International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

An Advanced Low Complexity Adaptive Filter for Echo Cancellation

Deepak Sharma[1], Nidhi Sharma[2]

[1]Research Scholar, Maharana Pratap College of Technology, Gwalior (M.P.), India

[2]Associate Professor-ECE Department, Maharana Pratap College of Technology, Gwalior (M.P.), India

Abstract: ***In Digital Signal Processing Adaptive filtering concept considered as one of the core fundamental concept. The concept of adaptive filtering is used in several DSP applications such as adaptive noise cancellation, including echo cancellation, adaptive equalization, and adaptive beam forming. Today's telecommunication systems are severely faces "Acoustic echo cancellation" problem i.e. the quality of the communication decays due to the interference caused by acoustic echo. Therefore in this paper we propose an advanced "LMS" adaptive filter to improve the communication quality by providing the channel equalization and reducing the unwanted echo. In this paper we not only restricted our simulated results for LMS but also discusses about NLMS which means that most efficient technique for echo cancellation. In this paper we also provide the simulation results for comparison of different adaptive techniques for Mean Square Error.***

Keywords: Digital Signal Processing, Adaptive Filters, Channel Equalization, LMS, NLMS and RLS etc

1. Introduction

In Digital Signal Processing adaptive filtering is one of the core technologies, where we find its applications in several areas of science. Advanced electric circuits which are used to allow a specific range of electric of electric signals within interested frequency bands and suppress the signals the outside the specific range called as Filters. If the input of the filter is static in nature then the resultant solution of the filter is known as Wiener Filter, but in real time environment the input to the filter is dynamic in nature so we propose another advanced method i.e. adaptive filtering. Adaptive filters required set of predetermined initial values (as filter coefficients). In dynamic environment, the adaptive filter algorithm shall estimate time variations in the statistics of input data, provided that the variations are sufficiently slow. In this paper we proposed advanced adaptive filers for channel equalization and Echo cancellation. Generally echo signals are resultant signals of combination of original data signal plus time delayed data signal. An adaptive filter is a self-designing filter that uses a recursive algorithm (known as adaptation algorithm or adaptive filtering algorithm) to "design itself."

Geneally echo signal consists of two signals as one is original data signal and another one is Reverberated signal of original signal, the second one is attenuated signal of message signal. This paper mainly concentrates on the suppressing of echo signal of the data signal and performs the channel equalization using advanced adaptive filters.

Remaining of this paper is organised as section II discusses about the introduction adaptive filter and criteria for considering MSE in designing of adaptive filters. LMS algorithm introductions, implementation of LMS algorithm, importance of step size and tap length are discussed in section III. Section IV and V consists of discussion about Normalized LMS and RLS. The simulated results are discussed in section VI as generated data and echo signal. System response of the designed adaptive filter for intended input and comparison of various adaptive filters in terms of Mean Square Error. Finally paper is concluded with the future scope.

2. Introduction to Adaptive Filters

Adaptive filters are dynamic in nature i.e. in order to achieve the desired output the characteristics of the filters are changed iteratively. The most important note for adaptive filter is "*Cost Function*" which is determined as *the difference between the desired output d(n) and actual output y(n).*

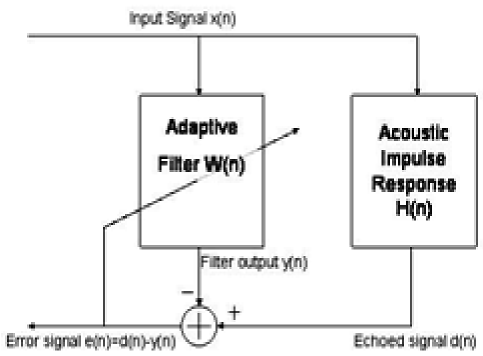

Figure 1: Adaptive echo Cancellation system

Block diagram of the adaptive echo cancellation is shown in above figure 1. Where
H (n): impulse response of the system.
W (n): represents the adaptive filter used to cancel the echo signal.
e(n): Error signal
$e(n) = d(n)-y(n)$
e(n) is a feedback signal for dynamically changing the filter coefficients.

Adaptive filters are designed to equate the actual output y(n) to desired signal d(n). Therefore the error signal is feedback for each iteration to obtain the desired output. Whenever the error signal is zero it means that filter output is equal to desired output. At this situation the echoed signal is completely cancelled.

