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A New ECG Signal Enhancement Strategy using Non-Negative Algorithms

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Abstract: Extraction of high resolution electro cardiogram (ECG) signals is an important task for remote health care monitoring. For this the weak cardiac signal must be enhanced. Among the different filtering techniques, adaptive artifact cancellation (AAC) is a promising technology. Least mean square (LMS) algorithm is the basic enhancement technique in the adaptive filtering. But, in the non-stationery environment it suffers with slow convergence and weight drift problems. During critical conditions the filter weights may be negative and cause an imbalance in the convergence. To overcome this problem, we introduce non-negative adaptive algorithms in the proposed artifact canceller. To accelerate the performance of the AAC, we introduce data normalization for the non-negative LMS algorithm called normalized non-negative (N^3LMS) to update the filter coefficients. Further to improve convergence characteristics, filtering ability and to minimize computational complexity we also implement some sign versions of N^3LMS algorithms. Finally, the proposed AACs are tested using actual ECG signals obtained from MIT-BIH data base. The performance evaluation is carried out based on signal to noise ratio improvement (SNRI), excess mean square error (EMSE) and weights. Among the AACs evaluated, sign regressor normalized non-negative LMS (SRN^3LMS) based adaptive artifact canceller achieves better performance than others.

Keywords: Arrhythmia, artifacts, convergence, computational complexity, least mean square.

1. INTRODUCTION

In the modern days, health issues related to Cardiac are one of the major health problems. The deaths rate is high every year due to these deceases [1]. Monitoring the heart health of a patient at regular intervals of time reduces the risk. It is possible to do this by different ways. The easier and much instructive way to do this is monitoring the cardiac signal (CS). Monitoring the CS is one of the most generally used techniques to examine the heart's health. Letters P, Q, R, S, and T indicate the parameters of the signal and these usually play an important role in identifying various arrhythmia conditions. The arrhythmias show the diseases with the help of the parameters of the signal. The amplitude, onset, offset etc., of the parameters is used to identify the arrhythmia and differentiate them. A situation of heart health, the myocardial infarction is identified if the amplitude of the T wave exceeds

0.15mV [2]. Similarly the depression in the ST interval indicates the ventricular re-polarization [3]. In [4] the authors have shown that the changes in the T wave can be used to detect the sudden cardiac deaths. In clinical monitoring and diagnosis, the amplitude levels and the duration of the signal parameters are important. But these features may be masked by the artifacts present in the CS. These artifacts combine with the CS and mask the features of the CS, which are essential in clinical diagnosis. The generally encountered artifacts in CS are Power line interference (PLI), Muscle Artifact (MA), Electrode Motion (EM) Artifact and Base line wandering (BW) Artifact. The artifacts are unavoidable and occur during signal acquisition. For example due to the respiration base line wandering artifacts occur, which are unavoidable. The artifacts cause ambiguities in detecting the arrhythmia. For example in [5] the authors have shown that the changes in the T wave which are critical for identifying the severe cardiac problems is also affected by the artifacts.

From the literature it is clear that with help of filtering techniques the minimization of these artifacts can be done. In [6] authors developed a low power amplifier for the front end for fetal monitoring. Similarly in [7] a new type of electrodes is proposed to reduce the impact due to the drying of electrodes. David et. al., [8] introduced a motion tolerant acquisition system with low power consumption. Also in [9] Nick Van et. al., has improved the motion artifact reduction system with much focus on hardware.

