An Efficient and Low Complex Noise Canceler for ECG Signal Enhancement

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Abstract—In this paper, we present a simple and efficient signed regressor LMS (SRLMS) algorithm, that can be applied to ECG signal in order to remove various artifacts from them. This algorithm enjoys less computational complexity because of the sign present in the algorithm and good filtering capability because of the normalization in the signum function. As a result it is particularly suitable for applications requiring large signal to noise ratios with less computational complexity. Simulation studies show that the proposed realization gives better performance compared to existing realizations in terms of signal to noise ratio. The SRLMS algorithm mostly employs simple additions and one multiplication operation and achieves considerable speed up over the other LMS based realizations.

Keywords—adaptive noise canceler; artifact; ECG; sign regressor.

I. INTRODUCTION

The electrocardiogram (ECG) is a graphical representation of the cardiac activity and it is widely used for the diagnosis of heart diseases. Several noises contaminates the ECG signal while recording, 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 may be important for clinical monitoring and 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. The extraction of high-resolution ECG signals from recordings contaminated with background 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. In general these methods can be categorized in to non-adaptive and adaptive filtering. The non adaptive filtering approaches mainly include IIR filter, FIR filter and notch filter. In recent years, adaptive filtering techniques has become one of the most effective, popular approaches for the processing and analysis of the ECG and other biomedical signals [1]-[3]. 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. In [1], 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 these papers, the LMS algorithm operates on an instantaneous basis such that the weight vector is updated every new sample within the occurrence, based on an instantaneous gradient 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. Another strategy was considered to overcome this drawback for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [7]. In this algorithm the coefficient vector is updated only once every occurrence based on a block gradient estimation. In all these algorithms no effort has been made to reduce the computational complexity of the adaptive algorithm employed to cancel the noise from ECG signals.

Complexity reduction of the noise cancelation 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 increase. 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 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 affecting the signal quality. In order to achieve this, we considered the signed regressor LMS (SRLMS) algorithm [5]-[6]. The simulation results show that the performance of the proposed adaptive filter is better than the LMS based adaptive filter.

II. SIGNED REGRESSOR LMS ALGORITHM FOR REMOVAL OF NOISE FROM ECG SIGNAL

Consider a length L LMS based adaptive filter, depicted in Fig. 1, that takes an input sequence x(n), generates the output y(n) as per the following:

\[ y(n) = w^t(n)x(n), \]  
(1)

and updates the weights as,

\[ w(n + 1) = w(n) + \mu x(n)e(n), \]  
(2)

The computational complexity of the two algorithms are calculated and shown in Table I. Among the two algorithms the SRLMS is less complex. The conventional LMS algorithm requires \( L+1 \) MACs. Whereas the SRLMS algorithm requires \( L+1 \) additions and only one multiplication. Moreover, it should be noted that the computational complexity is independent of filter length. The convergence characteristics of various algorithms are shown in Fig.2. From the convergence curve also, it is clear that SRMLS is just inferior to LMS.

Where \( w(n) = [w0(n), w1(n), \ldots, wL−1(n)]^t \) is the tap weight vector at the \( n \)th index, \( x(n) = [x(n), x(n − 1), \ldots, x(n − L + 1)]^t \), \( e(n) = M(n) − w^t(n)x(n) \), with \( M(n) \) being the so-called desired response available during initial training period and \( \mu \) denoting the so-called step-size parameter.

\[ w(n + 1) = w(n) + \mu \text{sgn}(x(n)) e(n), \]  
(4)

where \( \text{sgn}(\cdot) \) is the well known signum function.

Between the two adaptive algorithms presented above, the SRA 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 SRA is much less compared to LMS algorithm.

Figure 2. Convergence Characteristics of various algorithms.

III. SIMULATION RESULTS

In order to prove the filtering capability of the proposed SRLMS based adaptive filter we have 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). 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 10mV range. In the simulation we collected the first 4000 samples of ECG signal, a random noise with variance of 0.001 was added to the ECG signals to evaluate the performance of the algorithm. Through out the work step-size parameter (\( \mu \)) is chosen as 0.001.
and the filter length as 5. The performance contrast of LMS and SRLMS algorithms for artifacts cancelation are shown in Table II. For the evaluating the performance of the proposed filter the SNR improvement is measured and compared with LMS algorithm. Table II shows the contrast of the both algorithms in SNR. From computed SNR values it is clear that the SRLMS algorithm performs better for the removal of non stationary noise like base line wander, muscle artifacts and motion artifacts.

A. Baseline Wander Removal

The drift of the baseline with respiration can be represented by a sinusoidal component at the frequency of the respiration added to the ECG signal. The amplitude and the frequency of the sinusoidal component should be variables. To prove baseline wander (BW) removal we have taken a real ECG signal with natural BW (data 105) and is applied as primary input to the adaptive filter of Fig.1. A low amplitude synthetic BW is generated with frequency 0.5Hz and is applied as the reference signal. The adaptive filter was implemented using the LMS and normalized signed regressor LMS algorithms to study the relative performance and results are plotted in Fig.3. The LMS algorithm gets SNR after filtering 2.8486dB, where as SRLMS algorithm gets 6.3729dB.

