

Statistical Approach for Noise Removal in Speech Signals Using LMS, NLMS, Block LMS and RLS Adaptive filters

D. Hari Hara Santosh, Member, IACSIT, Vusl Sravya Pendyala, V. N. Lakshman Kumar, and N. Shanmukh Rao

Abstract— In this paper the application of different adaptive filters in removing the noise present in the speech signals is presented. To analyze the performance of different adaptive filter family members, the parameters like convergence, output PSNR and CPU consumption time are considered. Results show that NLMS filter shows the better performance in CPU time consumption and output PSNR. Block LMS has the highest Convergence factor among all the members of the adaptive filter family.

Index Terms— Adaptive filters, LMS, RLS, NLMS, NLMS

I. INTRODUCTION

Adaptive noise cancellation is being used as a prominent solution in a wide range of fields. From the standpoint of performance, it is widely known [1] that the Recursive Least-Squares (RLS) algorithm offers fast convergence and good error performance in the presence of both white and coloured noise. This robustness makes this algorithm highly useful for adaptive noise cancellation. Unfortunately even as the computational power of devices today increases, it remains largely difficult to utilize the RLS algorithm for real-time signal processing. All the members of the Adaptive filter family are seen in terms of output PSNR, convergence and CPU time consumption. Section II gives the brief introduction of LMS algorithm, Section III gives the overview of Block LMS algorithm, Section IV gives the RLS algorithm and Section V gives the results and discussions.

II. LMS ALGORITHM

Least mean squares (LMS) algorithms[2] are a class of adaptive filters used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). The Least Mean Square (LMS) algorithm is an adaptive algorithm, which uses a gradient-based method of steepest descent. 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

The LMS algorithm is a linear adaptive filtering algorithm,

which in general consists of two basic processes:

- 1) A filtering process, which involves
 - (a) Computing the output of a linear filter in response to an input signal
 - (b) Generating an estimation error by comparing this output with a desired response
- 2) An adaptive process, which involves the automatic adjustment of the parameters of the filter in accordance with the estimation error

LMS algorithm is important because of its simplicity and ease of computation and because it does not require off-line gradient estimation or repetitions of data.

A. LMS Algorithm Formulation:

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

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

We assume that the signals involved are real valued

The LMS algorithm changes (adapts) the filter tap weights so that $e(n)$ is minimized in the mean square sense. when the process $x(n)$ and $d(n)$ are jointly stationary, this algorithm converges to a set of tap-weights which on average are equal to the Wiener-Hopf solution

The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm.

$\zeta = E[e^2(n)]$ by its instantaneous coarse estimate $\zeta = e^2(n)$

Substituting $\zeta = e^2(n)$ for ζ in the steepest descent recursion, we obtain

$$\bar{W}(n+1) = \bar{W}(n) - \mu \nabla e^2(n) \quad (3)$$

where

$$\bar{W}(n) = [w_0(n) w_1(n) \dots \dots \dots w_{N-1}(n)]^T$$

$$\nabla = \left[\frac{\partial}{\partial w_0} \quad \frac{\partial}{\partial w_1} \quad \dots \dots \dots \quad \frac{\partial}{\partial w_{n-1}} \right]^T$$

The i^{th} element of the gradient vector $\nabla e^2(n)$ is

$$\frac{\partial e^2}{\partial w_i} = 2e(n) \frac{\partial e(n)}{\partial w_i} = -2e(n)x(n-i) \quad (4)$$

Then

$$\nabla e^2(n) = -2e(n)\bar{x}(n)$$

Finally we obtain

$$\bar{W}(n+1) = \bar{W}(n) + 2\mu e(n)\bar{x}(n) \quad (5)$$

Manuscript received April 10, 2012; revised May 30, 2012.
The authors are with department of ECE.
(e-mail:8ant08h-ece2005@yahoo.com).

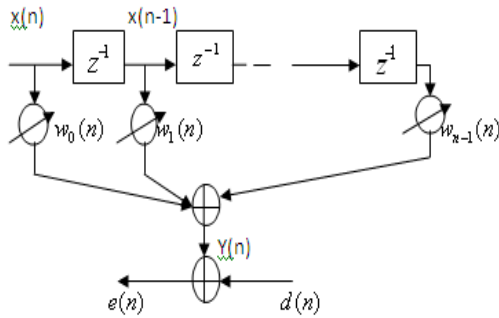


Fig. 1. Block diagram of LMS filtering scheme

III. BLOCK LMS ALGORITHM

The block LMS (BLMS) algorithm works on the basis of the following strategy. The filter tap-weights are updated once after the collection of every block of data samples. The gradient vectors, $-2e(n)X(n)$, used to update the filter tap-weights are calculated during the current block.