3. Criteria of MSE in Designing of Adaptive Filters

The goal behind the designing of adaptive filters is to estimate the desired signal d(n) from input signal sample x(n). In the concept of designing adaptive filters we consider both noise and signals are as stochastic in nature. Below figure displays the linear filter with the aim of estimating the d(n)

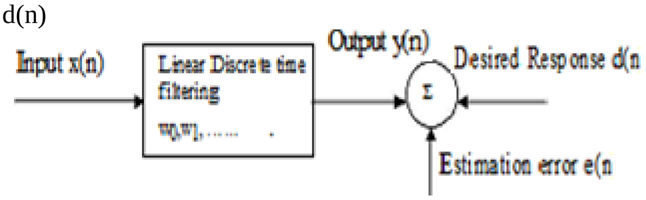

Figure 2: Prototype Adaptive Filtering Scheme

4. LMS Algorithm

Least Mean Square algorithm is a stochastic gradient based algorithm type adaptive filter and it utilises the gradient vector of the filter weights [2-4]. LMS algorithm is well known adaptive filter because of its less complexity and simplicity.

Therefore the filter weights for the LMS adaptive filter at each and every iteration is

$$w(n+1) = w(n) + 2\mu e(n)x(n) \quad (1)$$

x(n) : time delayed input vector values and x(n) is defined as

$$x(n) = [x(n)\ x(n-1)\ x(n-2)\ ..\ x(n-N+1)]^T$$

w(n): coefficients of the adaptive filter and

$$w(n) = [w_0(n)\ w_1(n)\ w_2(n)\ ..\ w_{N-1}(n)]^T$$

μ : Positive step size parameter.

Performance of the LMS algorithm depends on updating factor i.e. step size parameter and it controls the influence of the updating factor.

If the μ is too small adaptive filter consumes more convergence time for optimal desired output and if it is very large the output of the system is deviates from desired signal and the system becomes unstable [5-8].

5. LMS Algorithm Implementation

For every iteration we can write the LMS algorithm as

1. Filter output :

$$y(n) = w\ x(n)$$

2. Error Estimation :

$$e(n) = d(n) – y(n)$$

3. Tap Weight adaptation:

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

LMS algorithm is a method of steepest descent algorithm and it is implemented as

$$w(n+1) = w(n) - \mu\nabla_n\xi \quad (2)$$

$\nabla_n\xi$ is a gradient vector evaluated at point w=w(n)

$$w(n+1)=w(n)-\mu\nabla_n e^2(n) \quad (3)$$

∇e^2 (n) is defined as

$$\frac{\partial e^2(n)}{\partial w_i} = 2e(n)\frac{\partial e(n)}{\partial w_i} \quad (4)$$

The derivative of the first equality in

$$\frac{\partial e(n)}{\partial w_i} = 0 - \frac{\partial y(n)}{\partial w_i}$$

Therefore

$$\frac{\partial e^2(n)}{\partial w_i} = -2e(n)\frac{\partial y(n)}{\partial w_i} \quad (5)$$

$$\frac{\partial e^2[n]}{\partial w_i} = -2e(n)x(n) \quad (6)$$

$\nabla e^2(n)=-2e(n)x(n)$ (7)

Therefore from equation 2 and 6

$$w(n+1) = w(n) + 2\mu e(n)x(n) \quad (8)$$

The above equation is known as *LMS tap weight adaption.* Tap weight adaption is dynamic in nature and it changes for every iteration to minimizing the cost function. However, the performance of the LMS algorithm is often sub-optimal and the convergence rate is small. This, therefore, provides the motivation to explore and study variable step size LMS adaptive algorithms for various applications.

6. Importance of Step Size

Step size is a very important factor in designing of adaptive filters. In LMS adaptive filters the step size is constant or fixed. Larger step size will reduces the convergence time but it increases the Mean Square Error. Therefore the selection of step size will affects the entire system performance and the selection of the step size is application specific with priority requirements such as fast convergence, robustness, tracking capability and adaptation accuracy. The efficient and optimum step size will be determined using cost function at each iteration for obtaining minimum MSE.

For maintaining the stability with the LMS filter the step size of the filter is designed as

$$0 \le \mu \le (2/tapweightpower) \quad (9)$$

Tap weight power is defined as *sum of the all tap inputs in the transversal filter*.

Importance of Filter TAP Length

The filter tap length plays a very important role in performance of filters. The performance of adaptive filters depends on tap length of the filter, how much it is sufficient to cover the impulse response of the channel. However the long tap length leads to poor convergence rates and small tap lengths leads to computational complexity. From equation 4, when the power of the input signal is unstable and large i.e. varies continuously LMS algorithm becomes unstable and there is no optimal solution which is known as gradient noise amplification. To deal with this problem, a modified version of LMS known as *Normalized* algorithm can be implemented.

