Australian Journal of Basic and Applied Sciences, 10(6) March 2016, Pages: 135-141

AUSTRALIAN JOURNAL OF BASIC AND APPLIED SCIENCES

ISSN:1991-8178 EISSN: 2309-8414
Journal home page: www.ajbasweb.com

Reduction of Artifacts from ECG Signal Using Efficient Fast Block LMF Based Adaptive Algorithm

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ARTICLE INFO

Article history:
Received 12 February 2016
Accepted 12 March 2016
Available online 20 March 2016

Keywords:
Adaptive filter, Artifacts, ECG, Noise Cancellation.

ABSTRACT

In the biotelemetry system, it is very important to extract high resolution and valid ECG signal from the corrupted Signal. When acquiring ECG signal in the laboratory, it undergoes several artifacts, which strongly degrades the signal quality. The predominate artifacts in ECG signal are Power Line Interference, Muscle Artifacts, Baseline Wander, Electrode Motion Artifacts; and sometimes channel noise also added during transmission. The tiny features of (PQRST) ECG signal are masked due to these noises. Adaptive filters are best choice to monitor these random variations in noisy signals. In this paper, we proposed less computational efficient Fast Block Leaky LMF based adaptive algorithms. These algorithms are used to remove PLI and EM artifacts from ECG signals. We compared these proposed algorithms with Block LMS algorithm, which shows better performance in reducing artifacts in ECG signal. The simulation results show that, less computational complexity (time delay calculation) is required for Fast Block LMF based adaptive algorithm and gives good Signal to Noise Ratio.

INTRODUCTION

In this industrialized world, ever year, millions of people suffer cardiovascular disease (CVDs) (WHO 2005) reported by the World health organization, because they are not treated promptly. Biotelemetry is an effective tool for the diagnosis of cardiac abnormalities, when the patient is far from specialist help, there a doctor analyzes the signal and decides on what action to be taken, the decision sent to the patient site for immediate action (Derya *et.al* 2011 and McMurray *et.al* 2005).

In clinical laboratory when we acquiring ECG signal, the signal sometimes corrupted by numerous types of artefacts. The commonly occurred artefacts are Power Line Interference (PLI) (Suzanna *et.al* 1996), Baseline Wander (BW) (Sayadi *et.al* 2007), Electrode Motion (EM) (Wiese *et.al* 2005) and Muscle Artefacts (MA). These artefacts strongly affect the signal quality and are very important for clinical monitoring, diagnosis and making their efficient cancellation imperative. Therefore the separation of pure quality ECG signal from background noise corrupted ECG signal is a great importance for examination. So by using filtering techniques we have to distinct valid signal can be separated from the undesired artefacts.

Filtering is used to process a signal either to enhance the Signal to Noise Ratio (SNR) or to eliminate certain types of noises. In biomedical signal analysis when the input signal and artifacts are both stationary and their statistical characteristics are approximately known, and then an optimal filter like a Wiener filter or a matched filter can be used. In practical cases like biomedical signal analysis, a priori information is not available or when the signal or noise is non-stationary; then optimal design is not possible (Widrow *et.al* 1975 and Patrick

To Cite This Article: Gowri T. and Rajesh Kumar P.., Reduction of Artifacts from ECG Signal Using Efficient Fast Block LMF Based Adaptive Algorithm. ***Aust. J. Basic & Appl. Sci.**, 10(6): 135-141, 2016*

et.al 1996). In such a case adaptive filter has an ability to adjust their weight coefficients based on the incoming signal.

(Thakor, *et.al* 1991) presented an adaptive recurrent filter to remove muscle noise using LMS algorithm, which is useful method to acquire the impulse response of the normal QRS complex. The cancellations of baseline wanders, power line interferences by using an efficient finite impulse response and state space recursive least square filter with a reduced number of taps are described in (Van Alste. *et.al* 1985, Razzaq. *et.al* 2013, Rehman. *et.al* 2012, Robertson. *et.al* 2011). (Manuel *et.al* 2008) developed an ECG signal enhancement method based on the empirical mode decomposition for non stationary signals.

In this paper, we proposed three algorithms: Fast Block Leaky LMF (FB-LLMF), Data Normalized Fast Block Leaky LMF (DNFB-LLMF), Error Normalized Fast Block Leaky LMF (ENFB-LLMF) and for double validation we considered FB-LLMFtoFB-LLMF algorithm. These algorithms are derived from block LMS algorithms. The efficiency of the proposed algorithms is taken by the removal of noises from ECG signals under unconventional conditions such as ECG signal with PLI and EM artefacts. The simulation results shows that FB-LLMFtoFB-LLMF algorithm and ENFB-LLMF algorithm gives the better elimination of noises present in the ECG signal of less computational complexity.

