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Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG signals: Application to wireless biotelemetry

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ABSTRACT

In this paper, several simple and efficient sign based normalized adaptive filters, which are computationally superior having multiplier free weight update loops are used for cancelation of noise in electrocardiographic (ECG) signals. The proposed implementation is suitable for applications such as biotelemetry, where large signal to noise ratios with less computational complexity are required. These schemes mostly employ simple addition, shift operations and achieve considerable speed up over the other least mean square (LMS) based realizations. Simulation studies shows that the proposed realization gives better performance compared to existing realizations in terms of signal to noise ratio and computational complexity.

1. Introduction

The electrocardiogram (ECG) is a graphical representation of hearts functionality and is an important tool used for diagnosis of cardiac abnormalities. In clinical environment during acquisition, the ECG signal encounters with various types of artifacts. The predominant artifacts present in the ECG includes: baseline wander (BW), power-line interference (PLI), muscle artifacts (MA) and motion artifacts (EM). These artifacts strongly affects the ST segment, degrades 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. 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 [1–13], 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 an 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. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. In such a case, the LMS algorithm operates on an instantaneous basis such that the weight vector is updated for every new sample within the occurrence based on an instantaneous gradient estimate. In a study, however, a steady state convergence analysis for the LMS algorithm with

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deterministic reference inputs showed that the steady-state weight vector is biased and thus the adaptive estimate does not approach the Wiener solution [14]. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [15], in which the coefficient vector is updated only once for every occurrence based on a block gradient estimation. The BLMS algorithm has been proposed in the case of random reference inputs and when the input is stationary, the steady state misadjustment and convergence speed is same as the LMS algorithm. A major advantage of the block, or the transform domain LMS algorithm is that the input signals are approximately uncorrelated. In [16], Kotas presented an application of principal component analysis and its robust form for ECG enhancement, Floris et al. elaborates fast lane approach using improved versions of LMS and normalized LMS(NLMS) algorithms for the prediction of respiratory motion signals [17], subtraction procedure without affecting the components of ECG signal [18], Sayadi et al. [19] proposed bionic wavelet transform for the correction of baseline drift and Sameni et al. [20] established a framework of Bayesian filtering for ECG denoising. Apart from these ECG enhancement techniques several adaptive signal processing techniques are also published, e.g., NLMS algorithm with decreasing step size, which converge to the global minimum [21], a variable step size NLMS algorithm with faster convergence rate [22], Costa et al. in [23] proposed a noise resilient variable step size LMS which is specially indicated for biomedical applications. Also several modifications are presented in literature to improve the performance of the LMS algorithm [24–28].

In recent years biotelemetry has become more important, recently in [29] Sufi et al. proposed ECG compression algorithms for wireless telecardiology. Complexity reduction of the noise cancelation system, particularly, in applications such as wireless biotelemetry system has been 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. The resulting increase in complexity makes the real time operation of the biotelemetry system difficult, specially in view of simultaneous shortening of the symbol period, which means that lesser and lesser time will be available to carry out the computations while the volume of the computations goes on increasing. Thus far, to the best of the author's knowledge, no effort has been made to reduce the computational complexity of the adaptive algorithm without effecting the signal quality. The computational complexity can be reduced by using the sign based algorithms, namely, the signed regressor algorithm, the sign algorithm and the sign–sign algorithm [32], all the three requires only half as many multiplications as in the LMS algorithm, thus making them attractive from practical implementation point of view. In order to cope up with both the complexity and convergence issues without any restrictive tradeoff we propose various adaptive filter structures based on normalized signed regressor LMS (NSRLMS) algorithm, normalized sign LMS (NSLMS) algorithm and normalized sign–sign LMS (NSSLMS) algorithm. These algorithms enjoy less computational complexity because of the sign present in the algorithm and good filtering capability because of the normalized term [30,31]. To study the performance of the filter structures which effectively remove the artifacts from the ECG signal we carried out simulations on MIT-BIH database for different noises. The simulation results shows that the performance of sign based algorithms is better than the LMS counterpart.

2. Computationally efficient adaptive filtering techniques

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

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)e(n), \tag{1}$$

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

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. 1. If the noise signal $p_2(n)$, 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 $e(n)=[s_1(n)+p_1(n)]-y(n)$. Where, $y(n)$ is the filter output and it is given by,

$$y(n) = \mathbf{w}^t(n)\mathbf{x}(n), \tag{2}$$

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

$$E[e^2(n)] = E\{[s_1(n)-y(n)]^2\} + E[p_1^2(n)] \tag{3}$$

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

New algorithms that make use of the *signum* (polarity) of either the error or the input signal, or both [32], have been derived from the LMS algorithm for the simplicity of implementation, enabling a significant reduction in

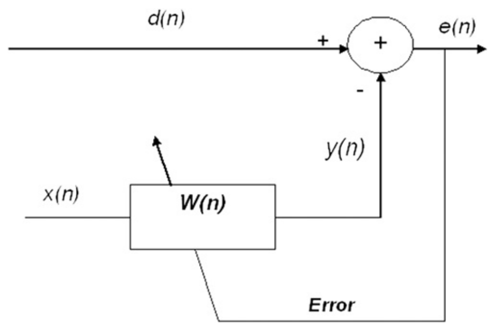

Fig. 1. Adaptive filter structure.

computing time, particularly the time required for "multiply and accumulate" (MAC) operations. These algorithms are attractive for their assured convergence and robustness against the disturbances in addition to the ease of implementation. The most important members of this class of algorithms are : signed regressor algorithm (SRA), sign algorithm (SA) and sign–sign algorithm (SSA). The weight update relations for these algorithms, respectively, are

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu\,\mathrm{sgn}\{\mathbf{x}(n)\}\{e(n)\}, \tag{4}$$

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu\{\mathbf{x}(n)\}\,\mathrm{sgn}\{e(n)\}, \tag{5}$$

and

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mu\,\mathrm{sgn}\{\mathbf{x}(n)\}\,\mathrm{sgn}\{e(n)\}. \tag{6}$$

where sgn{.} is the well known signum function.

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm accounts the 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:

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\left[\frac{\mu}{p+\mathbf{x}^t(n)\mathbf{x}(n)}\right]\mathbf{x}(n)e(n), \tag{7}$$

The variable step can be written as

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

Table 1
A computational complexity comparison table.

Algorithm	MACs	ASC	Divisions	Shifts
LMS	L+1	Nil	Nil	Nil
SRLMS	1	Nil	Nil	Nil
SLMS	L	Nil	Nil	Nil
SSLMS	Nil	L	Nil	Nil
NLMS	2L+1	Nil	1	Nil
NSRLMS	1	Nil	1	Nil
NSLMS	L	Nil	1	Nil
NSSSLMS	Nil	L	1	L
BB-NSRLMS	Nil	L	1	1
BB-NSLMS	L	Nil	1	Nil
BB-NSSLMS	Nil	L	1	Nil