7. NLMS Algorithm

For non stationery input signals determining the upper bound step size is not as easy as possible. But in the most of the applications the input signals are dynamic in nature, to

overcome this problem Normalized LMS is proposed. In this scheme the step size is normalized by the input signal power, which increases the convergence speed at low MSE. The only difference between LMS and NLMS is the normalized step size which normalized using the input power in NLMS.As the name implies, the NMLS algorithm is an effective approach particularly when the variation of the input signal power is large, by normalizing the update step size with an estimate of the input signal variance.
The estimated tap weight for the NLMS is defined as

$$w(n+1) = w(n) + \frac{\alpha}{\|x(n)\|^2} e(n)x(n) \tag{10}$$

α is adaption constant and it is defined as $0 < \alpha < 2$
Therefore the Normalized Least Mean Square algorithm is always considerable filter fast convergence and low mean square error. Since from the above equation the convergence rate is proportional to adaption constant and inversely proportion to signal power, so by choosing the approximate α value, the NLMS algorithm convergence faster than LMS filters.

8. RLS Algorithm

The main advantage of LMS algorithm is its simplicity, but it is designed only for stable input signals only, it provides low convergence and less auto correlation. LMS filters are designed only for limited purposes with less upper bound and slower convergence. Therefore to attain faster convergence rate we required dynamic step size selection as per dynamic signal input power, which is possible by the concept of *Recursive Least Square Algorithm.* The RLS algorithm is based on error estimation of input signal and desired signal i.e. least square estimation. The difference between statistical approach and RLS is, RLS scheme adopted the least squares concept instead of MSE. The cost function for RLS algorithm is defined as

$$\phi(n) = \sum_{k=1}^{n} \lambda^{n-k} e_n^2(k) \tag{6}$$

From the above equation it is clear that the cost of RLS algorithm requires values of previous samples to produce the required desired signal. λ Is a positive integer as $0 < \lambda$ .RLS algorithms are known for excellent performance when working in time varying environments. These advantages come with the cost of an increased computational complexity and some stability problems

9. Analysis of Results

The simulation results of this paper are analysed using MATLAB software. The simulated results are discussed in this section as generated data and echo signal. System response of the designed adaptive filter for intended input and comparison of various adaptive filters in terms of Mean Square Error. This analysis is discussed as

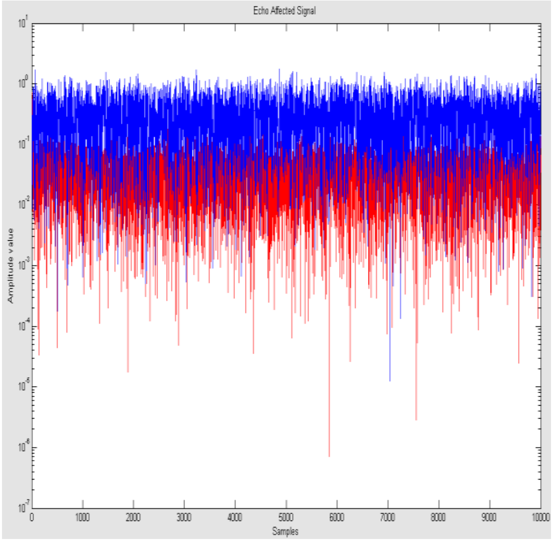

Figure 3: Echo affected signal

Figure 3 represents the echo affected signal. It consists of original data signal and as well as time delayed original data signal which is termed as echo signal. As echo signal is additive n nature the original data signal is completely affected by echo signal as shown in above figure. For our project investigation we consider 10000 samples. Echo signal has the characteristics same as Additive White Gaussian Noise.

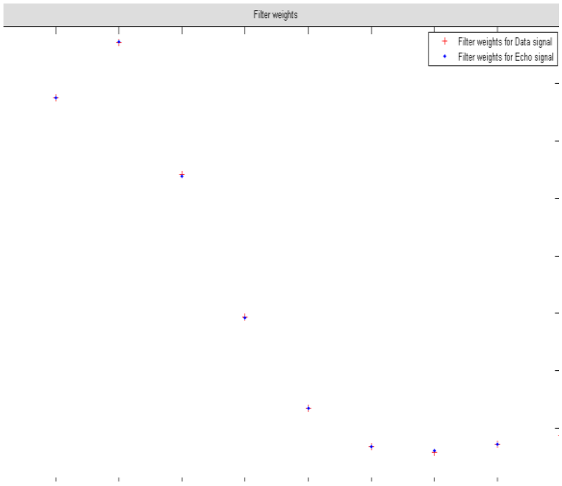

Figure 4: Design of filter coefficients

Above figure represents the design of filter coefficients for data signal and as well as echo signal. As shown in above figure LMS filter has the constant tap weights. Since very short time delay exists between original signal and echo signal we design adaptive filter with two different time delays which are corresponded to signal and echo. These coefficients are nothing but tap weights of the filters. These coefficients ate stable for Least Mean Square adaptive filters.

