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RLS Algorithm for Adaptive Echo Cancellation

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ABSTRACT : Echo cancellation is a common occurrence in telecommunication systems. For echo cancellation we use digital filter, it is Adaptive FIR filters are a class of filters that iteratively alter their parameters in order to minimize a function of the difference between a desired target output and their output. In the case of Echo in telecommunications, 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. This paper illustrates the ability of the RLS algorithms to extract useful information from a noisy signal. The information bearing signal is a sine wave that is corrupted by additive white gaussian noise. The adaptive noise cancellation system assumes the use of two microphones. A primary microphone picks up the noisy input signal, while a secondary microphone receives noise that is uncorrelated to the information bearing signal, but is correlated to the noise picked up by the primary microphone. The RLS algorithm was simulated using Matlab. This algorithm proved to be very effective and the error estimation signal is very small and the average of the MSE becomes to zero.

Keywords : Echo cancellation, RLS Algorithm.

I. INTRODUCTION

This paper will focus on the occurrence of echo cancellation from input signal to improve the quality of communication .Echo cancellation system consists of coupled input and output devices, both of which are active concurrently. An example of this is a hands-free telephony system. In this chapter we will study basic background theory and digital filter which is used in echo cancellation, the system has both an active loudspeaker and microphone input operating simultaneously. The system then acts as both a receiver and transmitter in full duplex mode. When a signal is received by the system, it is output through the loudspeaker into an acoustic environment. This signal is reverberated 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

Echo Cancellation Schemes is used to cancel echo signal in various fields of communication. It is used to remove the coupling between the loudspeaker(s) and the microphone(s); if this echo signal is not cancelled, this give results in an undesired echo, which significantly degrades the sound quality. The reason for this is that the loudspeaker signal is measured by the microphone, and is transmitted back to the remote speaker if not cancelled, yielding an echo.

Schematically, we describe the EC system as follows: the far-end signal, here denoted $x(t)$, is filtered by the room acoustic filter, ht, producing an acoustic echo, termed $y(t)$. The microphone receives this echo together with the near-end speaker signal, $v(t)$; the received signal, $z(t)$, thus consist of both the echo signal

$$z(t) = y(t) + v(t) = \Sigma h_t(k) \times (t - k) + v(t) \qquad \text{... (1)}$$

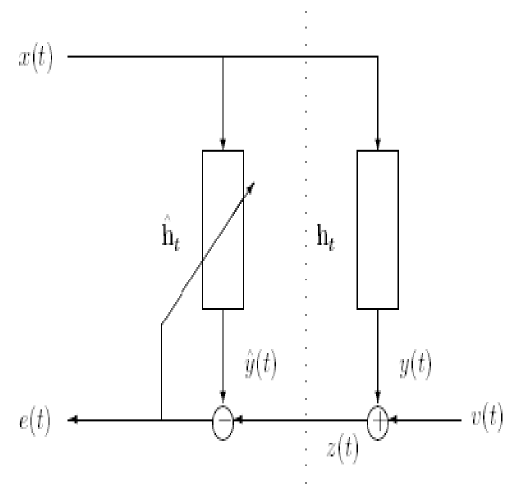


Fig. 1. Echo cancellation system.

A. Performance of an Adaptive Algorithm

The factors that determine the performance of an algorithm are clearly stated below. Essentially, the most important factors as described in:

Rate of Convergence: This is defined as the number of iterations required for the algorithm to converge to its steady state mean square error. The steady state MSE is also known as the Mean asymptotic square error or MASE.

Misadjustment: This quantity describes steady-state behavior of the algorithm. This is a quantitative measure of the amount by which the ensemble averaged final value of the mean-squared error exceeds the minimum mean-squared error produced by the optimal Wiener filter. The smaller the misadjustment, the better the asymptotic performance of the algorithm.

