Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PERFORMANCE ANALYSIS OF ADAPTIVE ALGORITHMS FOR NOISE CANCELLATION IN SPEECH PROCESSING

[1]M.A.RAJA, [2]Dr.A.SHANMUGAM

[1]Assistant Professor Electronics and Communication Engineering, Park College of Engineering and Technology, Tamil Nadu, India

[2]Principal, Bannariamman Institute of Technology, Tamil Nadu, India

E-mail: [1]rajalecturer@gmail.com

ABSTRACT

This paper is proposed to remove the noise from the speech signal in real time environment. The quality of audio signal can be improved by filtering the degraded speech signal through adaptive filters. For Noise cancellation widrow & hoff's Least Mean Square (LMS) algorithms are being used for simplicity in implementation. But LMS algorithm has limitation in selection of a certain values such as step size which implies dilemma in fast convergence rate and Excess mean square error (EMSE) and results in computational complexity. This paper analyse the performance of Variable Step Size Normalised LMS , Normalised Differential LMS with proposed VSSNDLMS with different input signals. Finally, through simulation results the proposed VSSNDLMS algorithm converges fastly with minimum mean square error and it is useful in predicting the adaptive filter performance of various algorithms and the implementation indicate the improvement in quality of the speech signal.

Keywords: *Adaptive Noise canceller (ANC), Excess mean square error (EMSE), VSSNDLMS.*

1. INTRODUCTION

Noise cancellation and echo cancellation [2] in a signal is an important core area of the digital signal processing. Adaptive filter is a digital filter that has self-adjusting characteristics which can adjust its filter coefficients automatically and gets adapted to the input signal. Adaptive filters work generally for adaptation of signal-changing environments like spectral overlap between noise and signal, noise like telephone echo cancellation, equalization of communications channels, biomedical signal enhancement, active noise control, and adaptive control systems. Adaptive filtering is one of the approaches used to remove the noise from the desired signal.

Adaptive filtering (AF) finds application in noise cancellation in speech called as Adaptive Noise cancellation (ANC) which involves in time-varying signals and systems. In adaptive filter least mean square (LMS) algorithm [3] is the most popular algorithm. Because of its simplicity, robustness, and low computational complexity, it has been widely used in noise cancellation, linear prediction and so on. Least Mean Square (LMS) algorithm is one of the well-known adaptive algorithms which is based on stochastic gradient approach.

Various adaptive algorithms have been proposed for noise cancellation. R.Bilcu et.al has proposed a new variable length LMS algorithm theoritical and implemented [1]. The sub band adaptive filters have been proposed [6] to analyse the convergence and complexity in adaptive filters. Gorriz et.al, proposed a novel LMS algorithm for filtering speech sounds in the adaptive noise cancellation[4]. J. E. Greenberg has modified the LMS algorithm and used to cancel the noise in speech signal [3]. Y.Gong and C.Cowan proposed a variable tap-length algorithm based on MSE output from different filter segments, which combines the traditional segmented filter approach with a gradient descent-based method [5].

2. ADAPTIVE ALGORITHMS

In this paper, the various LMS adaptive algorithms were analysed and a novel algorithm named Variable Step Size Normalized Difference LMS (VSSNDLMS) algorithm is proposed to remove the noise in signal recorded in various environments like in street or inside a car. The variable step size LMS algorithm converges fastly and NDLMS algorithm has minimised mean square error. By combining the VSS and NDLMS, the proposed VSSNDLMS algorithm converges fastly

Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

with minimum mean square error. Figure 1 shows the general system identification of adaptive filter.

