ISSN:2249-5789
Mohammad Zia-Ur-Rahman et al, International Journal of Computer Science & Communication Networks,Vol 1(1),September-October 2011

Noise Removal from Electrocardiogram Signals using Leaky and Normalized version of Adaptive Noise Canceller

Sk. Nore Johny Basha, Mohammad Zia-Ur-Rahman and Dr B V Rama Mohana Rao
Dept. of E.C.E., Narasaraopeta Engg. College, Narasaraopeta-522 601, India
E-mail: mdzr_5@ieee.org

Abstract— *Adaptive filter is a primary method to filter electrocardiogram (ECG) or Cardiac signal, because it does not need the signal statistical characteristics. In this paper we present an adaptive filter for denoising the ECG signal based on Leaky Normalized Least Mean Square (LNLMS) algorithm. The adaptive filter 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: baseline wander and 60 Hz power line interference. 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 LNLMS based algorithm is superior to that of the LMS based algorithm in noise reduction.*

Keywords – *adaptive noise cancelation, artifacts, ECG signals, LMS algorithm., Noise cancelation.*

1. INTRIDUCTION

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 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]-[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]-[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 Nonlinearity LMS (LNLMS) algorithm. Thus far, to the best of the author’s knowledge, LNLMS algorithm is not used in the contest of ECG signal noise cancelation. In this paper various adaptive filter structures are presented to eliminate different kinds of noises from cardiac signals. 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. The simulation result shows that the performance of LNLMS algorithm is better than the LMS counterpart.

2. PROPOSED IMPLEMENTATION

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

$$w(n+1) = w(n) + \mu\, x(n)\, e(n); \qquad (1)$$

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

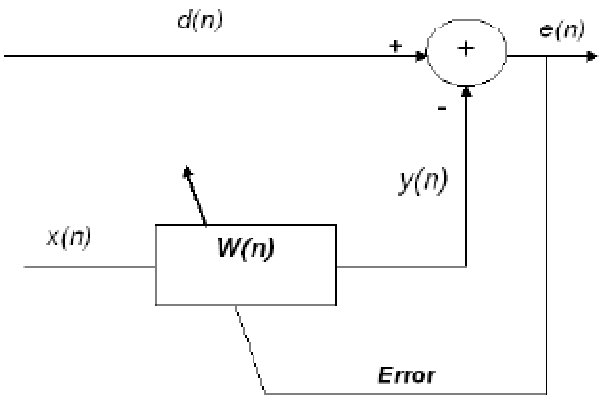

Fig. 1. Adaptive filter structure

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 $p1(n)$ 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,

$$y(n) = w^t(n)x(n); \qquad (2)$$

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

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

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

The LMS algorithm is use widely in numerous applications because of its simplicity. The direct implementation of LMS algorithm is sensitive to round-off errors and causes some other disturbances as the weight update equation is essentially an integrator [24]. For example, inadequate excitation in the input sequence can result an unbounded parameter estimates. By introducing a small leakage factor γ to the tap-weight vector should protect the algorithm from such numerical problems. Now the weight update equation becomes

$$w(n+1) = (1 - \mu\gamma)w(n) + \mu e(n)X^*(n) \qquad (4)$$

In the above recursion it is chosen such that the product $\mu\gamma$ is greater than but close to 0. The leaky LMS algorithm (LLMS) has been used to improve the characteristics of an adaptive filter, few are listed below [25].

1. Ill conditioned input signal ie., it is useful for improving the convergence properties when the input correlation matrix is ill-conditioned. As a result, the input correlation matrix will exhibit unbalanced values on the main diagonal. In this manner we can increase the energy of values at the main diagonal and therefore regularize the correlation matrix.
2. Algorithm stalling when the correction term is too small.
3. Overflow due to finite-precision arithmetic.

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 a stable as well as fast converging algorithm. The weight update relation for NLMS algorithm is as follows

$$w(n+1) = w(n) + \left[\frac{\mu}{p + x^t(n)x(n)}\right] x(n)\, e(n) \qquad (5)$$

The variable step can be written as,

$$\mu(n) = \frac{\mu}{p + x^t(n)x(n)} \qquad (6)$$

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. 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-cancelled signal.

