Adaptive LMS and NLMS algorithms for cancellation of Acoustic echo

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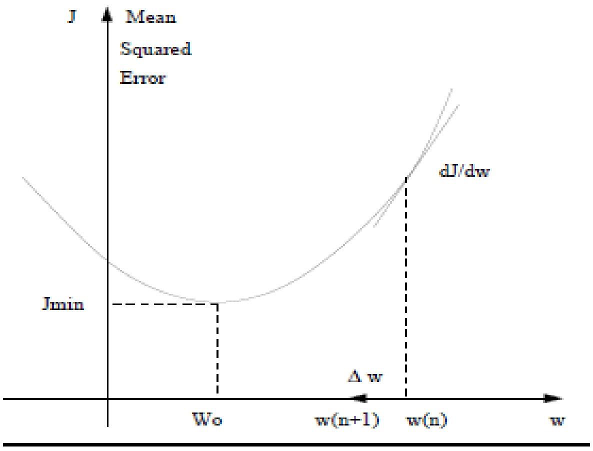
ABSTRACT

Acoustic echo arise in hand free communication environment due to poor voice coupling between Microphone and Loudspeaker. This paper shows the implementation of Acoustic echo cancellation using gradient based LMS algorithm it also focused on NLMS algorithm to remove the unwanted echo and increase the quality of speech in communication applications .The LMS algorithms uses the estimates of the gradient vector from the available data.LMS and NLMS incorporates an iterative procedure that updates weight vector in the direction opposite of the gradient vector which evenly leads to the minimum mean square error.



Keywords

LMS and LMS Algorithm, error estimation, adaptive filter

1. INTRODUCTION

Echo is phenomenon where distorted or delayed version of an original sound reflected back to the source. The acoustic echo is produced by poor voice coupling between the microphone and loudspeaker in hand free devices. Usually acoustic echo canceller is used to remove unwanted echo signal component from microphone signal

[1]. This can be achieved by modeling the echo path impulse response with FIR filter and subtract an echo from microphone signal. This acoustic echo can be removed using adaptive filter is illustrated in fig 1.

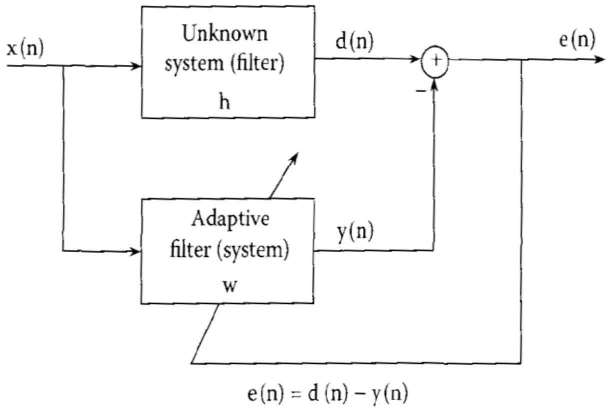


Fig.1 Echo cancellation system

The output of adaptive filter and desired signal are given to the summing circuit which will provide the difference the between the two signal. The difference signals i.e. error signal is fed back to the adaptive filter. The tap weights of adaptive filter are changed by using gradient based algorithm.

2. GRADIENT BASED ADAPTIVE ALGORITHMS.

Gradient based algorithm is the iterative search algorithm which is used to find optimum weights of the FIR filter by considering the arbitrary initial point in the weight vector space and progressively moves towards the optimum tap weight vector in steps i.e. we compute the gradient vector by using this initial guess and updates the parameters by taking a step in opposite direction of the gradient vector. This corresponds to a step is chosen so that the underlying cost function is reduced [4]. We have used following Iterative algorithms to find the optimum tap weight of the FIR filter.

Fig.2 Illustration of gradient search of the mean square error surface for the minimum error point

2.1 Least Mean Square Algorithm (Lms)

The Least Mean Square (LMS) algorithm is developed by Widrow and Hoff in 1959 [2] is an adaptive algorithm, which uses a gradient-based method of steepest decent [3]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple it does not require correlation function calculation nor does it require matrix inversions. The tap weights will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion.

