

Comparison between LMS & NLMS Algorithms in Adaptive Noise Cancellation for Speech Enhancement

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Abstract

This paper is concerned with the comparison between LMS (Least Mean Squared) and NLMS (Normalized Least Mean Squared) algorithms on noise cancellation problems. Cancellation of noise was attempted on contaminated speech segments. Uttered speech signal samples were recorded from an individual in a quiet atmosphere. The speech sample signals appeared almost noiseless to a listener when played back through a headphone. These speech samples were taken as noiseless in this work. Computer generated white and filtered noise samples were added purposefully with the speech segment. As a result contaminated speech segments were formed. The contaminated speech was processed with an adaptive filter where LMS and NLMS algorithms were used. The effectiveness of the algorithms was tested by comparing Nrr (Noise Reduction Ratio) attained after filtering the contaminated speech segment using both algorithms. Also human subjects listened to the recovered and noisy speech to grade the result. In this work, Nrr and mean squared errors (MSE) of the algorithms attained in noise cancellation application were taken as the basis of the comparison of LMS and NLMS algorithms. Variation of results with respect to input SNR and filter length were observed in the work. Convergence speeds for both algorithms were also shown in the work.

Keywords: Adaptive filtering; Least Mean Squared (LMS); Normalized Least Mean Squared (NLMS); Noise Reduction Ratio (Nrr); noise cancellation.

1. Introduction

Signal, while transmitting from the source to the receiver end, often becomes corrupted by noise from the surroundings. Due to this, the quality of the signal degrades and often becomes unusable. Speech signal mainly gets corrupted by the acoustic noise. Simple digital filtering cannot be used to recover the noiseless signal because simple digital filters have fixed coefficients which cannot cope with the unpredictable input signal characteristics. For the purpose of noise cancellation and production of an output signal which is close to the noiseless signal we have to use adaptive filters [1]-[3]. Adaptive filter has the property of self-adjusting its coefficients and hence its frequency response to adapt the characteristics changes of the input signal. Various adaptive algorithms have been used for adaptive filtering. Two of the simplest and widely used adaptive algorithms are Least Mean Squared (LMS) algorithm and Normalized Least Mean Squared (NLMS) algorithm.

2. Adaptive Noise Cancellation (ANC) System

An ANC system consists of two sensors (primary and reference sensors), an adaptive filter and a subtracting unit [1]-[3] (Fig. 1). An adaptive filter consists of two distinct parts: a digital filter with adjustable coefficients and an adaptive algorithm part which is used to modify the coefficients. The primary sensor receives the corrupted signal and the reference sensor receives the noise signal. The medium between the primary sensor and the noise source acts as a filter itself. So noise signals at the two sensors are not same. For proper noise cancellation, the two noise inputs must be correlated.

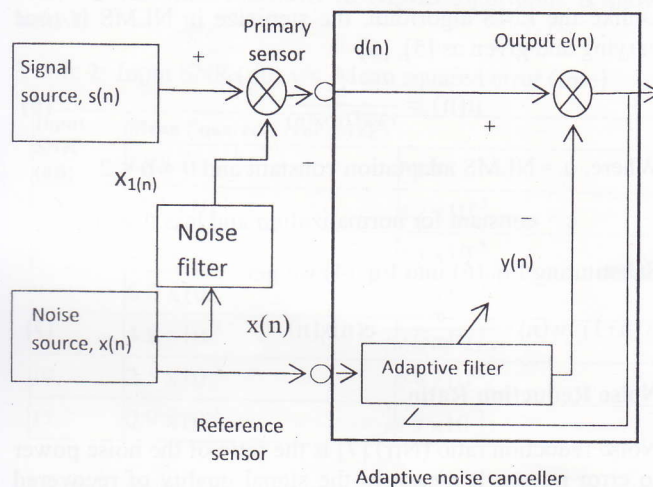


Fig. 1: Adaptive noise cancellation system

The reference signal $x(n)$ is processed by the adaptive filter [4] to produce the noise estimate:

$$y(n) = \sum_{i=0}^{M-1} \hat{w}_i(n)x(n-i) \quad (1)$$

Where the $\hat{w}_i(n)$ are the adjustable (real) tap weights of the filter and n is no. of iterations. The filter output $y(n)$ is subtracted from the primary signal $d(n)$ and produces error signal:

$$e(n) = d(n) - y(n) \quad (2)$$

$$e(n) = s(n) + x_1(n) - y(n) \quad (3)$$

The error signal serves two purposes: as an estimate of the desired output and to adjust the coefficients/tap weights of the adaptive filter.

