Adaptive Power Line Interference Removal from Cardiac Signals Using Leaky Based Normalized Higher Order Filtering Techniques

Thumbur Gowri  Injeti Sowmya  Zia Ur Rahman  Rama Koti Reddy Dodda
Dept. of ECE  Dept. of ECE  Dept. of ECE  Dept. of Inst. Technology
GIT, GITAM University  GIT, GITAM University  K L University  Andhra University
Visakhapatnam, A.P, India  Visakhapatnam, A.P, India  Vaddeswaram, A.P, India  Visakhapatnam, A.P, India
gowri3478@yahoo.com  sowmyainjeti@gmail.com  mdzr55@gmail.com  rkreddy_67@yahoo.co.in

Abstract—In this paper we present an adaptive filter for denoising the ECG signal based on Least Mean Fourth (LMF) algorithms. LMF algorithm exhibits lower steady state error than the conventional LMS algorithm. This is due to the fact that the excess mean-square error of the LMS algorithm is dependent only on the second order moment of the noise. The second order moment, or variance of the noise evaluates to be same for all the noise environments. Based upon this other types of mean fourth based algorithms are implemented. These are Normalized LMF (NLMF) and Error Normalized LMF (ENLMF). In order to increase the stability of the filter leakage factor is introduced. Based on these considerations Normalized Leaky LMF (NLLMF) and Error Normalized Leaky LMF (ENLLMF) adaptive cancellers are developed for cardiac signal enhancement. Different filter structures are presented to eliminate the 60 Hz power line interference from the ECG signal. Finally, we have applied this algorithm on ECG signals from the MIT-BIH data base and compared its performance with the conventional LMS algorithm. The results show that the performance of the ENLLMF based noise reduction filter is superior than the other implementations in terms of signal to noise ratio increment.

Keywords—adaptive noise cancellation; artifacts; ECG signals; LMS; LMF.

I. 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) and Power-line Interference (PLI). These artifacts strongly affects the ST segment, degrades the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST wave forms and masks tiny features that are important for clinical monitoring and diagnosis. Cancellation 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 [1,2,3,4,5,6], adaptive filtering techniques permit to the detect time varying potentials and to track the dynamic variations of the signals. In [2], Thakor et al. proposed 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 deterministic reference inputs showed that the steady-state weight vector is biased and thus the adaptive estimate does not approach the Wiener solution [7]. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [8], 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 [9], 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 [10], subtraction procedure without affecting the components of ECG signal [11], Sayadi et al. [12] proposed bionic wavelet transform for the correction of baseline drift and Sameni et al. [13] 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 [14], a variable step size NLMS algorithm with faster convergence rate [15], Costa et al. in [16] 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 [17,18,19,20].

Recently in [21] Rahman et al. presented several less computational complex adaptive algorithms in time domain, but these algorithms exhibits slower convergence rate. A small modification to NLMS algorithm results a variable step is inversely proportional to the squared norm of the error vector. The length of the error vector is the instantaneous number of iterations. Because the step size is normalized with reference to error this algorithm is called as Error Normalized LMS (ENLMS) algorithm. Thus far, to the best of the author’s knowledge, LMF algorithm is not used in the context of ECG signal noise cancellation. In this paper various LMF based adaptive filter structures are presented to eliminate different kinds of noises from cardiac signals. These are NLMF and ENLMF algorithms. However in critical conditions some of the samples in the ECG signal become zeros, i.e., the excitation is inadequate. At these samples the weights vary drastically. The fluctuations in weights are called weight drift. By introducing a small leakage factor we can overcome this problem. The resultant algorithm is called Leaky LMF (LLMF) algorithm. The variants of these algorithms are NLLMF and ENLLMF algorithms. Finally 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. To show the performance of the considered algorithms we measured signal to noise ratio improvement (SNRt). The structure of the paper is as follows. In Section II, the fundamentals of LMS algorithms and developments of related algorithms for removal of PLI are discussed. In Section III we have discussed about the Simulation results using Mat Lab for PLI noise removal using LMS, LMF NLLMF and ENLLMF algorithms. Finally conclusions are presented in Section IV.