By combining LLMS and NLMS we derive Leaky NLMS (LNLMS) algorithm, this algorithm enjoys both stability and filtering capability because of the leaky component and normalization factor. The weight update relation for LNLMS algorithm is as follows

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

The variable step can be written as,

$$\mu(n) = \frac{1-\mu\gamma}{p + x^t(n)x(n)} \qquad (8)$$

3. SIMULATION RESULTS

To show that LNLMS algorithm is 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 MITBIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). In our simulations we consider both stationary (PLI) and non-stationary (BW) noises. 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 101, 102, 103, 104 and 105) but due to space constraint simulation results for record 100 are shown in this paper. In our simulation we collected 4000 samples of ECG signal, a random noise with variance (¾) of 0.001, 0.01 and 0.1 is added to the ECG signals to evaluate the performance of the algorithm in terms of minimum MSE (MMSE), MSE, excess MSE (EMSE) and misadjustment (M). For evaluating the performance of the proposed adaptive filter we have also measured the 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. Table I gives the contrast of the considered algorithms in terms of SNR improvement (SNRI).

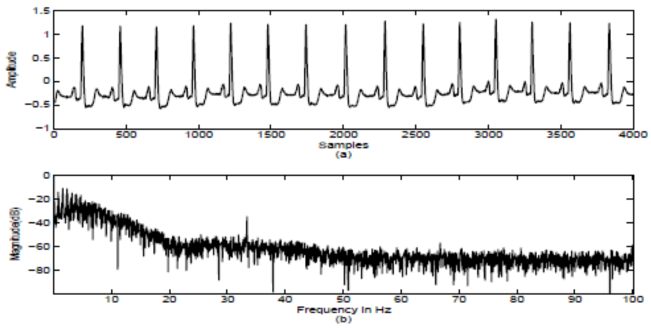

Fig. 2. MIT-BIH recorded ECG signal (data 105) and its frequency spectrum.

A. Baseline Wander Reduction

In this experiment, first we collected 4000 samples of the pure ECG signal from the MIT-BIH arrhythmia database(data100) and it is corrupted with real baseline wander (BW) taken from the MIT-BIH Noise Stress Test Database (NSTDB). This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrhythmias. The contaminated ECG signal is applied as primary input to the adaptive filter of Fig.1. The real BW is given as reference signal. Different filter structures were implemented using the LMS and LNLMS algorithms to study the relative performance and results are plotted in Fig.2. The LMS algorithm gets SNR improvement 5.3286dB, where as LNLMS gets 9.4863dB.

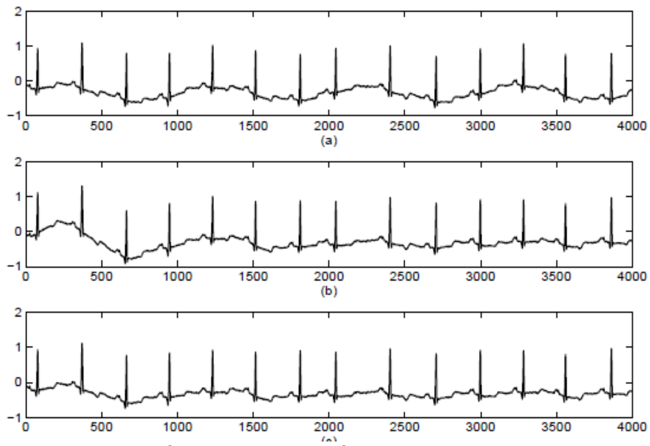

Fig. 3. Typical filtering results of baseline wander reduction (a) ECG with real BW (b) recovered signal using LMS algorithm, (c) recovered signal using LNLMS algorithm.

B. Adaptive Power-line Interference Canceller

To demonstrate power line interference (PLI) cancelation we have chosen MIT-BIH record number 100. The input to the filter is ECG signal corresponds to the data 100 corrupted with synthetic PLI with amplitude 1mv and frequency 60Hz, sampled at 200Hz. The reference signal is synthesized PLI, the output of the filter is recovered signal. These results are shown in Fig.3. In SNR measurements it is found that LNLMS algorithm gets SNR improvement 11.3728dB, where as the LMS algorithm improves 7.6815dB. Fig.4 shows the power spectrum of the noisy signal before and after filtering with LMS and LNLMS algorithms.