Figure 3. Typical filtering results of baseline wander reduction (a) MIT-BIH record 105 with natural baseline wander, (b) recovered signal using LMS algorithm, (c)recovered signal using Signed regressor LMS algorithm.

B. Power-line Interference Removal

Power-line interference is a most common source of noise during ECG recording. Adaptive filtering can track the statistical nature of the noise by updating filter coefficients and finally eliminates the noise. To demonstrate power line interference cancelation we have chosen MIT-BIH record number 105. The input to the filter is original ECG signal and is corrupted with synthetic PLI of amplitude 1mv and frequency 60Hz, sampled at 200Hz. The synthesized PLI is given as

reference. These results are shown in Fig.4. In SNR measurements it is found to be signed regressor LMS algorithm gets SNR after filtering 6.3511dB, where as the conventional LMS

Figure 4. Typical filtering results of PLI Cancelation (a) ECG with 60Hz noise, (b) recovered signal using LMS algorithm, (c) recovered signal using Signed regressor LMS algorithm.

was taken from the MIT-BIH NSTDB. This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrythmias. The MA originally had a sampling frequency of 360Hz and therefore they were anti-alias re-sampled to 128Hz in order to match the sampling rate of the ECG. The filtering performance of both algorithms are shown in Fig.5. The SNR after filtering for Signed regressor LMS algorithm is 7.6006dB, and conventional LMS algorithm gets 3.7049dB. From this result it is clear that SRLMS is more suitable for non-stationary artifact removal.

C. Muscle Artifacts Removal

To show the filtering performance in the presence of non-stationary noise, ECG with real artifacts are considered in this experiment. The real muscle artifact (MA)
signal using Normalized Signed regressor LMS algorithm.

**Table I: A COMPUTATIONAL COMPLEXITY COMPARISON TABLE**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>No of Additions</th>
<th>No of Multiplications</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMS</td>
<td>L + 1</td>
<td>L + 1</td>
</tr>
<tr>
<td>SRLMS</td>
<td>L + 1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table II: PERFORMANCE CONTRAST OF LMS AND SRLMS ALGORITHMS FOR THE CANCELATION OF ARTIFACTS**

<table>
<thead>
<tr>
<th>Type of Noise</th>
<th>Algorithm</th>
<th>SNR Before Filtering (in dBs)</th>
<th>SNR After Filtering (in dBs)</th>
<th>SNR Improvement (in dBs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BW</td>
<td>LMS</td>
<td>1.25</td>
<td>4.0986</td>
<td>2.8486</td>
</tr>
<tr>
<td></td>
<td>SRLMS</td>
<td>1.25</td>
<td>7.6229</td>
<td>6.3729</td>
</tr>
<tr>
<td>PLI</td>
<td>LMS</td>
<td>1.25</td>
<td>5.3963</td>
<td>4.1463</td>
</tr>
<tr>
<td></td>
<td>SRLMS</td>
<td>1.25</td>
<td>7.6011</td>
<td>6.3511</td>
</tr>
<tr>
<td>MA</td>
<td>LMS</td>
<td>1.25</td>
<td>4.9549</td>
<td>3.7049</td>
</tr>
<tr>
<td></td>
<td>SRLMS</td>
<td>1.25</td>
<td>8.8506</td>
<td>7.6006</td>
</tr>
<tr>
<td>EM</td>
<td>LMS</td>
<td>1.25</td>
<td>5.7501</td>
<td>4.5001</td>
</tr>
<tr>
<td></td>
<td>SRLMS</td>
<td>1.25</td>
<td>9.5276</td>
<td>8.2776</td>
</tr>
</tbody>
</table>

**D. Electrode Motion Artifacts Removal**

Motion artifacts are transient base line changes caused by changes in the electrode-skin impedance with electrode motion (EM). The usual cause of motion artifacts are vibrations or movements of the subjects. The peak amplitude and duration of this artifact are variable. Here the non stationary real electrode motion artifact (EM) is taken from the MIT-BIH NSTDB. The ECG signal of record 105 is corrupted with real EM. Both LMS and SRLMS algorithms are applied to clean the ECG signal and the results are shown in Fig. 6. The SNR improvements for Signed regressor LMS algorithm is 8.2776dB, that for conventional LMS algorithm are found as 4.5001dB.

Figure 6. Typical filtering results of motion artifacts removal (a)ECG with real motion artifacts, (b) recovered signal using LMS algorithm, (c) recovered signal using Signed regressor LMS algorithm.

**IV. CONCLUSION**

In this paper the problem of artifact cancelation from ECG signal using normalized signed regressor LMS based adaptive filter is proposed and tested on ECG signals with different artifacts 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. From the simulated results it is clear that SRLMS removes non-stationary noise efficiently. The proposed treatment provides high signal to noise ratio with less computational complexity. The computational complexity in terms of computational burden and SNR contrast are shown in Tables I and II. Hence the proposed SRLMS based adaptive filter is more suitable for wireless biotelemetry ECG systems.

**REFERENCES**