II. PROPOSED IMPLEMENTATION
Consider a length \( L \), LMS based adaptive filter as depicted in Fig. 1 which takes an input sequence \( x(n) \) and updates the weights as

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

(1)

where, \( w(n) = [w_0(n), w_1(n), ..., w_{L-1}(n)]^T \) is the tap weight vector at the \( n \)th index,

\[x(n) = [x(n), x(n-1), ..., x(-1)]^T,
\]

error signal \( e(n) = d(n) - w'(n)x(n) \), with \( d(n) \) being so-called the desired response available during initial training period and \( \mu \) denoting so-called step-size parameter.

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

\[y(n) = w'(n)x(n).
\]

(2)

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

\[E[e^2(n)] = E[(s_t(n) - y(n))^2] + E[p_t^2(n)].
\]

(3)

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

A. The Least Mean Fourth (LMF) Algorithm

LMF algorithm is another class of adaptive algorithm used to train the coefficients the adaptive filter. The LMF algorithm is based on the minimization of the mean-fourth error cost function. The speed of convergence of this algorithm depends on the input signal statistics, or more specifically on the eigenvalue spread of the input autocorrelation matrix, and for convergence, the proper range of the step size has to be chosen. The tracking behavior of this algorithm is independent of the input data correlation statistics. Moreover the tracking capability in presence of non stationary noises is good.

The weight update relation for LMF algorithm is as follows:

\[w(n+1) = w(n) + \mu x(n) e(n)^4.
\]

(4)

Hence the LMF algorithm has a convergence rate and a steady state error better than LMS algorithm.

In ECG signal processing under critical conditions
some of the samples in the ECG signal becomes zero, i.e., the excitation is inadequate. At these samples the weights vary drastically. The fluctuations in weights is called weight drift problem. By introducing a small leakage factor we can overcome this problem. So here we make use of leaky LMF algorithm. The name stems from the fact that, when the input is turned off, the weight vector of the regular LMF algorithm stalls. With leaky LMF in the same scenario, the weight factor instead leaks out. It has been shown that leaky LMF can be used to improve stability in a finite-precision implementation, to ameliorate the effects of non-persistent excitation, and to reduce undesirable effects like stalling, bursting, etc. Detailed analysis of the performance of this algorithm is given in [24,25,26].

Now the weight update equation becomes

\[ w(n+1) = (1-\gamma)w(n) + \mu x(n)e(n)^3. \]  

(5)

B. Normalized Algorithms

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm takes into account variation in the signal level at the filter output and selecting the normalized step size parameter that results in good filtering as well as fast converging algorithm. In this algorithm step size is normalized with respect to input data sequence, this results instantaneous change in step size and resembles NLMS as a variable step size algorithm. The weight update relation for NLMS algorithm is as follows

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

(6)

The variable step can be written as

\[ \mu(n) = \frac{\mu}{p + x'(n)x(n)}. \]  

(7)

Here $\mu$ is fixed convergence factor to control maladjustment. The parameter $p$ is set to avoid denominator being too small and step size parameter too big. A common major drawback of adaptive noise cancellers using these LMS-based algorithms is the large value of excess mean-square error which results in signal distortion in the noise-canceled signal.

By combining LMF and NLMS we derive Normalized Least Mean Fourth (NLMF) algorithm, this algorithm enjoys both fast convergence and filtering capability because of the normalization factor and higher order. The weight update relation for NLMF algorithm is as follows:

\[ w(n+1) = w(n) + \frac{\mu x(n)e(n)}{p + x'(n)x(n)}. \]  

(8)

In another approach the step size can be normalized with respect to the error instead of data. Such an operation on LMS results Error Normalized LMS (ENLMS) algorithm. By combining LMF and ENLMS gives Error Normalized LMF (ENLMF) algorithm. The weight update relation for NLMF algorithm is as follows

\[ w(n+1) = w(n) + \frac{\mu}{p + e'(n)e(n)} x(n)e(n)^3. \]  

(9)

Using these algorithms, by introducing leaky factor to increase stability various filter structures are constructed to eliminate PLI from the ECG signals, these are NLLMF and ENLLMF algorithms.

