Performance Study of Various Adaptive Filter Algorithms for Noise Cancellation in Respiratory Signals

A.Bhavani Sankar absankar72@gmail.com
Assistant Professor, Dept. of E.C.E,
Anjalai Ammal- Mahalingam Engineering College,,Kovilvenni
Tamil Nadu,India

D.Kumar kumar_durai@yahoo.com
Dean/Research,
Periyar Maniyammai University,Vallam,Thanjavur.
Tamil Nadu,India

K.Seethalakshmi seetha.au@gmail.com
Senior lecturer, Dept. of E.C.E,
Anjalai Ammal- Mahalingam Engineering College,,Kovilvenni.
Tamil Nadu,India

Abstract

Removal of noises from respiratory signal is a classicl problem. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the respiratory 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. This paper focuses on (i) Model Respiratory signal with second order Auto Regressive process. Then synthetic noises have been corrupted with respiratory signal and nullify these noises using various adaptive filter algorithms (ii) to remove motion artifacts and 50Hz Power line interference from sinusoidal 0.18Hz respiratory signal using various adaptive filter algorithms. 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.

Keywords: Adaptive filter, Least Mean Square (LMS), Normalized LMS (NLMS), Block LMS (BLMS), Sign LMS (SLMS), Sign-Sign LMS (SSLMS), Signed Regressor LMS (SRLMS), Motion artifact, Power line interference

1. INTRODUCTION

Various biomedical signals are present in human body. To check the health condition of a human being it is essential to monitor these signals. While monitoring these signals, various noises interrupt the process. These noises may occur due to the surrounding factors, devices connected and physical factors. In this paper, noises associated with the respiratory signals are taken into account. The monitoring of the respiratory signal is essential since various sleep related disorders like sleep apnea (breathing is interrupted during sleep), insomnia (inability to fall asleep), narcolepsy can be detected earlier and treated. Also breathing disorders like snoring, hypoxia (shortage of O2), hypercapnia (excess amount of CO2) hyperventilation (over breathing) can be treated. The respiratory rate for new born is 44 breathes/min for adults it is 10-20 breathes/min. Various noises affecting the respiratory signal are motion artifact due to instruments, muscle contraction, electrode contact noise, powerline interference, 50HZ interference, noise generated by electronic devices, baseline wandering, electrosurgical noise.

One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might (hypothetically) wander between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive filter has been used. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates.

Several papers have been presented in the area of biomedical signal processing where an adaptive solution based on the various algorithms is suggested. Performance study and comparison of LMS and RLS algorithms for noise cancellation in ECG signal is carried out in [1]. Block LMS being the solution of the steepest descent strategy for minimizing the mean square error is presented in [2]. Removal of 50Hz power line interference from ECG signal and comparative study of LMS and NLMS is given in [3]. Classification of respiratory signal and representation using second order AR model is discussed in [4]. Application of LMS and its member algorithms to remove various artifacts in ECG signal is carried out in [5]-[7]. Mean square error behavior, convergence and steady state analysis of different adaptive algorithms are analyzed in [8]-[10]. The results of [11] show the performance analysis of adaptive filtering for heart rate signals. Basic concepts of adaptive filter algorithms and mathematical support for all the algorithms are taken from [12].

In [13] the authors present a real-time algorithm for estimation and removal of baseline wander noise and obtaining the ECG-derived respiration signal for estimation of a patient's respiratory rate. In [14], a simple and efficient normalized signed LMS algorithm is proposed for the removal of different kinds of noises from the ECG signal. The proposed implementation is suitable for applications requiring large signal to noise ratios with less computational complexity. The design of an unbiased linear filter with normalized weight coefficients in an adaptive artifact cancellation system is presented in [15]. They developed a new weight coefficient adaptation algorithm that normalizes the filter coefficients, and utilize the steepest-descent algorithm to effectively cancel the artifacts present in ECG signals. The paper [16] describes the concept of adaptive noise cancelling, a method of estimating signals corrupted by additive noise. In [17], an adaptive filtering method is proposed to remove the artifacts signals from EEG signals. Proposed method uses horizontal EOG, vertical EOG, and EMG signals as three reference digital filter inputs. The real-time artifact removal is implemented by multi-channel Least Mean Square algorithm. The resulting EEG signals display an accurate and artifact free feature.

