A Fast Converging and Robust Stability of Acoustic Echo Cancellation using Adaptive Filter.

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***Abstract-* In this paper we introduce an Acoustic echo cancellation (AEC) based on an adaptive algorithms to design the adaptive filtering. The main aim in hands-free telephony and in teleconference systems is to provide a good free voice quality when two or more people communicate from different places. The problem that arises during the conversation is often due to acoustic echo. This problem will cause a bad quality of voice signal. Acoustic echo cancellation (AEC) is common in modern telecommunication systems, and it is one of the most popular applications of adaptive filters. This paper focuses on the use of filtering as LMS algorithms to reduce this unwanted echo. The results indicate that the LMS is the simplest to implement and is stable when the step size parameter is selected appropriately. For large step size, a moderate large value of leads to faster convergence but if step size is too high, it leads to instability of LMS and erroneous results. In this paper we propose the robust technique is referred to based diagonal loading (DL). The performance evaluation of the robust adaptive filter using diagonal loading provides faster speed of convergence among other variable step size algorithms while retaining the same small level of misadjustment and the mean square error is almost similar to that of the (fixed step size least mean square) DL-LMS algorithm under similar conditions. more robust variant of the LMS algorithm, exhibits a better balance between simplicity and performance than the pure LMS algorithm.**

***Keywords* - Acoustic Echo Cancellation (AEC), Least Mean Square (LMS), Recursive Least Square (RLS).**

I. Introduction.

Acoustic Echo Cancellation (AEC) is one of the most popular applications that apply. The goal of the adaptive algorithms is to identify the acoustic echo path between a loudspeaker and a microphone placed in an acoustic enclosure (i.e., the room acoustic impulse response) and generate the estimate of the acoustic echo that is removed from the output of the microphone. Most of the adaptive echo cancellation techniques proposed in literature is based on an assumption that the echo path is linear. Acoustic echo occurs when an audio signal is reverberated in a real environment, resulting in the original intended signal plus attenuated, time delayed images of this signal. Today's telecommunication systems consist of mostly full duplex mode. In that, coupled acoustic input and output devices, both are active concurrently in full duplex mode. The system then acts as both a receiver and transmitter in full duplex mode. In this situation the received signal is output through the telephone loudspeaker (audio source) from Far End Speech, (FES), this audio signal is then reverberated through the physical environment and picked up by the systems microphone (audio sink) at near end speech (NES). This signal is reverberated within the environment and returned to the system via the microphone input. These reverberated signals contain time delayed images of the original signal, which are then returned to the original sender. The occurrence of acoustic echo in speech transmission causes signal interference and reduced quality of communication. Modern full-duplex communication systems make use of an acoustic echo canceller (AEC) to prevent the echo from being transmitted back to the channel. The AEC basically estimates the echo and subtracts the estimated echo from the microphone signal. The method used to cancel the echo signal is known as adaptive filtering.

Adaptive filter are dynamic filters, which iteratively alter their characteristics in order to achieve an optimal desired output. An adaptive filter algorithmically alters its parameters in order to minimize a function of the difference between the desired output d(n) and its actual output y(n). This function is known as the cost function of the adaptive algorithm. Fig. 1, shows a block diagram of the adaptive echo cancellation system implemented throughout this paper. Here the filter h(n) represents the impulse response of the acoustic environment, w(n) represents the adaptive filter used to cancel the echo signal.

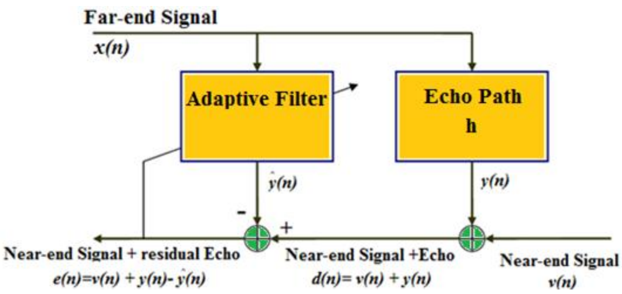

Fig. 1. Block diagram of the adaptive echo cancellation.

