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Research Article

# Analysis of Adaptive Filter Algorithms using MATLAB

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***Abstract***

*In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the signals with noise especially of the biomedical signals. 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. The aim of this paper is to study, analyze various adaptive filter algorithms and apply Mat lab to investigate their performance behaviors with two step sizes of 0.02 and 0.04. Further to remove motion artifacts from Electrocardiogram signal as an application of this concepts. At the end of this paper, a performance study has been done between these algorithms based on various step sizes. It has been found that there will be always tradeoff between step sizes and Mean square error. The Electrocardiogram signals used in this paper are from the MIT-BIH database. Elimination of noises from Electrocardiogram signal example is a classical problem.*

***Keywords:*** *Adaptive filter, Least Mean Square (LMS), Normalized LMS (NLMS), Block LMS (BLMS), Sign LMS (SLMS), Signed Regressor LMS (SRLMS), Motion artifact.*

## 1. Introduction

A system is said to be adaptive when it tries to adjust its parameters with the aid of meeting some well- defined goal or target that depends upon the state of the system and its surroundings. So the system adjusts itself so as to respond to some phenomenon that is taking place in its surroundings. An event related signal could be considered as a process, which can be decomposed into an invariant deterministic signal time locked to a stimulus and an additive noise uncorrelated with the signal. The most common signal processing of this type of bioelectric signal separates the deterministic signal from the noise. Several techniques can be considered of which we are considering the adaptive signal processing technique. Adaptive filters are self-designing filters based on an algorithm which allows the filter to learn the initial input statistics and to track them if they are time varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal. The principle of adaptive filter is as shown in Figure 1.

Obtained signal d (n) from sensor contains not only desired signal s (n) but also undesired noise signal n (n). Therefore measured signal from sensor is distorted by noise n (n). At that time, if undesired Noise signal n(n) is known, desired signal s(n) can be obtained by subtracting noise signal n(n) from corrupted signal d(n). However entire noise source is difficult to obtain, estimated noise signal n' (n) is used. The estimate noise signal n' (n) is calculated through some filters and measurable noise source X(n) which is linearly related with noise signal n(n). After that, using estimated signal n' (n) and obtained signal d (n), estimated desired signal s' (n) can be obtained. If estimated noise signal n' (n) is more close to real noise signal n(n), then more desired signal is obtained.

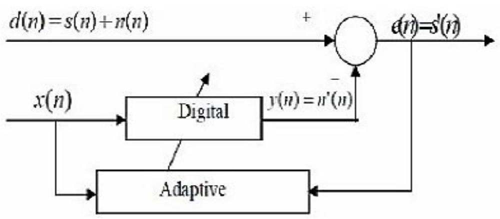


**Fig.1** The principle of adaptive filter

In the active noise cancellation theory, adaptive filter is used. Adaptive filter is classified into two parts, adaptive algorithm and digital filter. Function of adaptive algorithm is making proper filter coefficient. General digital filters use fixed coefficients, but adaptive filter change filter coefficients in consideration of input signal, environment, and output signal characteristics. Using this continuously changed filter coefficient, estimated noise signal n' (n) is

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made by filtering X (n). The different types of adaptive filter algorithms can be explained as follows.

*(a) LMS Algorithm*

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e (n) is minimized in the mean- square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function
$\xi (n) = E [e2 (n)]$
by its instantaneous coarse estimate. The error estimation e(n) is

$$e (n) = \mathbf{d}(n) - w(n) X(n) \quad (2)$$

Coefficient updating equation is

$$\mathbf{w} (n+1) = \mathbf{w}(n) + \mu\, x(n)\, e(n), \quad (3)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < 0.2$, for the convergence of the algorithm. The larger step sizes make the coefficients to fluctuate wildly and eventually become unstable. The most important members of simplified LMS algorithms are:

*(b) SRLMS Algorithm*

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap- input vector x (n) with the vector sgn{x(n)} .Consider a signed regressor LMS based adaptive filter that processes an input signal x(n) and generates the output y(n) as per the following:

$$y (n) = \mathbf{w}t (n)x(n) \quad (4)$$

where, $\mathbf{w}(n) = [\ w0(n), w1(n), \ldots , wL\text{-}1(n)\ ]t$ is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$\mathbf{w} (n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}e(n) \quad (5)$$