3. LMS ALGORITHM

One of the simplest and most successful adaptive algorithms is LMS algorithm [4]. LMS is based on the steepest descent algorithm where the weight vector is updated by using the error signal $e(n)$ (from eq. 2) and the reference noise signal $x(n)$ from sample to sample by equation 4 [5]

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (4)$$

Where, μ = step size or convergence factor

The condition for convergence is:

$$0 < \mu < 1/\lambda_{\max} \quad (5)$$

Where λ_{\max} is the maximum eigenvalue of the input data covariance matrix.

4. NLMS ALGORITHM

NLMS algorithm [4] can be considered as a special implementation of LMS algorithm which takes into account the variation in signal level at the filter input and selects a normalized step-size parameter which results in a more stable as well as more converging adaptive algorithm. Unlike the LMS algorithm, the step-size in NLMS is time varying and given as [5], [6]

$$\mu(n) = \frac{\alpha}{c + x^T(n)x(n)} \quad (6)$$

Where, α = NLMS adaptation constant and $0 < \alpha < 2$

c = constant for normalization and less than 1

Substituting Eq. (6) into Eq. (4) we get

$$w(n+1) = w(n) + \frac{\alpha}{c + x^T(n)x(n)} e(n)x(n) \quad (7)$$

Noise Reduction Ratio

Noise reduction ratio (Nrr) [7] is the ratio of the noise power to error power. It measures the signal quality of recovered signal. Error is calculated from the difference of the noisy signal and the noise estimation.

$$Nrr = \frac{\text{noise power}}{\text{error power}} \quad (8)$$

$$Nrr \text{ (db)} = 10 \log_{10}(Nrr) \quad (9)$$

$$\text{Ideally, } Nrr \text{ (dB)} = -\text{SNR (dB)} \quad (10)$$

5. EXPERIMENTAL RESULTS

A. Simulation Environment

Noise less signal : Speech clip
 Clip Duration : 2 seconds
 Sampling rate : 8000 samples/second
 Algorithms used : LMS & NLMS
 μ for LMS : 0.005
 α for NLMS : 0.15
 c for NLMS : 0

Software used : MATLAB R2009a
 Noise used : White Gaussian noise
 Default SNR : -4dB
 No. of iterations : 16000
 Default filter length N: 32

