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Acoustic Echo Cancellation For Speech And Random Signal Using Estimated Impulse Responses

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***Abstract*— In this paper, the Acoustic Echo Cancellation (AEC) are investigated by using Finite Impulse Responses Adaptive Filter with the analysis of Mean Square Error (MSE) and its convergence property. It is the result of a project in the course Fundamental of Signal Processing at Chongqing University of Posts and Telecommunications. It focuses on Normalized Least Mean Square (NLMS) algorithm of adaptive filtering, employing a discrete signal processing in MATLAB for simulation with speech and random signals.**

***Keywords*— AEC, Adaptive Filter, MSE, LMS, NLMS**

I. Introduction

In telephony system, the received signal by the loudspeaker, is reverberated through the environment and picked up by the microphone. It is called an echo signal. This is in the form of time delayed and attenuated image of original speech signal and causes a reduction in the quality of the communication. Adaptive filters are a class of filters that iteratively alter their parameters in order to minimize a difference between a desired output and their output. In the case of acoustic echo, the optimal output is an echoed signal that accurately emulates the unwanted echo signal. This is then used to negate the echo in the return signal. The better the adaptive filter simulates this echo, the more successful the cancellation will be [1].

Acoustic echo cancellation reduces the acoustic coupling between a loudspeaker and a microphone by estimating the impulse response of the loudspeaker-enclosure-microphone (LEM) system as shown in Fig. 1.

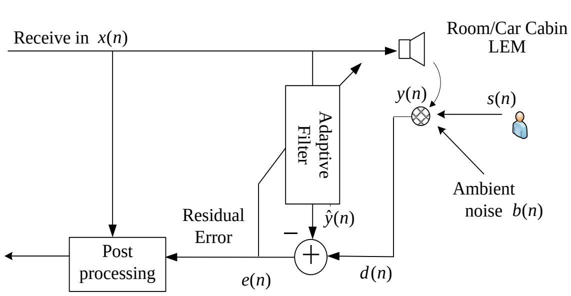

Fig. 1. Principle of acoustic echo cancellation

The echo signal *y(n)* which originates from the far-end speech *x(n)* can be estimated by the output signal of the adaptive filter $\hat{y}(n)$ given by:

$$\hat{y}(n)=x(n)*\hat{h}(n)=\sum_{i=0}^{M-1} x(n-i)\hat{h}_i(n) \quad (1)$$

Where $\hat{h}_i(n)$ denotes the i^{th} coefficient of the vector at time *n* of the adaptive filter and *M* is the filter length. Local speech can be obtained by subtracting this estimated echo from the microphone signal.

Due to the environmental changes such as the movement of local speaker, background noise, or temperature variance, the impulse response **h**(n) of the LEM system is time varying. Thus the impulse response of adaptive filter $\hat{\mathbf{h}}$(n)should be estimated adaptively as close to **h**(n) as possible to reduce error [2]. In this paper, the NLMS algorithm is adopted for this purpose.

II. AEC Implementation

This paper is divided into three major sections: The first one explains the properties of different impulse response and how to model them by an adaptive filter. The second and main section of the paper is devoted to the solution of the echo cancellation problem by the application of adaptive filters with NLMS algorithm. In the third section, we show how to cope with implementation problems with analysing the MSE properties for both random and speech signal.

A. Impulse Response of Adaptive Filter

In general, the acoustic coupling within an enclosure is formed by a direct path between the loudspeaker and the microphone and a very large number of echo paths. The impulse response can be described by a sequence of delta impulses delayed proportionally to the geometrical length of the related path. Reflectivity of the boundaries of the enclosure and the path length determine the impulse amplitude [3][4]. The reverberation time of an office is typically on the order of a few hundred, of the interior of a car, a few tens of milliseconds. Since a long impulse response has to be modeled, a recursive (IIR) filter seems best suited at first glance.

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At second glance, however, the impulse response exhibits a highly detailed and irregular shape.

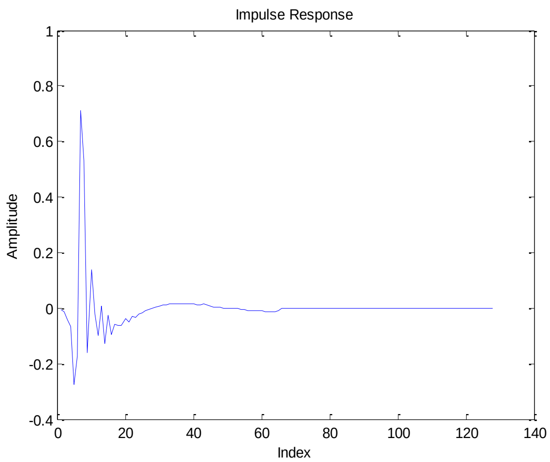

Fig. 2. Impulse Response of Adaptive Filter

The LEM system here is characterized by a very small enclosure leading to a short impulse response as shown in Fig. 2.