III. SIMULATION RESULTS

To show that LMF based algorithms are really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDDB). In our simulations we considered PLI. 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. In our experiments we used a data set of five records (records 100, 101, 102, 103 and 104) but due to space constraint simulation results for record 101 are shown in this paper. Fig. 2 shows a clean ECG signal and its frequency spectrum. In our simulation we collected 4000 samples of ECG signal, a random noise with variance ($\sigma$) of 0.01 is added to the ECG signals. For evaluating the performance of the proposed adaptive filter we have also measured the SNR and compared with conventional LMS algorithm. For all the figures number of samples are taken on x-axis and amplitude on y-axis, unless stated.

Table I gives the contrast of the considered algorithms in terms of SNR improvement (SNRI).

![A clean ECG signal and its frequency spectrum.](image)

**Fig. 2. A clean ECG signal and its frequency spectrum.**

A. Adaptive Power-line Interference Canceller

To demonstrate power line interference (PLI) cancellation we have chosen MIT-BIH record number 101. The input to the filter is ECG signal corresponds to
the data 100 corrupted with PLI with amplitude 1mV and frequency 60Hz, sampled at 200Hz. The reference signal is synthesized PLI some what correlated with the noise component present in the contaminated ECG, the output of the filter is recovered signal. These results are shown in Fig.3. In SNRI measurements for the entire data set, it is found that ENLLMF algorithm gets SNRI 11.2086dB, NLLMF gets 9.8399, LMF gets 8.0268 where as the LMS algorithm improves 7.0642dB. Fig.4 shows the power spectrum of the noisy signal before and after filtering with LMS and ENLLMF algorithms.

![Fig. 3. Typical filtering results of PLI Cancellation (a) ECG (record 101) with 60Hz noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLLMF algorithm (e) recovered signal using ENLLMF algorithm.](image)

![Fig. 4. Typical filtering results of PLI Cancellation (a) ECG (record 103) with 60Hz noise, (b) recovered signal using LMS algorithm, (c) recovered signal using LMF algorithm, (d) recovered signal using NLLMF algorithm (e) recovered signal using ENLLMF algorithm.](image)

![Fig. 5. (a) Frequency spectrum of ECG with PLI, (b) Frequency spectrum after filtering with LMS algorithm, (c) Frequency spectrum after filtering with ENLLMF algorithm.](image)

### TABLE I. PERFORMANCE CONTRAST OF VARIOUS ALGORITHMS FOR THE CANCELLATION OF PLI IN TERMS OF SNRI (ALL VALUES ARE IN DECIBLES)

<table>
<thead>
<tr>
<th>Rec. No.</th>
<th>LMS</th>
<th>LMF</th>
<th>NLLMF</th>
<th>ENLLMF</th>
</tr>
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<tbody>
<tr>
<td>100</td>
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<td>8.1509</td>
<td>10.4605</td>
<td>11.5577</td>
</tr>
<tr>
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<td>7.0185</td>
<td>8.1008</td>
<td>10.1413</td>
<td>11.3036</td>
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<td>7.8522</td>
<td>10.2817</td>
<td>11.2097</td>
</tr>
<tr>
<td>103</td>
<td>7.0859</td>
<td>7.8070</td>
<td>7.8378</td>
<td>11.0324</td>
</tr>
<tr>
<td>103</td>
<td>7.0859</td>
<td>7.8070</td>
<td>7.8378</td>
<td>11.0324</td>
</tr>
<tr>
<td>104</td>
<td>7.0118</td>
<td>8.2231</td>
<td>10.4785</td>
<td>10.9398</td>
</tr>
<tr>
<td>Average</td>
<td>7.0642</td>
<td>8.0268</td>
<td>9.8399</td>
<td>11.2086</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

In this paper the process of PLI removal from ECG signal using LMF based adaptive filtering is presented. In this attempt we have implemented various filter structures using LMF, NLLMF and ENLLMF algorithms. 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. The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed over the respective LMS based realizations. Our simulations, however, confirm that the performance of the ENLLMF and NLLMF is better than the LMS algorithm in terms of SNRI, this is shown in Table I. Hence ENLLMF based adaptive noise canceller may be used in all practical applications.
REFERENCES