Because of the replacement of x(n) by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

*(c) SLMS Algorithm*

This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, x(n)\, \mathrm{sgn}\{e(n)\} \quad (6)$$

*(d) Block LMS Algorithm (BLMS)*

To reduce the computational requirements of LMS algorithm, block LMS is introduced. Here the filter coefficients are held constant over each block of L samples, and the filter output y(n) and the error e(n) for each value of n within the block are calculated using the filter coefficients for that block. Then at the end of each block, the coefficients are updated using an average for the L gradients estimates over the block.

*(e) Normalized LMS Algorithm (NLMS)*

In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\beta}{||x(n)||2} \quad (7)$$

Where β is a normalized step size with 0< β<2. When x(n) is large, the LMS experiences a problem with gradient noise amplification. With the normalization of the LMS step size by ||x(n)||2 in the NLMS, noise amplification problem is diminished.

**2. Methodology**

Electrocardiogram is a method of monitoring and recording the electric currents generated during the alternating contractions of the atria and ventricles of the heart. The device used to monitor and record these signals is an electrocardiogram more commonly referred to as an Electrocardiogram. When using an Electrocardiogram, electrodes are applied to the skin in places where the heart's signals can be measured easily. Cables connect the electrodes to the Electrocardiogram where the electrical signal is turned into a waveform on a computer or a paper plot. The results produced from this machine allow physicians to observe the performance and condition of the heart as well as diagnose any problems they may find in the signal. When the doctors are examining the patient on-line and want to review the Electrocardiogram signal waveform in real-time, there is a good chance that the signal has been contaminated by baseline wander (BW), power line interference (PLI), muscle artifacts (MA) and electrode motion artifacts (EM) etc., mainly caused by patient breathing, movement, power line noise, bad electrodes and improper electrode site preparation. All these noises mask the tiny features of the signal and leads to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the artifacts in order to better obtain and interpret the respiratory signal data.

In this proposed methodology simulation was carried out using powerful MATLAB tool to investigate the performance behaviors of various adaptive filter algorithms in non-stationary environment with two step sizes of 0.02 and 0.004. The principle means of comparison is the error cancellation capability of the algorithms which depends on the parameters such as step size, filter length and number of iterations. A synthetically generated motion artifact is added with Electrocardiogram signals. It is then removed using adaptive filter algorithms such as LMS, Sign LMS, Signed Regressor, BLMS and NLMS. All Simulations presented are averages over 1000 independent runs.

*Motion Artifact*

A number of signal-distorting events are noteworthy. Electrocardiograms operate best when the subject is in resting position. Motion artifacts are unwanted signal and are generally caused by relative motion between electrode and skin surface. When the skin stretches, the voltage changes which is recorded by the electrodes and summed with the Electrocardiogram signal. Pushing and pulling on the lead wires and patient movement are the most recurring causes change in charge boundary at the electrode-electrode paste interface or electrode-skin interface can also cause motion artifact

## 3. Results and discussions

The extraction of high-resolution ECG signals from recordings infected with back ground 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 (N. V. Thakor et al,1991). In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical signals. 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, quite a few papers have been presented in the area of biomedical signal processing where an adaptive solution based on the LMS algorithm is suggested (Allan Kardec Barros et al,1997). The fundamental principles of adaptive filtering for noise cancelation were described by Widrow et al. Thakor and Zhu proposed an 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 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. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm , in which the coefficient vector is updated only once every occurrence based on a block gradient estimation. A major advantage of the block, or the transform domain LMS algorithm is that the input signals are approximately uncorrelated. Mean square error behavior, convergence and steady state analysis of different adaptive algorithms are analyzed by S.C.Chan et al. The results of Desmond B show the performance analysis of adaptive filtering for Electrocardiogram. Basic concepts of adaptive filter algorithms and mathematical support for all the algorithms are taken from (Monson Hayes H,2002).