To achieve a sufficiently good match, the replica must offer a large number of adjustable parameters. Therefore, an IIR filter does not show an advantage against a non recursive (FIR) filter [5][6]. The irrefutable argument for preferring an FIR filter, however, is its guaranteed stability during adaptation.

B. The Least Mean Square 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 [7].

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

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. The μ has to be chosen as 0<μ<0.5 for the convergence of the algorithm. The larger steps sizes make the coefficients to fluctuate wildly and eventually become unstable [8].

C. The Normalized Least Mean Square algorithm

The primary disadvantage of the LMS algorithm is its slow convergence rate [7]. In NLMS μ is normalized by the energy of the signal vector as in Mathematical formula 4 and therefore achieves a much faster convergence rate then LMS at a low cost. To avoid division by zero a small number is often added to the energy.

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \frac{\mu\, X(n)\, e(n)}{X^T(n)X(n)+\varepsilon} \qquad (4)$$

Where μ is the step-size, X(n) and e(n) are the loud-speaker and error signals after de-correlation, respectively. The step-size governs the convergence rate and the miss adjustment of the adaptive filter. In this paper, the step-size is chosen appropriately as μ=0.5 for the convergence of the algorithm.

III. SIMULATIONS

A. Simulation Setup

I used a very small enclosure leading to a short impulse response as discussed in section II.A for this project. I also used two different types of input signal to observe the Adapter Filter convergence. The input voice was approximately 1,682ms and the length was 13,454 samples at 8,000 Hz sampling rate and the random input signal was approximately 625ms and the length was 5,000 samples at 8,000 Hz sampling rate for NLMS implementation. The step sizes were chosen as μ=0.50. The filter run time was chosen as 1, 50, 100 and 300 to see how the results get finer as more averaging is implemented.

Finally I plot and observe the MSE curve and understand how it converges to zero. Also, I plot coefficients of AF and compare them with corresponding system channel coefficients.

B. Simulation Result

This section presents the results of simulation using MATLAB to investigate the performance behavior of NLMS adaptive algorithm. The principle means of the comparison is the mean square error of the algorithm by varying the number of run times.

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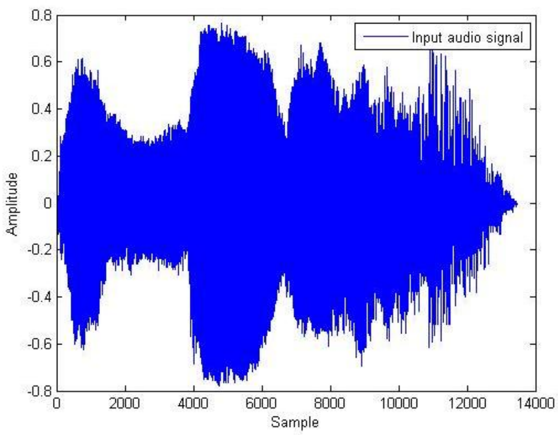

Fig. 3. Speech signal as input

Figure 3 and 4 shows the speech and random signals used in the simulation.

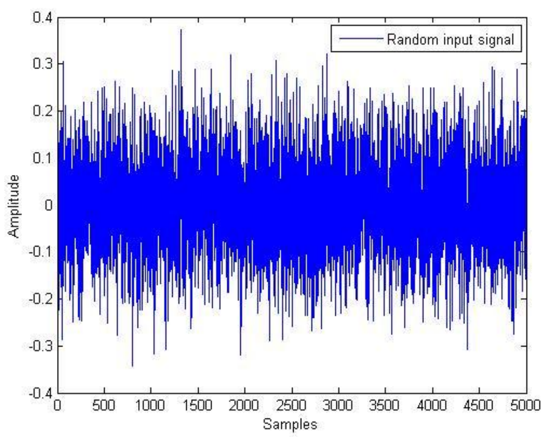

Fig. 4. Random audio signal as input

To evaluate the performance of AEC, mean square error for speech input signal has calculated in next step as shown in figure 5, 6, 7 and 8 for run time 1, 50, 100 and 300 accordingly.