The adaptive filter input is x (n) is the input vector of time delayed input values, x(n) = [x(n) x(n-1) x(n-2) .. x(n-N+1)]T, desired signal is d(n), and the filter output is given by

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) \qquad (1.1)$$

From the method of steepest descent, the weight vector equation is given by [10]

$$w(n+1) = w(n) - \mu \nabla E\{e^2(n)\} \qquad (1.2)$$

The vector $w(n) = [w0(n)w1(n) \ \ldots \ wN-1(n)]^T$ represents the coefficients of the adaptive FIR filter tap weight vector at time n. The parameter μ is known as the step size parameter which controls the convergence of the LMS algorithm and is a small positive integer, $e(n)$ is the mean square error between the filter output y(n) and the desired signal d(n) which is given by,

$$\mathbf{e(n) = d(n) - y(n)} \qquad (1.3)$$

The gradient vector in the above weight update equation can be computed as

$$\nabla E\{e^2(n)\} = -2P + 2Rw(n) \qquad (1.4)$$

Where $R = x(n)x^T(n); and\ P = x(n)d(n)$ For the application of steepest descent algorithm correlation matrix R and cross-correlation matrix P is known so that we may compute the gradient for given value of tap weight vector $w(n)$[1-4].Therefore the weight update can be given by the following equation

$$\mathbf{w(n+1) = w(n) + 2\mu e(n)x(n)} \qquad (1.5)$$

The LMS algorithm is initiated with an arbitrary value w (0) for the weight vector at n=0. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error.

2.2 Normalized Lms Algorithm (Nlms)

The Normalized LMS algorithm may be viewed as special implementation of the LMS algorithm which takes into account the variation in the signal level at the filter input and select a normalized step size parameter which results in stable as well as fast converging adaption algorithm. The NLMS algorithm developed by Nitzberg in 1985 to obtain NLMS recursion by running the conventional LMS algorithm many times, for every new sample of the input [5-7]

We consider the LMS recursion

$$\mathbf{w(n+1) = w(n) + 2\mu e(n)x(n)} \qquad (1.6)$$

Where the step size parameter μ is time varying. we can select μ so that posterior error is minimized.

$$e^+(n) = d(n) - w^T(n+1)x(n) \qquad (1.7)$$

Substitute equation (1.7) in equation (1.6) and remaining we obtain.

$$e^+(n) = \left(1 - 2\mu x^T(n)x(n)\right)e(n) \qquad (1.8)$$

Minimizing $e^+(n)^2$ with respective to μ result in the following [4-9]

$$\mu = \frac{1}{2x^T(n)x(n)}$$

which force to $e^+(n)$ to zero Substitute the value of μ in equation (1.6) we get

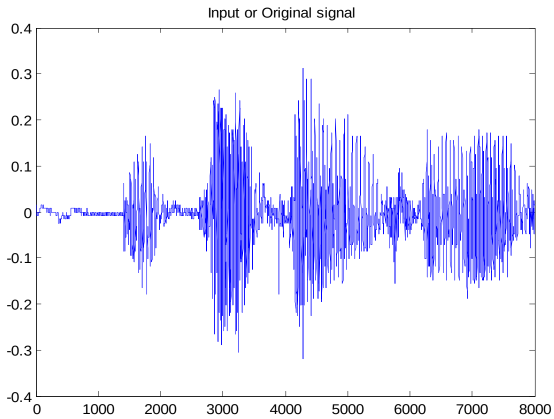
$$\mathbf{w(n+1) = w(n) + \frac{1}{x^T(n)x(n)} e(n)x(n)}$$

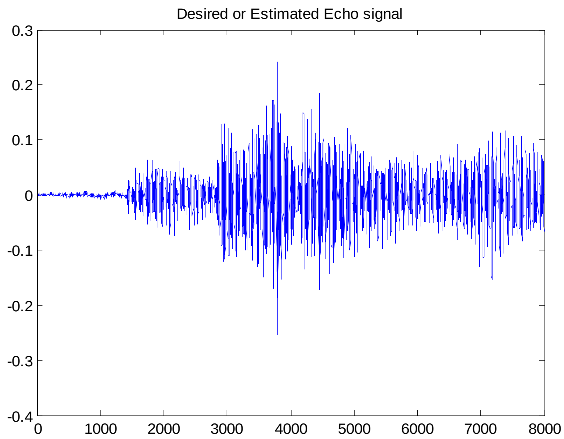
(1.10)