In case of filtering, signal enhancement can be achieved with both the adaptive and non adaptive filtering methods [10]-[15]. The LMS filtering is one of the basic adaptive filtering algorithms. ECG Filtering with the help of the LMS algorithm is seen in [16]. The LMS filtering is a simpler form of the adaptive filtering but the limitations exists in stability. In a real-time clinical environment, and in critical conditions from an abnormal heart rhythm, the filter weights may be negative. The negative weights cause an imbalance in the convergence, resulting in poor filtering capability. To overcome this problem, we introduce non-negative adaptive algorithms in the proposed artifact canceller. To accelerate the performance of the AAC, we propose normalized non-negative algorithms to update the filter coefficients. The computational complexity of the filtering section in a remote health care system is important to avoid inter-symbol interference of the incoming samples. This can be achieved by combining sign-based algorithms with the adaptive filtering section. The remedy for unbalanced convergence and poor filtering performance of the algorithm is a modified LMS algorithm, in which a diagonal vector of the input is introduced in the weight update equation, i.e., a non-negative LMS (N^2LMS) algorithm [17]. This N^2LMS keeps the filter weights from becoming negative from the abnormal rhythms of the heart. To improve the performance of the AAC, the N2LMS algorithm is varied, resulting in a normalized N^2LMS (N^3LMS) [18]-[19]. To reduce the computational complexity of the proposed algorithms, we combine the N^3LMS with sign variants, resulting sign regressor N^3LMS (SRN^3LMS), sign N^3LMS (SN^3LMS), and sign N^3LMS (SSN^3LMS) algorithms. The theory, the analysis of the algorithms and the simulation results of the various implementations are presented in the next sections. Using these algorithms various AACs are developed and performance evaluation is carried. The parameters SNRI, EMSE, convergence and weights are taken as performance measures. Real cardiac signals obtained from MIT-BIH data base are taken to prove the enhancement process. The theory, the analysis of the algorithms and the simulation results of the various implementations are presented in the next sections.

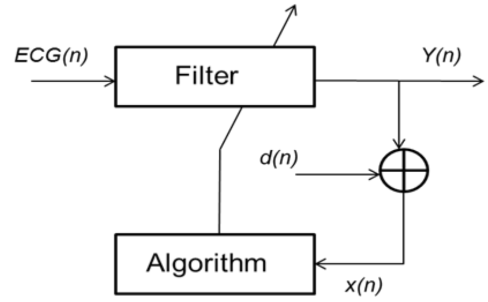

Figure 1: Block Diagram of an adaptive filter

2. PROPOSED CARDIAC ENHANCEMENT ALGORITHMS

In this paper, we introduce a new method of artifact removal in ECG signals for remote health care monitoring systems. During signal acquisition in a typical ECG remote health care monitoring system, some physiological and non-physiological contaminants add to the actual heart activity, leading to ambiguous diagnoses and measurements. The major artifacts encountered with heart activity are the Power line interference (PLI), Muscle Artifact (MA), Electrode Motion (EM) Artifact and Base line wandering (BW) Artifact. The BW artifacts are base-line drift of the ICG signal from respiration activity. The EM artifacts are caused by muscle activity, and the IM artifacts are caused by an impedance mismatch between the electrodes and the skin, or from a mismatch of the electrodes. At the receiving end, a clear high-resolution signal is required to present to the doctor for diagnosis. In this context, AAC plays an important role. Figure 1 shows a block diagram of AAC for remote health care monitoring systems.

The recorded ECG signal with artifact contaminants is expressed as follows:

$$\mathrm{ECG}(n) = o(n) + n_1(n)$$

where, ICG(n) is the recorded ICG signal;

$o(n)$ is the original ICG signal generated from heart activity; and

$n_1(n)$ is the artifact component. In a remote system, $n_1(n)$ also includes channel noise.

The basic working principle of the proposed AAC is the following. The raw signal ECG(n) is input to the filter unit of length M taps. A reference signal is constructed for any type of contamination present in the raw input ECG signal. The constructed reference signal is used as the reference signal for the adaptive algorithm to update its weight coefficients. The proposed AAC thus plays a vital role in the implementation of an intelligent remote health care monitoring system that is reference-free by constructing the reference signal itself from the contaminated input signal.

The weight coefficients are updated based on the weight update mechanism of various algorithms. The weight update mechanism for the basic LMS algorithm is as follows,

$$\mathbf{U}(n + 1) = \mathbf{U}(n) + \chi \boldsymbol{d}(n)x(n), \tag{1}$$

where, U(n + 1) is the next weight coefficient; U(n) is the previous weight coefficient;

χ is the step size; $d(n)$ is the reference signal, which is required for training to eliminate noise from the raw signal ECG signal and $x(n)$ is the error generated, which is used as a feedback to the adaptive algorithm.

