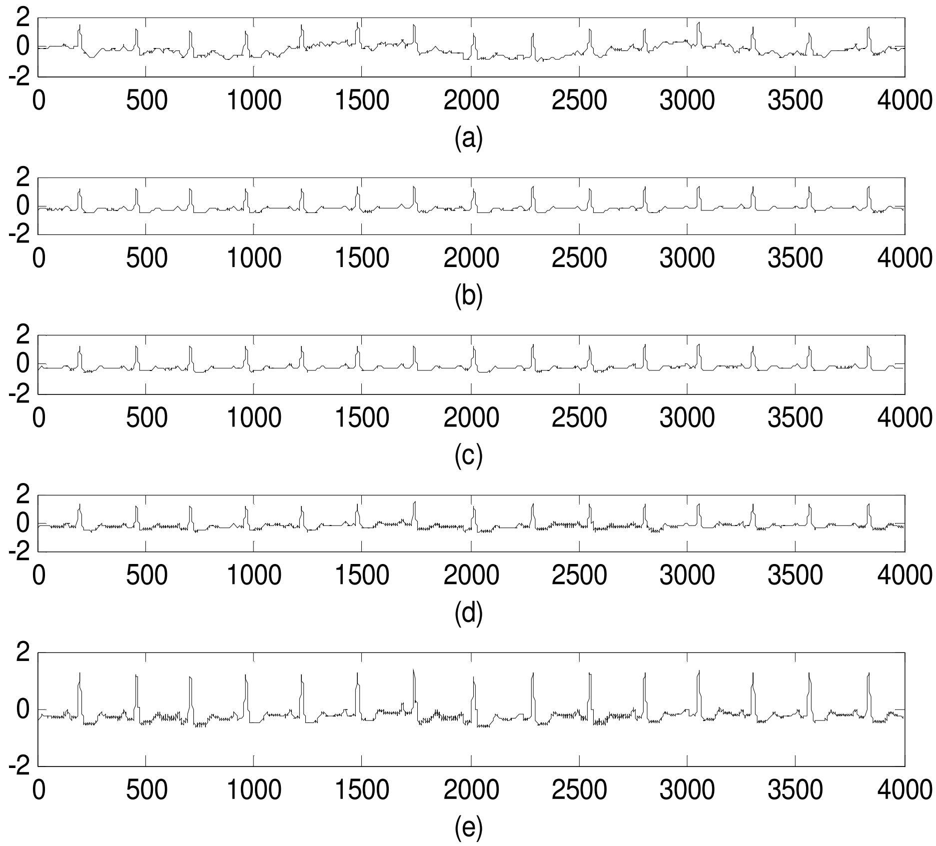

FIGURE 9: Typical filtering results of motion artifacts removal (a) MIT-BIH record 105 with real motion artifacts, (b) recovered signal using LMS algorithm, (c) recovered signal using signed regressor LMS algorithm, (d) recovered signal using sign LMS algorithm, (e) recovered signal using sign sign LMS algorithm.

4. CONCLUSION

In this paper the problem of noise removal from ECG using Signed LMS based adaptive filtering is presented. For this, the same formats for representing the data as well as the filter coefficients as used for the LMS algorithm were chosen. As a result, the steps related to the filtering remain unchanged. The proposed treatment, however exploits the modifications in the weight update formula for all categories to its advantage and thus pushes up the speed over the respective LMS-based realizations. Our simulations, however, confirm that the corresponding show-down effect with regard to the algorithm convergence is quit minor and is acceptable for all practical purposes. From the simulation results it is clear that the signed regressor LMS algorithm performs better than LMS in both SNR improvement and computational complexity, hence it is more suitable for wireless biotelemetry ECG systems.

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