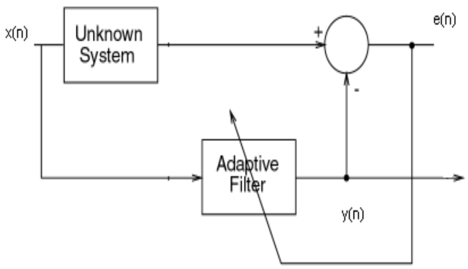

Figure 1: System Identification

A. LMS Algorithm

The LMS is one of the simplest algorithms used in the adaptive structures due to their simplicity and robustness to signal statistics. LMS algorithm expressions for finding the error signal and the filter weights is,

$$e(n) = d(n) - \mathbf{W}^T(n) * u(n). \quad (1)$$

$$W(n+1) = W(n) + \mu * u(n) * e^*(n). \quad (2)$$

LMS is entirely based on wide-sense stationary stochastic signals, the algorithm is also applied to the following other situations: A deterministic environment, in which the tap-input vector x (n) and desired response d (n) are both deterministic signals and a non-stationary environment i.e., the tracking of statistical variations in the environment.

B. NDLMS Algorithm

A slight modification is made in LMS algorithm equations and a Normalised Differential LMS[6] Algorithm and is proposed by J Zhang and H.M Tai used for finding the error signal and the filter weights. In this case the algorithm improves the steady state performance for cancelling noise in speech processing. The excess error and misadjustment by NDLMS are much less than that of the NLMS and MNLMS algorithms.

$$e(n) = d(n) - \mathbf{W}^T(n) * x(n) * d(n). \quad (3)$$

$$w(n+1) = w(n) + \mu \times \nabla x(n) \times \nabla d(n) \quad (4)$$

here the weight is adjusted according to the difference of the signals x(n) and d(n) are shown in equation 4, instead of the signals themselves.The important process in the adaptive filter is to determine the length of M. If the length M of the adaptive filter is low then the speech signal processing results in less number of parameters which are inaccurate. High value of the adaptive filter length M leads to inaccurate speech signal processing by the influence of estimated variance increase.

C. VSSNLMS Algorithm

This algorithm overcomes the problem of convergence speed and estimation accuracy in real time environment, the variable step size normalised LMS[7] algorithm is proposed. The signal to noise (SNR) ratio is defined as the ratio of the average power of the original signal to that of the noise signal. The main aim of proposing this algorithm is that with the help of SNR, the step size adjustment can be controlled. It is efficient to have lesser value of SNR because such a value gives the maximized step size that provides faster tracking. At the same time, the larger value of SNR results in minimized step size producing smaller mis-adjustment.

To estimate the SNR, the average power of the speech signal $p_s(n)$ and the noise signal $p_n(n)$ respectively are considered as,

$$P_S(n) = \sum_{j=0}^{M-1} [s(n-1) - (n-j)]^2 \quad (5)$$

$$p_N(n) = \sum_{j=0}^{m-1} y^2(n-j) \quad (6)$$

Where, $P_S(n)$ and $P_N(n)$ can be estimated by the number of samples M from equation 5 and 6. SNR(n) is given as

$$SNR(n) = 10\log_{10}\frac{p_s(n)}{P_N(n)} db \quad (7)$$

The updating of the normalized coefficients is given by (8)

$$w(n+1) = w(n) + \frac{\mu}{X^T(n)X(n)} e(n)X(n) \quad (8)$$

Where, μ is the step size coefficient.

When the value of SNR is small, step size will increase and thus leads to fast convergence and when the SNR is high step size μ will be small. So

Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

step size and SNR values are interrelated. The following equation determines the step size μ.

$$\mu = \begin{cases} \mu_{\min} \ldots\, if SNR(n) > SNR_{\max} \\ \mu_{man} \ldots\, if SNR(n) > SNR_{\min} \\ aSNR(n) + b \ldots\, if SNR_{\min} \le SNR(n) \ge SNR_{\max} \end{cases} \quad (9)$$

Here the excess error and misadjustment by NDLMS are much less than that of the NLMS and VSSNLMS algorithms.