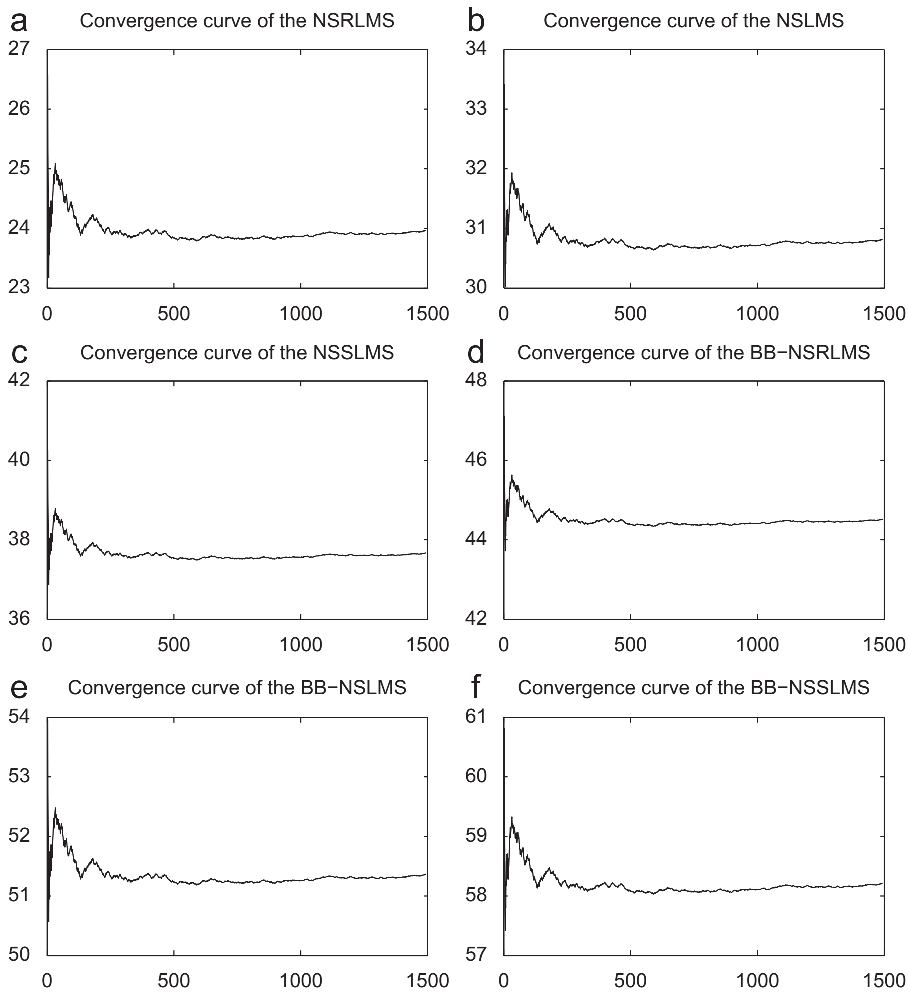

Fig. 2. Convergence characteristics of various algorithms.

Here μ is fixed convergence factor to control maladjustment. The parameter p is set to avoid denominator being too small and step size parameter too big.

Among the adaptive algorithms presented above, the SRA, SA and SSA has a convergence rate and a steady-state error that are slightly inferior to those of the LMS algorithm for the same parameter setting. But, the computational complexity of these algorithms is much less compared to the LMS algorithm. The advantage of the NLMS algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence the NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm. On the other hand some additional computations are required to compute $\mu(n)$. In order to cope up with both the complexity and convergence issues without any restrictive tradeoff, we propose normalized sign based algorithms such as normalized signed regressor LMS (NSRLMS) algorithm, normalized sign LMS (NSLMS) algorithm and normalized sign–sign LMS (NSSLMS) algorithm for the removal of noise from ECG signal. The weight update relations for these algorithms, respectively, are

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\,\mathrm{sgn}\{\mathbf{x}(n)\}\{e(n)\}, \tag{9}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\{\mathbf{x}(n)\}\mathrm{sgn}\{e(n)\}, \tag{10}$$

and

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\,\mathrm{sgn}\{\mathbf{x}(n)\}\mathrm{sgn}\{e(n)\}. \tag{11}$$

The additional computations required to compute $\mu(n)$ in Eqs. (9)–(11) can be further reduced by using a block based NLMS (BB-NLMS) algorithm in which the input data is partitioned into blocks and the maximum magnitude within each block is used to compute $\mu(n)$. With this, the weight update relations in (9)–(11) for $x_{L_i} \neq 0$ and $p=0$ takes the following form

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{x_{L_i}^2}\,\mathrm{sgn}\{\mathbf{x}(n)\}\{e(n)\}, \tag{12}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{x_{L_i}^2}\{\mathbf{x}(n)\}\mathrm{sgn}\{e(n)\}, \tag{13}$$

and

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{x_{L_i}^2}\,\mathrm{sgn}\{\mathbf{x}(n)\}\mathrm{sgn}\{e(n)\}, \tag{14}$$

where $x_{L_i} = \max\{|x_k|, k \in Z_i'\}$, $Z_i' = \{iL, iL+1, \ldots, iL+L-1\}$, $i \in Z$. And for $x_{L_i} = 0$ and $p=0$ the Eqs. (9)–(11) becomes $\mathbf{w}(n+1)=\mathbf{w}(n)$.

These algorithms are known as block based NSRLMS (BB-NSRLMS), block based NSLMS (BB-NSLMS)and block based NSSLMS (BB-NSSLMS), respectively.

The convergence characteristics of various algorithms discussed above are shown in Fig. 2. From these characteristics it is clear that the NSRLMS algorithm exhibits better convergence characteristics in terms of both convergence rate and excess mean square error.

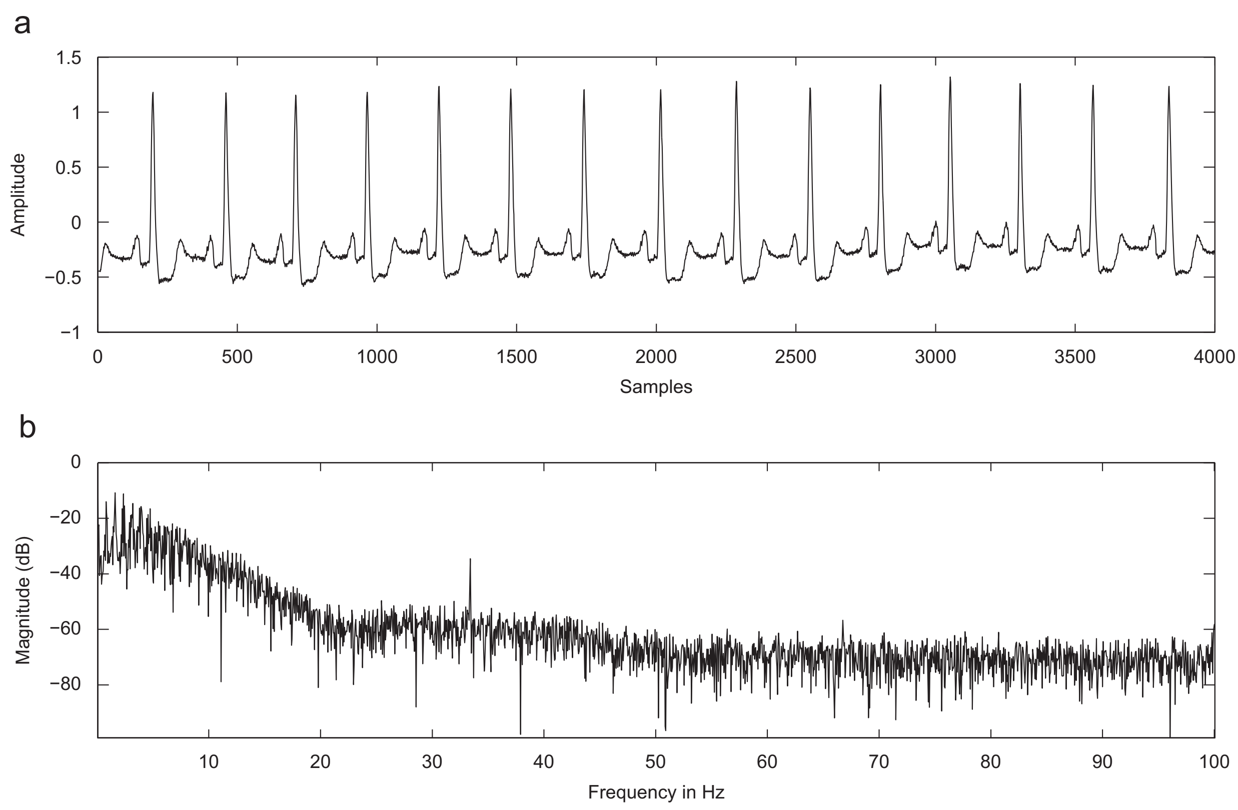

Fig. 3. MIT-BIH recorded ECG signal (data 105) and its frequency spectrum.