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The adaptive filter aims to equate its output y(n) to the desired output d(n) (the signal reverberated within the acoustic environment). At each iteration the error signal, e(n)=d(n)-y(n), is fed back into the filter, where the filter characteristics are altered accordingly [1],[2].

II. ADAPTIVE ECHO CANCELLATION FILTERING

A filter is designed and used to extract or enhance the desired information contained in a signal. Adaptive filter is the most important component of acoustic echo canceller and it plays a key role in acoustic echo cancellation. It performs the work of estimating the echo path of the room for getting a replica of echo signal, [3]. An adaptive filter is a filter with an associated adaptive algorithm for updating filter coefficients so that the filter can be operated in an unknown and changing environment. If the inputs to the filter are stationary, the resulting solution of the filtering problem is known as the Wiener Filter, which is said to be optimum in mean square sense. But it requires a priori information about the statistics of the data to be processed. If the environment is unknown then another efficient method is to use an adaptive filter using recursive algorithm, [4].The adaptive algorithm determines filter characteristics by adjusting filter coefficients (or tap weights) according to the signal conditions and performance criteria (or quality assessment). A typical performance criterion is based on an error signal, which is the difference between the filter output signal and a given reference (or desired) signal. an adaptive filter is a digital filter with coefficients that are determined and updated by an adaptive algorithm. Adaptive filtering constitutes one of the core technologies in digital signal processing and finds numerous application areas in science as well as in industry. Adaptive filtering techniques are used in a wide range of applications, including echo cancellation, adaptive equalization, adaptive noise cancellation, and adaptive beamforming, [5].

Fig. 2, shows the block diagram for the adaptive filter method utilized in this paper.

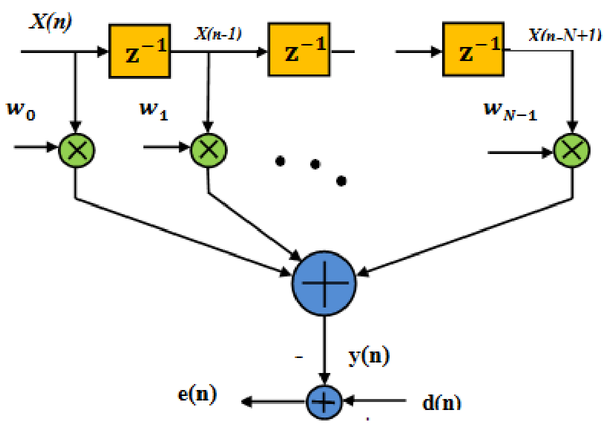

Fig. 2. Adaptive filter block diagram [5].

Here w represents the coefficients of the FIR filter tap weight vector, x(n) is the input vector samples, z^{-1} is a delay of one sample periods, y(n) is the adaptive filter output, d(n) is the desired echoed signal and e(n) is the estimation error at time n.

The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function. In the case of acoustic echo cancellation, the optimal output of the adaptive filter is equal in value to the unwanted echoed signal. When the adaptive filter output is equal to desired signal the error signal goes to zero. In this situation the echoed signal would be completely cancelled and the far user would not hear any of their original speech returned to them.

This section examines adaptive filters and various algorithms utilized. The various methods used in this paper can be divided into two groups based on their cost functions.

