ISSN 2320 - 2602
Volume 3, No.4, April 2014
International Journal of Advances in Computer Science and Technology
Available Online at http://warse.org/pdfs/2014/ijacst02342014.pdf

Acoustic Echo Cancellation using Adaptive Algorithms

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ABSTRACT

This paper presents the comparison between different adaptive algorithms usages in acoustic echo cancellation. This comparison includes the cancellation of echo generated in room using different adaptive algorithms Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Improved Proportionate Normalized Least Mean Square (IPNLMS) and Recursive Least Squares (RLS) Algorithms. The goal of this work is to choose an optimal algorithm for cancelling acoustic echo noise from the speech signal. There are many adaptive algorithms available in the literature for echo cancellation and every algorithm has its own properties. Our aim is to achieve higher ERLE (amount of echo cancelled) in dB at a higher rate of convergence with low complexity and achieve good amount of SNR (signal to noise ratio). The results verified by using subjective analysis.

Key words : Signal to noise ratio, Echo return loss enhancement, LMS, NLMS, IPNLMS and RLS.

1. INTRODUCTION

Acoustic echo cancellation is a common occurrence in today's telecommunication systems. It occurs when an audio source and sink operate in full duplex mode , an example of this is a hands-free loudspeaker telephone. In this situation the received signal is output through the telephone loudspeaker (audio source), this audio signal is then reverberated through the physical environment and picked up by the systems microphone (audio sink). The effect is the return to the distant user of time delayed and attenuated images of their original speech signal.

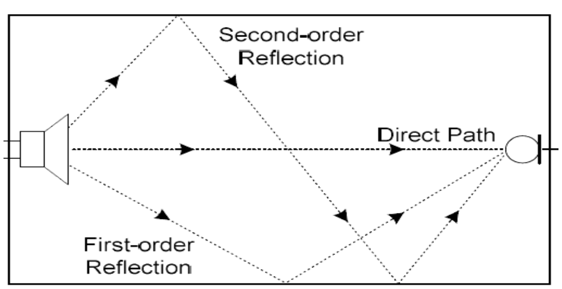

Figure 1: Acoustic echo phenomenon

As shown in Figure 1, first a direct sound reaches the destination, then we have different reflection which also reaches the destination with time delay which we call as echo.

The Adaptive Echo Cancellation Process

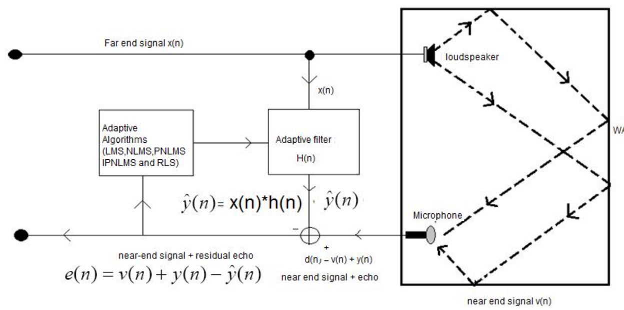

Figure 2: Adaptive Echo cancellation

As shown in Figure 2, a sound signal, from a loudspeaker is heard by a listener. However, this same sound also is picked up by the microphone, both directly and indirectly, after bouncing off the wall. The result of this reflection is the creation of echo which is transmitted back to the far end and is heard by the talker as echo.

The receiver which picks up the time varying signal $x(n)$ from a speech source via impulse response of the transmission room $h(n)$. The input signal $x(n)$ is then transmitted to the loudspeaker in the near-end receiving room. The receiving room's microphone receives the desired signal $y(n)$ which is the convoluted sum of the input signal and the impulse response of the receiving room $h(n)$ along with near-end speech signal.

$$y(n) = h^T(n)x(n) + w(n) \qquad (1)$$

In absence of echo canceller, the received signal $y(n)$ will be transmitted back to the origin with some delay. In the presence of an adaptive echo canceller, its objective is to estimate $h(n)$ by taking into account the error signal $e(n)$ at each iteration, where the $e(n)$ is defined as output of the receiving room – output of the adaptive filter.

$$e(n) = y(n) - \hat{y}(n) \qquad (2)$$

Adaptive filters consist of two parts. The first part is to filter the echo signal. An adaptive algorithm represents the other part and its purpose is to update the filter one at a time [8].