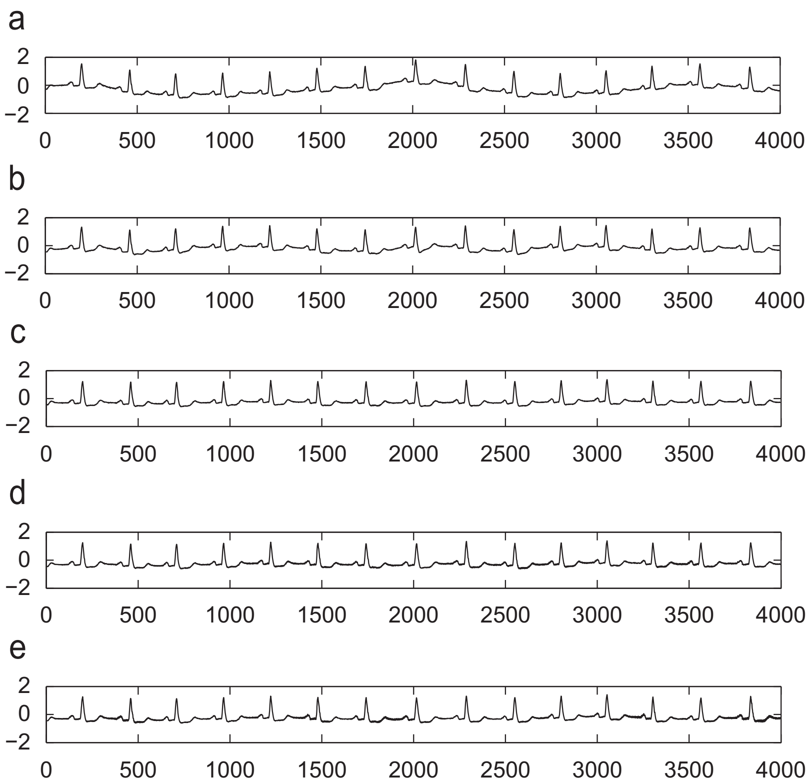

Fig. 4. Typical filtering results of baseline wander reduction: (a) ECG with real BW, (b) recovered signal using LMS algorithm, (c) recovered signal using NSRLMS algorithm, (d) recovered signal using NSLMS algorithm, (e) recovered signal using NSSLMS algorithm.

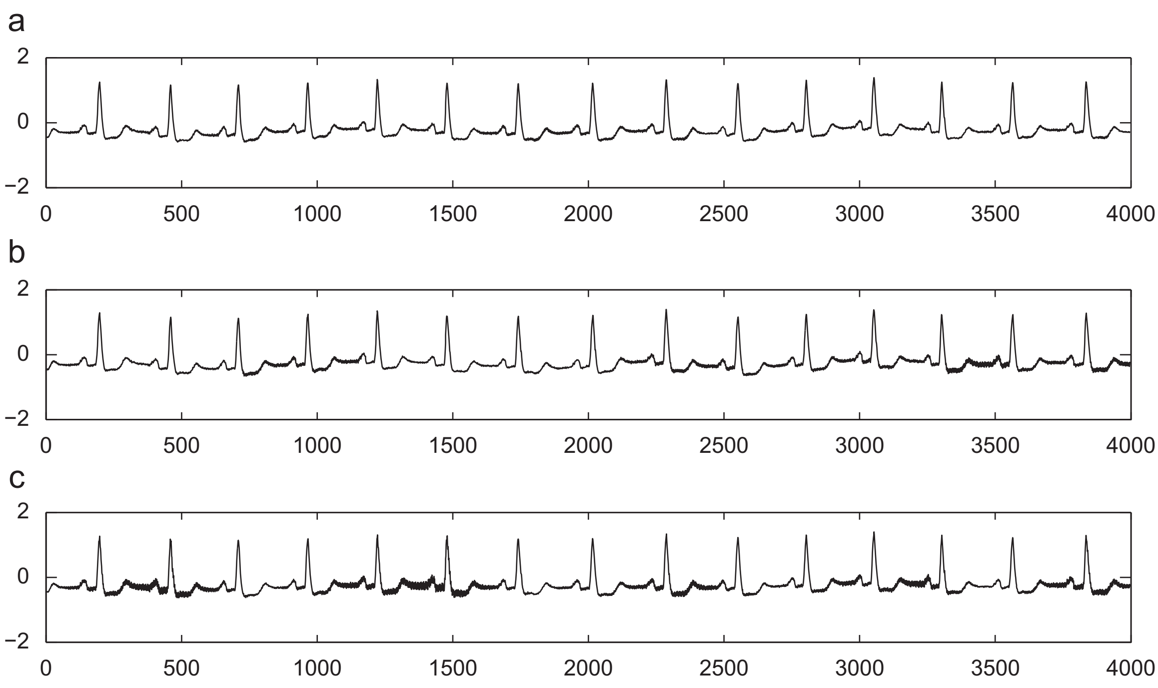

Fig. 5. Typical filtering results of baseline wander reduction: (a) recovered signal using BB-NSRLMS algorithm, (b) recovered signal using BB-NSLMS algorithm, (c) recovered signal using BB-NSSLMS algorithm.

3. Computational complexity issues

As the sign based algorithms are largely free from the MAC operations, the proposed schemes provide elegant means to remove the noise from the ECG signal. Table 1 provides comparative account of different commonly used algorithms and the proposed algorithm in terms of number of operations required. Among all the algorithms the NLMS is more complex, it requires $2L+1$ MACs and 1 division. The conventional LMS algorithm requires $L+1$ MAC operations to implement the weight updating Eq. (1) on DSP processor. For SSLMS algorithm, to evaluate $\mathbf{w}(n+1)$ from $\mathbf{w}(n)$ using Eq. (4), only L add with sign check (ASC) operations are required. But, from Fig. 2 it is clear that the rate of convergence of this algorithm is very slow. Hence, the SSLMS algorithm alone will not be a suitable candidate for the removal of noise from the ECG signal. The NSSLMS algorithm, which is the combination of SSLMS and NLMS is very much suitable as this algorithm requires L shift L ASC operations in case of block based realization or if we choose the value of $\mu(n)$ as a power of 2. From the Table 1 it is also clear that the number of computations required for the proposed block based NSRLMS is *independent* of filter length L. Note that ASC and shift operations requires less logic circuitry when compared with MAC operations.

4. Simulation results

To show that the normalized signed algorithms are really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies taken from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG records as the reference to our work. 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 11-bit resolution over a 10 mV range. The concept of filtering is tested with real noise

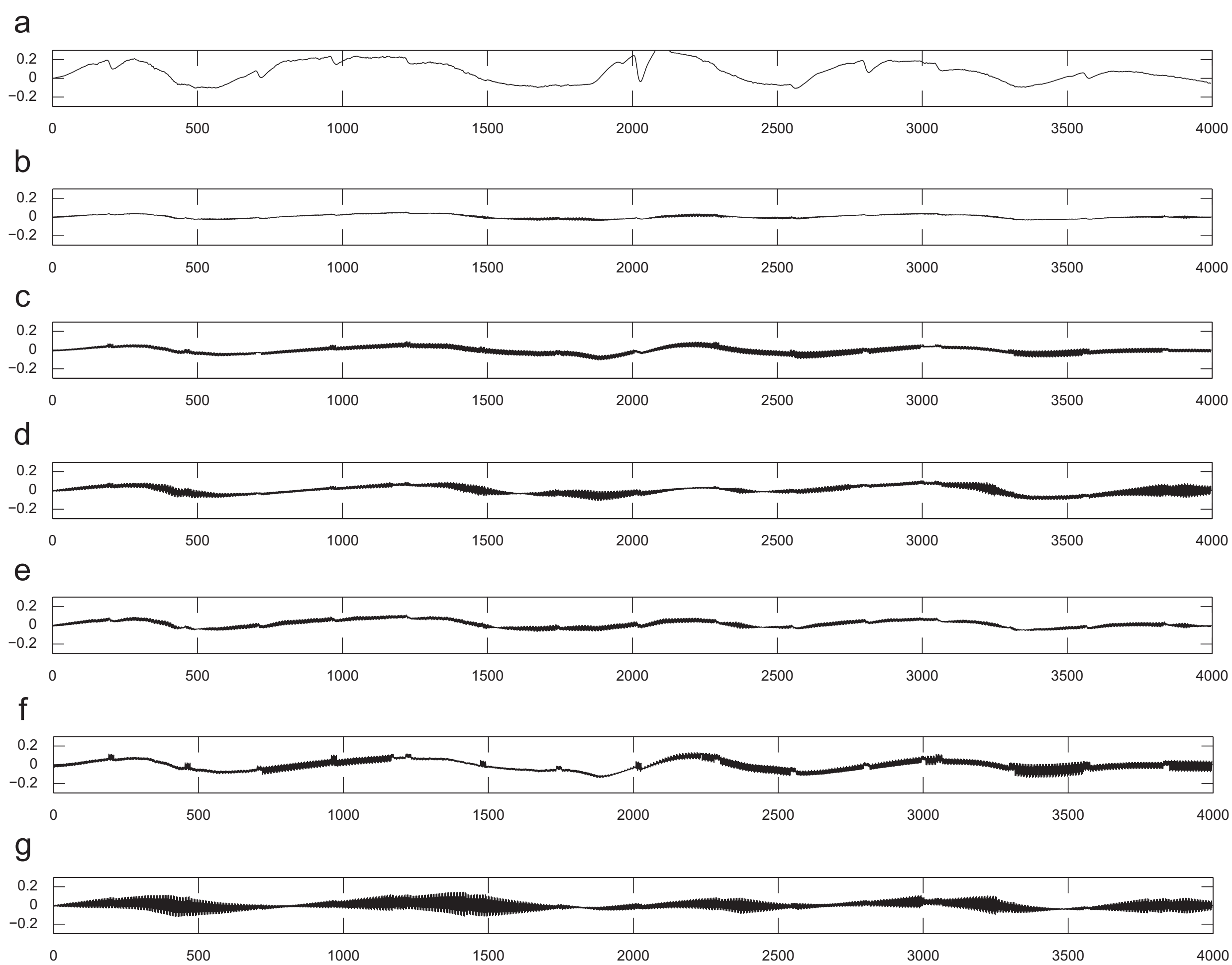

Fig. 6. Typical filtering results of baseline wander reduction: (a) difference signal after LMS filtering, (b) difference signal after NSRLMS filtering, (c) difference signal after NSLMS filtering, (d) difference signal after NSSLMS filtering, (e) difference signal after BB-NSRLMS filtering, (f) difference signal after BB-NSLMS filtering, (g) difference signal after BB-NSSLMS filtering.

obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). In our simulation we used first 4000 samples of the ECG signals. For evaluating the performance of the proposed filter structures we have measured the signal-to-noise ratio (SNR) improvement and compared with LMS algorithm. For all the figures *number of samples* are taken on *x*-axis and *amplitude* on *y*-axis, unless stated. Tables 2–5 gives the contrast of all algorithms in terms of SNR improvement (dBs). In our experiments we have considered a dataset of five ECG records: data100, data105, data108, data203 and data228 to ensure the consistency of results. Fig. 3 shows clean ECG (data 105 of MIT-BIH database) and its frequency spectrum, simulation results for this record are shown in this paper. Various adaptive filter structures are implemented using LMS, NSRLMS, NSLMS, NSSLMS, BB-NSRLMS, BB-NSLMS and BB-NSSLMS algorithms.

4.1. *Noise generator*

The reference signal n2 shown in Fig. 1 is taken from noise generator. A synthetic PLI with 1 mv 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 128 Hz 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 1.25 dB. 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 improves the performance of the filter.

Table 2
Performance contrast of various algorithms for the removal of BW.

Rec. no.	LMS	NSRLMS	NSLMS	NSSLMS	BB-NSRLMS	BB-NSLMS	BB-NSSLMS
100	2.1986	8.8575	8.2527	6.4445	7.4645	6.9348	4.912
105	3.4080	11.1317	8.8560	7.9423	9.3007	6.9696	6.2112
108	2.2791	9.4754	8.7383	6.9345	6.7958	6.6014	5.2817
203	2.6438	8.2857	6.7347	5.9609	7.0365	5.5887	4.8235
228	3.2148	10.4830	8.9809	7.6581	8.4255	7.1900	6.2572
Average	2.7488	9.6426	8.3125	6.9880	7.8046	6.6569	5.4971

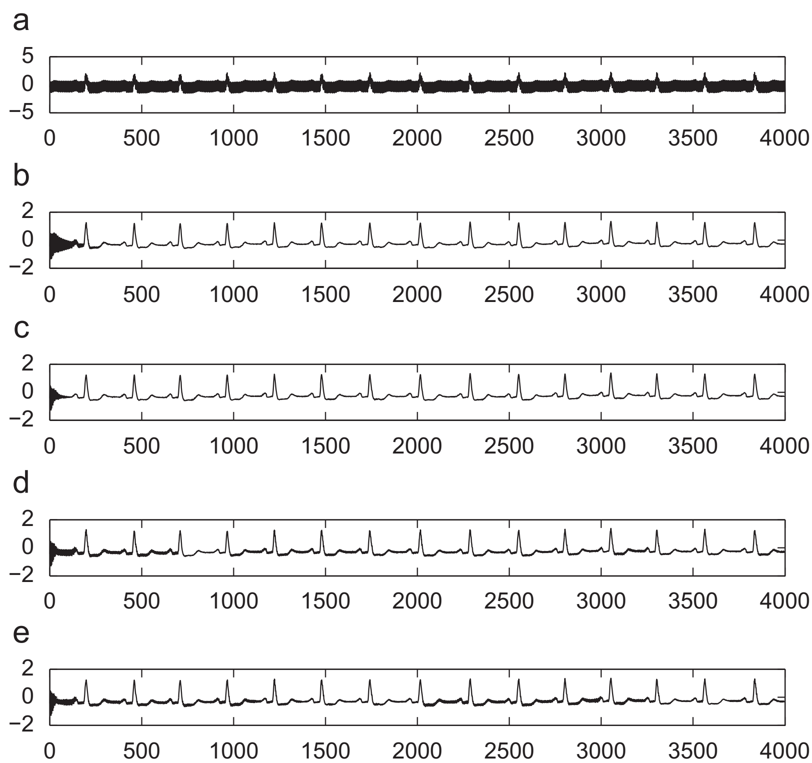

Fig. 7. Typical filtering results of PLI Cancelation: (a) ECG with PLI, (b) recovered signal using LMS algorithm, (c) recovered signal using NSRLMS algorithm, (d) recovered signal using NSLMS algorithm, (e) recovered signal using NSSLMS algorithm.

4.2. Baseline wander reduction

In this experiment we collected first 4000 samples of the ECG signal corrupted with real baseline wander (BW). The contaminated ECG signal is applied as primary input to the adaptive filter of Fig. 1. The noise generator a real BW with additive random noise and tiny sinusoidal interference is given as reference signal. Simulation results are

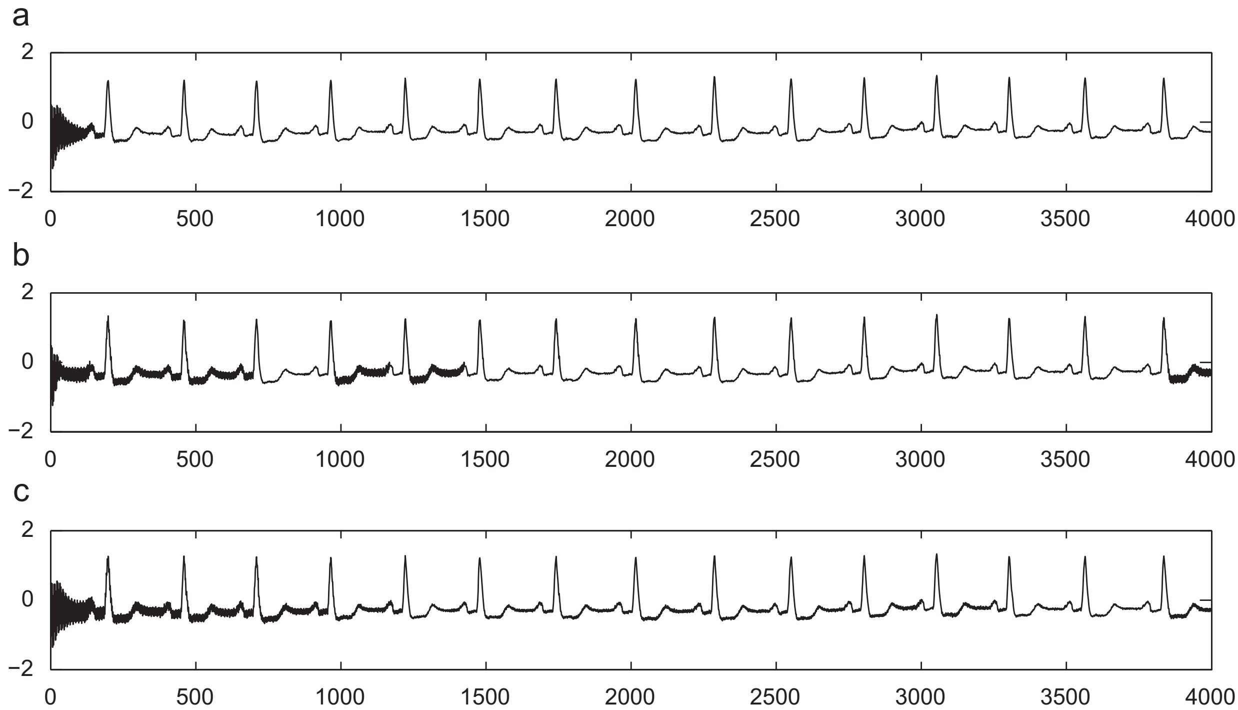

Fig. 8. Typical filtering results of PLI Cancelation: (a) recovered signal using BB-NSRLMS algorithm, (b) recovered signal using BB-NSLMS algorithm, (c) recovered signal using BB-NSSLMS algorithm.