The first class are known as Mean Square Error (MSE) adaptive filters, they aim to minimize a cost function equal to the expectation of the square of the difference between the desired signal d(n), and the actual output of the adaptive filter y(n) (1).

$$\xi(n) = E[e^2(n)] = E[(d(n) - y(n))^2] \qquad (1)$$

The second class are known as Recursive Least Squares (RLS) adaptive filters and they aim to minimize a cost function equal to the weighted sum of the squares of the difference between the desired and the actual output of the adaptive filter for different time instances. The cost function is recursive in the sense that unlike the MSE cost function, weighted previous values of the estimation error are also considered. The cost function is shown below in equation 3.5, the parameter λ is in the range of 0<λ<1. It is known as the forgetting factor as for λ<1 it causes the previous values to have an increasingly negligible effect on updating of the filter tap weights [6]. The value of 1/(1- λ) is a measure of the memory of the algorithm this paper will primarily deal with infinite memory, i.e. λ =1. The cost function for RLS algorithm, ζ(n), is stated in equation.

$$\xi(n) = \sum_{k=1}^{\infty} \rho_n(k) e_n^2(k) \qquad \rho_n(k) = \lambda^{n-k} \qquad (2)$$

Where k=1, 2, 3.n., k=1 corresponds to the time at which the RLS algorithm commences. Later we will see that in practice not all previous values are considered, rather only the previous N (corresponding to the filter order) error signals are considered. As stated previously, considering that the number of processes in our ensemble averages is equal to one, the expectation of an input or output value is equal to that actual value at a unique time instance. However, for the purposes of deriving these algorithms, the expectation notation shall still be used.

III. IMPLEMENTATION OF ADAPTIVE ALGORITHM FOR AEC

A- Implementation of the LMS algorithm

The derivation of the LMS algorithm builds upon the theory of the wiener solution for the optimal filter tap weights, w.

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It also depends on the steepest descent algorithm as stated, this is a formula which updates the filter coefficients using the current tap weight vector and the current gradient of the cost function with respect to the filter tap weight coefficient vector. Each iteration of the LMS algorithm requires 3 distinct steps in this order:

1. The output of the FIR filter, y(n) is calculated using equation:

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-1) = w^{T}(n)x(n) \qquad (3)$$

2. The value of the error estimation is calculated using equation 4.

$$e(n)= d(n)- y(n) \qquad (4)$$

3. The tap weights of the FIR vector are updated in preparation for the next iteration, by equation 5.

$$W(n+1) = W(n) + 2\mu(n)x(n) \qquad (5)$$

The main reason for the LMS algorithms popularity in adaptive filtering is its computational simplicity, making it easier to implement than all other commonly used adaptive algorithms. For each iteration the LMS algorithm requires 2N additions and 2N+1 multiplications (N for calculating the output, y(n), one for 2μe(n) and an additional N for the scalar by vector multiplication) [7].

B- Simulation Results for Echo Cancellation Using LMS Algorithm

Computer simulations are performed using MATLAB to verify the theoretical background obtained in the previous sections. In the simulations the following Fig.s shows the input speech signal, desired signal, adaptive filter output signal, estimation error, cost function (MSE), and Echo Return loss Enhancement (ERLE) for the LMS algorithm.

The results have been obtained for 7500 iterations, 30000 iterations and step size (μ) of 0.02 (determined empirically) with a filter length of 1000. The MSE shows that as the algorithm progresses the average value of the cost function decreases, this corresponds to the LMS filters impulse response converging to the actual impulse response, more accurately emulating the desired signal and thus more effectively canceling the echo signal. The results have been shown only for no of iterations equal to 30000 and filter order 1000.

Fig. 3, shows the input speech signal which is collected from the computer system through microphone, with sampling rate equal to 8000 Hz, and five seconds in duration.

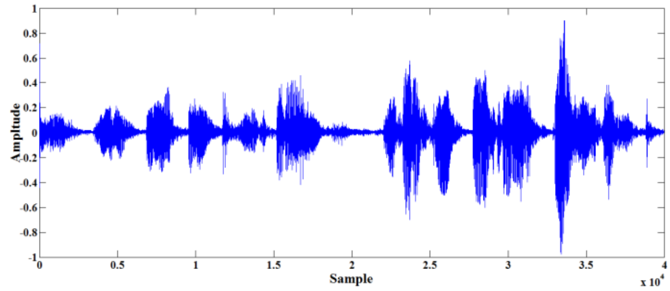

Fig. 3. Amplitude & sample number for the input signal.