2. ADAPTIVE ALGORITHMS

(a) LMS Algorithm

The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff in 1959 through their studies of pattern recognition. From there it has become one of the most widely used algorithms in adaptive filtering. The LMS algorithm is a type of adaptive filter known as stochastic gradient-based algorithms as it utilizes the gradient vector of the filter tap weights to converge on the optimal wiener solution. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula.

$$\hat{h}(n+1) = \hat{h}(n) + 2\,\mu x(n)e(n) \qquad (3)$$

Here $x(n)$ is the input vector of time delayed input values, $x(n) = [x(n)x(n-1)x(n-2) \ldots\ldots x(n-N+1)]^{T}$. The vector $h(n) = [h_0(n)\, h_1(n)\, h_2(n) \ldots\ldots h_{N-1}(n)]^{T}$ represents the coefficients of the adaptive FIR filter tap weight vector at time n. The parameter μ is known as the step size parameter and is a small positive constant. This step size parameter controls the influence of the updating factor. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges.

(b) NLMS Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. . In the LMS algorithm the weight adjustment is directly proportional to the amplitude of input vector samples Therefore, when the vector $x(n)$ is large, the LMS suffers from a gradient noise amplification problem. To overcome this problem, the adjustment applied to the weight vector at each iteration is normalized. The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by calculating maximum step size ue $\mu(n)$. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector $x(n)$. This sum of the expected energies of the input samples is also equivalent to the dot product of the input vector with itself, and the trace of input vectors auto-correlation matrix, **R.** The recursion formula for the NLMS algorithm is

$$\hat{h}(n+1) = \hat{h}(n) + \frac{1}{x^{T}(n)x(n)}\, e(n)x(n) \qquad (4)$$

(c) IPNLMS Algorithm

Proportionate adaptive filters, such as the improved proportionate normalized least-mean-square (IPNLMS) algorithm, have been proposed for echo cancellation as an interesting alternative to the normalized least-mean-square (NLMS) filter. Proportionate schemes offer improved performance when the echo path is sparse. An improvement of PNLMS is the IPNLMS algorithm, which employs a combination of proportionate (PNLMS) and non-proportionate (NLMS) updating technique, with the relative significance of each controlled by a factor α. The update is accomplished by replacing the diagonal matrix Q defined in equation 5 by a diagonal matrix K whose diagonal elements k_{ll} are obtained by replacing the corresponding elements q_{ll} of Q a

$$Q(n) = \mathrm{diag}\{q_0(n)\; q_1(n) \ldots\ldots\ldots q_{L-1}(n-1)\}$$

$$= \begin{bmatrix} q0(n) & 0 & \ldots & \ldots & 0 \\ 0 & q1(n) & \ldots & \ldots & \ldots \\ . & . & . & . & . \\ . & . & . & . & 0 \\ 0 & 0 & \ldots & \ldots & qL-1(n-1) \end{bmatrix}$$

$$q_{ll}(n) = \frac{k_l(n)}{\frac{1}{L}\sum_{i=0}^{L=1} ki(n)} \qquad (5)$$

$$k_l(n) = \max\{\rho * \max\{\gamma, |\widehat{h0}(n)| \ldots\ldots |\hat{h}_{L-1}(n-1)|\}, |\hat{h}_l(n)|\}$$

$$k_{ll}(n) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|\hat{h}_l(n)|}{2\sum_{l=1}^{L}|\hat{h}_l(n)| + \epsilon} \qquad (6)$$

Where ϵ is a small positive number and α is a parameter such that $-1 \leq \alpha < 1$. For $\alpha = -1$, k_{ll} is constant independent of l, so IPNLMS is identical to NLMS. For α close to 1, k_{ll} is essentially proportional to $|h_l(n)|$, so IPNLMS behaves like PNLMS.

$$\delta_{IPNLMS} = \frac{1-\alpha}{2L}\,\delta_{NLMS}$$

(d) RLS Algorithm

The least square algorithms require all the past samples of the input signal as well as the desired output at every iteration. RLS filter is a simple adaptive and time update version of Weiner filter. For non-stationary signals, this filter tracks the time variations but in case of stationary signals, the convergence behavior of this filter is same as wiener filter. This algorithms attempt to minimize the cost function in equation 7. Where $k = 1$ is the time at which the RLS algorithm commences and λ is a small positive constant very close to, but smaller than 1. With values of $\lambda<1$ more importance is given to the most recent error estimates and thus the more recent input samples, this results in a scheme that places more emphasis on recent samples of observed data and tends to forget the past.

$$\xi(n) = \sum_{k=1}^{n} \lambda^{n-k} e_n^2(k) \qquad (7)$$

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.