3. PROPOSED ALGORITHM

In our work a novel new approach called Variable step size Normalized Differential LMS (VSSNDLMS) algorithm is proposed. The objective of proposing this algorithm is to design an adaptive filter which works on both strong and weak signal. Proposed algorithm combines variable step size NLMS[7] and NDLMS to increase convergence speed, minimise excess mean square error , reduce misadjustment and increase estimation accuracy.

In case of LMS algorithm, under non-stationary environment some errors occur leading to deviation of filter weights from the optimal weight of the filter. Whereas the analysis says that variable step size algorithm is suitable for such an environment.

The expression for updating the Coefficient is given by

$$w(n+1) = w(n) + \frac{\mu_{\text{var}}}{\varepsilon + \ \nabla X(k)\ ^2} \nabla x(n) * \nabla e(n) \quad (10)$$

Where,

$$\nabla e(k) = e(k) - e(k-1) \quad (11)$$

$$\nabla x(k) = x(k) - x(k-1) \quad (12)$$

and the μ_{var} is the variable step size which is given by

$$\mu_{\text{var}} = \begin{cases} \mu_{\max \ldots}\, if\, \mu_i > \mu_{\max} \\ \mu_{\min \ldots}\, if\, \mu_i < \mu_{\min} \end{cases} \quad (13)$$

$\mu_i = \alpha * \mu + \gamma\varepsilon_k^2$ and

$\alpha = 0.97; \gamma = 4.8 * 10^{-4}$

where, Spectral density of the tap inputs x (n) and the filter length M is moderate to large. Given,
x(n) (M-by-1 tap input vector at time n) = [x(n) ,x(n-1) ,…..,x(n-M+1)].
Initialize, If prior knowledge of the tap weight vector w (n) is available, use it to set an appropriate value for w(0).Otherwise set w (0) =0. It is known that adaptive filters reduces the mean square error (MSE) and it is given as,

$$MSE = E\left\{ \ d(n) - \hat{d}(n)\ ^2 \right\} \quad (14)$$

Therefore, the graph of MSE quantity is essential to evaluate the performance of the adaptive filter.

4. EXPERIMENTAL RESULTS

The comparison results of two speech signals with NDLMS, VSSNLMS[8] and VSSNDLMS Algorithm are presented in this section. Experiments are carried out and simulated using Matlab7 version. Two different speech signals are considered to analyse the mean square errors found using all the above mentioned algorithms. Speech signals are recorded in various environments such as in street and inside a car and they are given as input to various algorithms. Both the recorded signals are individually given as inputs to all the algorithms and output signals are obtained. The output signal responses of all the filters are plotted for analysis.

The results shows that VSSNDLMS algorithms have least mean square error and converges effectively thus gives better performance when compared to all other algorithms. The VSSNDLMS responses for both street signal and car signal are shown respectively in Figure 2 and 3. For variance of 0.499 of speech signal with street Noise the mean square error is 5.6737 x 10^{-8} and For variance of 0.499 of speech signal with car engine Noise the mean square error is 1.31 x 10^{-5}, from the Figure 2, we can see the noise present in the speech is more and from the figure 3,In the speech signal with car engine, the noise is less. For the same variance the mean square error differs for strong and weak noise signal.

The comparison of MSE for LMS, NDLMS and VSSNDLMS algorithms is shown in Table 1.

Journal of Theoretical and Applied Information Technology
20th February 2013. Vol. 48 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