Different Adaptive Noise Cancellers:

The adaptive filter structure for noise cancellation is shown in the Fig. 1. Let the reference input to the filter assigned as **x(**s). The tap inputs x(s), x(s – 1), x(s – 2), ... x(s –M + 1) forms the elements of the M-by-1 tap input vector **x**(s), Correspondingly, the weight vector represented as $w(s) = [w_0, w_1, ...w_{M-1},]^T$. The output y(s) is the FIR filter output.

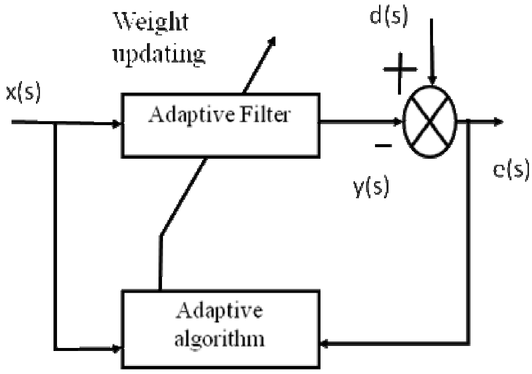

Fig. 1: Adaptive filter structure.

The error e(s) is defined as the difference between the desired response d(s) and the actual response y(s) i.e. e(s)= d(s) – y(s). The reqcursive weight equation for the LMS algorithm is as follows.

$$\boldsymbol{w}(s+1) = \boldsymbol{w}(s) + \mu e(s)\boldsymbol{x}(s) \tag{1}$$

The convergence of the LMS algorithm (Haykin *et.al* 1986) and mean square value mainly depends on the step size parameter μ, its value is chosen according to steepest decent phenomena is 2/ λ_{max}, where λ_{max}, is the maximum value in the input auto correlation matrix.

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 are varies drastically. The fluctuations in weights is called weight drift problem. For the tap weight vector in (1), we place small leakage factor γ, then in that algorithm the weight drift problem can be minimized (Gowri. *et.al* 2013, 2014 and Tobias. *et.al* 2004). This algorithm is known as the leaky LMS (LLMS) algorithm. The weight update equation for the LLMS algorithm is as follows.

$$\boldsymbol{w}(s+1) = (1-\mu\gamma)\boldsymbol{w}(s) + \mu e(s)\boldsymbol{x}(s) \tag{2}$$

In the above recursion (2), the product $\mu\gamma$ is much closer to zero.

In order to achieve lower steady state error (Walach *et.al* 1984) and increasing stability, compared to the conventional LMS algorithm, we combine the features of LMF and LLMS. The resultant algorithm is Leaky Least Mean Fourth (LLMF) algorithm and mathematically it can be written as follows.

$$\boldsymbol{w}(s+1) = (1-\mu\gamma)\boldsymbol{w}(s) + \mu\{e^3(s)\}\boldsymbol{x}(s) \tag{3}$$

Development of Efficient Fast Block Leaky LMF Based Adaptive Algorithm:

When input signal length is large then amount of adaptive filter length also required excessively long lengths. In such cases, the conventional LMS algorithm, which is simple, is computationally expensive to implement. The block processing of the data samples can significantly reduce the computational complexity of adaptive filters (Farhang-Boroujeny. *et.al* 1998, 2000). A typical block adaptive filter structure is shown in Fig. 2. From the figure we can observe that input signal is converted into parallel form as a specified length of the filter. Finally the result is obtained using parallel to serial converter.

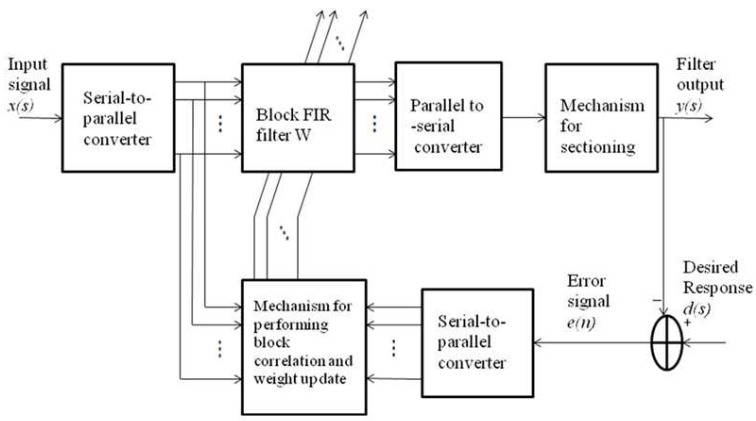

Fig. 2: Block Adaptive filter structure.