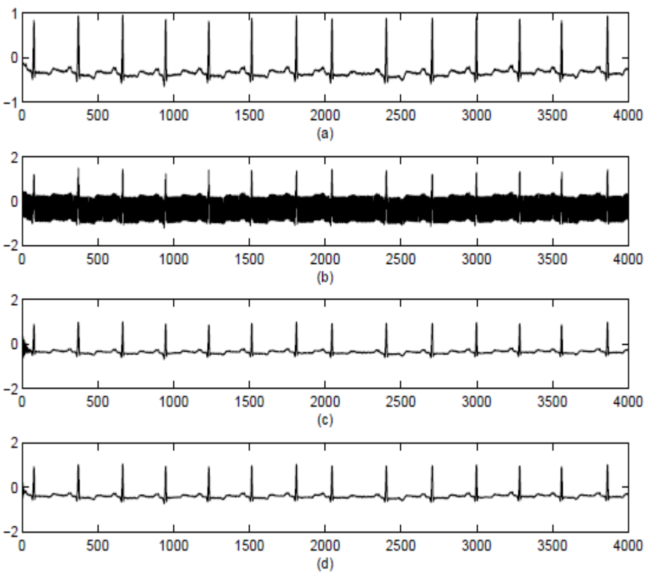

Fig. 4. Typical filtering results of PLI Cancelation (a) clean MIT-BIH record 100, (b) ECG with 60Hz noise, (c) recovered signal using LMS algorithm, (d) recovered signal using LNLMS algorithm.

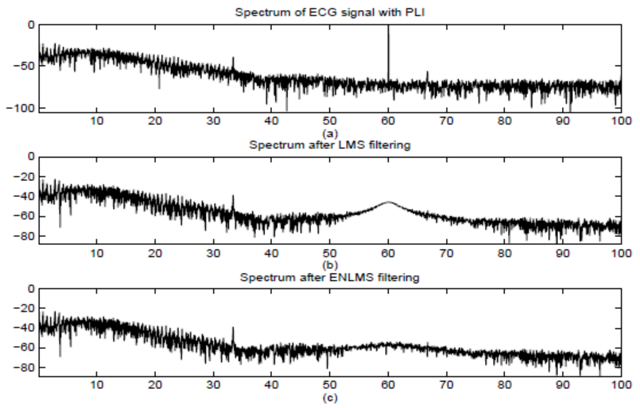

Fig. 5. (a) Frequency spectrum of ECG with PLI, (b) Frequency spectrum after filtering with LMS algorithm, (c) Frequency spectrum after filtering with LNLMS algorithm.

TABLE I
PERFORMANCE CONTRAST OF LMS AND LNLMS ALGORITHMS FOR THE CANCELATION OF ARTIFACTS (ALL VALUES ARE IN DECIBELS)

Noise	Rec. No	SNRI after LMS	SNRI after LNLMS
BW	100	5.2387	9.8429
	101	5.5376	9.7891
	102	4.9744	8.6820
	103	5.4557	9.4072
	104	5.4370	9.7105
	Average	5.3286	9.4863
PLI	100	7.8700	11.7140
	101	7.9841	11.8843
	102	6.5674	10.9553
	103	8.2735	11.0548
	104	7.7129	11.2560
	Average	7.6815	11.3728

4. CONCLUSION

In this paper the process of noise removal from ECG signal using LNLMS based adaptive filtering is presented. 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 LNLMS is better than the LMS algorithm in terms of SNRI, MSE and misadjustment, this is shown in tables I and II. Hence LNLMS based adaptive noise canceller may be used in all practical applications.