The results in [18] show that the performance of the signed regressor LMS algorithm is superior than conventional LMS algorithm, the performance of signed LMS and sign-sign LMS based realizations are comparable to that of the LMS based filtering techniques in terms of signal to noise ratio and computational complexity. An interference-normalized least mean square algorithm for robust adaptive filtering is proposed in [19].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 [20].In the proposed algorithm in [21], 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 [22] to preprocess the electrocardiogram (ECG) signals. A distinct feature of this proposed algorithm is its ability to detect the presence of PLI in the ECG 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 [23] two types of adaptive filters are considered to reduce the ECG signal noises like PLI and Base Line Interference. Various methods of removing noises from ECG signal and its implementation using the Lab view tool was referred in [24]. Results in [25] indicate that respiratory signals alone are sufficient and perform even better than the combined respiratory and ECG signals.

2. MATHEMATICAL MODEL OF RESPIRATION SIGNALS

The respiratory systems' function is to allow gas exchange to all part of the body. In addition to supplying oxygen, the respiratory system aids in removing of carbon dioxide. It prevents the lethal buildup of this waste product in body tissues. The respiratory system carries out its life-sustaining activities through the process of respiration. Respiration is the process by which the atmospheric oxygen is inhaled in to the body and the unwanted carbon dioxide is exhaled out through the nostrils and mouth.

Respiratory signals are not a constant signal with common amplitude and regular variations from time to time. Hence to estimate the signal it is necessary to frame an algorithm which can analyze even the small variations in the input signal. Respiratory signal is modeled in to a second order AR equation so that the parameters can be utilized for determining the fundamental features of the respiratory signal. The autoregressive (AR) model is one of the linear prediction formulas that attempt to predict an output Y(n) of a system based on the previous inputs {x(n), x(n-1), x(n-2)...}. It is also known in the filter design industry as an infinite impulse response filter (IIR) or an all pole filter, and is sometimes known as a maximum entropy model in physics applications.

The respiration signal can be modeled as a second order autoregressive model [4] as the following,

$$X(n)=a_1X(n-1)+a_2X(n-2) + e(n) \qquad (1)$$

Where e (n) is the prediction error and $\{a_1,a_2\}$ are AR model coefficients to be determined through burgs method.

3. NOISES IN RESPIRATORY SIGNALS

Methods of respiration monitoring fall into two categories. Devices such as spirometers and nasal thermocouples measure air flow into and out of the lungs directly. Respiration can also be monitored indirectly, by measuring body volume changes; transthoracic inductance and impedance plethysmographs, strain gauge measurement of thoracic circumference, pneumatic respiration transducers, and whole-body plethysmographs are examples of indirect techniques. When the doctors are examining the patient on-line and want to review the respiratory 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.

3.1 Motion Artifact

Motion artifact cause false alarms during patient monitoring, which can reduce clinician confidence in monitoring equipment alarms and, consequently, slow response time. When motion artifact is introduced to the system, the information is skewed. Motion artifact causes irregularities in the data. Motion artifact can be reduced by proper design of the electronic circuitry and set-up. The shape of the baseline disturbance caused by motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifact are variables since the respiratory unit is a sensitive device, it can pickup unwanted electrical signals which may modify the actual respiratory signal.

3.2 Power line interference

Power line interference consists of 50Hz pickup and harmonics which can be modelled as sinusoids and combination of sinusoids. Characteristics which might need to be varied in a model of power line noise include the amplitude and frequency content of the signal. These characteristics are generally consistent for a given measurement situation and, once set, will not change during a detector evaluation. Power line interference is often a nuisance in bio potential measurements, mostly because of the long wires between the subject and the amplifier, the separation between the measurement points (electrodes), capacitive coupling between the subject (a volume conductor) and power lines, and the low amplitude of the desired signals. High-resolution measurements searching for potentials as small as 1 V further exacerbate the problem. It is a common interference source with low frequency and weak amplitude in signal detection and transmission.

3.3 Electrode Contact Noise

Electrode contact noise occurs due to the loss of contact between electrode and skin. The measurement of bioelectric events is exposed to various sources of noise. The reactions that take place at the electrode make the electrode itself a source of noise. Electrode contact noise can be modeled as a randomly occurring rapid baseline transition (step) which decays exponentially to the baseline value and has a superimposed 50 Hz component. This transition may occur only once or may rapidly occur several times in succession. Characteristics of this noise signal include the amplitude of the initial transition, the amplitude of the 50 Hz component and the time constant of the decay.