In the Block LMS algorithm the computations are reduced with the help of Fast Fourier Transform (FFT) technique. For evaluating of FFT we used overlap and save method. This FFT technique gives high resolution and good accuracy. The input sequence x(s) is divided into non-overlapping blocks of length T using serial to parallel converter. These blocks of data are applied to an FIR filter of length M, one block at a time. So the processing is based on block by block (Haykin *et.al* 1986). The best results are achieved to choose filter length is equal to the block length. Let for the j^{th} block the weight vector for Block LMS is given as

$$\boldsymbol{w}(j+1)=\boldsymbol{w}(j)+\mu\sum_{i=0}^{T-1}\boldsymbol{x}(jT+i)e(jT+i) \tag{4}$$

Where μ is step size parameter. We considered, $\boldsymbol{w}(j)$ is weight vector, $\boldsymbol{x}(jT+i)$ is the input filter coefficients and $e(jT+i)$ is output error. The filter output is written as,

$$y(jT+i)=\boldsymbol{w}^{T}(j)\boldsymbol{x}(jT+i) \tag{5}$$

The output error is given by

$$e(jT+i)=d(jT+i)-y(jT+i) \tag{6}$$

To achieve better filtering capability, for the elimination of weight drift problem and reduced steady state error we added to LLMF algorithm to (3), then the modified weight update equation for B-LLMF algorithm in time domain is given by

$$\boldsymbol{w}(j+1)=(1-\mu\gamma)\boldsymbol{w}(j)+\mu\sum_{i=0}^{T-1}\boldsymbol{x}(jT+i)e^{3}(jT+i) \tag{7}$$

The computational complexity is more for evaluating of $y(jT+i)$ and $\boldsymbol{w}(j+1)$ factors. So for reducing this complexity we applied FFT technique based on overlap save method that is padding of zeros. The FB-LLMF weight vector is given as

$$\boldsymbol{W}(j+1)=(1-\mu\gamma)\boldsymbol{W}(j)+\alpha FFT\begin{bmatrix}\phi(j)\\ \mathbf{0}\end{bmatrix} \tag{8}$$

Where $\boldsymbol{W}(j)=FFT\begin{bmatrix}\boldsymbol{w}(j)\\ \mathbf{0}\end{bmatrix}$, α is constant.

Here $\phi(j)=IFFT[\boldsymbol{D}(j)\boldsymbol{X}(j)\boldsymbol{E}(j)]$, where **D**(j) is related to diagonal matrix of average signal power. This factor indicates that due to overlapping method used in FFT, for each overlapping method we can change the step size that is changing of signal power. E(j) is transform error vector and **X**(j) is input vector. Normalization of LMS (Haykin *et.al* 1986) algorithm gives variations in the signal level at the filter output, which also gives fast convergence characteristic. So we applied data normalization and error normalization techniques to Fast block LLMF algorithm (8) named as Data Normalized Fast Block LMMF (DNFB-LLMF) and Error Normalized Fast Block LLMF (ENFB-LLMF) algorithms. To study the performance of the efficient adaptive noise cancellers, we carried our experiments on real ECG signals recorded from humans. For increasing of signal quality we used double validation method. That is we taken FB-LLMF final weight residue as starting value for another FB-LLMF algorithm, due to this convergence rate increases fastly and with good SNR ratio. This algorithm is known as FB-LLMFtoFB-LLMF algorithm.

Convergence Characteristics:

The convergence curves for various BLMS variant adaptive algorithms discussed in the previous sections are shown in Fig. 3. These curves are plotted between MSE and number of iterations. MSE is calculated for each sample for 5000 iterations and the average value is taken for the characterization.

These curves are obtained during the adaptive power line interference (60 Hz) cancellation using various adaptive noise cancellers individually with a adaptive filter of length 5, random variance of 0.01 and step size 0.01. From Fig. 3 it is clear that, among all the algorithms FB-LLMFtoFB-LLMF outperforms. The performance of DNFBLLMF and ENEB-LLMF are comparable to each other and superior to BLMS algorithm.