The INLMS algorithm extends the gradient-adaptive learning rate approach to the case where the signals are nonstationary. It is shown that the INLMS algorithm can work even for highly nonstationary interference signals, where previous gradient- adaptive learning rate algorithms fail. The use of two simple and robust variable step-size approaches in the adaptation process of the Normalized Least Mean Square algorithm in the adaptive channel equalization is investigated in (S. A. Jimaa et al,2007).

In the Convergence Evaluation of Variable Step-Size NLMS Algorithm in Adaptive Channel Equalization, the input power and error signals are used to design the step size parameter at each iteration. Simulation results demonstrate that in the scenario of channel equalization, the proposed algorithm accomplishes faster start-up and gives better precision than the conventional algorithms. A novel power-line interference (PLI) detection and suppression algorithm is presented in (Hideki et al,2008)to preprocess the electrocardiogram signals. A distinct feature of this proposed algorithm is its ability to detect the presence of PLI in the Electrocardiogram signal before applying the PLI suppression algorithm. An efficient recursive least-squares (RLS) adaptive notch filter is also developed to serve the purpose of PLI suppression. In (Yue-Der Lin et al,2008)two types of adaptive filters are considered to reduce the Electrocardiogram signal noises like PLI and Base Line Interference. Various methods of removing noises from Electrocardiogram signal and its implementation using the Lab view tool was referred in (Yue-Der Lin et al,2008). Results in (Tutorial in Labview) indicate that respiratory signals alone are sufficient and perform even better than the combined respiratory and Electrocardiogram signals.

### Removal of Motion Artifacts

Respiratory signal is represented by second-order autoregressive process that is generated according to the difference equation

$$x(n)=1.2728x(n-1) - 0.81x(n-2) + v(n) \quad (8)$$

Where v (n) is randomly generated noise

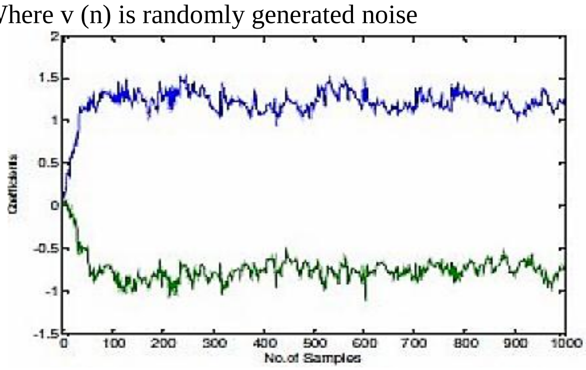


**Fig.2**. LMS adoptive filter co-efficient plot of trajectories for μ=0.02

Figures 2, 3, 4, 5 and 6, 7, 8, 9 show the convergence of filter coefficients and Mean squared error using LMS and NLMS algorithms. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculations.