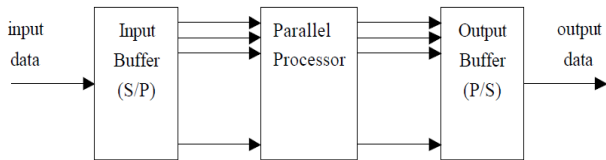


Fig. 2. Block diagram of Block LMS Algorithm

Using k to denote the block index, the BLMS recursion is obtained as [3][4]

$$\bar{W}(k+1) = \bar{W}(k) + 2\mu_B \frac{\sum_{i=0}^{L-1} e(kL+i)\bar{X}(kL+i)}{L}$$

where L is the block length and is the step-size parameter. Also,

$$e(kL+i) = d(kL+i) - y(kL+i)$$

for $i = 0, 1, 2, \dots, L-1$

IV. RLS ALGORITHM

The Recursive least squares (RLS) adaptive filter [5], [6] is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This in contrast to other algorithms such as the least mean squares 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

The RLS algorithm exhibits the following properties:

Rate of convergence that is typically an order of m magnitude faster than the LMS algorithm.

Rate of convergence that is invariant to the Eigen value spread of the correlation matrix of the input vector.

RLS Algorithm Formulation:

The idea behind RLS filters is to minimize a cost function C by appropriately selecting the filter coefficients updating the filter as new data arrives. The error signal $e(n)$ and desired signal $d(n)$ are defined in the diagram :

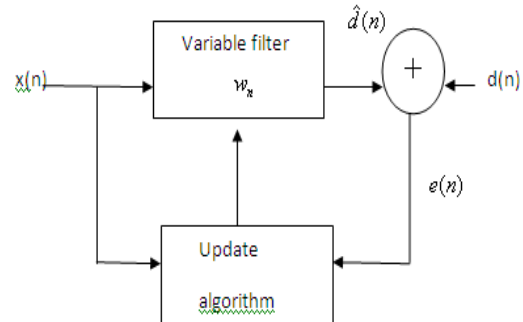


Fig. 3. Block diagram of RLS filtering scheme

The error implicitly depends on the filter coefficients through the estimate

$$e(n) = d(n) - \hat{d}(n) \quad (6)$$

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[7],[8]:

$$C(w_n) = \sum_{i=0}^n \lambda^{n-i} e^2(i) \quad (7)$$

This form can be expressed in terms of matrices as

$$R_x(n)w_n = r_{dx}(n) \quad (8)$$

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 [9]

$$w_n = R_x^{-1}(n)r_{dx}(n) \quad (9)$$

We have

$$P(n) = R_x^{-1}(n) = \lambda^{-1}p(n-1) - g(n)x^T(n)\lambda^{-1}p(n-1) \quad (10)$$

where $g(n)$ is gain vector

With the recursive definition of $P(n)$ the desired form follows

$$g(n) = p(n)x(n)$$

we derive

$$w_n = p(n)r_{dx}(n) = w_{n-1} + g(n)[d(n) - x^T(n)w_{n-1}] = w_{n-1} + \alpha(n)g(n) \dots (11)$$

Where $\alpha(n) = d(n) - x^T(n)w_{n-1}$ is a priori error. Compare this with the a posterior error; the error calculated after the filter is updated