Numerical Robustness: The implementation of adaptive filtering algorithms on a digital computer, which inevitably operates using finite word-lengths, results in quantization errors. These errors sometimes can cause numerical instability of the adaptation algorithm. An adaptive filtering algorithm is said to be numerically robust when its digital implementation using finite-word-length operations is stable.

Computational Requirements: This is an important parameter from a practical point of view. The parameters of interest include the number of operations required for one complete iteration of the algorithm and the amount of memory needed to store the required data and also the program. These quantities influence the price of the computer needed to implement the adaptive filter.

Stability: An algorithm is said to be stable if the mean-squared error converges to a final (finite) value.

B. Wiener Filter Transversal FIR filter

Wiener filter is a class of FIR filter, it is used in the echo cancellation algorithm to minimize the cost function, if the filter input $x(n)$ and the desired signal $d(n)$ are real valued stationary processes. The filter tap weights Q_0, Q_1, $\ldots Q_{N-1}$ are also assumed to be real valued, where N equals the number of delay units or tap weights. The filter input $x(n)$ and tap weight vectors, Q can be defined as column vectors,

$$X(n) = [x(n), x(n-1)\ldots\ x(n-N+1)]^T \quad \ldots (2)$$

$$Q = [Q_0, Q_1, \ldots\ldots Q_{N-1}] \quad \ldots (3)$$

The filter output is defined as

$$Y(n) = Q^T x(n) = x^T(n)Q \quad \ldots (4)$$

Subsequently, the error signal can be written as

$$e(n) = d(n) - y(n) = d(n) - Q^T x(n) = d(n) - x^T(n)Q \quad \ldots (5)$$

Substituting 5 into 2, the cost function is obtained as,

$$\hbar(n) = E[e(n)2] = E[d(n) - Q^T x(n))(d(n) - x^T(n)Q)] \ldots (6)$$

Expanding the last expression of 6 we obtain,

$$\hbar(n) = E[d(n)2] - E[d(n)x^T(n)]\ Q - Q^T E[d(n)x(n)] + Q^T E[x(n)x^T(n]w \quad \ldots (7)$$

Next, we can express $E[d(n)x(n)]$ as an $N \times 1$ cross correlation vector

$$p = E[d(n)/x(n)] = [p0, p^1], \ldots\ pN - 1] \quad \ldots (8)$$

And $E[x(n)x^T(n)]$ as a $N \times N$ autocorrelation matrix R

$$R = E[x(n)x^T(n)] \quad \ldots (9)$$

From 9, $p^T = E[d(n)x^T(n)]$ and hence $p^T Q = Q^T p$

This implies that $E[d(n)x^T(n)]Q = E[d(n)x(n)]Q^T$

Subsequently, we get

$$\hbar(n) = E[d(n)2] - E[d(n)x^T(n)]Q - Q^T E[d(n)x(n) + Q^T E[x(n)x^T(n)]Q$$

$$= E[d(n)2] - 2p^T Q + Q^T RQ \quad \ldots (10)$$

This is a quadratic function of tap weight vector 'Q' with a single global minimum. To obtain the set of filter tap weights that minimizes the cost function, ?(n), solve the system of equations that results from setting the partial derivatives of ?(n) with respect to every tap weight of the filter *i.e.* the gradient vector to zero. That is

$$\partial\hbar / \partial Q_i = 0 \quad \ldots (11)$$

For $i = 0, 1, \ldots\ N - 1$

where N = Number of tap weights

The gradient vector in 11 can also be expressed as

?? = 0 ... (12)

$$\nabla = \left[\frac{\partial}{\partial Q_0}, \frac{\partial}{\partial Q_i}\right]\ldots\frac{\partial}{\partial Q_{N-1}} \quad \ldots (13)$$

and 0 on the right hand side of 11 denotes the column vector consisting of N zero. It has been further proved that the partial derivatives of ξ with respect to the filter tap weights can be solved such that

$$\nabla\hbar = 2RQ - 2p \quad \ldots (14)$$

By letting $\nabla\hbar = 0$, the following equation is obtained, in which the optimum set of Wiener filter tap weights can be obtained, $RQ = p$. This implies that

$$Q = R^{-1}p = Q_0 \quad \ldots (15)$$

Where Q_0 indicates the optimum tap weight vector. This equation is known as the Wiener Hopf equation and can be solved to obtain the tap weight vector, which corresponds to the minimum point of the cost function.