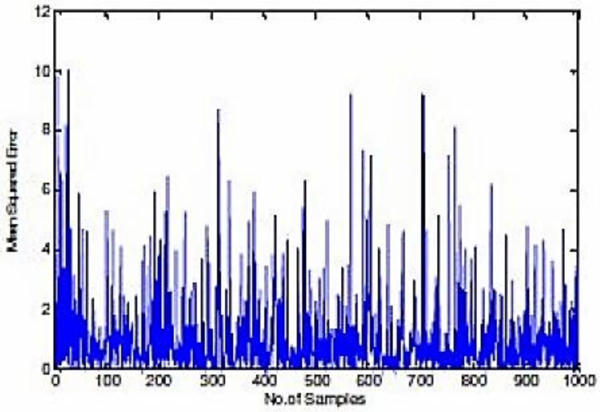


**Fig.3**. LMS adoptive filter squared error plot of trajectories for μ=0.02

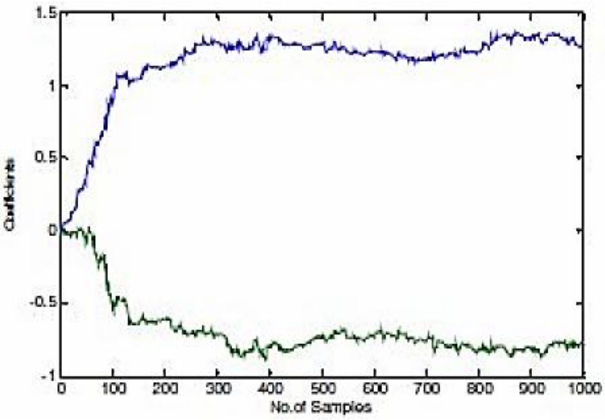


**Fig.4.** LMS adoptive filter co-efficient plot of trajectories for μ=0.004

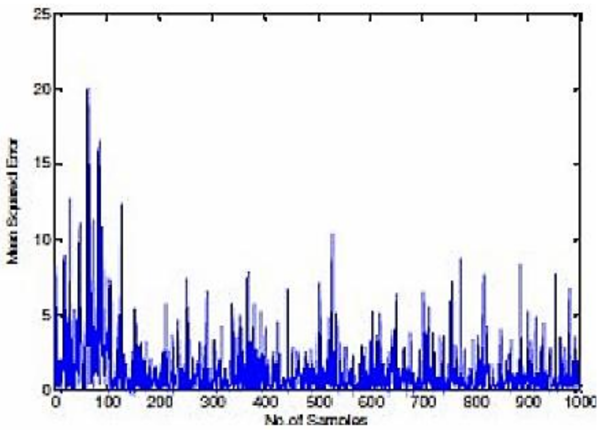


**Fig.5.** LMS adoptive filter squared error plot of trajectories for μ=0.004

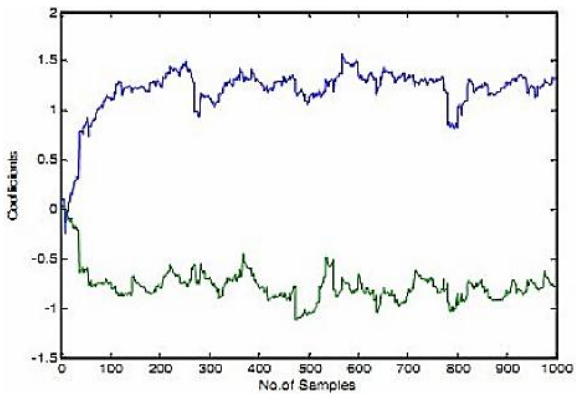


**Fig.6.** NLMS adoptive filter co-efficient plot of trajectories for μ=0.02

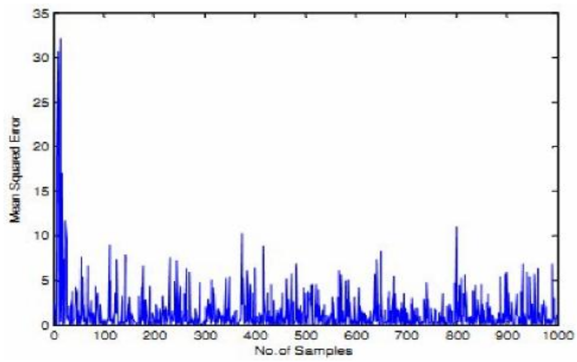


**Fig.7.** NLMS adoptive filter squared error plot of trajectories for μ=0.02

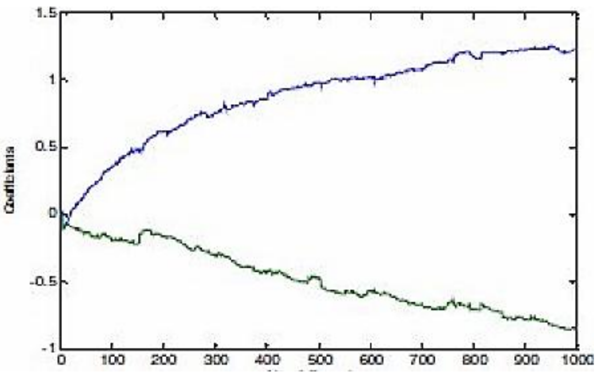


**Fig.8.** NLMS adoptive filter co-efficient plot of trajectories for μ=0.004

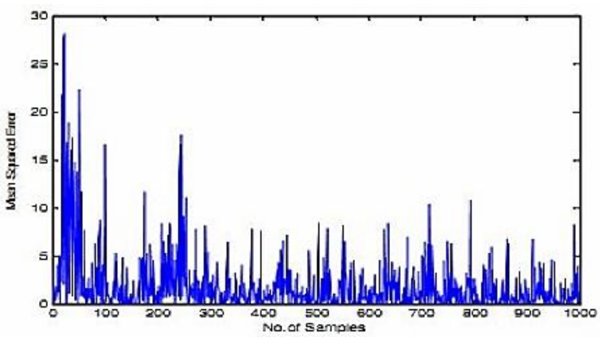


**Fig.9.** NLMS adoptive filter squared error plot of trajectories for μ=0.004

## 4. Comparative assessment of results

Table 1 provides the comparison of mean squared error (MSE) and Convergence rate (C in terms of number of iterations that the filter coefficients converge) of different algorithms. It is observed from Figure 2 and Figure 3, the convergence speed for μ =0.02 is faster than μ=0.004. But MSE performance is comparatively better for μ=0.004 than μ=0.02. Convergence rate of LMS algorithm is better when μ=0.02 and low MSE value when μ=0.004. It is also inferred that the MSE performance of Sign Regressor LMS (SRLMS) at the step size of 0.02 is better when compared to other algorithms. But there is always tradeoff between convergence rate and mean squared error. Hence choosing an algorithm depends on the parameter on which system has more concern.

**Table 1:** Comparison of MSE and Convergence Rate

| Algorithm | μ=0.02 | | μ=0.004 | |
|---|---|---|---|---|
| | MSE | C | MSE | C |
| LMS | 2.3873e -004 | 10 0 | 5.4907e -005 | 25 0 |
| SRLMS | 8.5993e -006 | 10 0 | 5.3036e -004 | 55 0 |
| SLMS | 1.3406e -004 | 10 0 | 4.9436e -005 | 55 0 |
| BLMS | 4.9514e -004 | 20 0 | 8.7072e -004 | 50 0 |
| NLMS | β=0.05, 6.8306e -004 | 10 0 | β=0.01, 0.0012 | 70 0 |