REFERENCES

[1] Y. Der Lin and Y. Hen Hu, "Power-line interference detection and suppression in ECG signal processing," *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 354-357, January, 2008.
[2] N. V. Thakor and Y. S. Zhu, "Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection," *IEEE Transactions on Biomedical Engineering*, vol. 38, no. 8, pp. 785-794, August, 1991.
[3] J. M. Leski and N. Henzel,"ECG baseline wander and power line interference reduction using nonlinear filter bank," *Signal Processing*, vol. 85, pp. 781-793, 2005.
[4] C. Meyer, J. F. Gavela, and M. Harris,"Combining algorithms in automatic detection of QRS complexes in ECG signals," *IEEE Transactions on Information Tech. in Biomedicine*, vol. 10, no. 3, pp. 468-475, July, 2006.
[5] C. Brouse, G. A. Bumont, F. J. Herrmann, and J. M. Ansermino, "A wavelet approach to detecting electrocautery noise in the ECG," *IEEE Eng. Med. and Biol. Mag.*, vol. 25, no. 4, pp. 76-82, August, 2006.
[6] P. Laguna, R. Jan, S. Olmos, N. V. Thakor, H. Rix, and P. Caminal, "Adaptive estimation of QRS complex by the Hermite model for classification and ectopic beat detection," *Med. Biol. Eng. Comput.*, vol. 34, no. 1, pp. 58-68, January, 1996.
[7] S. Olmos and P. Laguna, "Steady-state MSE convergence analysis in LMS adaptive filters with deterministic reference inputs for biomedical signals, *IEEE Transactions on Signal Processing*, vol. 48, pp. 2229-2241, August, 2000.
[8] S. Olmos, L. Sornmo and P. Laguna, "Block adaptive filter with deterministic reference inputs for event-related signals : BLMS and BRLS," *IEEE Transactions on Signal Processing*, vol. 50, pp. 1102-1112, May, 2002.
[9] M. Kotas, "Application of projection pursuit based robust principal component analysis to ECG enhancement," *Biomedical Signal Processing and Control*, vol. 1, pp. 289-298, February, 2007.
[10] Floris. E, A. Schlaefer, S. Dieterich and A. Schweikard, "A Fast Lane Approach to LMS prediction of respiratory motion signals," *Biomedical Signal Processing and Control*, vol. 3, pp. 291-299, July, 2008.
[11] G. Mihov and I. Dotsinsky, "Power-line interference elimination from ECG in case of non-multiplicity between the sampling rate and the powerline frequency," *Biomedical Signal Processing and Control*, vol. 3, pp. 334-340, June,2008.
[12] O. Sayadi and M. B. Shamsollahi, "Model-based fiducial points extraction for baseline wander electrocardiograms," *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 347-351, January, 2008.
[13] Sameni. R, Shamsollahi. M. B, Jutten. C, Clifford. G. D, "A nonlinear Bayesian filtering framework for ECG denoising," *IEEE Transactions on Biomedical Engineering*, vol. 54, pp. 2172-2185, December, 2007.
[14] Ching-An Lai, "NLMS algorithm with decreasing step size for adaptive IIR filters," *Signal Processing*, vol. 82, pp. 1305-1316, 2002.
[15] Ning Li, Y. Zhang, Yanling. H and J. A. Chambers, "A new variable stepsize NLMS algorithm designed for applications with exponential decay impulse responses," *Signal Processing*, vol. 88, pp. 2346-2349, March, 2008.
[16] M. H. Costa and J. C. M. Bermudez, "A noise resilient variable step-size LMS algorithm," *Signal Processing*, vol. 88, pp. 733-748, 2008.
[17] D. S. Brito, E. Aguiar, F. Lucena, R. C. S. Freire, Y. Yasuda and A. K. Barros, "Influence of low frequency noise in adaptive estimation using the LMS algorithm," *Signal Processing*, vol. 89, pp. 933-940, 2009.
[18] Ning Li, Y. Zhang, Y. Zhao and Yanling. H, "An improved variable taplength LMS algorithm," *Signal Processing*, vol. 89, pp. 908-912, 2009.
[19] S. Zhao, Z. Manb, S. Khoo and Hong. R. W, "Variable step-size LMS algorithm with a quotient form," *Signal Processing*, vol. 89, pp. 67-76, 2009.
[20] A. I. Sulyman and A. Zerguine, "Convergence and steady-state analysis of a variable step-size NLMS algorithm," *Signal Processing*, vol.83, pp. 1255-1273, 2003.
[21] M. Z. U. Rahman, S. R. Ahamed and D. V. R. K. Reddy, " Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ECG signals : Application to wireless biotelemetry", *Signal Processing*, vol. 91, pp. 225-239, Feb, 2011.
[22] S. C. Douglas and Teresa H.-Y. Meng, "Normalized Data Nonlinearities for LMS Adaptation," *IEEE Transactions on Signal Processing*, vol. 42, pp. 1352-1365, June, 1994.
[23] S. C. Douglas,"A Family of Normalized LMS Algorithms," *IEEE Signal Processing Letters*, vol. 1, pp. 1352-1365, March, 1994.
[24] K. Mayyas and Tyseer Aboulnasr, " Leaky LMS Algorithm: MSE Analysis for Gaussian Data", *IEEE Trans. Signal Processing*, vol. 45, no. 4, pp. 927-934, April, 1997.
[25] Orlando Jos Tobias and Rui Seara, "Leaky-FXLMS Algorithm: Stochastic Analysis for Gaussian Data and Secondary Path Modeling Error", *IEEE Trans. on Speech and Audio Processing*, vol. 13, no. 6, pp. 1217- 1230, November, 2005.