Fig. 4, depicts the desired echo signal (it is convolution between the input signal and room impulse response) with number of samples derived from the input signal.

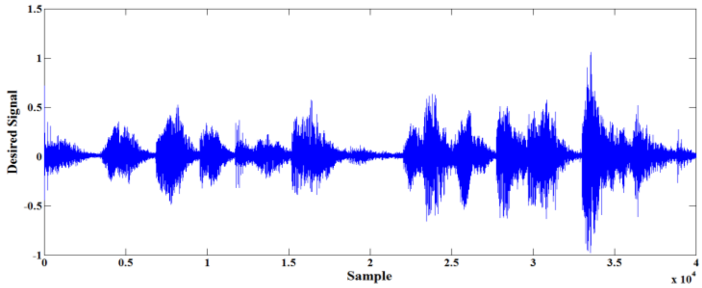

Fig. 4. Desired signal and sample number.

Fig. 4, shows the desired echo signal which is the image of original signal, obtain by convolving the input signal with the impulse response of the acoustic environment.

Fig. 5, shows the adaptive filter output of the LMS algorithm, is an estimate of the echo signal. From Figure shows the adaptive filter output that extract the echo signal from input signal, using length of the order filter equal to 1000 with step size(μ) equal to 0.02 and for each iteration the LMS algorithm requires 2N additions and 2N+1 multiplications.

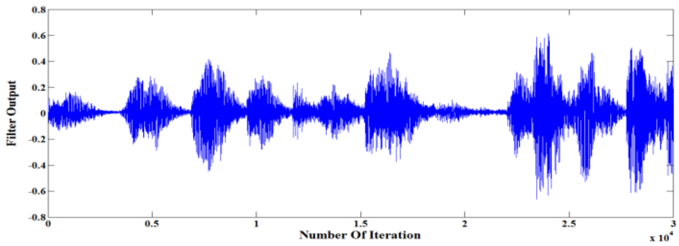

Fig. 5. The adaptive filter output versus number of iteration (μ=0.02, Number of Iterations =30000, N=1000).

Fig. 6, depicts the error signal versus the number of iterations using LMS algorithm.

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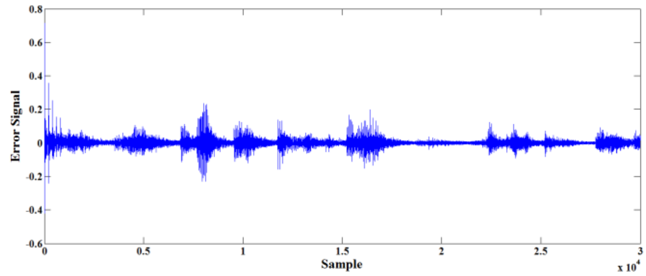

Fig. 6. Error signal versus number of iteration for LMS algorithm (Number of Iterations = 30000, N=1000).

Fig. 7, shows the mean square error versus the number of iterations using adaptive filtering LMS algorithm (measure how much the algorithm minimize the echo)

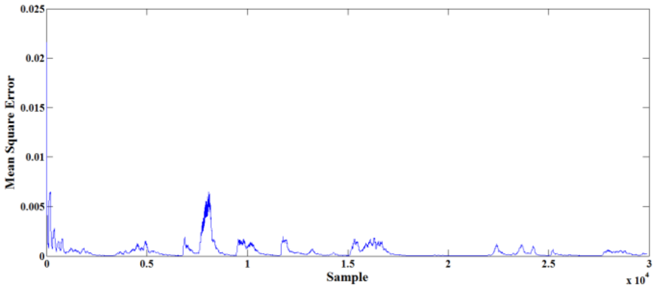

Fig. 7. Mean Square Error versus sample number (μ = 0.02, Number of Iterations =30000, N=1000).