3.4 Baseline Drift

The wandering of baseline results from the gross movements of the patients or from mechanical strain on the electrode wires. If there is no proper application of jelly between the electrode and the skin, during that time also baseline wandering occurs. Respiration, muscle contraction, and electrode impedance changes due to perspiration or movement of the body are the important sources of baseline drift. The drift of the baseline with respiration can be represented as a sinusoidal component at the frequency of respiration. The amplitude and frequency of the sinusoidal component should be variables. The amplitude of the respiratory signal also varies by about 15 percent with the original signal. The variation could be reproduced by amplitude modulation of the respiratory by the sinusoidal component which is added to the baseline.

4. ADAPTIVE FILTER ALGORITHMS

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.

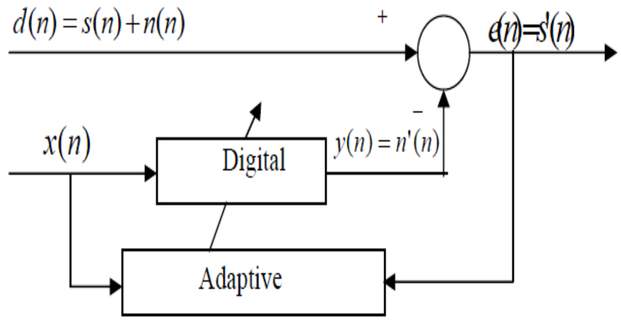


FIGURE 1: Principle of Adaptive Filter

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

4.1 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 $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate.

The error estimation e(n) is

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

Coefficient updating equation is

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

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:

4.2 Signed-Regressor Algorithm (SRLMS)

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:

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

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,

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

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.

4.3 Sign Algorithm (SLMS)

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

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

4.4 Sign – Sign Algorithm (SSLMS)

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathrm{sgn}\{x(n)\}\, \mathrm{sgn}\{e(n)\}, \qquad (7)$$

Where sgn{ . } is well known signum function, e(n) = d(n) – y(n) is the error signal. The sequence d (n) is the so-called desired response available during initial training period. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behavior is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

4.5 Block LMS (BLMS) Algorithm

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.

4.6 Normalized LMS (NLMS) Algorithm

In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\beta}{\left\|x(n)\right\|^2} \qquad (8)$$

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.

5. SCOPE OF THE PROPOSED WORK

The work carried out in [1]-[7], [13]-[18], [24] analyzes the removal of noises in ECG and EMG signal using adaptive filter algorithm. An ECG recording requires more number of electrodes on the skin and people may wear it continuously for effective monitoring. EEG measurements are always random in nature. For the complete detection, we need more number of samples for analysis. Also, the mathematical modeling of EMG signals is very complex. Removal of motion artifacts and power line interference from ECG or EMG is complex since it requires more number of electrodes for measurement. From the results in [25], the respiratory signals alone are sufficient and perform even better than ECG, EEG and EMG. In our paper, we consider only the respiratory signal for noise removal since it is more convenient and do not require more number of electrodes on the skin. We studied the performance of various adaptive filter algorithms for the removal of noises in respiratory signal. Autoregressive **(AR)** spectral estimation techniques are known to provide better resolution than classical periodogram methods when short segments of data are selected for analysis. In our study, we adopted the Burg's method to compute AR coefficients. The major advantage of Burg method for estimating the parameters of the AR model are high frequency resolution, stable AR model and it is computationally efficient.

6. SIMULATION RESULTS

This section presents the results of simulation using MATLAB 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 artifacts and power line interference are added with respiratory signals. It is then removed using adaptive filter algorithms such as LMS, Sign LMS, Sign-Sign LMS, Signed Regressor, BLMS and NLMS. All Simulations presented are averages over 1000 independent runs.