B. Results of LMS on the speech segment

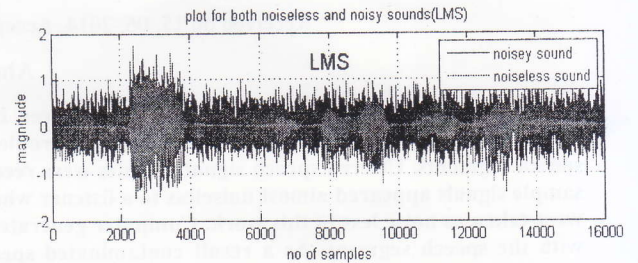


Fig. 2: plot for the noiseless and the noisy sounds for LMS

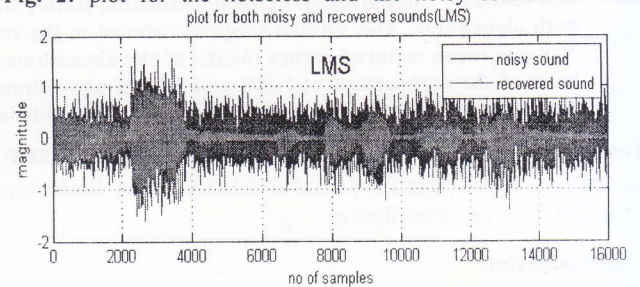


Fig. 3: plot for noisy and the recovered sounds for LMS

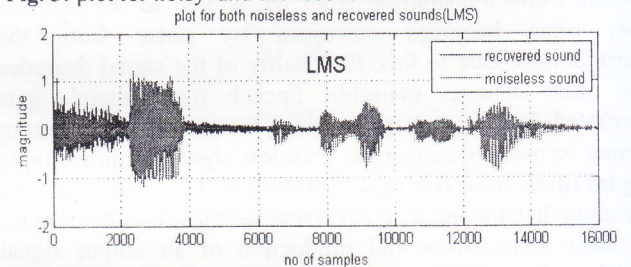


Fig. 4: plot for the noiseless and the recovered sounds for LMS

C. Results of NLMS on the speech segment

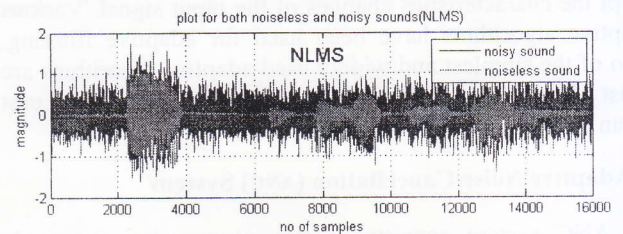


Fig. 5: plot for the noiseless and the noisy sounds for NLMS

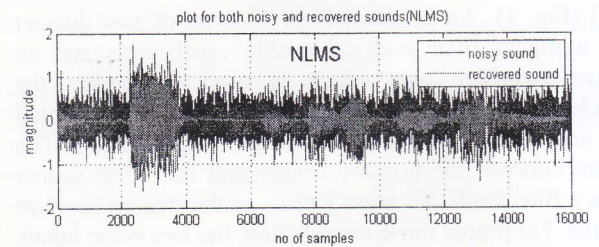


Fig. 6: plot for noisy and the recovered sounds for NLMS

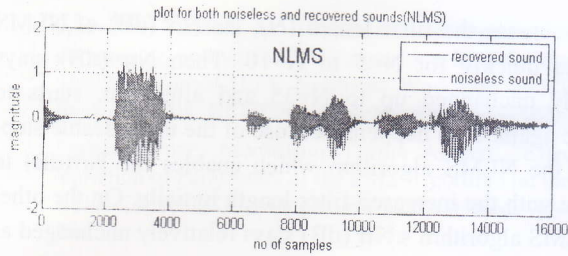


Fig. 7: plot for the noiseless and the recovered sounds for LMS.

D. Effect of input noise level on Noise reduction ratio Nrr(dB)

A table to show the effect of changing the input SNR (dB) on the noise reduction ratio (Nrr) (dB) for LMS & NLMS algorithms is shown below.

Table 1: Input SNR (dB) v/s noise reduction ratio (Nrr)(dB)

Input SNR (dB)	Noise Reduction Ratio (Nrr) (dB)	
	LMS	NLMS
-10	9.091	9.472
-5	4.164	4.57
0	-0.807	-0.395
5	-5.668	-5.385
10	-10.369	-10.382

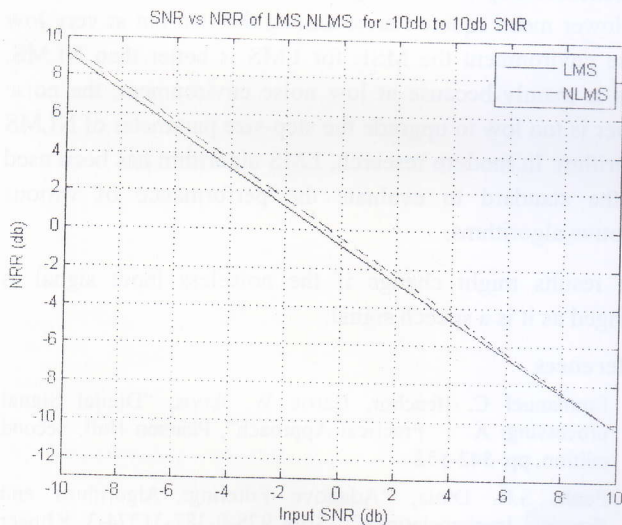


Fig. 8: Plot of input SNR (dB) v/s Nrr (dB)

From the above figure and table we can assume that NLMS has the better noise reduction capability among the two for almost the entire range of input SNR (dB). As the noise power increases the noise reduction ratio (Nrr) of LMS degrades more compare to NLMS's Nrr.

E. Effect of input noise level on Mean Squared Error (MSE)

A graph to show the impact of input noise level on the MSE of the ANC system for both LMS & NLMS algorithms is shown on Fig. 9

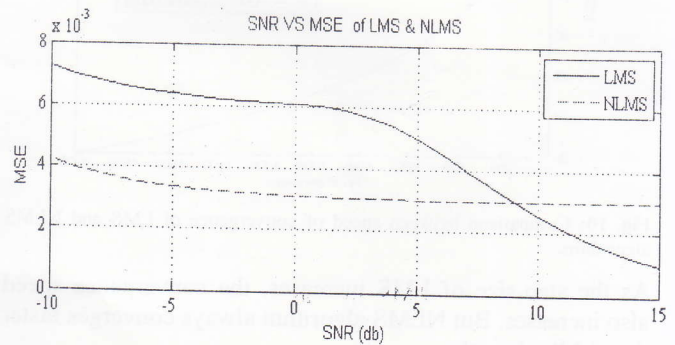


Fig. 9: Plot of input SNR (dB) v/s MSE

A table [6], [8] to show the effect of changing the input SNR (dB) on the MSE for LMS & NLMS algorithms is shown below.