$$e(n) = d(n) - x^T(n)w_n$$

Thus we have correction factor as

$$\Delta w_{n-1} = g(n)\alpha(n) \quad (12)$$

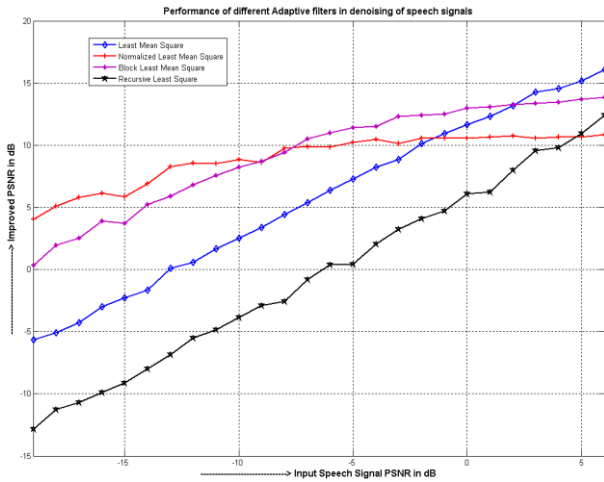


Fig. 4. Performance of different Adaptive Filters in denoising of Speech Signals

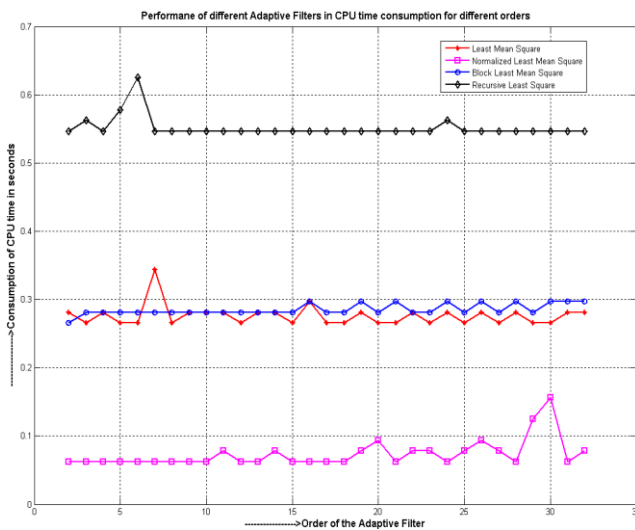


Fig. 5. Performance of different Adaptive Filters in CPU time consumption for different orders

V. RESULTS AND CONCLUSIONS

To see the performance of the adaptive filters the parameters convergence, output PSNR and the CPU time are considered. The performance of different adaptive filters namely LMS, BLMS, DLMS and RLS filters are shown for speech signals. The speech signals with input PSNR ranging from -20dB to 5dB as input to different Adaptive filters and the output PSNR are drawn in the figure 4. The normalized adaptive filter has the best performance among all the filters. Figure 5 show that Normalized Least Mean Square adaptive filter has the better performance. As per the Convergence parameter is concerned the Block LMS took fewer number of iterations to reach minimum error. This effect has been shown in Figure 6. Figure 7, 8 and 9 are the original noisy and denoised of one of the speech signal which has 117,000 coefficients. To give more clarity in the denoising procedure the part of speech signal from 75,200 to 76,000 is taken. These figures are shown in figure 10, 11 and 12. Although in theory RLS suppose to have highest convergence factor, but from the results it is shown that RLS is not a stable filter. Whereas the Block LMS has better performance than even

RLS. In conclusion the normalized LMS adaptive filter shows the highest performance as per the CPU time consumption and output PSNR. And the Block LMS shows the highest performance for convergence. All these results are seen in MATLAB[10].

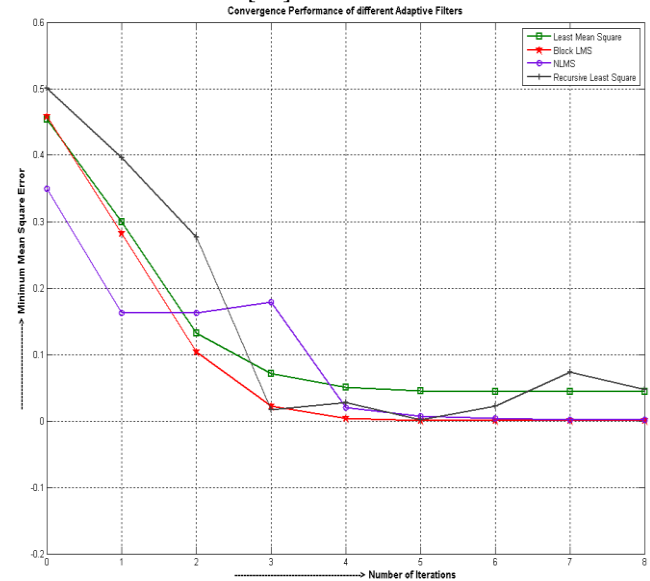


Fig. 6. Performance of different Adaptive Filters in Convergence time.

