Efficient Noise Cancellation Systems Based on Adaptive Algorithms and Their Performance Comparisons

Kiran.W.S Shalin.M Jayaram.J

***Abstract*—Noise cancellation systems with improved performance and low computational costs are presented in this paper. In speech applications, slow convergence and high computational burden are the main problems incorporating with conventional noise and echo cancellation method. Numerous algorithms have been formulated to overcome these problems. In this paper a comparison is made between LMS, NLMS and RLS algorithms. The analysis shows that NLMS algorithm performs well in case of convergence as well as in terms of Mean Square Error (MSE). Here the adaptive algorithms are implemented using MATLAB.**

***Keywords*— Adaptive filter, Noise cancellation, LMS, NLMS, RLMS algorithms, MATLAB**

I INTRODUCTION

Mobile telephones are often used in a noisy and reverberant environment. When such a device is used in hands-free mode the distance between the desired speaker and the microphone is usually larger than the distance encountered in handset mode. Therefore, the received microphone signal is degraded by the acoustic echo of the far-end speaker, room reverberation and background noise. The acoustic echo cancellation problem is usually solved by using an adaptive filter in parallel to the acoustic echo path. The adaptive filter is used to generate a signal that is a replica of the acoustic echo signal. An estimate of the near-end speech signal is then obtained by subtracting the estimated acoustic echo signal, i.e., the output of the adaptive filter, from the microphone signal. In practice there is always residual echo, i.e., echo that is not suppressed by the echo cancellation system. The residual echo results from the deficient length of the adaptive filter, the mismatch between the true and the estimated echo path, and nonlinear signal components.

A noise and echo cancellation system with an improved performance and low computational costs is presented in this paper. In speech applications, slow convergence and high computational burden are the main problems incorporating with conventional noise and echo cancellation method. The proposed noise canceller is based on using filter and uses the least mean square (LMS) algorithm to control a finite impulse response (FIR) filter to reduce the noise and echo in the input speech. The objective of the paper is to cancel the noise and echo of speech signal in noisy environment. The basic adaptive algorithm and filtering techniques are widely used to cancel the noise and suppress the echo. In this project we use the basic algorithm such as Least Mean Square algorithm. Least Mean Square (LMS) algorithm is the most successful adaptive algorithm. The LMS algorithm adjusts the filter coefficients from sample to sample in such a way to minimize Mean Square Error (MSE).

The significance of this project is to compare the different adaptive algorithms and to find the better one. Here the Mean Square Error (MSE) and attenuation using the three algorithms are found and compared.

II NOISE CANCELLATION

An adaptive filter is a filter that has time varying coefficients and frequency response. It is intelligent and flexible because it tracks the input signal characteristics, and automatically self-adjusts the filter coefficients to improve its performance according to some criterion. In my project, I had used an adaptive filter to cancel or reduce acoustic noise in a voice communication, a technique known as Adaptive Noise Cancellation (ANC). As the name implies, ANC relies on the use of noise cancelling by subtracting noise from a received signal. The block diagram of ANC is as shown in figure below.

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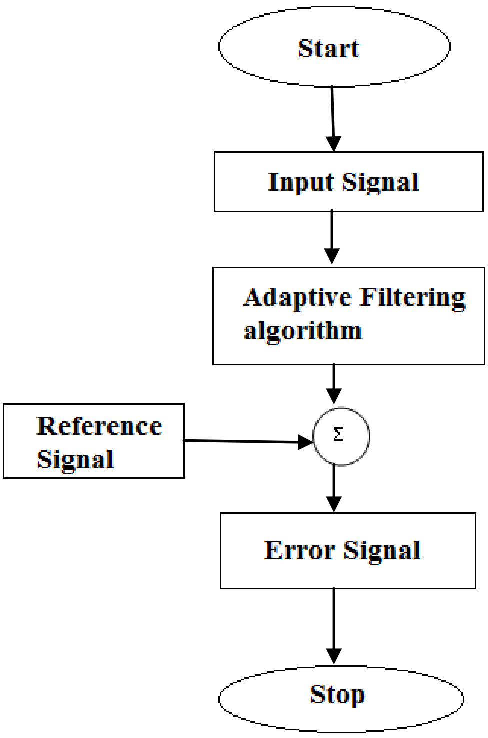

Fig 2: Noise Cancellation System Diagram

As shown in the block diagram, the system is a dual-input, closed-loop adaptive feedback system. The two input signals that are applied simultaneously to the system are given below.

i) The contaminated signal, d (n), which contains both the desired speech signal S (n), and the noise, N (n)

$$d(n) = S(n) + N(n)$$

ii) The reference noise signal, x (n).