II. RECURSIVE LEAST SQUARES (RLS) ADAPTIVE FILTER

A. Introduction of RLS Algorithms

The recursive least square method is other class of adaptive filtering algorithm this thesis is based on this algorithm methodology .All adaptive algorithm is based on the concept to minimize the cost function. Recursive least square cost function is defined by equation 16 where $k = 1$ is the time at which the RLS algorithm commences and l is a small positive constant very close to, but smaller than 1.

$$w(n) = \sum \lambda^{n-k} e_n^{\,2}(k) \quad \ldots (16)$$

LMS and NLMS algorithm is based on the mean square error and the derivatives of cost function ,but the RLS algorithm principal is based on the directly consideration of previous error estimations. RLS algorithms are known for excellent performance when working in time varying environments.

B. RLS Flow Graph for Adaptive Echo Cancellation

Recursive Least Squares is a deterministic approach to impulse response estimation. The Recursive least square method takes advantage of matrix algebra to reduce complexity. Faster than LMS, the error estimation signal is very small and the average of the MSE is zero. RLS algorithm, however it was used for easier comparison with the other algorithms. The RLS algorithm requires $4N^2$ multiplication operations. ~~All the~~ results of RLS simulation.

Flow graph of RLS algorithm is based on the implementation analysis, these steps of flow graph used in the MATLAB simulation.

Start

↓

Calculate filter out put signal $y(n)$

↓

Desired signal $d(n)$ = Conv (input, impulse)

↓

Create error $e(n) = d(n) - y(n)$

↓

Filter output in previous Weight

↓

$y_{n-1}(n) = Q^T(n-1)x(n)$

↓

Calculate update filter weight vector

$Q(n) = Q^T(n-1) + k(n)e_{n-1}(n)$

↓

Calculate inverse $\Psi^{-1}(n)$

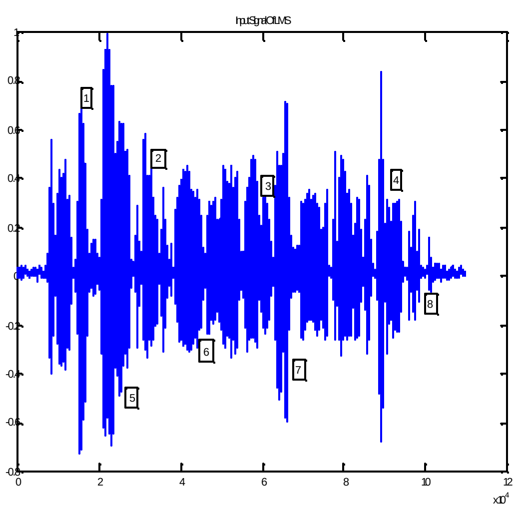
$= \lambda^{-1}(\Psi_{\lambda}^{-1}(n-1) - k(n)[x^T(n)\Psi_{\lambda}^{-1}(n^{-1})])$