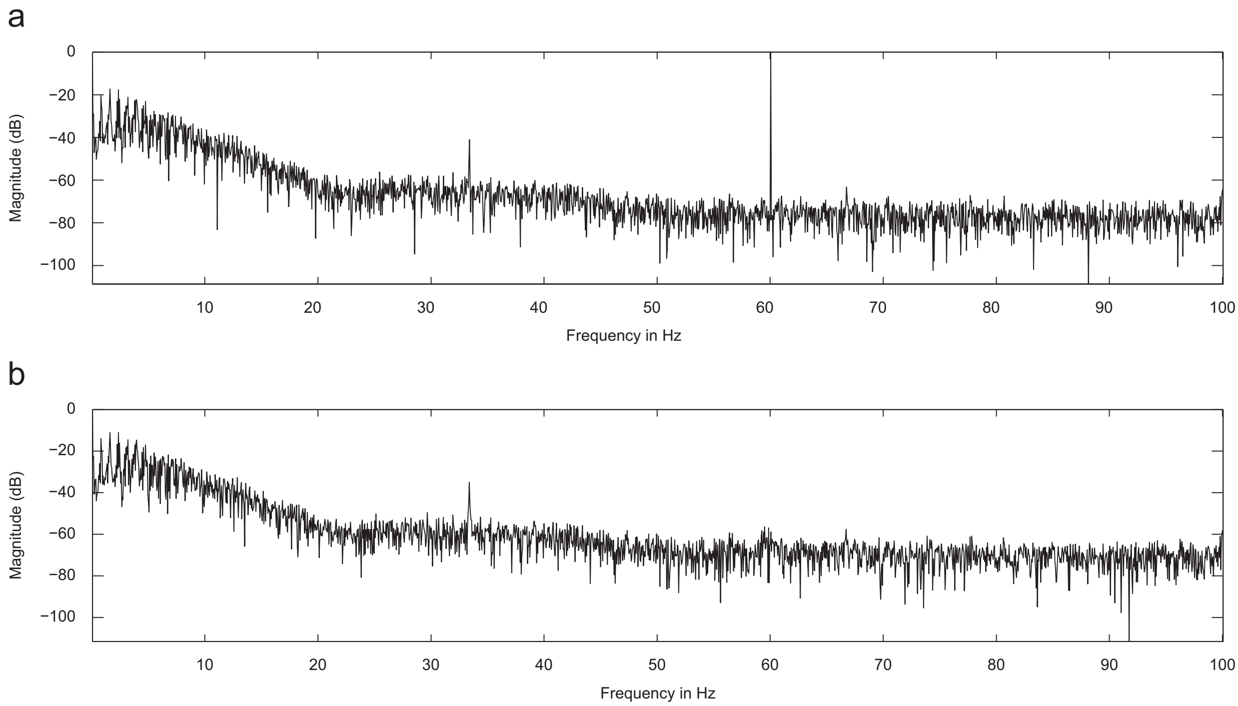

Fig. 9. (a) Frequency spectrum of ECG with PLI, (b) frequency spectrum after filtering with NSRLMS algorithm.

plotted in Fig. 4 and that for block based filters are shown in Fig. 5. From Fig. 4(c) it is clear that the output from NSRLMS based filter has high resolution. Fig. 6 shows the difference signals between original and restored signals due to various algorithms. From Figs. 4(b) and 6(a) it is clear that after LMS filtering some residual BW remains in the filter output, i.e, LMS based adaptive filter has low tracking capability of non-stationary variations. Figs. 4(c) and 6(b) shows the restored, difference signals for NSRLMS algorithms, here the amplitude of the difference almost approaches the DC line. Where as for NSLMS and NSSLMS filters, because of the sign term less amplitude residual noise present along with the baseline, but lower than that of LMS counterpart. The relative performance of the filters is measured with SNR. These are presented in Table 2 for the entire dataset. The average SNR improvement for NSRLMS is 9.6426 dB, NSLMS gets 8.3125 dB, NSSLMS gets 6.9880 dB, BB-NSRLMS gets 7.8046 dB, BB-NSLMS

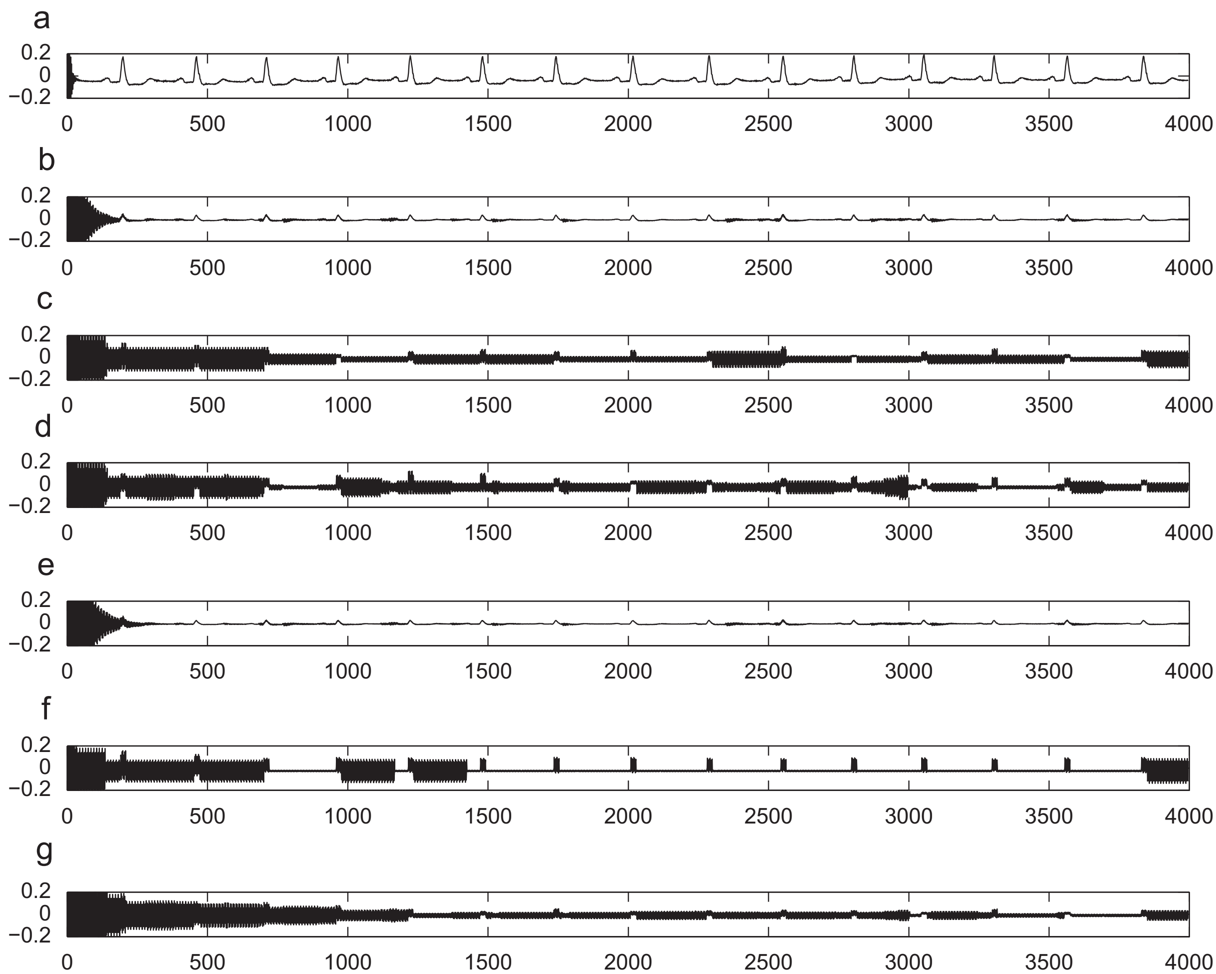

Fig. 10. Typical filtering results of PLI cancelation: (a) difference signal after LMS filtering, (b) difference signal after NSRLMS filtering, (c) difference signal after NSLMS filtering, (d) difference signal after NSSLMS filtering, (e) difference signal after BB-NSRLMS filtering, (f) difference signal after BB-NSLMS filtering, (g) difference signal after BB-NSSLMS filtering.

Table 3
Performance contrast of various algorithms for the removal of PLI.