The adaptive filter consists of two distinct parts: a digital filter with adjustable coefficients, W (n), and an adaptive algorithm which is uses feedback error signal, e (n), to adjust the coefficients of the filter. Reference noise, x (n), is processed by digital filter to produce an estimate of noise, y (n). Since the digital filter is realized using a transversal or finite impulse response (FIR) structure. An estimate of desired speech signal or error signal, e (n), is then obtained by subtracting estimate of noise, y (n), from contaminated signal, d (n):

$$e(n) = d(n) – y(n) = S(n) + N(n) – y(n)$$

A. Adaptive Algorithm Objective

Most adaptive algorithms have one objective, that is "to minimize the average power (or mean square value) of error signal, e (n), and thus to maximize the output signal-to-noise ratio (SNR)"

The estimated desired signal is given by

$$e(n) = d(n) – y(n) = S(n) + N(n) – y(n)$$

Squaring this equation:

$$e^2(n) = [S(n) + (N(n) – y(n))]^2 = S^2(n) + 2\,S(n)[N(n) – y(n)] + [N(n) – y(n)]^2$$

To find average power of error signal, take expectations, E [·], of both sides

$$E[e^2(n)] = E[S^2(n)] + 2E[S(n)\{N(n)-y(n)\}] + E[\{N(n)-y(n)\}^2]$$

Since the desired signal, S (n), is uncorrelated with

$$E[S(n)\{N(n) – y(n)\}] = 0$$

Hence,

$$\boxed{\underbrace{E[e^2(n)]}_{\text{Average power of output / error signal}} = \underbrace{E[S^2(n)]}_{\text{Average Signal Power}} + \underbrace{E[\{N(n)-y(n)\}^2]}_{\text{Average Remnant noise power}}}$$

If the estimate of noise is exactly replica of noise, that is the value y(n)=N(n), the average output power will contain only the average signal power, that is $E[e^2(n)] = E[S^2(n)]$. However, it is impossible to achieve y(n)=N(n). Practically, when y(n)≈N(n), the average remnant noise power will be minimized. This also means that the average output power will be minimized:

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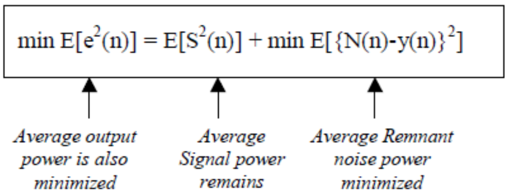

Thus, the filter coefficients can be adjusted to produce minimum average output power. The result of adjustment is known as the "optimum position". This adjustment does not affect the average desired signal power $E[S^2(n)]$ because S(n) is uncorrelated with N(n) that the effect of minimizing the average output power is to minimize the noise power (output noise) and hence maximizing the output signal-to-noise ratio.

B.LMS Algorithm

The idea behind LMS filters is to use steepest descent to find filter weights h(n) which minimize a cost function. We start by defining the cost function as

$$C(n) = E\{|e(n)|^2\}$$

where e(n) is the error at the current sample 'n' and E{.} denotes the expected value.

This cost function (C (n)) is the mean square error, and it is minimized by the LMS. Applying steepest descent means to take the partial derivative with respect to the individual entries of the filter coefficient (weight) vector

$$\nabla_h^H C(n) = \nabla_h^H E\{e(n))\, e^*(n)\}$$

where ∇ is the gradient operator.

$$\nabla_h^H(e(n)) = \nabla_h^H(d(n) - \hat{h}^H . X(n)) = -X(n)$$

$$\nabla C(n) = -2E\{X(n)\, e^*(n)\}$$

Now, ∇ C(n) is a vector which points towards the steepest ascent of the cost function. To find the minimum of the cost function we need to take a step in the opposite direction of ∇C (n).To express that in mathematical term.

$$\hat{h}(n+1) = \hat{h}(n) - \mu/2\, \nabla C(n) = \hat{h}(n) + \mu E(X(n)\, e^*(n))$$

where (μ/2) is the step size(adaptation constant). That means we have found a sequential update algorithm which minimizes the cost function. Unfortunately, this algorithm is not realizable until we know $E\{X(n)\, e^*(n)\}$.

