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Research Paper Engineering

Performance Comparison between LMS and NLMS Algorithm

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ABSTRACT

Interference or noise cancellation is one of the most important applications of adaptive filters. The objective of adaptive interference cancellation is to obtain by estimation of the interfering signal and subtracting it from corrupted signal. This procedure is helpful to produce a noise free signal. For this purpose, filter uses an adaptive algorithm to change the value of coefficients, so that it acquires a better approximation of the signal after each iteration. The LMS (Least Mean Square), and its variant the NLMS (Normalized LMS) are two of the adaptive algorithms widely in use. This paper presents comparative analysis of LMS and NLMS in case of interference cancellation from signals. For each algorithm, effects of two parameters filter length and step size have been analyzed and relation between them has been established. Finally, performances of the two algorithms in different cases have been compared.

Keywords : Algorithm, LMS, NLMS, Adaptive Filter, Noise.

I. INTRODUCTION

Interference cancellation is a technique of almost importance in the field of signal processing. It is especially essential for speech signal transmission and processing due to ever-growing application of telephone and cellular communication. Interference cancellation can be achieved by an adaptive filter. This is a type of filter which self-adjusts its transfer function according to an optimizing algorithm [1]. The most popular of such adaptive algorithms is the Least Mean Square (LMS) algorithm [2-4]. The normalized Least Mean Square (NLMS) algorithm [5] can be considered as a special case of the LMS recursion which takes into account the variation in signal level at filter output. The performance of these adaptive algorithms is dependent on their filter length and the selected convergence parameter (commonly known as 'step size') [4]. There have been researches in the past focusing on the comparison of the LMS and the NLMS algorithms [6-12]. Slock et al. [9] studied the convergence behavior of the two algorithms and concluded that NLMS algorithm is a potentially faster converging algorithm compared to LMS algorithm. Faster convergence, however, comes at a price of greater residual error. More recent studies that try to relax this trade-off have been directed towards adjustable step-size variations of the two algorithms [6, 11].

LMS algorithm [13, 14] is the basic short-memory algorithm of adaptive signal processing. This algorithm has proved its utility in numerous applications (such as equalization, adaptive noise cancelling), but a rigorous theoretical analysis to explain its widespread success has been hard to find. On the other hand, NLMS algorithm [15-17] is potentially faster converging algorithm [18] compared to the LMS algorithm, when the design of adaptive filter is based on the usually quite limited knowledge of its input signal statistic.

This paper takes different approaches by taking the cross-correlation of the original and the filtered signals. Extensive study has been carried out on human voice signals contaminated with interference signals. Hence, the performance of the LMS and the NLMS algorithms in interference cancellation [5] has been presented in terms of the correlation coefficient of the input and output signals. The effects of the filter length and step size parameters have been analyzed to reveal the behavior of two algorithms (LMS and NLMS).

II. LMS ALGORITHM FORMULATION

LMS algorithm uses a gradient-based method of steepest decent. It uses the estimation of gradient vector from available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in direction of negative of the gradient vector which eventually leads to minimum mean square error. LMS is relatively simple [18] with respect to other algorithms. It does not require correlation function calculation or matrix inversions. LMS algorithm can be formulated by using two mathematical methods:

- Method of Steepest Descent [19].
- Newton's Method [20].

A. Method of Steepest Descent

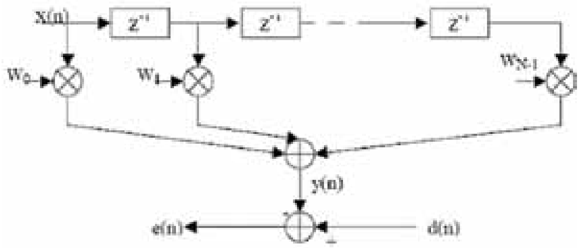

Figure 1: Traversal Winner Filter [19]

To analyze the method of steepest descent, first of all a traversal winner filter has been considered as shown in Fig. 1. Here, the assumption is taken that all signals involved are real valued signals. The tap-weight vector is considered as,

$$\overline{W} = [W_0, W_1, ..., W_{N-1}]^T \quad (1)$$

Signal input, filter output and error signal vectors are considered as,

$$\overline{x}(n) = [X(n), X(n-1), ..., X(n-N+1)]^T \quad (2)$$

$$y(n) = \overline{w}^T \overline{x}(n) \quad (3)$$

$$e(n) = d(n) - y(n) \quad (4)$$

Therefore, performance function will be,

$$\xi = E[e^2(n)]$$
$$= E[(d^2(n))] - 2\overline{W}^T \overline{p} + \overline{W}^T R \overline{W} \quad (5)$$

where $R = E[\overline{x}(n)\overline{x}^T(n)]$........ autocorrelation matrix of the filter input and $\overline{p} = E[\overline{x}(n)d(n)]$....... cross-correlation matrix vector between $\overline{x}(n)$ and d(n). Therefore, the performance function ξ is a quadratic function of the filter tap-weight vector

$\overline{W}$. ξ has a signal global minimum obtained by solving the Winner-Hopf equation,

$$R\overline{w}_0 = \overline{p} \quad (6)$$

if R and $\overline{p}$ are available.