Because of the abnormalities in the ICG signal, i.e., the drastic variations in the signal features, the weight coefficients may become negative. This leads to poor performance of the adaptive algorithm in terms of convergence, stability and filtering capability. To overcome this drawback, a non-negative LMS (N2LMS) algorithm is proposed [17]. The weight update mechanism is as follows:

$$\mathbf{U}(n + 1) = \mathbf{U}(n) + \chi \mathrm{Z}(n)d(n)x(n), \tag{2}$$

where, Z(n) is the diagonal matrix of the weight coefficients U(n). The elaborated theory and analysis of N^2LMS is presented by Chen et. al., [20].

In Eq. (2), each component of U(n + 1) is viewed as a variable step because of the combination of χZ(n). In the N^2LMS algorithm, when the weights tend to zero, the convergence becomes unbalanced and the algorithm may diverge, causing the AAC to be ineffective for noise removal.

The normalized N^{2}LMS (N^{3}LMS) is mathematically expressed as follows:

$$\mathbf{U}(n+1) = \mathbf{U}(n) + \chi(n)\mathbf{Z}(n)\mathbf{d}(n)x(n) \tag{3}$$

where, $\chi(n)$ is a variable step size with respect to the reference input as follows:

$$\chi(n) = \frac{\chi}{\zeta + d^t(n)d(n)} \tag{4}$$

where, ζ is a small constant used to avoid numerical difficulties. The elaborated theory and analysis of the N^{3}LMS algorithms are presented in the literature [19].

The mathematical equation of the signum function can be written as below,

$$\operatorname{sign}(\mathrm{ECG}(n)) = \begin{Bmatrix} 1, \mathrm{ECG}(n) > 0 \\ 0, \mathrm{ECG}(n) = 0 \\ -1, \mathrm{ECG}(n) < 0 \end{Bmatrix} \tag{5}$$

The weight update mechanism equations for the N^{3}LMS algorithm with *sign* variants are written as follows:

1. The sign regressor version of the N^{3}LMS algorithm uses the following weight update equation:

$$\mathbf{U}(n+1) = \mathbf{U}(n) + \chi(n)\mathbf{Z}(n)\operatorname{sign}(\boldsymbol{d}(n))x(n) \tag{6}$$

This algorithm is the sign regressor N^{3}LMS (SRN^{3}LMS) algorithm.

2. The sign error version of the N^{3}LMS algorithm uses the following weight update equation:

$$\mathbf{U}(n+1) = \mathbf{U}(n) + \chi(n)\mathbf{Z}(n)\boldsymbol{d}(n)\operatorname{sign}(x(n)) \tag{7}$$

This algorithm is the sign error N^{3}LMS (SEN^{3}LMS) algorithm.

3. The sign version of the N^{3}LMS algorithm uses the following weight update equation:

$$\mathbf{U}(n+1) = \mathbf{U}(n) + \chi(n)\mathbf{Z}(n)\operatorname{sign}(d(n))\operatorname{sign}(x(n)) \tag{8}$$

This algorithm is the sign N^{3}LMS (SSN^{3}LMS) algorithm.

3. SIMULATION RESULTS

In this section several experiments are performed to test the developed AACs in cardiac signal enhancement. The noisy cardiac signals are taken from MIT-BIH arrhythmia database [26]-[27]. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory CS recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory ages 23 years to 89 years. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory CS recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The ECG recordings were made using Del Mar Avionics model 445 two-channel reel-to-reel Holter recorders, and the analog signals were recreated for digitization using a Del Mar Avionics model 660 playback unit [28]-[29].

In our experiments we have considered a dataset of five cardiac activity records: data101, data102, data103, data104 and data105 to ensure the consistency of results, the simulation results for data 101 are shown in this paper. In these experiments we have used first 4000 samples of the CS. All the experiments were performed for 10 times and average values are tabulated. The length of the adaptive filter is chosen as 10, a random noise of variance 0.001 is added to the signals, which resembles the channel noise. For evaluating the performance of the proposed AAC structures we have measured the signal-to-noise ratio improvement (SNRI) in decibels (dBs) and EMSE. These values are tabulated for comparing the performance.