Table 2 shows the comparison of resulting mean square error while eliminating Motion Artifacts from respiratory signals using various adaptive filter algorithms with different step sizes. The observed MSE for LMS as shown in Figure 5 (a) is very low for μ =0.02 compared with μ =0.004. The performance of BLMS depends on block length L and NLMS depends on the normalized step size β. Observing all cases, we can infer that choosing μ =0.02 for the removal of power line interference is better when compared to μ =0.004. The step size μ =0.004 can be used unless the convergence speed is a matter of great concern. It is found that the value of MSE also depends on the number of samples taken for analysis.

From the simulation results, the proposed adaptive filter can support the task of eliminating motion artifacts with fast numerical convergence. The mean square value obtained in this work is found to be very low by varying the step sizes and increasing the number of iterations. An FIR filter order of 32 and adaptive step size parameter (μ) of 0.02 and 0.004 are used for LMS and modified step sizes (β) of 0.01 and 0.05 for NLMS. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration.

**Table 2:** Comparison of MSE in removing motion artifacts

| **Algorithm** | **Motion Artifacts** | |
|---|---|---|
| | μ=0.02 | μ=0.004 |
| | **MSE** | **MSE** |
| LMS | 1 .6e-007 | 2.66e-005 |
| BLMS | 3.2e-004 | 0.016 |
| SR LMS | 5.4e-007 | 2.153e-007 |
| SIGN LMS | 2.0e-007 | 1.213e-005 |
| SIGN-SIGN LMS | 3.5e-006 | 5.559e-007 |
| NLMS | β = 0.05 2. 1e-007 | β = 0.01 1 .057e-008 |

## Conclusion

This study has revealed useful properties of various adaptive filter algorithms. The objective is to optimize different adaptive filter algorithms so that we can reduce the MSE so as to improve the quality of eliminating interference. It is inferred that the MSE performance is better for NLMS when compared to LMS. The merits of LMS algorithm is less consumption of memory and amount of calculation. It has been found that there will be always tradeoff between step sizes and Mean square error. It is also observed that the performance depends on the number of samples taken for consideration. Choosing an algorithm depends on the parameter on which the system has much concern. The future work includes the optimization of algorithms for all kinds of noises and to use the optimized one in the implementation of DSP Microcontroller that estimates the respiratory signal.

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