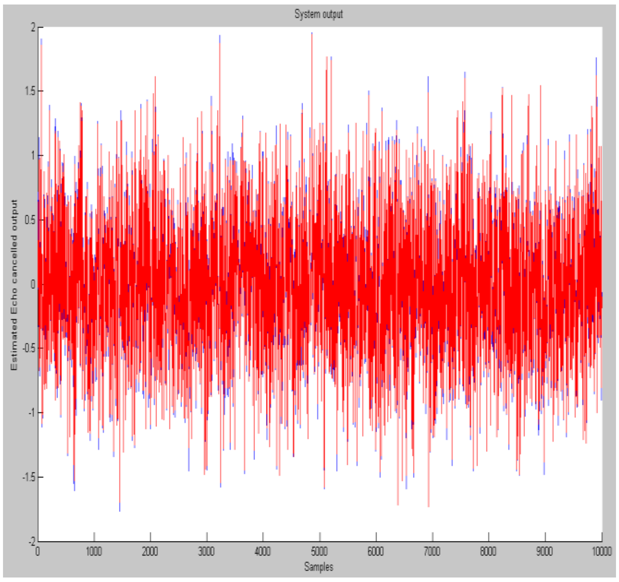

Figure 5: System Response of Adaptive Filter

Above figure represents the system response of the designed LMS adaptive filter. As from the above simulation results we observed that most of the echo components are from the signal. It is not possible to remove the echo completely from the signal, since the echo signal is additive in nature.

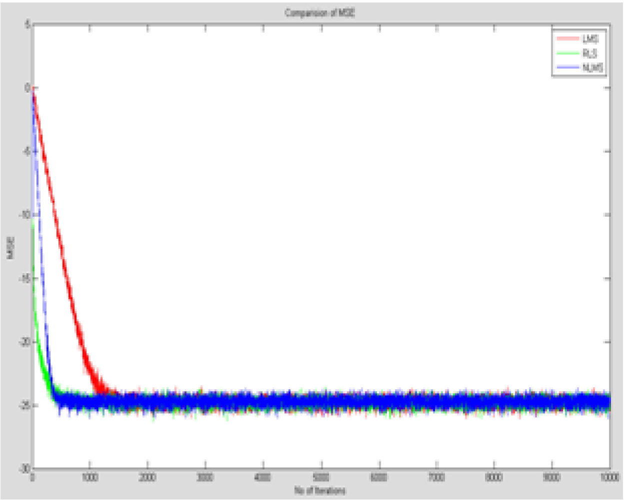

Figure 6: Comparison of Adaptive Filters

Above figure represents the comparison of three advanced adaptive filters as LMS, NLMS and RLS.

These parameters describes the dynamic nature of the filters and it is defined as the number of iterations needed to come stable MSE i.e. steady state MSE and it is also known as Mean asymptotic square error or MASE. This concerns how fast the algorithm will change the filter parameters to their final values.

As already discussed in previous sections the LMS adaptive filter has the stable step size irrespective of input signal and where as the NLMS has normalized step size, which is normalized by using input signal power. Both these filters are limited with input signal power and do not have the knowledge of previous samples. But these limitations are overcome by the concept of RLS. In RLS the step size varies as per input signal power and therefore there is less MSE when compared to previous which is proved in simulation results. Therefore the RLS algorithm is best suitable interms of MSE and LMS is preferable interms of less complexity.

10. Conclusion

From the analysis of simulation results, LMS algorithm is most suitable in terms of low complexity for known power signals and RLS is most suitable for dynamic natured signals. But the RLS algorithm faces high complexity and the LMS faces high MSE. RLS algorithm is used for high quality applications. NLMS is suitable for intermediate signals. However the usage of adaptive filters depends on priority of echo cancellation

References

[1] John G. Proakis, Dimitris G.Manolakis, " Digital signal processing: principles, algorithms and applications" , Prentice Hall, March 2002.

[2] S. Haykins , " Adaptive Filter Theory" , Prentice Hall ,New Jersey, 1996.

[3] S. Qureshi, " Adaptive Equalization," *Proceedings of the IEEE, vol.73*, No.9, pp. 1349-1387, Sept. 1985.