A. Power Line Interference (PLI) Removal from Cardiac Signals

In this experiment we prove the ability of the proposed ANCs in eliminating the PLI artifact. The noisy cardiac signal with PLI noise is given as input to the ANC as shown in the Figure 1. A synthetic PLI with 60Hz frequency is given as reference signal. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based ANC. The experiments are performed on the dataset consists of five records. The enhancement results are show in Figure 2. Next, to evaluate the performance of the ANCs we measure SNRI and EMSE. These are tabulated in Table I and Table II. Figure 6 and Figure 7 show the comparison of these performance measures. In our experiments, among the considered algorithms it is found that N^3LMS algorithm achieves highest SNRI 20.8671dB. However, based on the application of sign regressor operation SRN^{3}LMS needs less number of multiplications during the enhancement process. This algorithm achieves 19.6466dB SNRI. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRN^{3}LMS based ANC performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

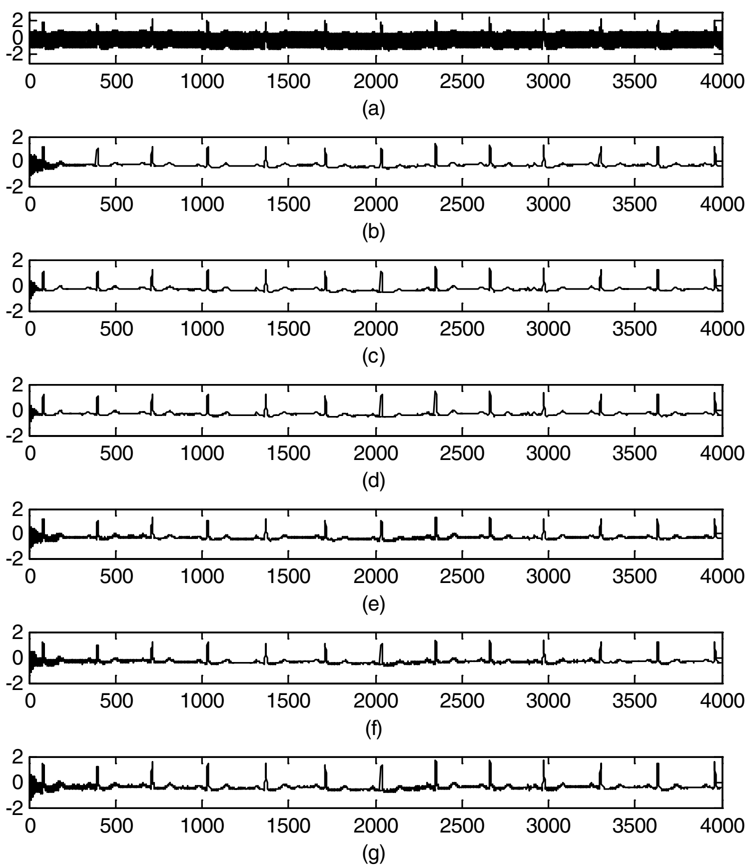

Figure 2: PLI Filtering results: (a) Cardiac Signal with Power Line Interference, (b) Filtering with LMS, (c) Filtering with N^{2}LMS, (d) Filtering with N^{3}LMS, (e) Filtering with SRN^{3}LMS, (f) Filtering with SN^{3}LMS, (g) Filtering with SSN^{3}LMS

B. Base line Wander (BW) Removal from Cardiac Signals

In this experiment we prove the ability of the proposed ANCs in eliminating the BW artifact. The noisy cardiac signal with BW noise is given as input to the ANC as shown in the Figure 1. A real base line wander artifact is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based ANC. The experiments are performed on the dataset consists of five records. The enhancement results are show in Figure 3. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table 1 and Table 2. Figure 6 and Figure 7 show the comparison of these performance measures. In our experiments, among the considered algorithms it is found that N^3LMS algorithm achieves highest SNRI 9.8376dB. However, based on the application of sign regressor operation SRN^3LMS needs less number of multiplications during the enhancement process. This algorithm achieves 9.1653dB SNRI. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRN^3LMS based ANC performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