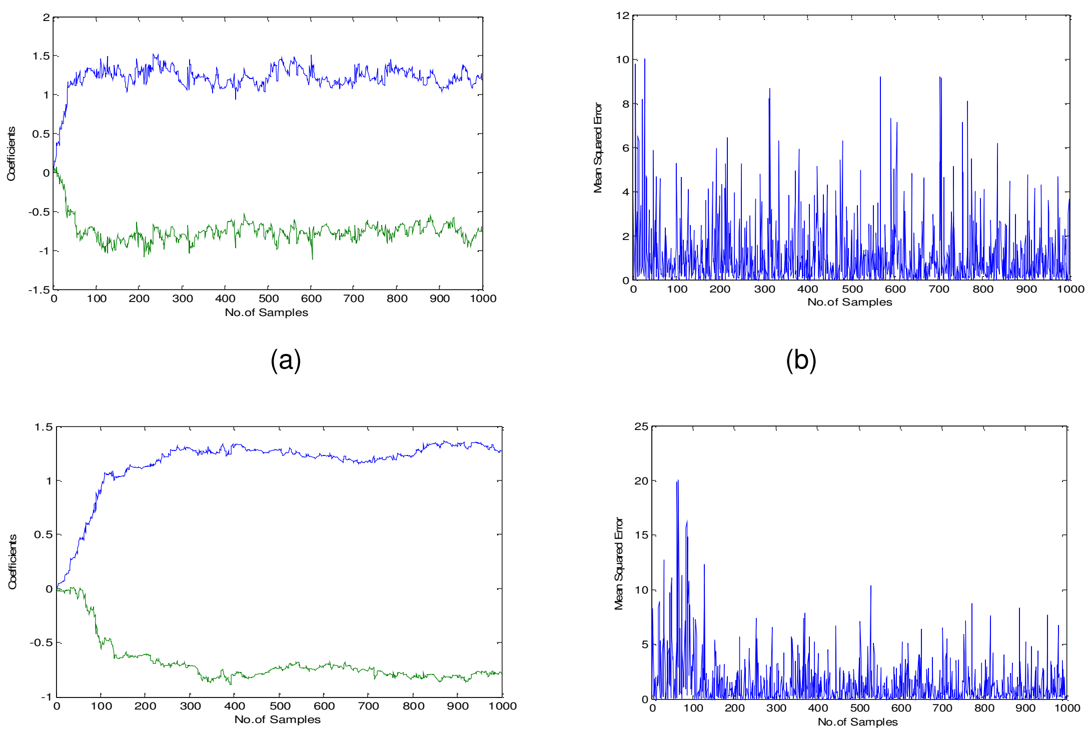
6.1 Removal of Motion Artifacts

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

$$x(n)=1.2728x(n-1) - 0.81x(n-2) + v(n) \qquad (9)$$

Where v (n) is randomly generated noise.

Figure 2 and Figure 3 shows 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 calculation.



(a) (b)

(c) (d)

FIGURE 2: Performance of LMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004