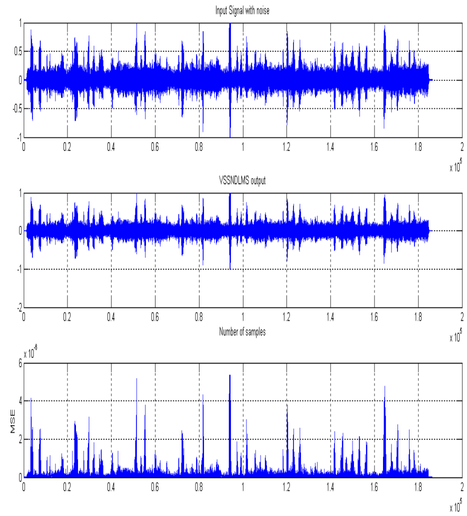

Figure 2 : VSSNDLMS Response For Input Speech Signal With Street Noise

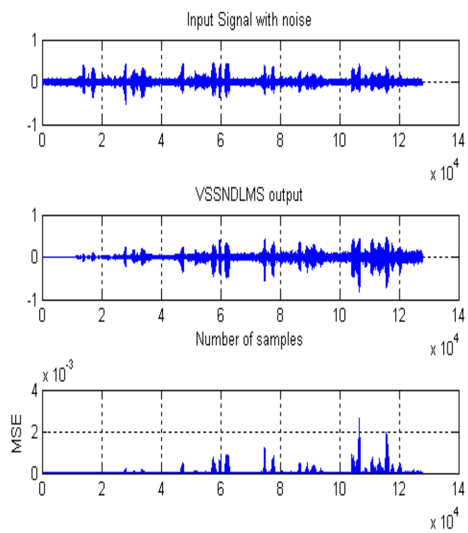

Figure 3 : VSSNDLMS Response For Input Speech Signal With Car Engine Noise

Table 1: Comparison Of Mean Square Error

Variance	Mean Square Error		
	LMS	NDLMS	VSSNDLMS
0.01	0.266	0.10	0.104
0.1	0.529	0.21	0.16
1.0	0.6714	0.354	0.31

5. CONCLUSION

A novel LMS algorithm called Variable Step Size Normalized Differential LMS (VSSNDLMS) algorithm for an adaptive filter is presented. In this paper the proposed algorithm has been compared with various other algorithms like LMS, NDLMS in order to find the efficiency. Speech signals recorded in various environments are taken and processed using all the algorithms which illustrates our proposed algorithm reduces the trade-off between misadjustment, tracking and removes the noise from the input signals. Also the results show that VSSNDLMS algorithm converges at a fast rate and the mean square error is reduced much and hence suitable for non-stationary environment. Thus the theoretical and simulation results prove that the proposed work is a promising method for removing the noise in the signal.

REFRENCES:

[1] R.Bilcu, P.Kuosmanen, K.Egiazarian, "A new variable length LMS algorithm: theoretical analysis and implementations", *9th International Conference on Electronics, Circuits and Systems*, Vol.3, 2002, pp.1031–1034.

[2] G.M. Vetterli, "Adaptive filtering in subbands with critical sampling: analysis, experiments, and applications to acoustic echo cancellation", *IEEE Trans. Signal Process*. 40 (August 1992) 1862–1875.

[3] J. E. Greenberg, "Modified LMS algorithms for speech processing with an adaptive noise canceller," *IEEE Trans. Speech audio process* vol 6, no4, pp 338-358 ,july 1998

[4] Gorriz, J.M. Ramirez, J. Cruces-Alvarez, S. Puntonet, C.G. Lang, E.W. Erdogmus, "A Novel LMS algorithm applied to adaptive noise cancellation" *IEEE signal Processing Letters* Vol 16 , pp 34-37.

[5] Y.Gong,C.Cowan, "A LMS style variable tap-length algorithm for structure adaptation", *IEEE Transactions on Signal Processing*, 2005,pp 2400–2407.

[6] Jiashu Zhang and Heng-Ming Tai, "Adaptive Noise Cancellation Algorithm for Speech Processing" , *The 33rd Annual Conference of the IEEE Industrial Electronics Society* (IECON) Taipei, Taiwan.

[7] QU Yan-bin, MENG Fan-gang , GAO Lei, "A New Variable Step Size LMS Adaptive Filtering Algorithm" *IEEE International Symposium on Industrial Electronics*, 2007.

[8] J.P Joonwan Kim, J. Lee, S. Kim, C. Lee, "Performance analysis of adaptive noise canceller in real-time automobile environments", *39th South eastern Symposium on System Theory*, Mercer University, March 2007.