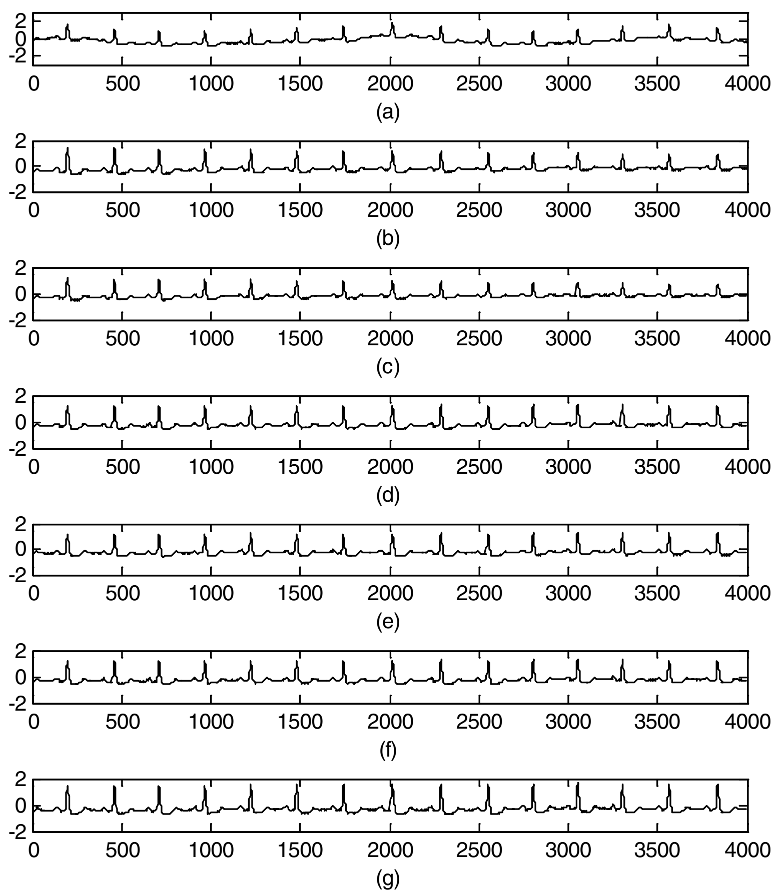

Figure 3: BW Filtering results: (a) Cardiac Signal with baseline wander, (b) Filtering with LMS, (c) Filtering with N^2LMS, (d) Filtering with N^3LMS, (e) Filtering with SRN^3LMS, (f) Filtering with SN^3LMS, (g) Filtering with SSN^3LMS

C. Muscle Artifact (MA) Removal from Cardiac Signals

In this experiment we prove the ability of the proposed ANCs in eliminating the MA. The noisy cardiac signal with MA noise is given as input to the ANC as shown in the Figure 1. A real MA is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based ANC. The experiments are performed on the dataset consists of five records. The enhancement results are show in Figure 4. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table 1 and Table 2. Figure 6 and Figure 7 show the comparison of these performance measures. In our experiments, among the considered algorithms it is found that N^3LMS algorithm achieves highest SNRI 8.7454dB. However, based on the application of sign regressor operation SRN^3LMS needs less number of multiplications during the enhancement process. This algorithm achieves 7.8979dB SNRI. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRN^3LMS based ANC performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