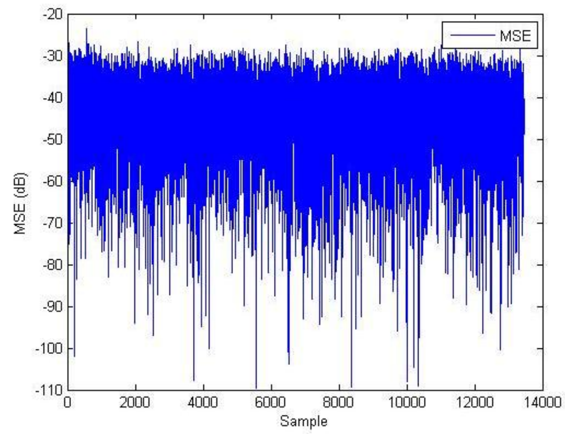

Fig. 5. MSE when runs=1

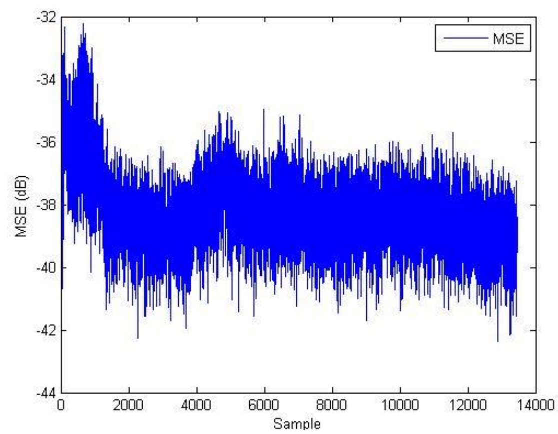

Fig. 6. MSE when runs=50

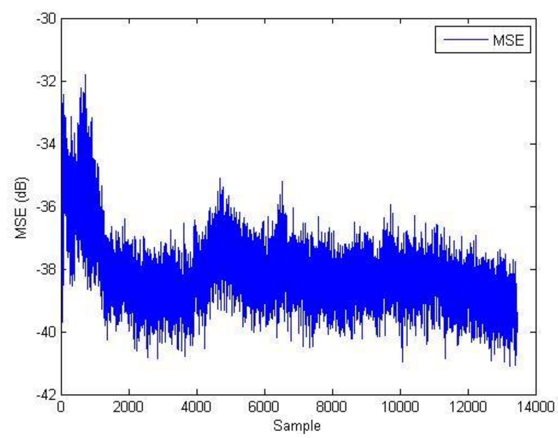

Fig. 7. MSE when runs=100

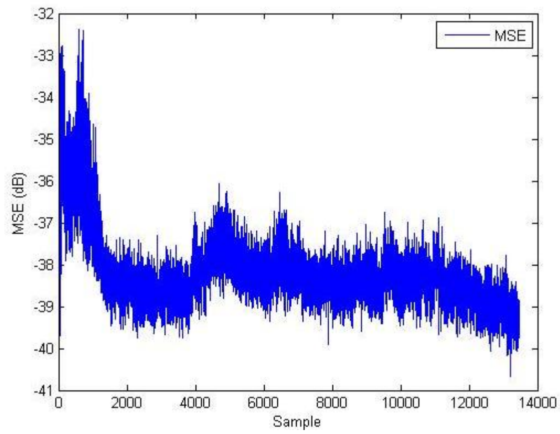

Fig. 8. MSE when runs=300

From simulation result shown in figure 5, 6, 7 and 8 we have seen that more the runs is more the faster convergence although it's time consuming but the results get finer as more averaging is implemented. Now in figure 9, 10, 11 and 12 we will see the performance for random input signal.