Fig. 6, and Fig. 7, shows estimation error and mean square error signal of the LMS algorithm which is to calculate the difference between desired signal and the output of the filter with step size(μ) 0.02, it is shown from Fig. 7, that, the mean square error decreases as the number of iteration increases, and equal to 0.0005. As the adaptive filter output is equal to desired signal the error signal tends to zero. In this situation the echoed signal would be completely cancelled and the far user would not hear any of their original speech returned to them.

Fig. 8, depicts the attenuation that is derived by dividing the echo signal power to the error signal power.

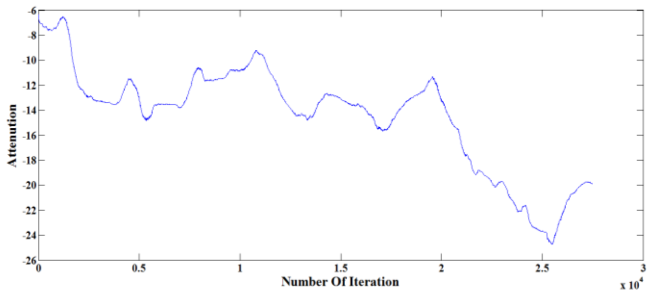

Fig. 8. Attenuation versus number of iteration for LMS algorithm (Number of Iterations =30000, μ= 0.02, N=1000).

Fig. 9, show measure the echo attenuation the echo canceller removed of the LMS algorithm, with step size (μ) equal to 0.02. The success of the echo cancellation can be determined by the ratio of the desired signal and the error signal..

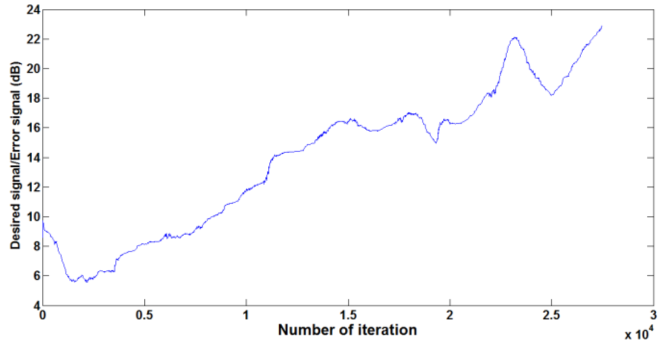

Fig. 9. Echo Return loss Enhancement (ERLE) performance with LMS.

From Fig. 9, it can be seen that the attenuation as expressed in decibels, and the average attenuation for this simulation of the LMS algorithm is -14.5827dB. In this situation the echoed signal would be completely cancelled and the far user would not hear any of their original speech returned to them

Fig. 10, shows the room impulse response (1000 taps length) is used in this simulation.

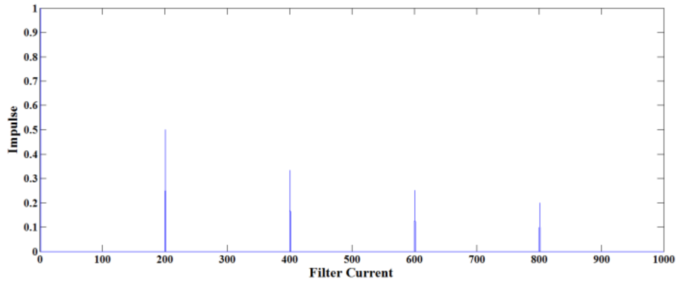

Fig. 10. Actual impulse response versus sample number (1000 taps length).

Fig. 11, depict filter current versus number of iteration with filter order equal to 1000.