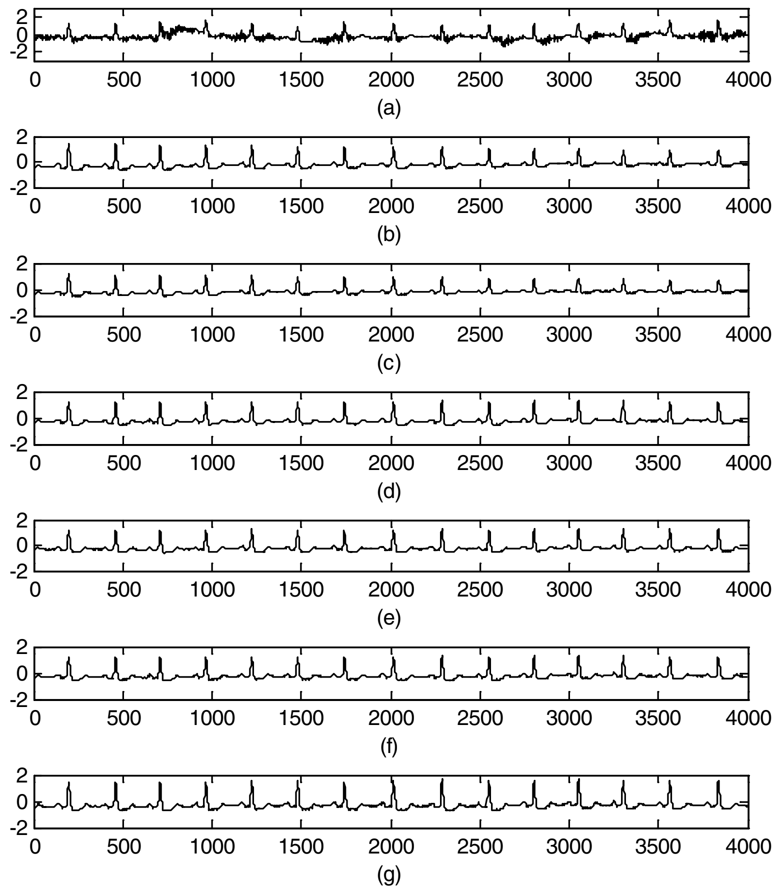

Figure 4: MA Filtering results: (a) Cardiac Signal with muscle artifacts, (b) Filtering with LMS, (c) Filtering with N^2LMS, (d) Filtering with N^3LMS, (e) Filtering with SRN^3LMS, (f) Filtering with SN^3LMS, (g) Filtering with SSN^3LMS

D. Electrode Motion Artifact Removal from Cardiac Signals

In this experiment we prove the ability of the proposed ANCs in eliminating the EM artifacts. The noisy cardiac signal with EM noise is given as input to the ANC as shown in the Figure 1. A real EM is taken as reference obtained from MIT-BIH data base. The noise cancellation experiments are performed using the algorithms discussed in the previous section. For comparison we also implement LMS based ANC. The experiments are performed on the dataset consists of five records. The enhancement results are show in Figure 5. The parameters SNRI and EMSE are taken as measures of performance. These are tabulated in Table 1 and Table 2. Figure 6 and Figure 7 show the comparison of these performance measures. In our experiments, among the considered algorithms it is found that N^3LMS algorithm achieves highest SNRI 8.3259dB. However, based on the application of sign regressor operation SRN^3LMS needs less number of multiplications during the enhancement process. This algorithm achieves 7.6958dB SNRI. Therefore, based on SNRI, EMSE and number of multiplications among all the considered algorithms SRN^{3}LMS based ANC performs better with tolerable SNRI. Hence, this algorithm can be used in practical remote health care monitoring systems for cardiac signal enhancement.

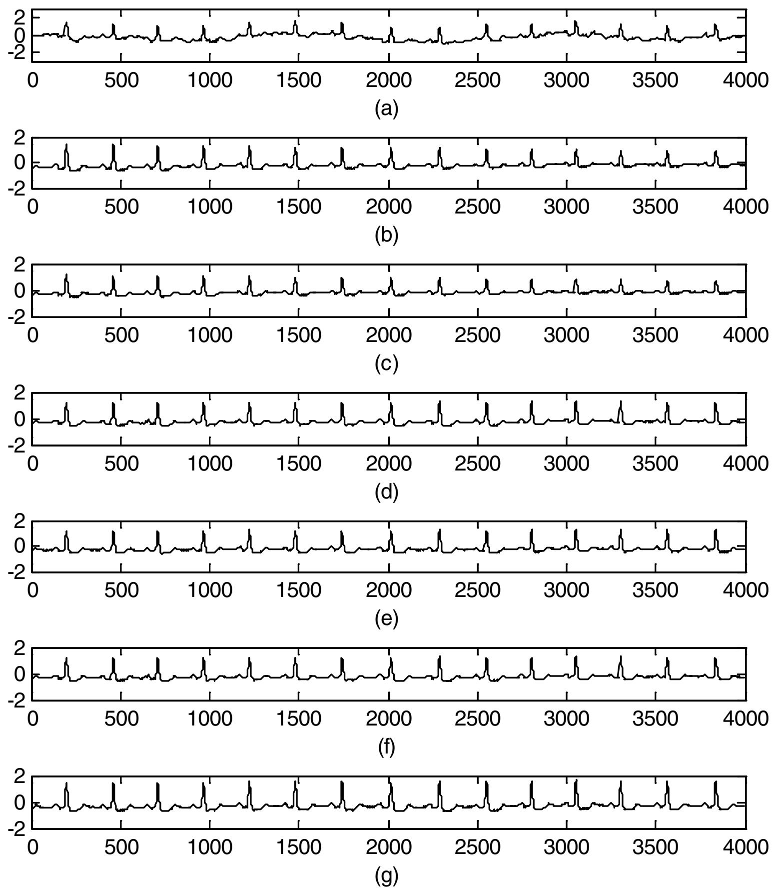

Figure 5: EM Filtering results: (a) Cardiac Signal with electrode motion artifacts, (b) Filtering with LMS, (c) Filtering with N^{2}LMS, (d) Filtering with N^{3}LMS, (e) Filtering with SRN^{3}LMS, (f) Filtering with SN^{3}LMS, (g) Filtering with SSN^{3}LMS