[4] A. Zerguine, C. F. N. Cowan, and M. Bettayeb, " Adaptive Echo Cancellation Using Least Mean Mixed-Norm Algorithm" , *IEEE Trans. On Signal Processing* vol. 45, No.5, pp. 1340-1343, May, 1997.

[5] Hosien Asjadi, Mohammad Ababafha, " Adaptive Echo Cancellation Based On Third Order Cumulant, International Conference on Information, Communications and Signal Processing, ICICS '97 Singapore, September 1997

[6] D. G. Messerschmitt, " Echo Cancellation in Speech and Data Echo transmission," *IEEE J. of Selected Areas in Comm., vol.* SAC-2, No.2, pp. 283-297, Mar. 1984

[7] Shoji Makino, Member, IEEE, Yutaka Kaneda, Member, IEEE and Nobuo Koizumi, " Exponentially weighted step size NLMS adaptive filter based on the statistics of a room impulse response" , *IEEE Trans. on speech and audio Processing*, vol. 1, No.1, pp.101-108, Jan 1993.

[8] Sudhakar Kalluri and Gonzalo R. Arce, " A General Class of Nonlinear Normalized Adaptive Filtering Algorithms" , *IEEE Trans. On Signal Processing* vol. 47, No.8, Aug, 1999

[9] B. Widrow, J. M. McCool, M. G. Larimore, and C. R. Johnson, Jr., " Stationary and non stationary learning characteristics of the LMS adaptive filter." *Proc. IEEE.* vol. 64, pp. 1151-1162, 1976.

[10] B.Widrow, " Adaptive Noise Canceling" , *proc. IEEE*, vol.63, pp. 1692-1716, Dec1975.

[11] B.Widrow, " Adaptive Noise Canceling" , *proc. IEEE*, vol.63, pp. 1692-1716, Dec1975.

[12] N.J. Bershad, "On the optimum gain parameter in the LMS adaptation" , *IEEE Trans. On Acoustic, Speech, Signal processing* vol. ASSP-35, pp.1065-1068, June 1981.

[13] S.Marcos and O.Macchi, " Tracking capability of the Least Mean square algorithm: Application of an asynchronous echo canceller" , *IEEE Trans. On Acoustic, Speech, Signal processing* vol. ASSP-35, pp.1570-1578, Nov 1987.

[14] Raymond H. Kwong and Edward W. Johnston, "A Variable Step Size LMS Algorithm", *IEEE Trans. On Signal Processing* vol. 40, No.7, pp. 1633-1642, July, 1992.

[15] Tyseer Aboulnasr, Member, IEEE, and K.Mayyas, " A robust variable step size LMS type algorithm: Analysis and Simulations" , *IEEE Trans. On Signal Processing* vol. 45, No.3, pp. 631-639, March 1997.

[16] S.Theodoridis ,et. Al., " Efficient least square Adaptive algorithms for FIR transversal filtering" , *IEEE Signal Processing Magazine*, vol. 16 , No.4, July,1999

[17] M.M. Sondhi, " An Adaptive Echo Canceller," *Bell Syst. Tech. J., vol. 46*, No.3, pp. 497-511, Mar. 1967

[18] B. Widrow, fellow, IEEE, J. M. McCool, senior member, IEEE, " **A** Comparison of Adaptive Algorithms Based on the Methods of Steepest Descent and Random Search" , *IEEE transactions on antennas and propagation*, vol. AP-24, No.5, Sept 1976.

[19] B.Widrow, Mac.Cool , and M.ball, " The Complex LMS Algorithm" , *proc.IEEE*,vol.63, pp. 719-720,1975.

[20] Geoffrey A. Williamson, Peter M. Clarkson, and William A. Sethares," Performance Characteristics Of the Median LMS Adaptive Filter" , *IEEE Trans. On Signal Processing* vol. 41, No.2, pp. 667-679, Feb 1993.

[20] Da-Zheng Feng, Xian-Da Zhang, Dong-Xia Chang, and Wei Xing Zheng , "A Fast Recursive Total Least Squares Algorithm for Adaptive FIR Filtering", *IEEE Trans. On Signal Processing* vol.52, No.10, pp.2729-2737, Oct 2004.

[21] Rabiner and Gold, "Theory And Applications Of Digital Signal Processing", Prentice Hall, Inc., 1975 Wee-Peng Ang and B. Farhang-Boroujeny, " A New Class of Gradient Adaptive Step-Size LMS Algorithms" , *IEEE Trans. on Signal Processing* vol. 49, No.4, April 2001