Gradient ξ is defined as,

$$\nabla\xi = 2R\overline{w} - 2\overline{p} \quad (7)$$

With an initial guess of $\overline{W}_0$at n = 0, tap-weight at the k-th iteration is denoted by $\overline{w}(k)$. The following recursive equation may be used to update $\overline{w}(k)$:

$$\overline{W}(k+1) = \overline{W}(k) - \mu\nabla_k\xi \quad (8)$$

where μ > 0 is called the step size and $\nabla_k\xi$ denotes the gradient vector $\nabla\xi$ evaluated at the point $\overline{W} = \overline{W}(k)$.

Substituting equation (7) in equation (8) gives,

$$\overline{W}(k+1) = \overline{W}(k) - 2\mu(R\overline{W}(k) - \overline{p}(k)) \quad (9)$$

The convergence of $\overline{w}(k)$ to the optimum solution $\overline{W}_0$ and the convergence speed are dependent on the step size parameter μ.

Now, the equation (9) can be rearranged as,

$$\overline{W}(k+1) = (1-2\mu R)(\overline{W}(k) - \overline{W}_0) \quad (10)$$

By following this way, the steepest descent algorithm has been formulated.

B. Newton's Method

Due to the large computational time for steepest descent algorithm, the Newton's algorithm has been used to computation for LMS algorithm. The formulation of this method starts with the steepest descent algorithm by using equation (9) where it can be formulated by the assumption of $\overline{p} = R\overline{W_0}$ and then equation (9) becomes,

$$\overline{W}(k+1) = \overline{W}(k) - 2\mu R(\overline{W}(k) - \overline{w_0}) \quad (11)$$

The presence of R in equation (9) causes the eigen value-spread problem in the steepest descent algorithm. Newton's method overcomes this problem by replacing the scalar step-size μ with a matrix step-size given by μR^{-1}. Thus the resulting algorithm becomes,

$$\overline{W}(k+1) = \overline{W}(k) - \mu R^{-1}\nabla_k\xi \quad (12)$$

Substituting $\nabla\xi = 2R\overline{W} - 2\overline{p}$ in equation (12), it becomes,

$$\overline{W}(k+1) = \overline{W}(k) - 2\mu R^{-1}(R\overline{W}(k) - \overline{p})$$
$$= (1-2\mu)\overline{W}(k) + 2\mu R^{-1}\overline{p}$$
$$= (1-2\mu)\overline{W}(k) + 2\mu\overline{W_0} \quad (13)$$

By subtracting $\overline{W}_0$ from both sides of equation (13), the result becomes

$$\overline{W}(k+1) - \overline{W_0} = (1-2\mu)(\overline{W}(k) - \overline{W_0}) \quad (14)$$

In this way, the eigen value-spread problem can be avoided and Newton's method can be formulated.

III. NLMS Algorithm Formulation

A general form of the adaptive filter is illustrated in Figure 2, where d(n) is a desired response (or primary input signal), y(n) is the actual output of a programmable digital filter driven by a reference input signal x(n), and the error e(n) is the difference between d(n) and y(n). The function of the adaptive algorithm is to adjust the digital filter coefficients to minimize the mean-square value of e(n) [21-23].

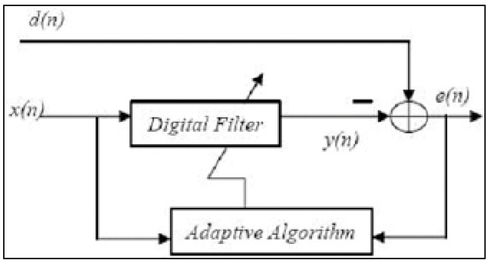

Figure 2: Basic concept of adaptive filter [2]

A technique to adjust the convergence speed is the NLMS algorithm. The NLMS is shown as follows,

$$W(n+1) = W(n) + \mu(n)X(n)e(n) \quad (17)$$

where μ(n) is adaptive step size.

IV. RESULTS AND DISCUSSIONS

The comparison starts with an audio signal which is used as input for this study whereas Adaptive White Gaussian Noise [AWGN] is used as the interfering signal. The two signals are added, and subsequently fed into mathematical simulation [24] of LMS and NLMS adaptive filters. The resulting output signals are then analyzed in order to study the behavior of the two algorithms. Though a large number of sample signals are used for the analysis, the results of two representative signals are presented here for brevity. Figure 3 shows the graphs of these input signals.