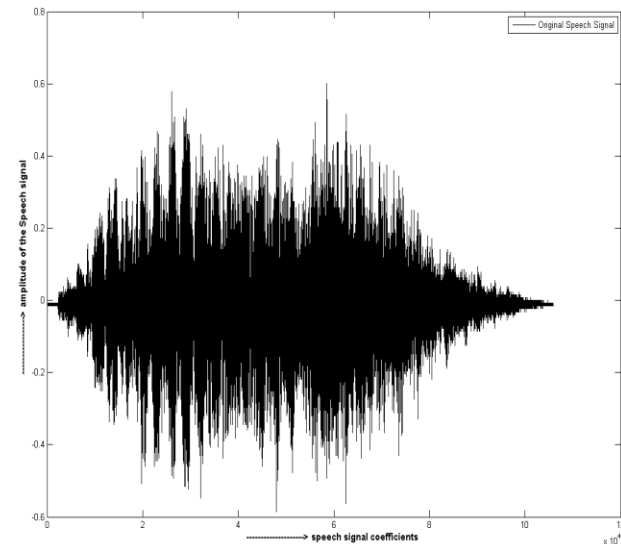


Fig. 7. Original Speech Signal.

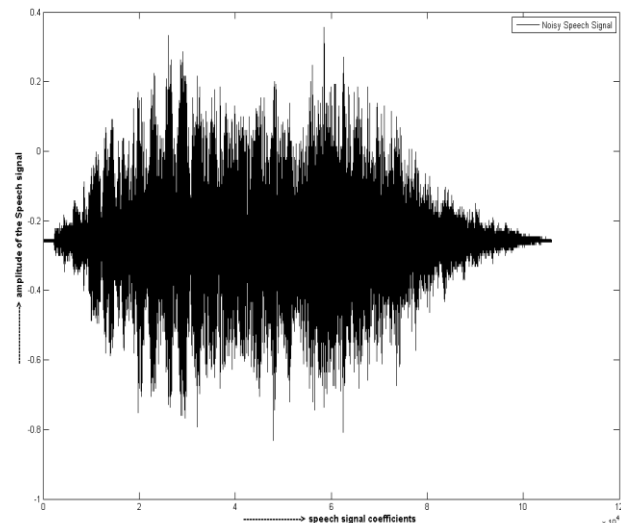


Fig. 8. Noisy Speech Signal.

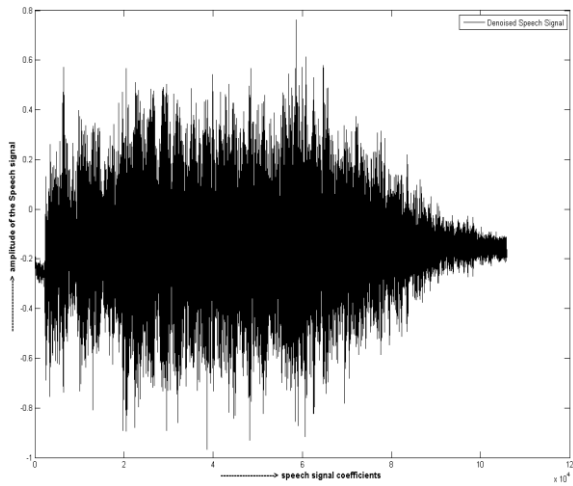


Fig. 9. Denoised Speech Signal.

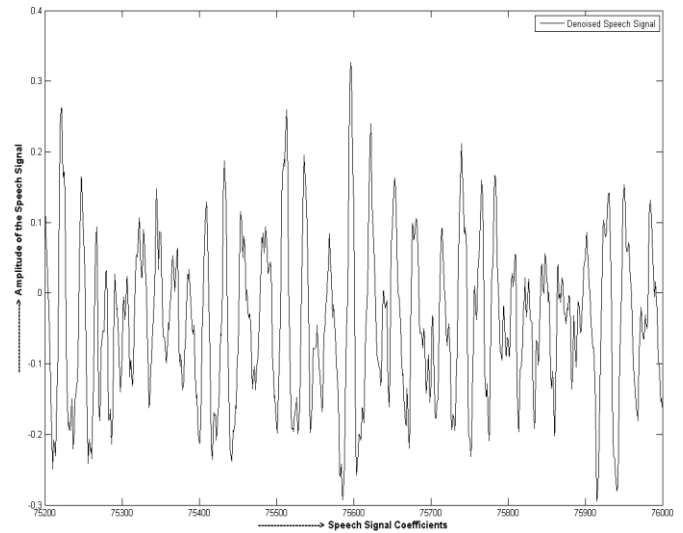


Fig. 12. Denoised Speech Signal with speech coefficients from 75,200 to 76,000.