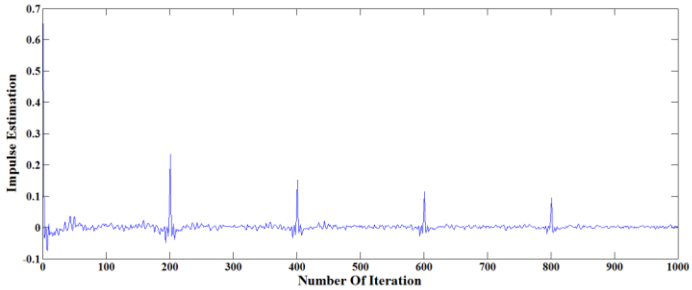

Fig. 11. Adaptive filter impulse response,(1000 taps length).

Fig. 11, shows the estimated impulse response of the LMS algorithm at integer of 30000 iterations. It can be seen that the adaptive filter more accurately represents the actual impulse response of the simulated echo as the algorithm progresses.

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According to the numerical and simulation results the following concluding remarks are obtained, For real-valued data, the LMS with a fixed step-size requires 2N+1 multiplications and 2Nadditions per iteration. The LMS is simple, therefore computationally cheap to implement and fast for real-time operation. It is also robust, and numerically stable. but It suffers from slow convergence speed due to the dependency on the variation in the input signal's power and step size. the LMS algorithm while any LTI system that is represented in a form of a FIR filter is stable in BIBO (bounded input bounded output) sense (as its transfer function does not have poles within the unit circle), it may become unstable if its coefficients are dynamically changing, according to some specific rules. So, the instability may be caused by the filter coefficient changes, not by the filter type. To overcome this problem, The robust technique is referred to Eigen-decomposition based diagonal loading (DL). These techniques calculate the new weights of a taped filter. The performance evaluation of the Robust Adaptive filter using Diagonal Loading is presented in next subsection.

IV. ROBUST ADAPTIVE AEC FILTER USING DIAGONAL LOADING.

In order to effectively overcome the divergence mean square error on the impact of the adaptive filter, this section presents a diagonal loading Robust Adaptive filter. The algorithm of the traditional diagonal loading algorithm is iterative calculations, based on LMS algorithm optimal weight vector, from pervious section, the solution of optimization problem in equation (5) by recalling the equation of DL-LMS.

The tap weights of the FIR vector are updated in using equation.

$$W(n+1) = W(n) + 2\mu(n)x(n) \qquad (6)$$

Where η the amount of discretion is loaded, this is done using the DL method to improve the LMS algorithm, to obtain Load algorithm, which is based on the sampling weight DL algorithm. This loading technique adds a fixed value diagonally with the correlation matrix of input signal to reduce the signal divergence of errors. The robust correlation matrix is given by.

$$R_{xx} = E[x(n) * x(n)^H] \qquad (7)$$

We know the R_{XX} decompose to V and U are left-singular and right-singular vectors respectively and S is diagonal matrix [8].

$$S = eig(R_{xx}) \qquad (8)$$

Where the S is diagonal of R_{xx} Eigen-values

$$S = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 & 0 \\ 0 & 0 & \lambda_3 & 0 & 0 \\ 0 & 0 & 0 & \lambda_4 & 0 \\ 0 & 0 & 0 & 0 & \lambda_n \end{bmatrix} \qquad (9)$$

Where η is a small positive diagonal loading factor, available update algorithm weight [8].

$$w(n+1)_{DL}(k) = (w(n) + \min(\eta(k)) \qquad (10)$$

Where η is the fixed diagonal loading factor taken to be equal to minimum Eigen value of correlation matrix of input signal x(k).

V. SIMULATION RESULTS

The modified update weight has been examined for LMS, the same assumption in simulation of conventional LMS and over comes the problem divergence mean square error. From Fig. 12, we see that there is significant improvement for all mean square error and with robust and more stability than conventional LMS . In case LMS, From Fig. 12, and Fig. 13, it is clear that the DL-LMS technique have better and converge faster than the pure LMS technique.