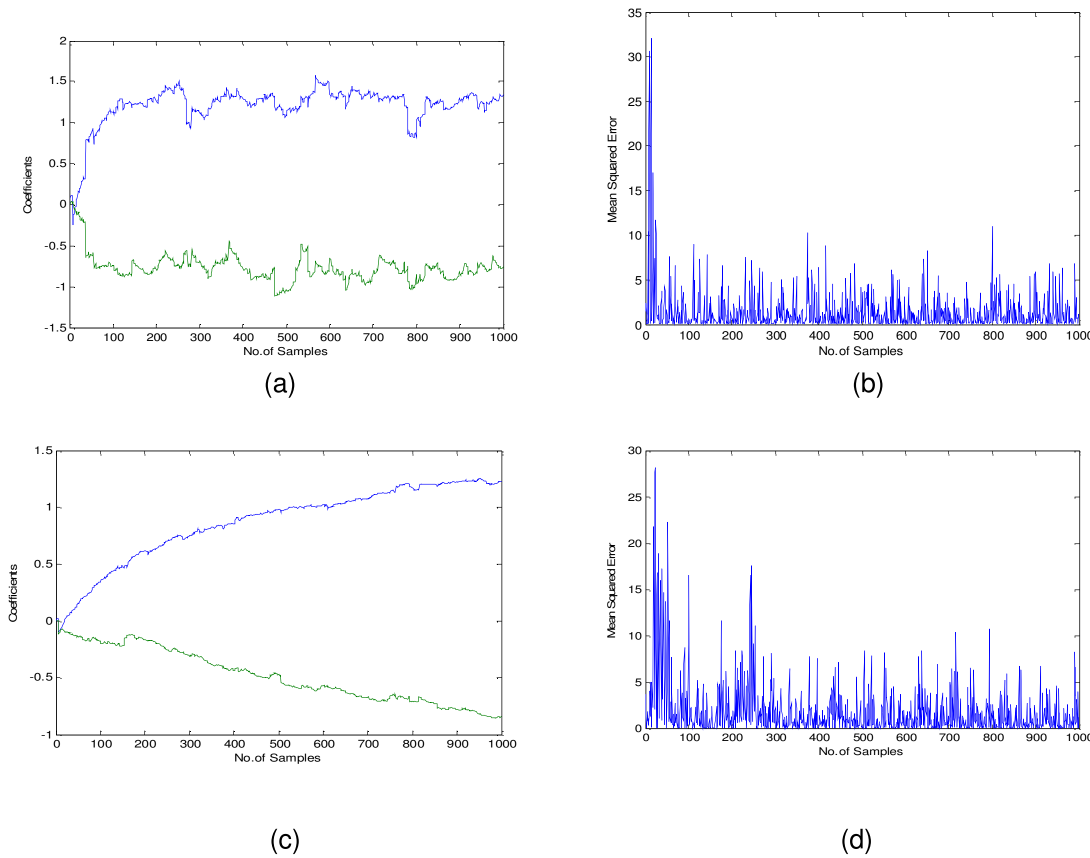


FIGURE 3: Performance of NLMS adaptive filter. (a),(b) Plot of trajectories of filter coefficients and Squared error for μ=0.02 (c),(d) Plot for μ=0.004

6.2 Removal of Power line Interference

A synthetic power line interference of 50 Hz with 1mv amplitude is simulated for PLI cancellation. Power line interference consists of 50Hz pickup and harmonics which can be modeled as sinusoids and combination of sinusoids. Figure 4 shows the generated power line interference.

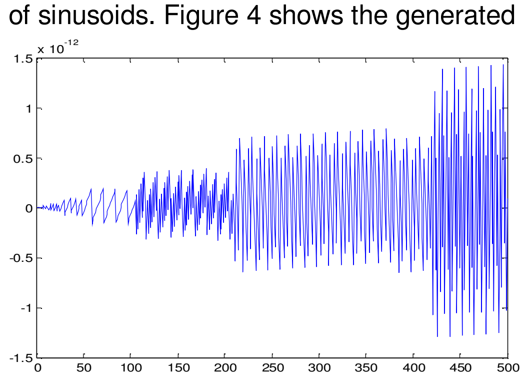


FIGURE 4: Power line interference

The mean square learning curves for various algorithms are depicted as shown in Figure 5. The input x(n) is 0.18Hz sinusoidal respiratory signal. It is observed that minimization of error is better with BLMS compared with other algorithms.