Rec. No.	LMS	NSRLMS	NSLMS	NSSLMS	BB-NSRLMS	BB-NSLMS	BB-NSSLMS
100	21.8102	25.7098	22.0193	21.5828	22.6596	18.4834	14.7717
105	21.5941	26.1090	24.3117	22.2586	22.7868	20.7158	18.3982
108	21.9815	25.9514	24.8089	21.8887	22.7595	21.0130	17.8503
203	20.2211	24.7975	20.8499	19.0398	21.5021	18.9741	17.5042
228	22.4014	26.6688	24.3587	22.3239	23.3588	21.5293	20.4374
Average	21.6016	25.8473	23.2697	20.8187	22.6133	20.1431	17.7923

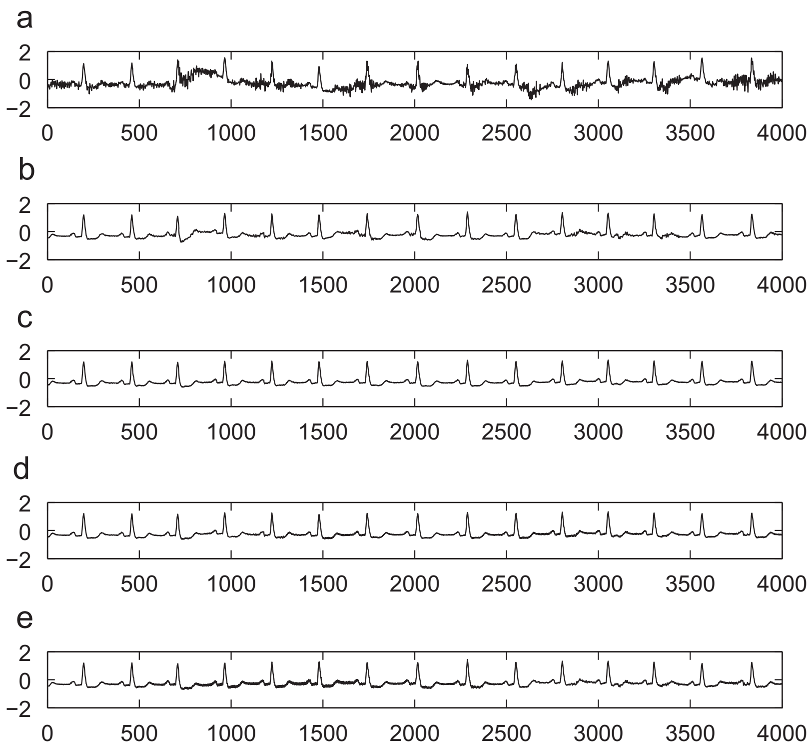

Fig. 11. Typical filtering results of muscle artifacts removal: (a) ECG with real MA noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NSRLMS algorithm, (d) recovered signal using NSLMS algorithm, (e) recovered signal using NSSLMS algorithm.

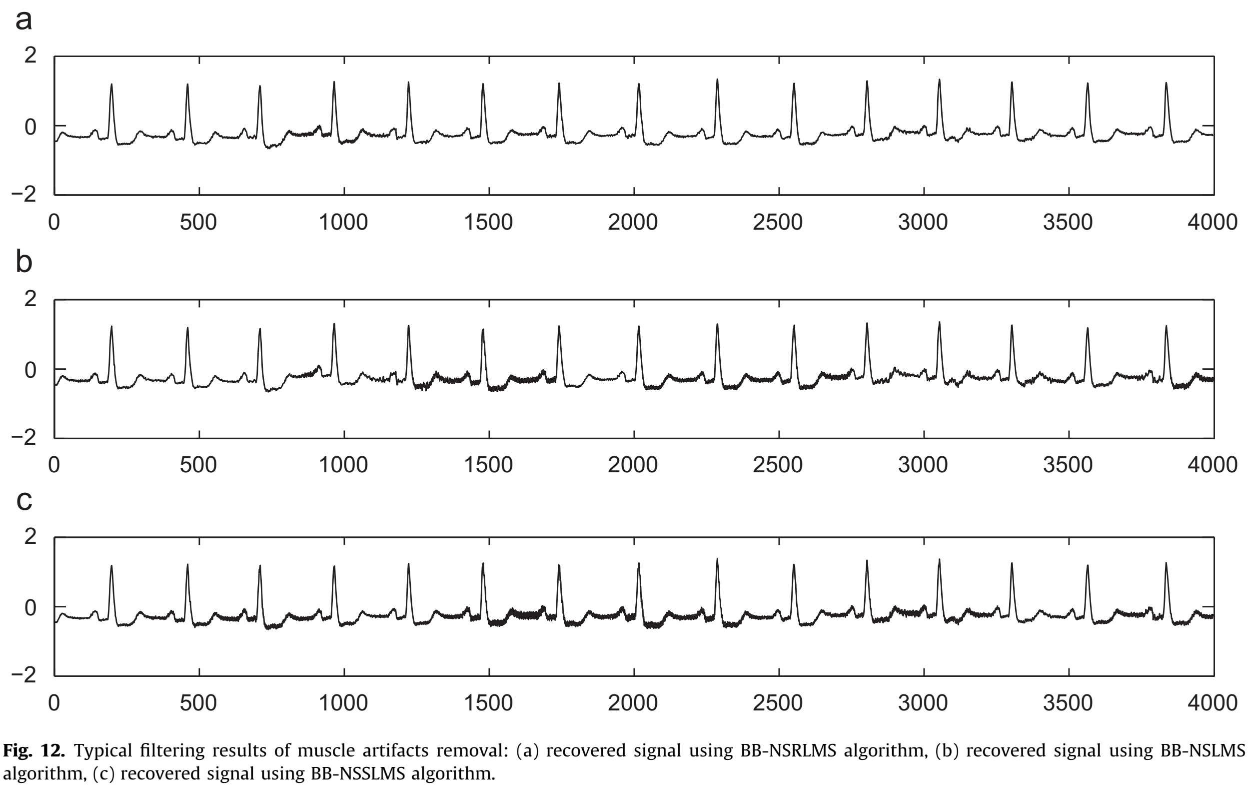

Fig. 12. Typical filtering results of muscle artifacts removal: (a) recovered signal using BB-NSRLMS algorithm, (b) recovered signal using BB-NSLMS algorithm, (c) recovered signal using BB-NSSLMS algorithm.

gets 6.6569 dB and BB-NSSLMS gets 5.4971 dB, where as conventional LMS gets 2.7488 dB. Therefore sign based normalized, block based normalized sign adaptive filters has good tracking and less computational complexity.

4.3. Adaptive power-line interference canceler

This experiment demonstrates power line interference (PLI) cancelation, i.e, stationary noise cancelation. The input to the filter is ECG signal corrupted with a synthetic PLI of amplitude 1 mv, frequency 60 Hz and sampled at 200 Hz, which is generated in the noise generator. The reference signal is synthesized PLI, the output of the filter is recovered signal. The filtered signals using normalized signed filters are shown in Fig. 7 and the corresponding results for block based algorithms are shown in Fig. 8. The frequency spectrum before filtering and after filtering using NSRLMS algorithm are shown in Fig. 9. The difference signals are shown in Fig. 10. These low