For most systems the expectation function $E\{X(n)\, e^*(n)\}$ must be approximated. This can be done with the following unbiased estimator

$$E\{X(n)\, e^*(n)\} = \frac{1}{N}\sum_{i=0}^{N-1} X(n-i)\, e^*(n-i)$$

where N indicates the number of samples we use for that estimate. The simplest case is N=1

$$E\{X(n)\, e^*(n)\} = X(n)\, e^*(n)$$

.For that simple case the update algorithm follows as

$$\hat{h}(n+1) = \hat{h}(n) + \mu X(n)\, e^*(n)$$

Indeed this constitutes the update algorithm for the LMS filter.

C. NLMS Algorithm

The main drawback of the "pure" LMS algorithm is that it is sensitive to the scaling of its input x (n). This makes it very hard (if not impossible) to choose a learning rate μ that guarantees stability of the algorithm. The Normalised Least Mean Square (NLMS) is a variant of the LMS algorithm that solves this problem by normalising with the power of the input.

It can be shown that if there is no interference (v (n) =0), then the optimal learning rate for the NLMS algorithm is

$$\mu_{opt} = 1$$

and is independent of the input x(n) and the real (unknown) impulse response h(n). In the general

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case with interference (v (n) ≠0), the optimal learning rate is

$$\mu_{opt}=\frac{E[|y(n)-\hat{y}(n)|^2]}{E[|e(n)^2|]}$$

The results above assume that the signals v(n) and x (n) are uncorrelated to each other, which is generally the case in practice.

D. RLS Algorithm

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean square (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity.

The idea behind RLS filters is to minimize a cost function C by appropriately selecting the filter coefficients W_n, updating the filter as new data arrives.

The error implicitly depends on the filter coefficients through the estimate $\hat{d}$(n):

$$e\ (n)=d(n)-\hat{d}(n)$$

The weighted least squares error function C—the cost function we desire to minimize—being a function of e (n) is therefore also dependent on the filter coefficients:

$$C\ (W_n) = \sum_{i=0}^{n} \lambda^{n-i}\, e^2(i)$$

where 0<λ≤1 is the "forgetting factor" which gives exponentially less weight to older error samples.

The cost function is minimized by taking the partial derivatives for all entries k of the coefficient vector W_n and setting the results to zero

$$\sum_{l=0}^{p} w_n(l)[\sum_{i=0}^{n} \lambda^{n-i} X\ (i-l)\ x\ (i-)]=\sum_{i=0}^{n} \lambda^{n-i} d\ (i)\ x\ (i-k)$$

This form can be expressed in terms of matrices

$$R_x(n)W_n=r_{dx}(n)$$

where R_x (n) is the weighted sample correlation matrix for x(n) , and r_{dx} (n) is the equivalent estimate for the cross-correlation between d(n) and x(n). Based on this expression we find the coefficients which minimize the cost function as

$$W_n= R_x^{-1}(n)r_{dx}(n)$$

The smaller λ is the smaller contribution of previous samples. This makes the filter more sensitive to recent samples, which means more fluctuations in the filter co-efficient. The λ=1 case is referred to as the growing window RLS algorithm.

The RLS algorithm is very efficient and involves same number of arithmetic operations between samples as W_k and P_k.However there are two problems encountered when RLS algorithm is implemented. The first referred as 'blow-up' results if the input signal is zero for a long time, when the matrix P_k will grow exponentially. The second problem is its sensitivity to computer round off errors, which leads to negative definite P matrix and eventually to instability.