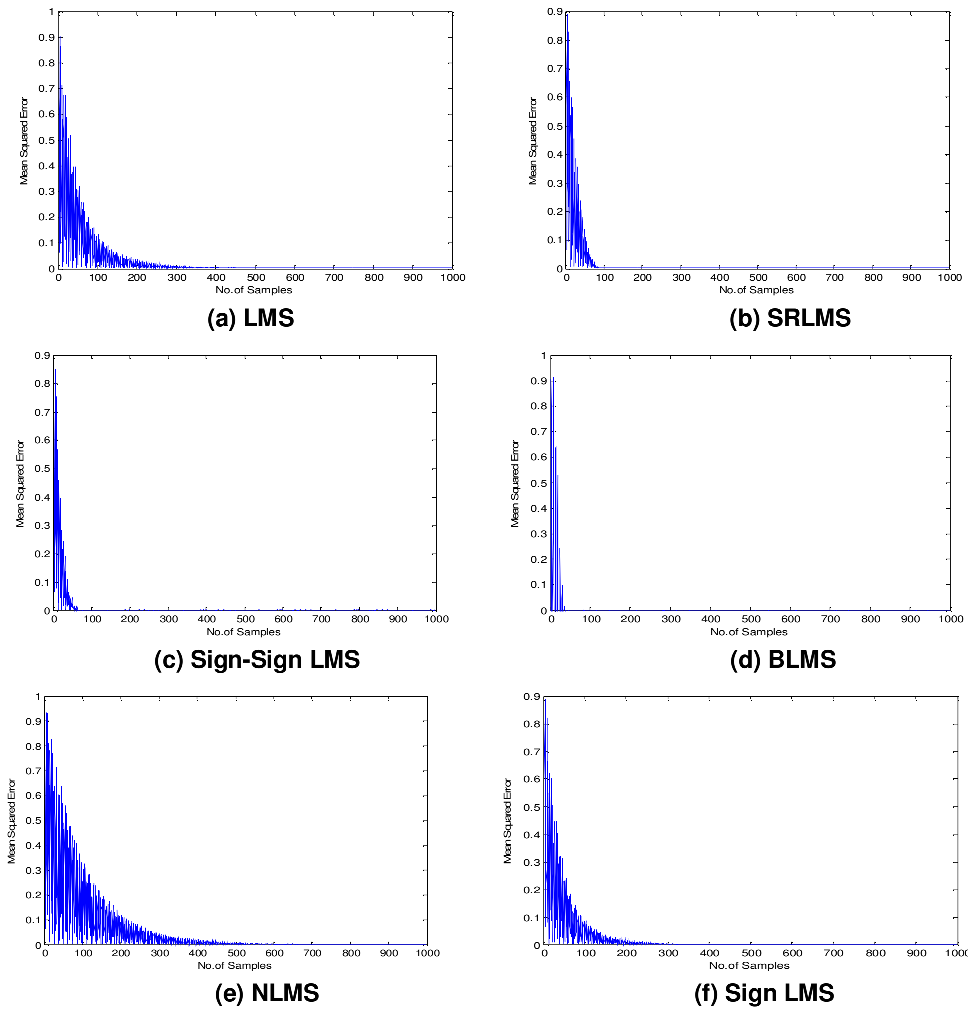


FIGURE 5: Mean Squared Error Curves for various Adaptive filter algorithms

7. COMPARITIVE EVALUATION AND DISCUSSION

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 the system has more concern.

Algorithm	μ=0.02		μ=0.004	
	MSE	C	MSE	C
LMS	2.3873e-004	100	5.4907e-005	250
SRLMS	8.5993e-006	100	5.3036e-004	550
SIGN LMS	1.3406e-004	100	4.9436e-005	550
SIGN-SIGN LMS	4.9514e-004	200	8.7072e-004	500
NLMS	β=0.05, 6.8306e-004	100	β=0.01, 0.0012	700

TABLE 1: Comparison of MSE and Convergence Rate

Table 2 shows the comparison of resulting mean square error while eliminating power line interference 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. The filter order is 32.

Algorithm	Motion Artifacts		Power line interference	
	μ=0.02	μ=0.004	μ=0.02	μ=0.004
	MSE	MSE	MSE	MSE
LMS	1.5973e-007	2.6776e-005	8.7683e-009	8.8808e-005
BLMS	3.1966e-004	0.0160	3.2675e-004	0.0160
SR LMS	5.3616e-007	2.1528e-007	3.8242e-010	4.8876e-005
SIGN LMS	1.9924e-007	1.2130e-005	2.1145e-007	5.7397e-010
SIGN-SIGN LMS	3.7528e-006	5.5596e-007	1.9290e-007	4.2355e-008
NLMS	β=0.05, 2.1528e-007	β=0.01, 1.0570e-008	β=0.05, 4.7339e-012	β=0.01, 3.6219e-005

TABLE 2: Comparison of MSE in removing motion artifacts and power line interference

From the simulation results, the proposed adaptive filter can support the task of eliminating PLI and motion artifacts with fast numerical convergence. Compared to the results in [23], 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.

7. CONCLUSION & FUTURE WORK

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.

8. REFERENCES

1. Syed Zahurul Islam, Syed Zahidul Islam, Razali Jidin, Mohd. Alauddin Mohd. Ali, "*Performance Study of Adaptive Filtering Algorithms for Noise Cancellation of ECG Signal",* IEEE 2009.

2. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik, D V Rama Koti Reddy, *" Adaptive Noise Removal in the ECG using the Block LMS Algorithm"* IEEE 2009.

3. Hong Wanl, RongshenFul, Li Shi*,"The Elimination of 50 Hz Power Line Interference from ECG Using a Variable Step Size LMS Adaptive Filtering Algorithm*" Life Science Journal, 3 (4), 2006*.*

4. J.D Bronzino and T.Ning, *"Automatic classification of Respiratory signals",* IEEE Proceedings/EMBS 11th International Conference, pp.669-670, Nov1989, Seattle,WA.

5. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik and D V Rama Koti Reddy, *"An Efficient Noise Cancellation Technique to remove noise from the ECG signal using Normalized Signed Regressor LMS algorithm*", IEEE International Conference on Bioinformatics and Biomedicine , 2009.

6. [6] Slim Yacoub and Kosai Raoof, *"Noise Removal from Surface Respiratory EMG Signal,"* International Journal of Computer, Information, and Systems Science, and Engineering 2:4 2008.