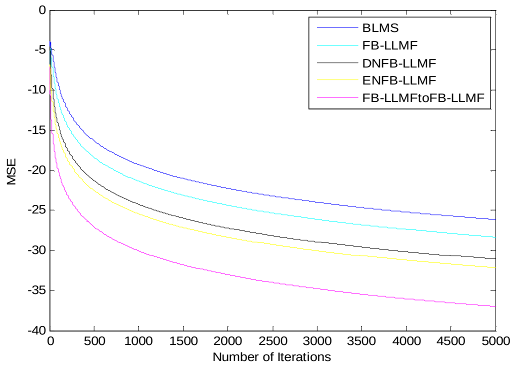

Fig. 3: Convergence Curves of Different BLMS based adaptive algorithms.

Simulation Results And Discussion:

In our simulation purpose we collected six ECG records from MIT-BIH database (physionet- mitdb), and calculated Signal to Noise Ratio (SNR) in decibels, correlation factor, and observed the Excess MSE using different adaptive filters with MATLAB software. The output graphs shown here for data 105 record only, because of space limitation, rest are compared using table form. The number of samples is taken on x-axis and amplitude on y-axis for all figures. In our experiments, we have considered two dominant artefacts, namely PLI and EM.

The ECG signal is corrupted with a power line noise of amplitude 1mV, with 60Hz frequency. This corrupted ECG signal is applied at input signal and sampled with a frequency of 200Hz. The reference signal is synthesized sinusoidal noise generated in the noise generator; and filter output is recovered signal. Four filter structures are designed using BLMS, FB-LLMF, DNFB-LLMF, ENFB-LLMF and FB-LLMFtoFB-LLMF algorithms. The simulation results for PLI cancellation using these algorithms are shown in Fig. 4 and Fig. 5.

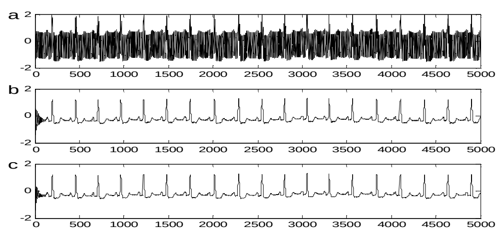

Fig. 4: PLI cancellation using different adaptive algorithms.(a) Corrupted ECG (b) using BLMS algorithm (c)FB-LLMF algorithm.

The performance of the various algorithms for the removal of PLI is measured in terms of SNR, and is tabulated in Table 1. From Table 1 it is clear that FB-LLMFtoFB-LLMF algorithm achieves maximum average SNR over the dataset is 17.4148 dBs, where as ENFB-LLMF gets 11.5744 dBs, DNFB-LLMF gets 11.4905dBs, FB-LLMF gets 9.833dBs and BLMS gets 8.6730dBs, these values correlate with the convergence characteristics shown in Fig. 3.

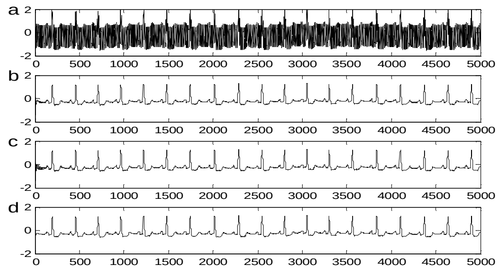

Fig. 5: PLI cancellation using different adaptive algorithms.(a) Corrupted ECG (b) using DNFB-LLMF algorithm (c)ENFB-LLMF algorithm (d)FB-LLMFtoFB-LLMF algorithm.

Table 1: SNR contrast of BLMS based adaptive algorithms for PLI removal.

S. No	Rec. No	BLMS	FB-LLMF	DNFB-LLMF	ENFB-LLMF	FB-LLMFtoFB-LLMF
1.	100	8.811	9.9785	11.7516	11.7801	18.89993
2.	102	7.8468	8.99	10.7698	10.6968	16.5703
3	105	8.9134	10.0103	11.3881	11.5478	14.3494
4	108	8.4783	9.6277	11.3464	11.4893	19.1618
5	203	9.9027	11.1458	12.6732	12.904	17.6157
6	228	8.0863	9.2457	11.0143	11.0284	17.8918
Avg.		8.6730	9.833	11.4905	11.5744	17.4148

From MIT-BIH normal sinus rhythm database and noise stress test (physionet- nsrdb) the real EM noise is collected for testing of the signal using different filters in non-stationary conditions. The simulation results for PLI cancellation using these algorithms are shown in Fig. 6 and Fig. 7. The SNR calculation for cancellation of EM, using various filtering methods is shown in Table 2. From this table it is clear that FB-LLMFtoFB-LLMF algorithm effectively filters EM noise, it got an average SNR of 9.5743 dBs, ENFB-LLMF gets 6.7573 dBs, DNFB-LLMF gets 6.6801 dBs and BLMS get 5.6607 dBs. The excess mean square error (EMSE) characteristics for the removal of PLI noise and EM noise as shown in Fig. 8 and Fig. 9 respectively.