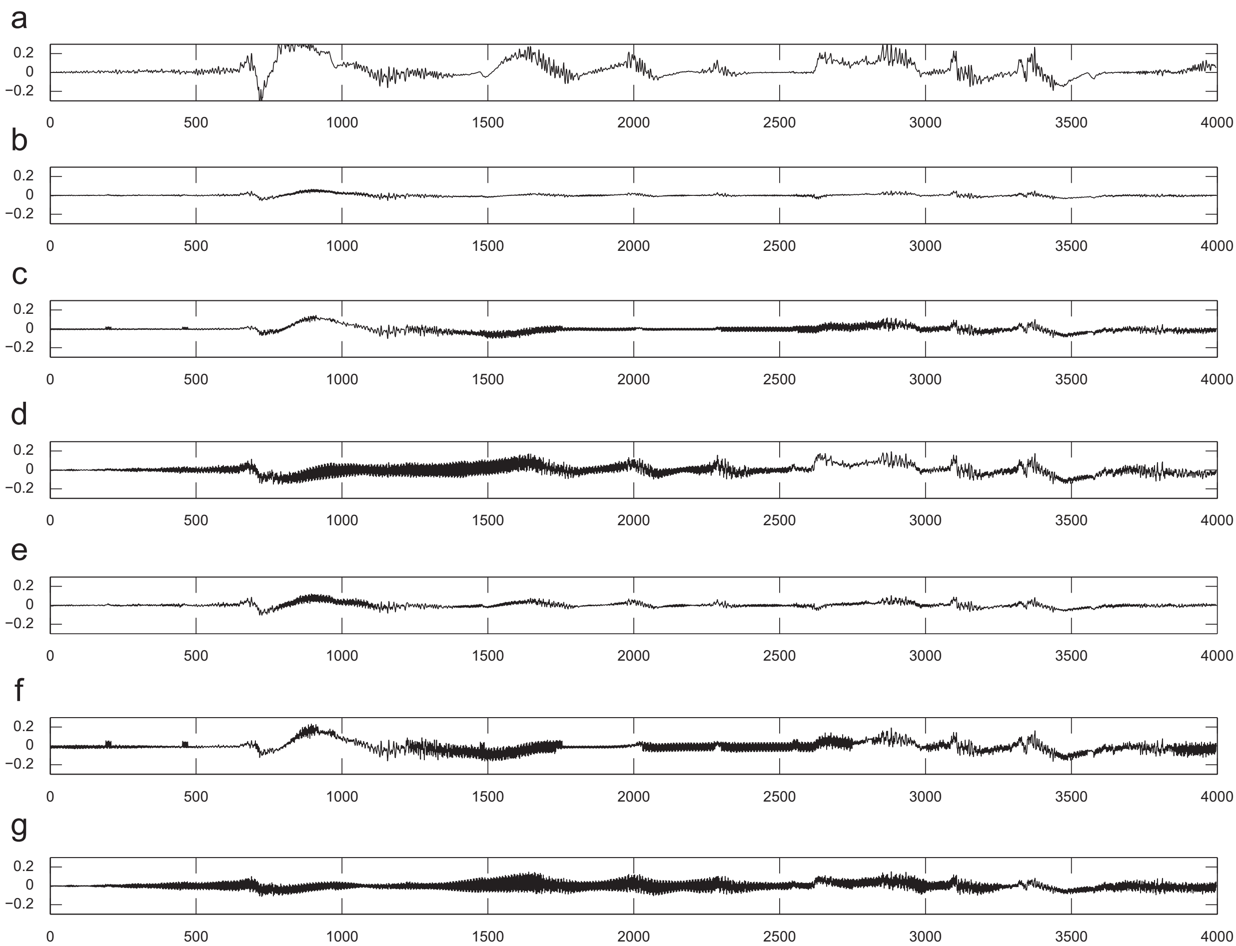

Fig. 13. Typical filtering results of muscle artifacts removal: (a) difference signal after LMS filtering, (b) difference signal after NSRLMS filtering, (c) difference signal after NSLMS filtering, (d) difference signal after NSSLMS filtering, (e) difference signal after BB-NSRLMS filtering, (f) difference signal after BB-NSLMS filtering, (g) difference signal after BB-NSSLMS filtering.

Table 4
Performance contrast of various algorithms for the removal of MA.

Rec. no.	LMS	NSRLMS	NSLMS	NSSLMS	BB-NSRLMS	BB-NSLMS	BB-NSSLMS
100	3.5006	8.6948	6.6882	5.1890	6.7857	5.0863	4.5237
105	4.9304	10.7969	7.8169	6.8141	9.6467	6.6011	4.8847
108	3.9917	9.7647	7.6231	5.5868	7.7298	6.2130	5.5384
203	5.9127	11.4005	9.6401	8.1926	9.4912	8.1992	7.0282
228	4.7286	9.0338	8.069	6.8312	8.6244	7.3276	6.5730
Average	4.6128	9.9381	7.9674	6.5227	8.4555	6.6847	5.7096

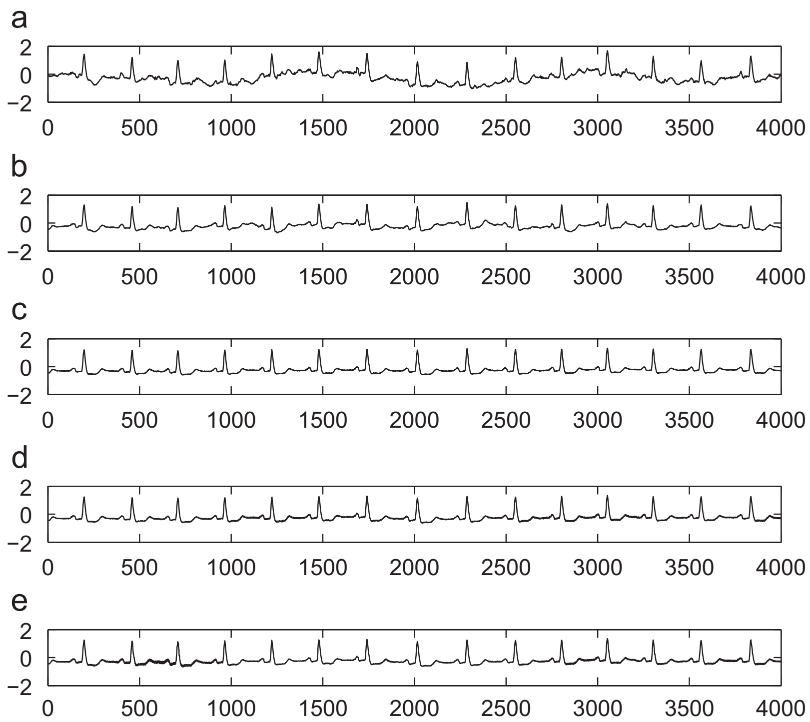

Fig. 14. Typical filtering results of motion artifacts removal: (a) ECG with real EM, (b) recovered signal using LMS algorithm, (c) recovered signal using NSRLMS algorithm, (d) recovered signal using NSLMS algorithm, (e) recovered signal using NSSLMS algorithm.

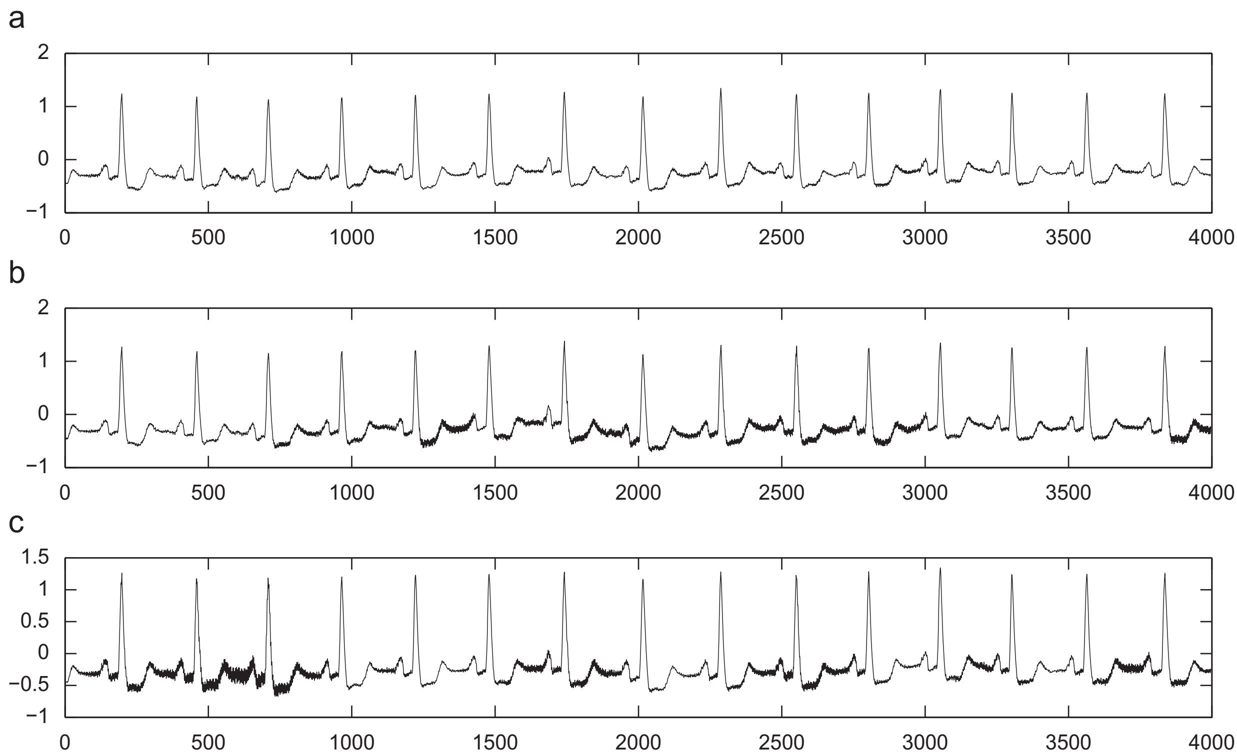

Fig. 15. Typical filtering results of motion artifacts removal: (a) recovered signal using BB-NSRLMS algorithm, (b) recovered signal using BB-NSLMS algorithm, (c) recovered signal using BB-NSSLMS algorithm.

amplitude difference signals show the noise removal ability of the filters. The SNR contrast for the dataset is shown in Table 3. In SNR measurements it is found that NSRLMS algorithm gets SNR improvement of 25.8473 dB, NSLMS gets 23.2697 dB, NSSLMS gets 20.0097 dB, BB-NSRLMS gets 22.6133 dB, BB-NSLMS gets 20.1431 dB and BB-NSSLMS gets 17.7923 dB, where as the conventional LMS algorithm improves to 21.6016 dB.