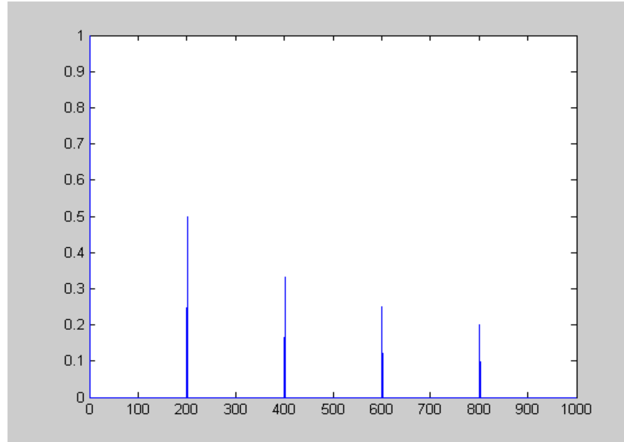
↓

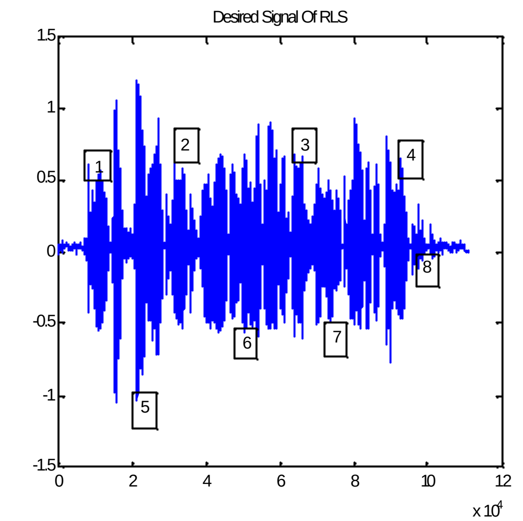
END

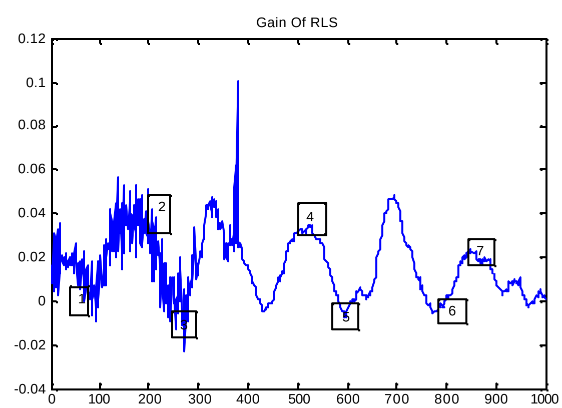
Fig. 2. RLS flow graph.

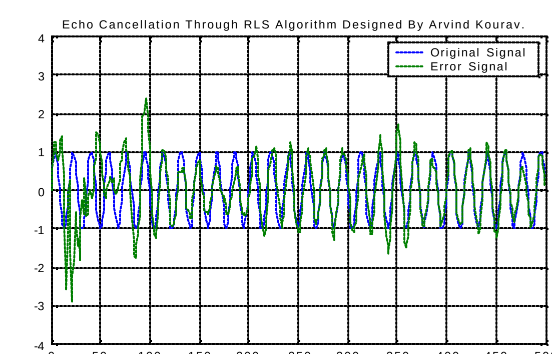
III. RESULTS AND ANALYSIS











DISCUSSION

Recursive least square (RLS) give the great performance then the other algorithms For 7500 iteration and 1000 filter order this method gives mean square error 0.003 attenuation -34.3 db, required $4N^2$ multiplication for each iteration.From this analysis of adaptive filter algorithm for mean square error and attenuation, we can see for the same value of iteration and filter order, recursive least square method give the minimum value of MSE, and iteration. This is the requirement of adaptive algorithms to minimize these value for echo cancellation to improve the quality of communication, RLS algorithm give the better performance than the other adaptive filter algorithms, but the RLS algorithm give $4N^2$ multiplication for each iteration, this is the complexity of this method to large order of FIR filter for the computation, the analysis of this method is based on the matrix inversion lemma, it is complicated to implement by the matlab simulation.

IV. CONCLUSIONS

RLS are well known to perform better. Due to the increase of computing power. RLS algorithm requires $4N^2$ multiplications. For echo cancellation systems the FIR filter order is usually in the thousands. Thus the number of multiplications required are very large because of which the RLS algorithm is too costly to implement

From the RLS Algorithm result analysis we can see the value of mean square error and attenuation for the different value of iteration is minimum, this method gives the better performance for echo cancellation then the other algorithms.

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