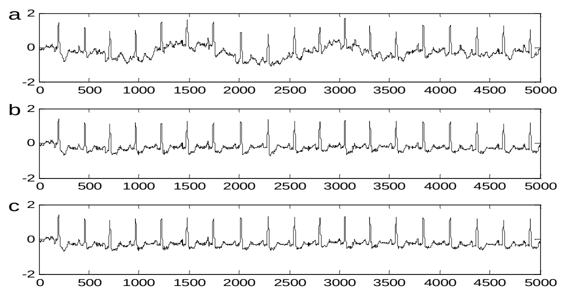

Fig. 6: EM cancellation using different adaptive algorithms.(a) Corrupted ECG (b) using BLMS algorithm (c)FB-LLMF algorithm.

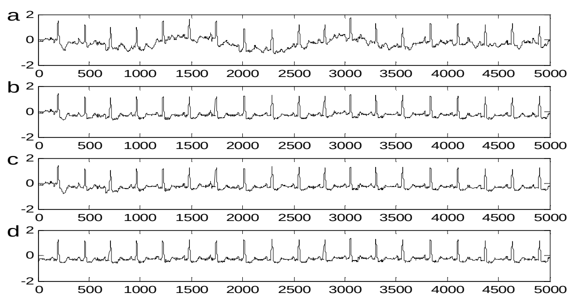

Fig. 7: EM cancellation using different adaptive algorithms.(a) Corrupted ECG (b) using DNFB-LLMF algorithm (c)ENFB-LLMF algorithm (d)FB-LLMFtoFB-LLMF algorithm.

Table 2: SNR contrast of BLMS based adaptive algorithms for EM removal.

S. No	Rec. No	BLMS	FB-LLMF	DNFN-LLMF	ENFB-LLMF	FB-LLMFtoFB-LLMF
1.	100	6.806	7.9272	8.0896	7.1177	11.132
2.	102	6.2559	6.594	7.1991	7.2429	10.4651
3	105	6.7647	7.2345	7.2245	7.1555	10.7862
4	108	4.9278	5.8219	5.9259	6.293	10.6195
5	203	3.6529	6.0199	5.3678	6.4121	4.6556
6	228	5.5569	6.0018	6.2742	6.3259	9.7875
Avg.		5.6607	6.5998	6.6801	6.7578	9.5743

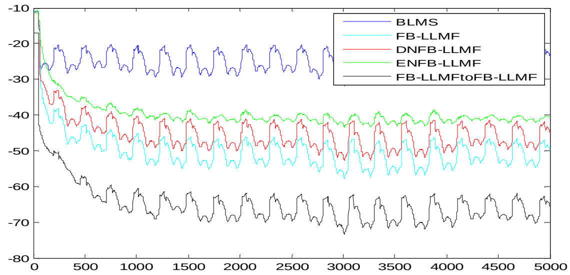

Fig. 8: EMSE characteristics for PLI reduction using different adaptive algorithms.

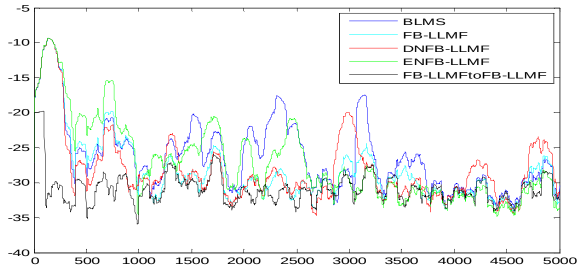

Fig. 9: EMSE characteristics for EM reduction using different adaptive algorithms.

Conclusion:

For fast transmission of the signal, we derived less computational based algorithms using frequency domain technique. In this paper we developed different weight update equations based on BLMS adaptive algorithms: FB-LLMF, DNFB-LLMF, ENFB-LLMF and FB-LLMFtoFB-LLMF algorithms. To evaluate the performance of the various adaptive noise cancellers we have plotted the convergence characteristics, EMSE characteristics, calculated computational complexity in terms of time and Signal to Noise Ratio. Among this FB-LLMF based algorithm performs better in the noise removal from corrupted ECG signal.

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