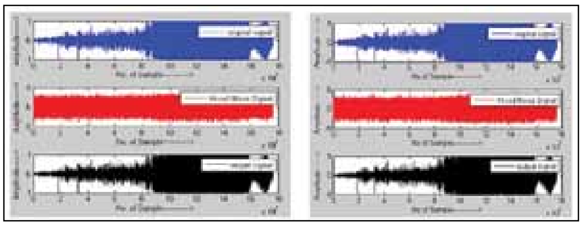

Figure 3: Comparison of LMS and NLMS in an audio signal different step-size with a fixed filter length

Two parameters of the adaptive filters are manipulated, namely the filter length and the step size. For each input signal, these parameters are varied, and for each combination of the parameters, a co-efficient of the cross-correlation of the output and the original input signal is calculated. In Figures 4 and 5, the correlation coefficients are shown for different step sizes while keeping a fixed filter length. It can be observed that for both the LMS and the NLMS, a particular optimum step size produces best approximation of the original signal. Value of the optimum step size is larger for LMS than NLMS. However, as filter length is increased, the gap closes down since the value decreases for the LMS and increases for the NLMS. Another notable difference is that the curve for LMS ascends sharply before reaching optimum level, and descends slowly afterwards. For NLMS, it is just reverse.

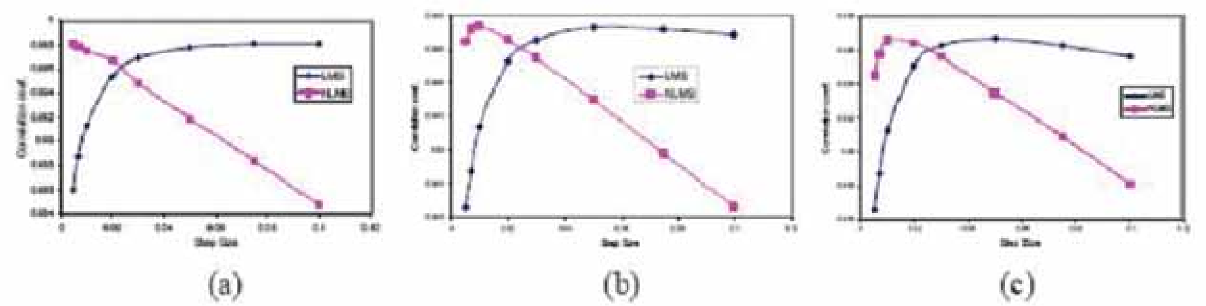

Figure 4: Comparison of the LMS and the NLMS in Signal 1 for different step sizes with a fixed filter length of (a) 10 (b) 30 (c) 50.

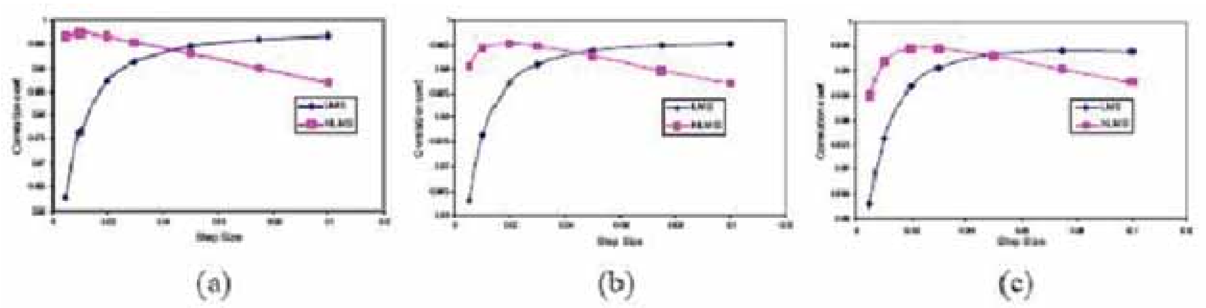

Figure 5: Comparison of the LMS and the NLMS in Signal 2 for different step sizes with a fixed filter length of (a) 10 (b) 30 (c) 50.

V. CONCLUSION

In this paper, the behavior of the LMS and the NLMS algorithms are studied for Interference cancellation of speech signals. Attempt is made to find out the effects of the filter length and the step size parameters of the two algorithms. The results are presented in terms of the co-efficient of the cross-correlation of the input and the filtered signals. Moreover, the analysis leads us to conclude that if the LMS is chosen for interference cancellation of speech signals, a larger step size should be chosen, and the filter length should be kept low. For NLMS, the step size should be smaller, in which case the filter length should also be low. But if a larger step size is chosen, the filter length should be increased for better performance. By utilizing the findings, new variable-step size algorithms can be developed in order to optimize filter performances.

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