Table 2: Input SNR (dB) v/s Mean squared error (mse)

Input SNR (dB)	Mean Squared Error (MSE)	
	LMS	NLMS
-10	7.2×10^{-3}	4.2×10^{-3}
-5	6.3×10^{-3}	3.3×10^{-3}
0	6.0×10^{-3}	3.1×10^{-3}
5	4.9×10^{-3}	3.0×10^{-3}
10	2.5×10^{-3}	2.9×10^{-3}
15	0.9×10^{-3}	2.9×10^{-3}

At high noise environment, NLMS has the lower MSE among the two. Both algorithms' MSE improves as the noise level decreases and eventually at very low noise environment (for SNR > 9db), LMS algorithm's MSE becomes lower than NLMS algorithm's MSE. This happens mainly because of the upgradeable step-size of the NLMS algorithm which varies with energy of the input noise. As the step-size for NLMS adjusts quickly with the noise level, it's MSE does not vary as much as the MSE for LMS algorithm does.

F. Convergence speed comparison

Fig. 10 shows the comparison between the speed of convergence of LMS and NLMS [8], [9]. LMS algorithm's convergence speed is shown for different step-size (0.005, 0.002 and 0.0009).

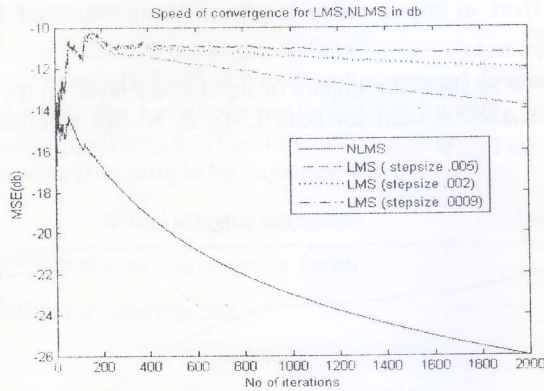


Fig. 10: Comparison between speed of convergence of LMS and NLMS algorithms.

As the step-size of LMS increases, the convergence speed also increases. But NLMS algorithm always converges faster than LMS algorithm.

G. Effect of filter length (N) on Mean Squared Error (MSE)

A graph to show the alteration of MSE for both LMS and NLMS algorithms with filter length (N) is shown in Fig. 11. [4].

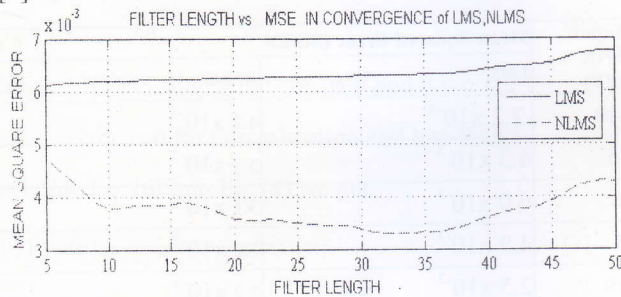


Fig. 11: Plot of filter length v/s Mean Squared Error (MSE) for LMS and NLMS algorithms.

As the filter length increases, the MSE for NLMS decreases up to a certain value (e.g. $N=35$). On the other hand, MSE for LMS algorithm always degrades (increases) with increasing N .

H. Effect of filter length (N) on Noise Reduction Ratio (Nrr)

A graph to show the variation in the noise reduction capability of the ANC system with filter length (N) is shown in Fig. 12.

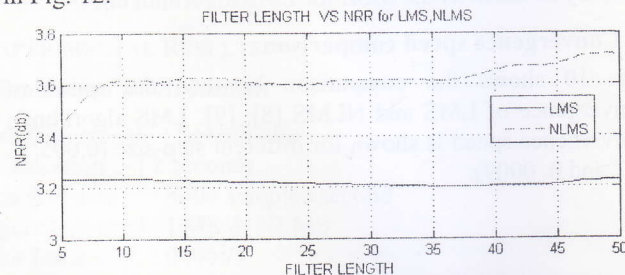


Fig. 12: Plot of filter length v/s Noise Reduction Ratio (Nrr) for LMS and NLMS algorithms.

As we increase the filter length (N), the Nrr (dB) of NLMS increases quickly for $N=5$ to $N=10$. Then Nrr (dB) stays relatively unchanged up to $N=35$ and after that, starts to increase again. This happens because of the upgradeable step-size of the NLMS algorithm which enables the Nrr (dB) to improve with the increased filter length initially. On the other hand, LMS algorithm's Nrr (dB) stays relatively unchanged as it has a fixed step-size.