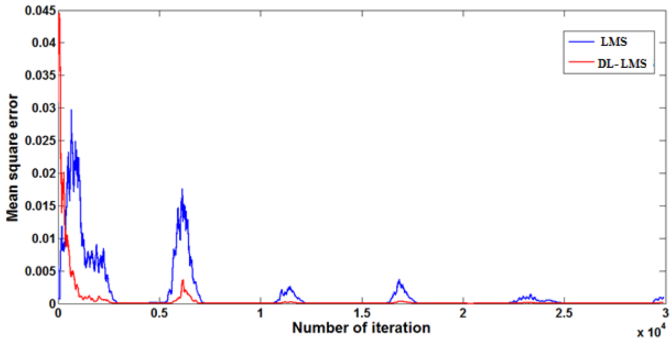

Fig. 12. The convergence of LMS and DL-LMS.

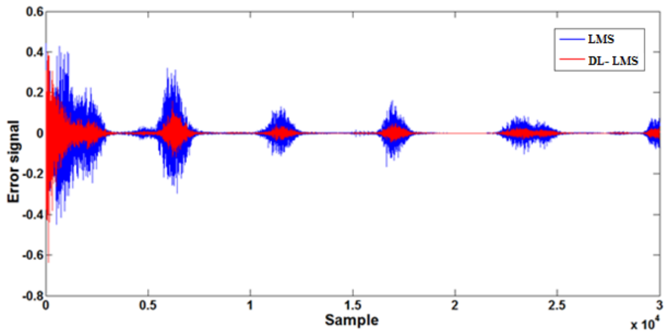

Fig. 13. The error of LMS and DL-LMS.

VI. CONCLUSION

The studied adaptive filter worked successfully for Acoustic Echo Cancellation and here are some conclusions of the analysis for the obtained results.

The LMS is the simplest to implement, but requires prior knowledge of the input signal which is not feasible for the echo cancellation system. from simulation results shows the LMS very good attenuation and simple complexity this was the obvious choice for real time implementation so it works as a better algorithm for echo cancellation application. For large step size, a moderate large value of leads to faster convergence but if step size μis too high, it leads to the instability of LMS and erroneous results. to

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converge much faster. This performance comes at the cost of computational complexity and considering the large FIR order required for echo cancellation, this is not feasible for real time implementation.

To overcome this problem, The robust techniques is referred to based diagonal loading (DL). The performance evaluation of the robust adaptive filter using diagonal loading provides faster speed of convergence among LMS with variable step size while retaining the same small level of misadjustment and the mean square error is almost similar to that of the (fixed step size least mean square) DL-LMS algorithm under similar conditions. more robust stability of the LMS algorithm, exhibits a better balance between simplicity and performance than the pure LMS algorithm. Due to its good properties it has been used in real-time applications.

References

[1] H. Simon, Adaptive FilterTheory. 2nd Edition. Prentice-Hall Inc., New Jersey, 1991.

[2] M. Hutson, "Acoustic echo cancellation using digital signal processing a thesis from the school of information technology and electrical engg," The University of Queensland. November 2000.

[3] H. Nguyen ,Majid D, Azhar S, Implementation of the LMS and NLMS algorithms for Acoustic Echo Cancellation in teleconference system using MATLAB, MSI Vaxjo University SE-351 95 VAXJO, December 2009.

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

[5] B. Farhang-Boroujeny, Adaptive Filters: Theory and Applications, New York: John Wiley & Sons, Inc., 1998.

[6] D. Paulo, S. R., Adaptive Filtering, Algorithms and Practical Implementation. Kluwer Academic Publishers, Boston. 1997.

[7] D.L. Duttweiler, "Proportionate Normalized Least Mean Square Adaptation in Echo Cancellers," IEEE Trans. Speech Audio Processing, vol. 8, pp. 508-518, Sept. 2000.

[8] M.Abd-alsalam, N. Adeep. S. Ali, and M. Alsaholi "Acoustic Echo Cancellation using Adaptive Filter," College of Electronic Technology – Bani wali. 2014.

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