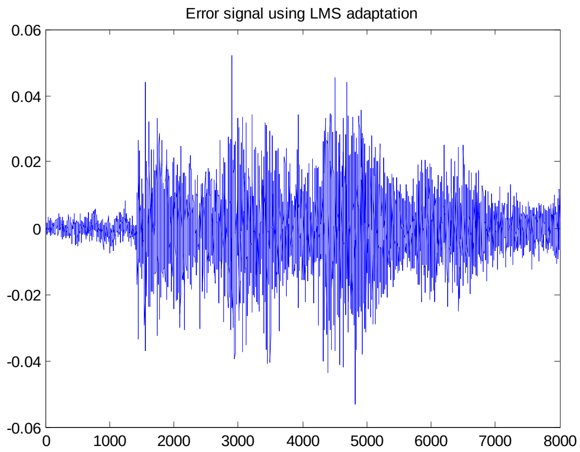
This is the NLMS recursion.

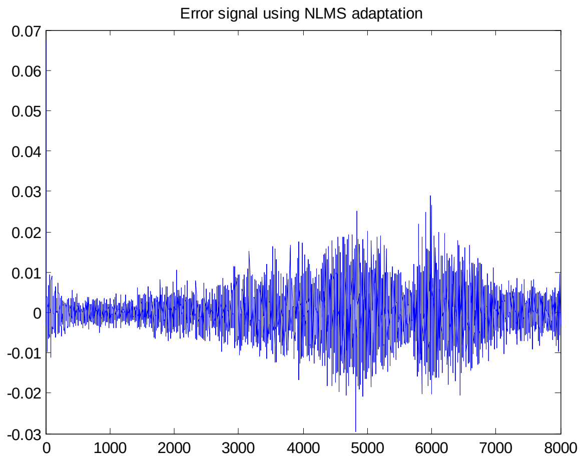
3. SIMULATIONS

3.1 Performance of LMS ALGORITHM

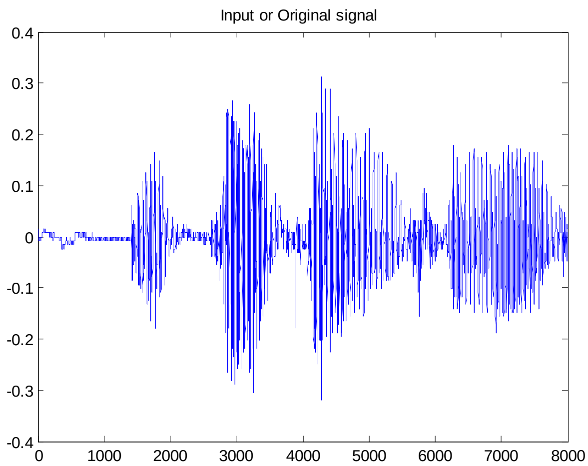


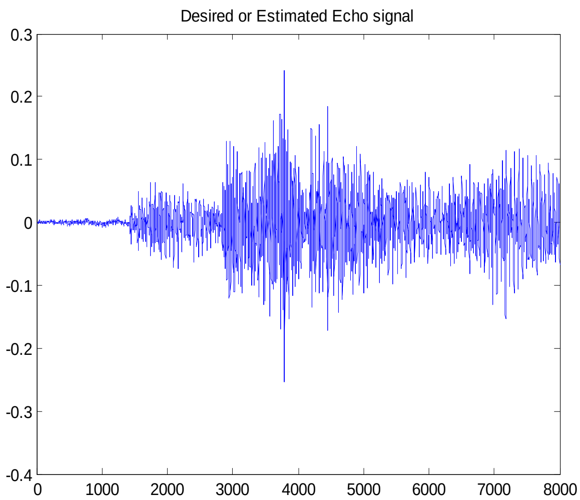






3.2 Performance of NLMS algorithm





4. CONCLUSION

The LMS algorithm is more popular because of its simplicity. It suggests a simple procedure for recursive adaptation of the filter coefficient after the arrival of every new input sample x (n) and its corresponding desired output y (n) [4]. It can operate in a stationary or non stationary environment also has the task of not only seeking the minimum point of the error surface, but also *tracking* it that means the smaller *μ* the better tracking behavior, however this means slow adaptation. The NLMS algorithm also simple. The constant μ may thought a step size parameter which controls the rate of convergence of the algorithm also its misadjustment

5. REFERENCES

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