4.4. Adaptive cancelation of muscle artifacts

To show the concept of artifacts removal in the presence of non-stationary noise, real muscle artifact (MA) was taken from the MIT-BIH Noise Stress Test Database. The MA originally had a sampling frequency of 360 Hz and therefore they were anti-alias resampled to 128 Hz in order to match the sampling rate of ECG signal. The ECG signal corrupted with muscle artifacts is given as input to the adaptive filter. Real MA is given as a reference signal. Figs. 11 and 12 shows the noise removal using various algorithms. The typical difference signals are shown in Fig. 13, which proves the tracking ability of normalized algorithms in the presence of non-stationary noise. The SNR improvement contrast for various algorithms are presented in Table 4. In SNR measurements it is found that NSRLMS algorithm gets SNR improvement of 9.9381 dB, NSLMS gets 7.4048 dB and NSSLMS gets 6.5227 dB, BB-NSRLMS gets 8.4555 dB, BB-NSLMS gets 6.6847 dB and BB-NSSLMS gets 5.7096 dB, where as the conventional LMS algorithm gets 4.6128 dB.

4.5. Adaptive motion artifacts cancelation

To show the concept of artifacts removal in the presence of non-stationary noise, we have also considered electrode motion artifact (EM). The ECG signal corrupted with motion artifacts is given as input to the adaptive filter. Real EM is taken as reference signal. Figs. 14 and 15 shows the noise removal using normalized and block based algorithms. The typical difference signals shown in Fig. 16 proves the tracking ability of normalized algorithms in presence of non-stationary noise. The SNR improvement contrast for various algorithms are shown

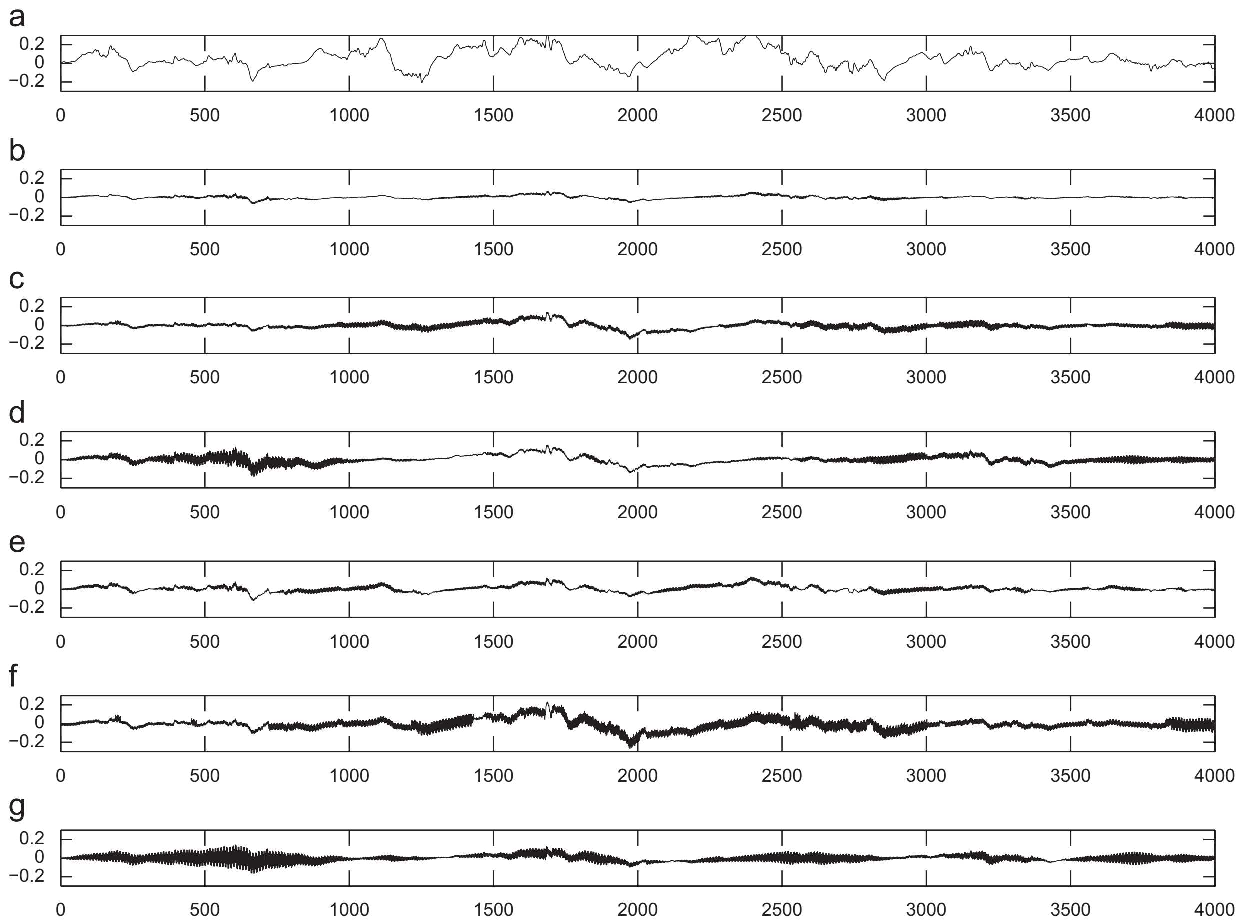

Fig. 16. Typical filtering results of motion artifacts removal: (a) difference signal after LMS filtering, (b) difference signal after NSRLMS filtering, (c) difference signal after NSLMS filtering, (d) difference signal after NSSLMS filtering, (e) difference signal after BB-NSRLMS filtering, (f) difference signal after BB-NSLMS filtering, (g) difference signal after BB-NSSLMS filtering.

Table 5
Performance contrast of various algorithms for the removal of EM.

Rec. no.	LMS	NSRLMS	NSLMS	NSSLMS	BB-NSRLMS	BB-NSLMS	BB-NSSLMS
100	2.7289	10.8200	7.8668	7.6165	8.9416	6.3333	5.6090
105	3.9484	12.2121	8.9552	8.0493	10.2849	7.8379	6.8032
108	3.0080	10.7172	8.6646	6.8205	8.0243	6.0553	5.5755
203	3.3268	9.5363	7.9293	7.3478	7.6493	6.7010	5.9975
228	3.6710	9.7255	7.9868	7.5365	7.6063	6.7485	6.2828
Average	3.3366	10.6022	8.2805	7.4741	8.5012	6.7352	6.0536

in Table 5. In SNR measurements it is found that NSRLMS algorithm gets SNR improvement of 10.6022 dB, NSLMS gets 8.2805 dB, NSSLMS gets 7.4741 dB, BB-NSRLMS gets 8.5012 dB, BB-NSLMS gets 6.7352 dB and BB-NSSLMS gets 6.0536 dB, where as the conventional LMS algorithm improves 3.3367 dB only.

5. Conclusion

In this paper the problem of noise cancelation from ECG signal using sign based normalized adaptive filters, their block based versions are proposed and tested on real signals with different artifacts obtained from the MIT-BIH database. 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. Among the six algorithms, the NSRLMS performs better than the other. From the simulated results it is clear that these algorithms removes non-stationary noise efficiently. The proposed treatment provides high signal to noise ratio with less computational complexity. The computational complexity in terms of MACs and SNR contrast are presented in Tables 1–5. Hence the proposed NSRLMS, NSLMS, NSSLMS based adaptive filters and their block based versions are more suitable for wireless biotelemetry ECG systems.

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