3. PERFORMANCE MEASURES

The choice of best algorithms is measured using performance measure parameter like ERLE and SNR.

a)Echo Return Loss Enhancement

The ERLE is defined as the ratio of send-in power (Pd) and the power of a residual error signal immediately after the cancellation (Pe), and it is measured in db. The ERLE measures the amount of loss introduced by the adaptive filter alone. ERLE depends on the size of the adaptive filter and the algorithm design. The higher the value of ERLE, the better the echo canceller. ERLE is a measure of the echo suppression achieved and is given by

$$ERLE = 10 \log_{10} \frac{P_d}{P_e}$$

b) Signal to Noise Ratio

SNR is defined as the ratio of signal power to the noise power corrupting the signal. The Signal to Noise Ratio is the defining factor when it comes to the measurement of quality of signal. A high SNR means good quality of signal with low distortions.

$$SNR = 20 \log_{10} \left| \frac{rms\ (speech)}{rms\ (noise)} \right|$$

4. SIMULATION RESULTS AND DISCUSSION

For testing the different adaptive echo cancellation algorithm, we have taken a male voice with utterance of "A B C D E F G H I J K L M". The sampling frequency of the speech signal is 8000Hz with duration of 11 seconds. From this clean speech we generated an echo signal which serves as the input to the adaptive algorithms and the results are analyzed.

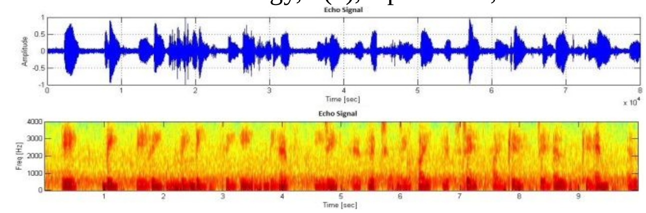

Figure 3: Echo signal and its spectrograph

a) LMS Algorithm

Figure 3 shown is an input echo speech signal and its spectrogram. An FIR filter with adaptive LMS algorithm with a step size of 0.0005 and filter coefficient of 1024 has been used for simulation experiment.

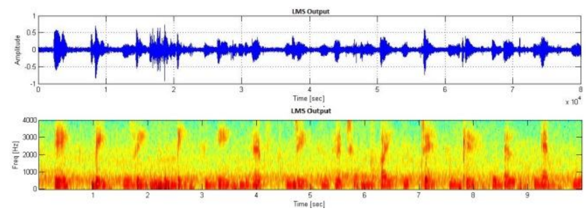

Figure 4: LMS output and its spectrograph

From Figure 5 we can observe the average ERLE is 12.27 dB and SNR of 7.4051 dB after echo cancellation. The SNR before echo cancellation was -0.8816.With the increase of step size there is an increase in performance of ERLE and SNR.

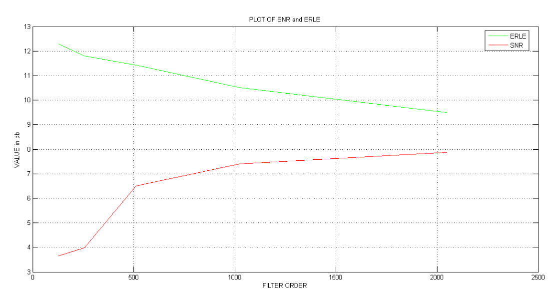

Figure 5: SNR and ERLE with different step sizes

b) NLMS Algorithm

Figure 6 shows the NLMS algorithm output which was simulated using matlab. Here the adaptive FIR filter is of the order of 1024. The step size was set to 0.00005.

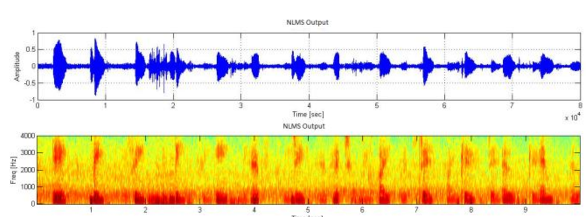

Figure 6: Normalized-LMS output and its spectrograph

From Figure 7 we can observe the average ERLE is *28.8003*dB and SNR of *2.0628*dB after echo cancellation, the SNR before echo cancellation was -0.8816.With the increase of step size there is an increase in performance of ERLE and SNR.