7. Nitish V. Thakor, Yi-Sheng Zhu, *"Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection"* IEEE Transactions on Biomedical Engineering. 18(8). August 1997.

8. Allan Kardec Barros and Noboru Ohnishi, *"MSE Behavior of Biomedical Event-Related Filters"* IEEE Transactions on Biomedical Engineering, 44(9), September 1997.

9. Ahmed I. Sulyman, Azzedine Zerguine, *"Convergence and Steady-State Analysis of a Variable Step-Size Normalized LMS Algorithm"*, IEEE 2003.

10. S.C.Chan, Z.G.Zhang, Y.Zhou, and Y.Hu, *"A New Noise-Constrained Normalized Least Mean Squares Adaptive Filtering Algorithm*", IEEE 2008.

11. Desmond B. Keenan, Paul Grossman, *"Adaptive Filtering of Heart Rate Signals for an Improved Measure of Cardiac Autonomic Control*". International Journal of Signal Processing- 2006.

12. Monson Hayes H. "*Statistical Digital Signal Processing and Modelling*" – John Wiley & Sons 2002.

13. Shivaram P. Arunachalam and Lewis F. Brown , *"Real-Time Estimation of the ECG-Derived Respiration (EDR) Signal using a New Algorithm for Baseline Wander Noise Removal*" 31st Annual International Conference of the IEEE EMBS Minneapolis,USA, September 2-6, 2009.

14. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik, D V Rama Koti Reddy, "*Cancellation of Artifacts in ECG Signals using Sign based Normalized Adaptive Filtering Technique*" IEEE Symposium on Industrial Electronics and Applications (ISIEA 2009), October 4-6, 2009, Malaysia.

15. Yunfeng Wu, Rangaraj M. Rangayyan,Ye Wu, and Sin-Chun Ng, *"Filtering of Noise in Electrocardiographic Signals Using An Unbiased and Normalized Adaptive Artifact Cancellation System*" Proceedings of NFSI & ICFBI 2007, Hangzhou, China, October 12-14, 2007.

16. Bernard Widrow, John R. Glover, John M. Mccool, "*Adaptive Noise Cancelling: Principles and Applications"*, Proceedings of the IEEE, 63(12), December 1975.

17. Saeid Mehrkanoon, Mahmoud Moghavvemi, Hossein Fariborzi, *"Real time ocular and facial muscle artifacts removal from EEG signals using LMS adaptive algorithm*" International Conference on Intelligent and Advanced Systems, IEEE 2007.

18. Mohammad Zia Ur Rahman, Rafi Ahamed Shaik and D V Rama Koti Reddy, *"Noise Cancellation in ECG Signals using computationally Simplified Adaptive Filtering Techniques: Application to Biotelemetry",* Signal Processing: An International Journal 3(5), November 2009.

19. Jean-Marc Valin and Iain B. Collings, *" Interference-Normalized Least Mean Square Algorithm",* IEEE Signal Processing Letters, 14(12), December 2007.

20. S. A. Jimaa, A.Simiri, R. M. Shubair, and T. Shimamura, *"Collings, " Interference-Normalized Least Mean Square Algorithm",* IEEE Signal Processing Letters, 14(12), December 2007.

21. *Convergence Evaluation of Variable Step-Size NLMS Algorithm in Adaptive Channel Equalization*" IEEE 2009.

22. Hideki Takekawa,Tetsuya Shimamura and Shihab Jimaa, *"An Efficient and Effective Variable Step Size NLMS Algorithm"* IEEE 2008.

23. Yue-Der Lin and Yu Hen Hu , *" Power-Line Interference Detection and Suppression in ECG Signal Processing"* IEEE Transactions on Biomedical Engineering, 55(1),January 2008.

24. Sachin singh and Dr K. L. Yadav ," *Performance Evaluation Of Different Adaptive Filters For ECG Signal Processing*" , International Journal on Computer Science and Engineering 02, (05), 2010.

25. Tutorial on *"Labview for ECG Signal Processing" developed by NI Developer Zone, National Instruments*, April 2010, [online] Available at : http://zone.ni.com/dzhp/app/main

26. Walter Karlen*,* Claudio Mattiussi, and Dario Floreano*,* "*Sleep and Wake Classification With ECG and Respiratory Effort Signals"*, IEEE Transactions on Biomedical Circuits and Systems, 3(2), April 2009.