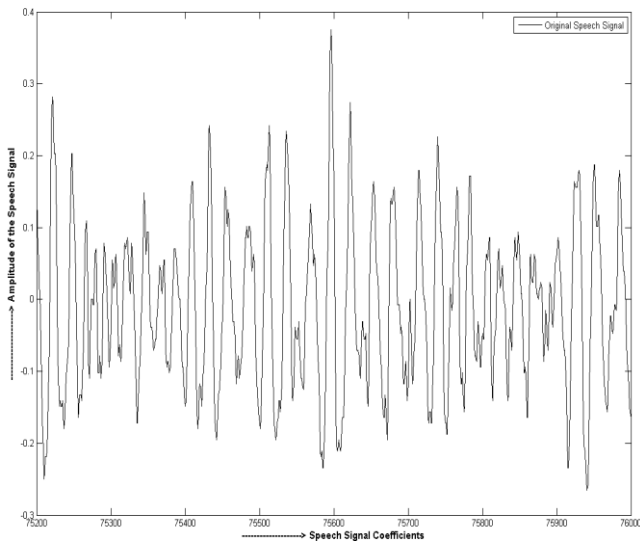


Fig. 10. Original Speech Signal with speech coefficients from 75,200 to 76,000.

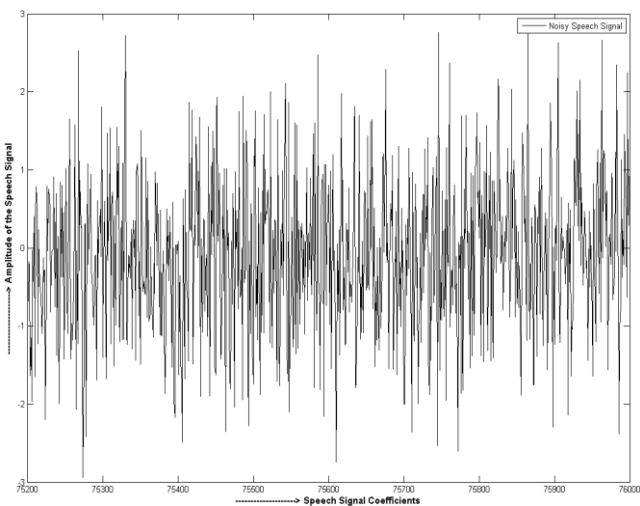


Fig. 11. Noisy Speech Signal with speech coefficients from 75,200 to 76,000.

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Mr. D. Hari Hara Santosh obtained his B. Tech. and M. Tech degrees from JNT University, Hyderabad in the year 2005 and 2010. He is presently working as Assistant Professor in MVGR College of Engineering, Vizianagaram, AP. He has 2 publications in both International and National Journals and presented 16 papers at various International and National Conferences. His areas of interests are Image Processing, Speech processing.



Ms. P.V.U.S.L.Sravya completed her B. Tech. from MVGR College of Engg., JNT University, Kakinada. She is presently doing MS in USA. She has presented many papers at various student symposiums on latest technologies. Her areas of interests are Image Processing, Speech processing.



Mr. N. Shanmukha Rao obtained his B. Tech. and M. Tech degrees from JNT University, Hyderabad and AU College of Engineering, Visakhapatnam in the years 2005 and 2010. He is presently working as Assistant Professor in MVGR College of Engineering, Vizianagaram, AP. He presented 16 papers at one International. His areas of interests are Image Processing, Speech processing.



Mr. V. N. Lakshmana Kumar obtained his B. Tech. and M. Tech degrees from JNT University, Hyderabad in the year 2005 and 2010. He is presently working as Assistant Professor in MVGR College of Engineering, Vizianagaram, AP. He has 2 publications in both International and National Journals and presented 8 papers at various International and National Conferences. His areas of interests are Image Processing, Speech processing.