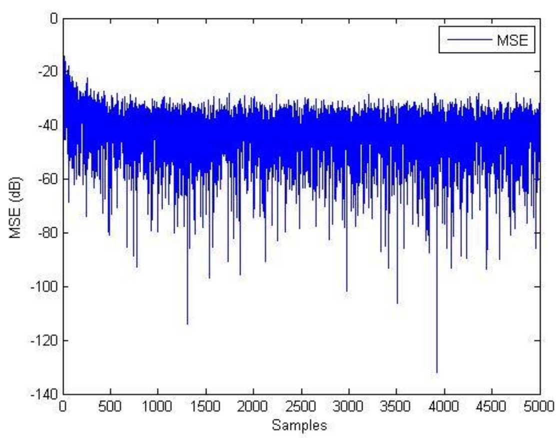

Fig. 9. MSE when runs=1

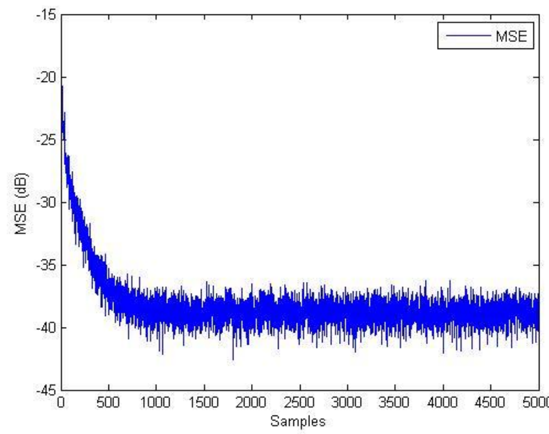

Fig. 10. MSE when runs=50

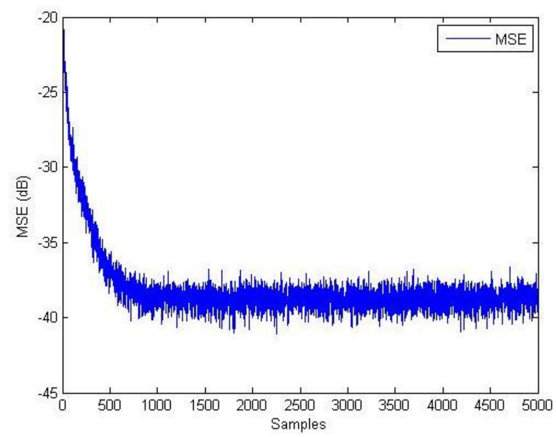

Fig. 11. MSE when runs=100

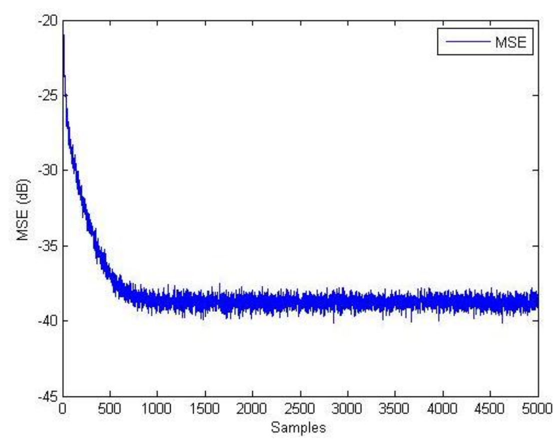

Fig. 12. MSE when runs=300

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So the MSE figures for random input signal has the same property that more the runs is more the faster convergence but another thing is also seen that MSE curve for random signal converge very quickly and sharply than the speech input signal because of its noisy nature. Speech signal contains lot of unpredictable parameters and nature is also unpredictable whether the nature of random signal is predictable.

For more simplification if we see the figure 13 and 14 for 20th AF filter coefficient of speech and random signal respectively it is clear that for a single coefficient of speech signal may not converge as like the random signal but averaging can help to reveal their trends.

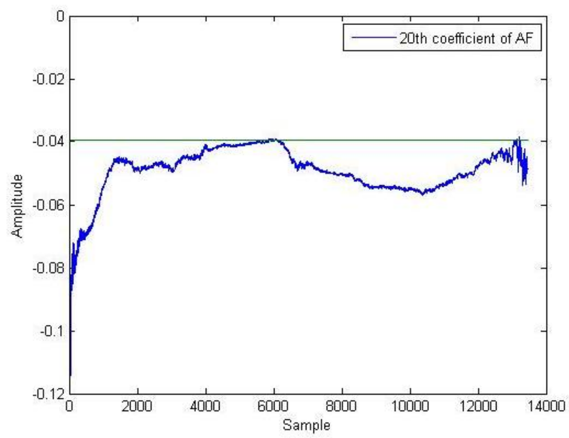

Fig. 13. 20th coefficient of AF filter of speech signal

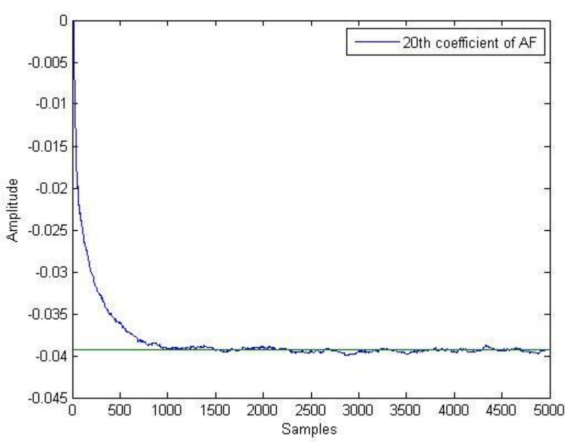

Fig. 14. 20th coefficient of AF filter of random signal

IV. CONCLUTION

In this paper, a basic AEC algorithm has been described in detail. Simulation results showed that its performance meets the standard requirement for convergence time and MSE. Although the underlying principle for speech and random signal inputs are the same but it observed the former is more difficult to deal. NLMS algorithm is useful for practical implementation and in this project it gives the convincing result. Future work will be focused on the algorithms of Voice Activity Detection (VAD), Double Talk Detection (DTD), advanced AF sub-band of AEC and the simulation in webRTC.

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