III SIMULATION AND RESULTS

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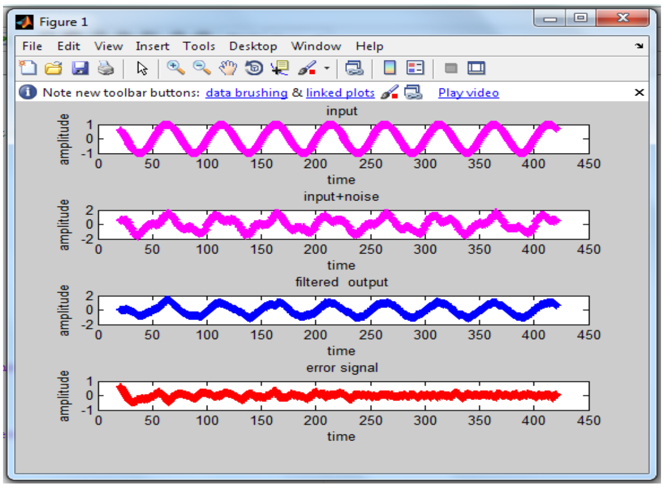

Fig 3.1: Output Plot of LMS Algorithm

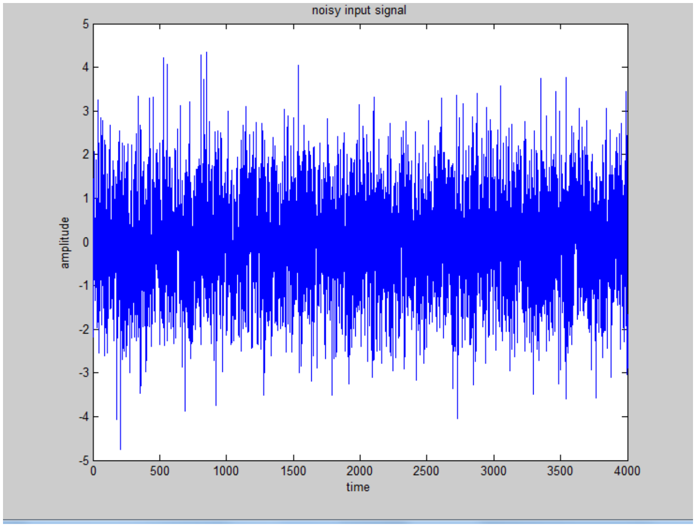

Fig 3.2.1:Noisy Input In NLMS Algorithm

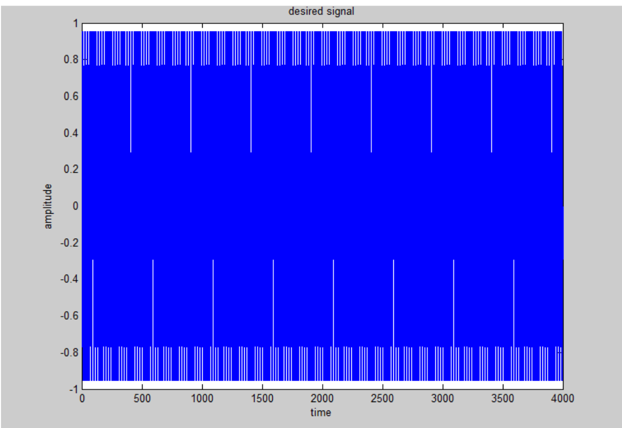

Fig 3.2.2:Desired Signal In NLMS Algorithm

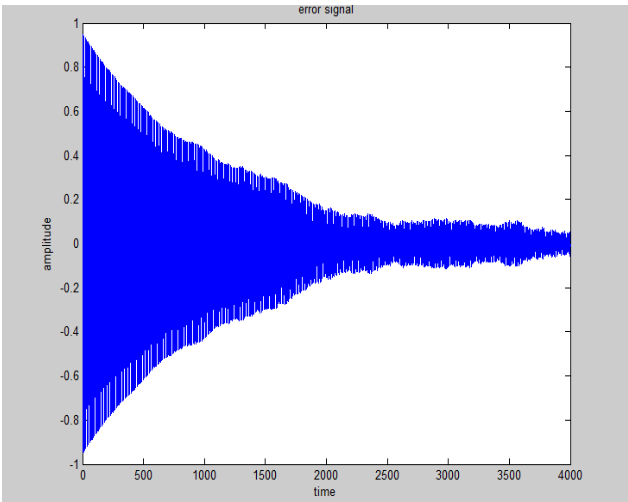

Fig 3.2.3: Error Signal In NLMS Algorithm

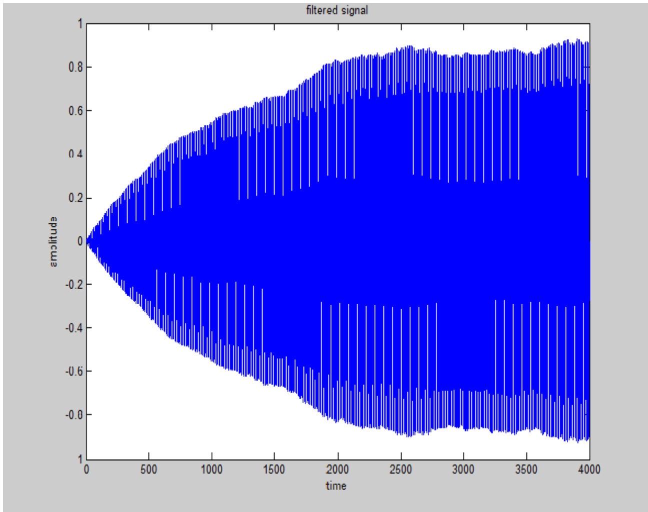

Fig 3.2.4: Filtered Signal in NLMS Algorithm

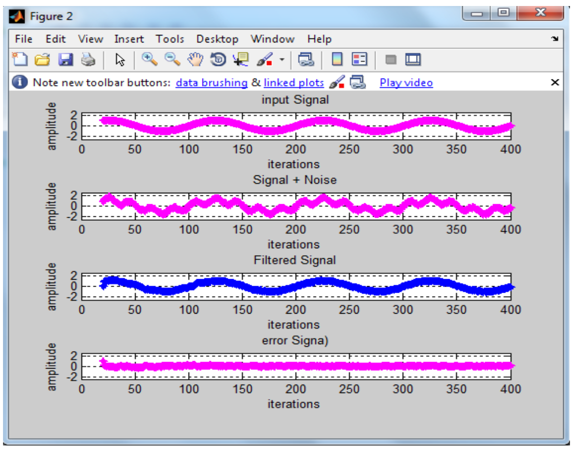

Fig 3.3: Output Plot of RLS Algorithm

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	μ	LMS	NLMS	RLS
MSE	0.01	0.0278	0.394	0.032
	10	0.0277	0.393	0.032
	100	0.0278	0.394	0.032
MMSE	0.01	0.0101	0.010	0.010
	10	0.0100	0.009	0.010
	100	0.0100	0.009	0.010
EMSE	0.01	0.0015	0.001	0.001
	10	0.0015	0.004	0.001
	100	0.0015	0.011	0.001
Time Consumed		Min	Least	Max
Complexity		Less	More	More
Convergence		0.8-0.9	0.3-0.4	0.6-0.7

Table 4.1: Performance Index Measure

From the above table of performance index we know that NLMS has the least Mean Square Error (MSE) value. We can also note that the convergence rate has been improved in NLMS algorithm and hence it is more efficient than the other two algorithms

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W.S.Kiran, Assistant Professor from Sivaji Engineering College, completed Bachelor of Engineering in Electronics and Communication in Vins college of engineering and Technology, Nagercoil and Master of Engineering in Communication Systems in Karpagam College of Engineering and Technology, Coimbatore. His area of Interests are Electronics Circuits Design and Signal Processing.

J.Jayaram, Assistant Professor from Sivaji Engineering College, completed Bachelor of Engineering in Electronics and Communication in Sun college of engineering and Technology, Nagercoil and Master of Engineering in Computer and Communication in Rajas Engineering College, Nagercoil. His area of Interests are Wireless System Design and signal processing.

M.Shalin, Assistant Professor from Sivaji Engineering College, completed Bachelor of Engineering in Electronics and Communication in Sun college of engineering and Technology, Nagercoil and Master of Engineering in Communication Systems in CSI Institute of Technology, nagercoil. His area of Interests are Electronics circuits Design and Antennas Wave Propagation.

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