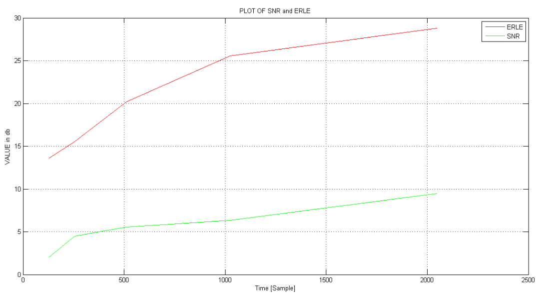

Figure 7: SNR and ERLE with different filter order

c) IPNLMS Algorithm

The output of adaptive FIR filter employs IPNLMS algorithm[3] shown in Figure 8. The step size of the algorithm and filter coefficient are 0.0005 and 1024 respectively.

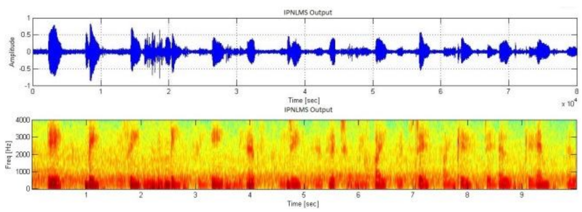

Figure 8: IPNLMS output and its spectrograph

The problem with PNLMS algorithm is it performs better when the impulse response is sparse but in case of non sparse impulse response PNLMS convergence is slower than NLMS, so we go for IPNLMS which has achieve ERLE of 39.30dB and SNR of 11.22dB.

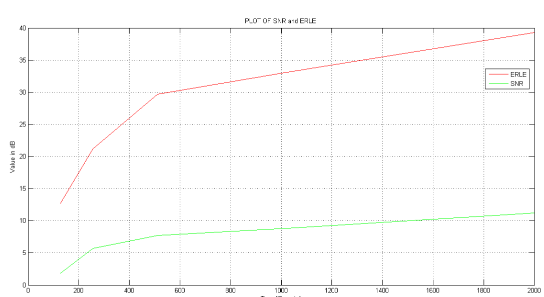

Figure 9: SNR and ERLE with different step sizes

d) RLS Algorithm

The coefficients of the adaptive FIR filter changes according to the RLS algorithm. The γ value and filter length was 128 and 0.99 respectively.

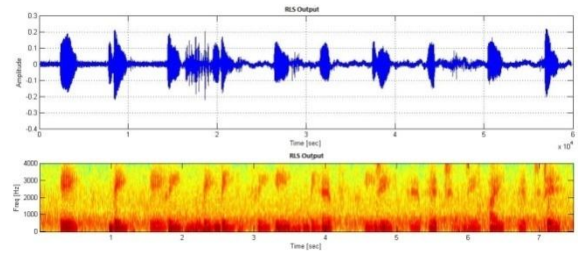

Figure 10: RLS output and its spectrograph

We achieve an ERLE of 64.5051 dB and SNR of 12.5569 dB with filter length of 128, but the problem of RLS is its computational complexity, it takes minimum of 2 hours to converge.

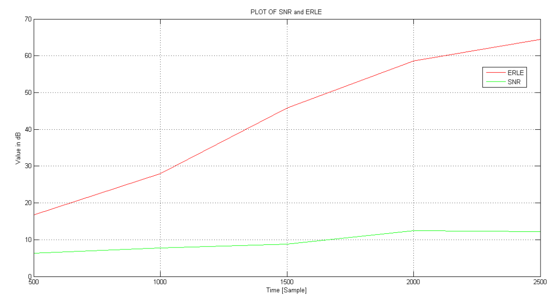

Figure 11: SNR and ERLE with different filter order

5. CONCLUSION

In this paper we have presented approaches for an acoustic echo canceller design using adaptive filter algorithms. We have compared various adaptive methods such as LMS, NLMS, IPNLMS and RLS.The goal of this work was to choose an optimal algorithm for cancelling acoustic echo. We have measured the performance using echo return loss

enhancement (ERLE) [4] and signal to noise ratio(SNR).The best algorithm we found is RLS but it has high computation complexity ,so we prefer IPNLMS whose computation complexity is less and it also has good amount of ERLE.

Table 1: Comparison of different algorithms

Algorithms	ERLE(db)	SNR(db)
LMS	12.2787	7.4051
NLMS	*28.8003*	*2.0628*
IPNLMS	39.3055	11.2201
RLS	64.5051	12.5569

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