Table 1
Performance Contrast of Various Algorithms in Terms of Snrifor the Removal of Artifacts from Cardiac Signals (In dbs)

Noise Type	*Record Number*	*LMS*	*N^{2}LMS*	*N^{3}LMS*	*SRN^{3}LMS*	*SN^{3}LMS*	*SSN^{3}LMS*
PLI	101	7.6492	7.9633	21.1536	20.8443	19.3443	18.8936
	102	9.3643	9.6878	26.6354	25.4645	23.5834	22.8563
	103	8.4673	8.7484	23.6288	22.6933	21.6353	20.4739
	104	9.2063	9.6836	24.3634	23.6422	22.2462	21.3563
	105	7.2854	7.7894	20.8671	19.6466	16.4782	14.1837
BW	101	4.4558	4.8358	10.9335	9.8548	7.4363	6.8653
	102	4.3652	4.7452	10.7276	9.6564	8.8464	7.6854
	103	4.8435	5.0745	10.6454	9.4376	8.4363	7.7543
	104	4.6424	4.9565	9.3345	8.8754	7.7835	6.9653
	105	4.5523	4.8562	9.8376	9.1653	7.7523	6.3773

Noise Type	*Record Number*	*LMS*	*N^2LMS*	*N^3LMS*	*SRN^3LMS*	*SN^3LMS*	*SSN^3LMS*
MA	101	3.5205	3.8954	7.8534	7.0767	5.5353	4.8937
	102	3.9012	4.2156	7.6786	6.9756	4.9373	3.5357
	103	4.2395	4.6732	7.7653	6.9954	4.4362	3.4220
	104	4.0408	4.4954	8.7345	8.0748	6.1635	5.9795
	105	4.1137	4.5673	8.7454	7.8979	6.5673	5.9053
EM	101	4.5511	4.9735	8.1634	7.7977	6.3784	5.5074
	102	4.9438	5.2643	8.9365	7.7465	6.1048	5.1463
	103	4.6517	4.9874	8.3628	7.3354	6.6852	5.8642
	104	4.7482	5.0464	8.7453	7.5833	6.8456	5.8949
	105	4.0083	4.4563	8.3259	7.6958	6.9783	5.9837

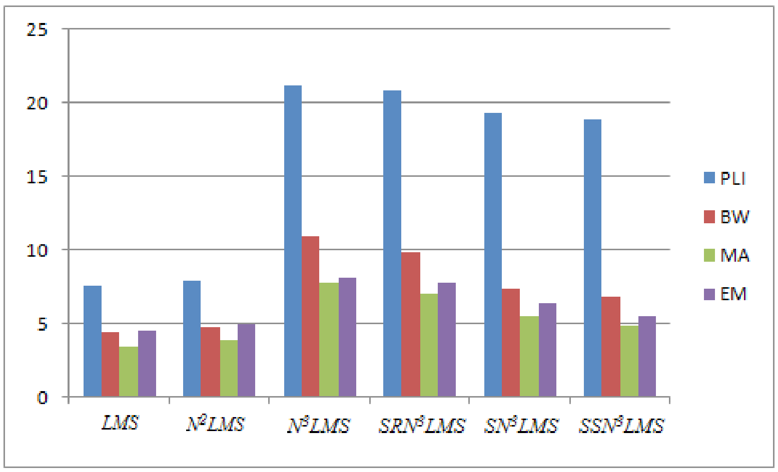

Figure 6: Comparison of SNRI in the ECG enhancement process

4. CONCLUSIONS

In this paper several adaptive noise cancellers are presented. These are based on variable step size normalized LMS algorithm and its variants. The variations are based on signed versions of N^3LMS algorithm. This reduced the computational complexity of the denominator of the normalization operation. The hybrid version of N^3LMS and sign regressor algorithm needs minimum number of computations among the considered algorithms. Therefore, based on our simulations results and computed performance measures, it is clear that among all the considered algorithms SRN^3LMS based ANC performs better than the counter parts, even though it is just inferior to N^3LMS due to reduced number of multiplications in the enhancement process. Hence, this implementation is well suited for remote health care monitoring systems in clinical environment.