6. Conclusions

In this work, the adaptive noise canceller has been developed by implementing LMS & NLMS algorithms. And then, these algorithms were analyzed and compared by investigating the effects of different system parameters such as input SNR, no. of iterations and filter length on the performance of the adaptive noise cancellation (ANC) system.

As LMS has a fixed step-size, it is not suitable to operate in non-stationary environment. But for NLMS the step-size changes according to the energy of the input signals. Hence, it is suitable to operate in non-stationary environment as well as in stationary environment.

NLMS algorithm has the better noise reduction capability and faster convergence speed than LMS algorithm due to its upgradeable step-size. At high noise environment, NLMS has the lower mean squared error among the two but at very low noise environment the MSE for LMS is better than NLMS. This is mainly because at low noise environment, the noise power is too low to upgrade the step-size parameter of NLMS algorithm. In modern research, LMS algorithm has been used as the standard to evaluate the performance of various adaptive algorithms.

The results might change if the noiseless input signal is changed as it is a speech signal.

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Abstract

Dynamic programming algorithm for RNA secondary structure prediction including pseudoknots is utilized here. On the other hand regular algorithm provides good alternative for effective solution. We present robust algorithm for RNA secondary structure prediction including pseudoknots. Main idea is to simplify it to find the optimal folding candidate whose which is a pseudo minimum free energy structure including pseudoknots. The algorithm is evaluated on 44 RNA sequences of various types. Experimental result suggest that robust protein secondary structure better in most cases in terms of accuracy and specificity compared to other well known algorithms like RNAfold, NUPACK and Dfam.

Keywords: RNA, Pseudoknots, Heuristic Algorithm, Dynamic Programming, RNA Secondary Structure.

1. Introduction

RNA carries genetic information for a cell which will express the protein synthesis. The key factor of RNA is its 3D structure. The 3D structure can be represented as 3D wrapping structure which contains the collection of folding points between the base pairs. Figure 1 represents the structure of Human Delta Virus (HDV) ribonucleic [1] tripartite genome. The genome contains stem and loop which help to maintain the structure. Figure 1 shows interaction by the pseudoknots are formed between separated base pairs and the formed ones represent the pseudoknots. Pseudoknots also play important role in protein function for example in ribosomal subunit [2] and regulation of translation and splicing [3].

We proposed a new algorithm to generate RNA secondary structure including pseudoknots. Experimental results suggest that this algorithm provides better result in terms of speed, accuracy and specificity than most of the available algorithms such as Dfam. This simplicity of the algorithm is O(N³) and space complexity is O(N²K) where K is number of allowed base pairs. It can be considered as RNA secondary structure prediction algorithm. The RNA sequence length.

2. Background and Related Work

Several researchers proposed dynamic programming algorithms for RNA prediction free energy minimization. In a related idea that includes certain pseudoknots structure [4, 5, 6]. Zuker and Stiegler proposed dynamic programming algorithm to predict secondary structure. Their algorithm calculate all possible secondary structure to choose best structure including pseudoknots. Zuker and Stiegler provides complete model with parameters to calculate the free energy of the structure. However, finding minimum free energy (MFE) rules, it difficult to find the algorithm to predict RNA secondary structure. In this study, we use another algorithm to predict RNA secondary structure of pseudoknots. In this study, we use the equality of the predicted as a reference, the resulting free energy prediction is also not correct [4]. The pseudoknots [4] is another dynamic programming algorithm proposed by Rander and Zuker with "association rule". They proposed their rule for structure prediction that help to reduce the runtime of [4]. Their algorithm also consider suboptimal structures [4] and the energy pseudoknots [7].

It is often hard to apply the available algorithms to predict RNA secondary structure but we can include RNA secondary structure in larger sequence and they are less accurate than the dynamic programming algorithm. Pseudoknot sequences are not found in existing long sequence alignment software that becomes more important for large sequence. In last few years, there have been significant advances in the development of heuristic algorithms, leading to improvements in solving RNA secondary structure prediction problems. [10]. Development of this type of approach is that it is not possible to find the exact structure but Van Dongen et al. [11] showed that genetic algorithm approach could be used to predict the pseudoknots structure by allowing the shortcomings of dynamic algorithm. He described results on a computer simulation of RNA folding pathways using a genetic algorithm for optimal prediction.

Fig. 1. Human Delta Virus (HDV) ribonucleic acid