Table 2
Performance Contrast of Various Algorithms in Terms of EMSE for the Removal of Artifacts from Cardiac Signals (In dbs)

Noise Type	*Record Number*	*LMS*	*N^2LMS*	*N^3LMS*	*SRN^3LMS*	*SN^3LMS*	*SSN^3LMS*
PLI	101	–20.7484	–21.6782	–25.2846	–24.3879	–22.7483	–20.0984
	102	–19.6373	–20.8365	–26.6838	–25.1937	–24.4378	–23.4648
	103	–20.2937	–21.9036	–25.8653	–24.3739	–23.9378	–21.3394
	104	–20.9372	–21.6395	–26.4829	–25.9367	–24.5792	–23.9583
	105	–18.8362	–19.9465	–26.8573	–25.3692	–24.8836	–23.2744

Noise Type	*Record Number*	*LMS*	*N^2LMS*	*N^3LMS*	*SRN^3LMS*	*SN^3LMS*	*SSN^3LMS*
BW	101	–10.9373	–11.8452	–27.7541	–26.0383	–25.3683	–23.1748
	102	–10.0383	–11.7733	–27.5753	–26.9273	–25.9073	–24.7734
	103	–7.3737	–8.0387	–27.8653	–26.6172	–25.7308	–23.9728
	104	–11.1839	–12.7309	–23.2479	–22.3367	–21.1775	–20.5548
	105	–9.2844	–10.2737	–25.5254	–24.2963	–23.5985	–22.5776
MA	101	–11.9338	–12.9978	–20.8302	–19.0639	–20.6492	–19.2845
	102	–10.6358	–11.6262	–18.9274	–17.1163	–16.9582	–14.8465
	103	–10.2832	–11.6273	–18.4926	–17.9732	–16.1748	–15.9464
	104	–12.9383	–13.2214	–19.4849	–18.0074	–17.9274	–15.9365
	105	–11.9603	–12.7353	–18.9947	–17.6239	–16.1274	–15.6458
EM	101	–9.3173	–10.5367	–15.3748	–14.1834	–13.5264	–12.9453
	102	–9.9363	–10.6285	–15.9362	–14.8834	–13.7453	–12.7354
	103	–8.3603	–9.9516	–14.5529	–13.9539	–12.8374	–11.9945
	104	–11.9037	–12.3683	–18.3074	–17.3964	–16.3298	–14.3387
	105	–8.5249	–9.8538	–15.3902	–14.1035	–13.9464	–11.8454

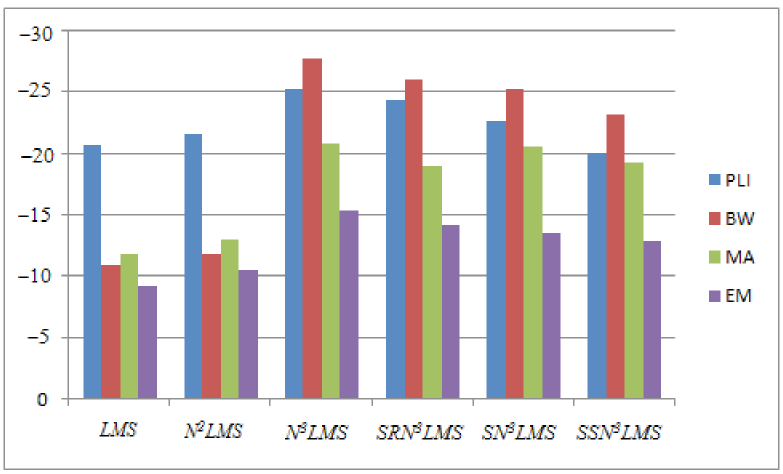

Figure 7: Comparison of EMSE in the ECG enhancement process

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