Performance Analysis of Noise Cancellation in Speech Signals Using LMS, FT-LMS and RLS Algorithms

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***Abstract*—In this paper the eminence of the Fast Transversal Least Mean Squares (FT-LMS) algorithm over LMS and RLS algorithms is provided. This algorithm is designed to provide similar performance to the standard LMS algorithm while reducing the computation order. Finite precision effects are also briefly discussed. Simulations are performed with these algorithms to compare both the computational burden as well as the performance for adaptive noise cancellation. Simulations show that FT-LMS offers comparable performance with respect to the standard RLS and LMS in addition to a large reduction in computation time for higher order filters.**

***Index Terms*—Adaptive filters, LMS, RLS, FT-LMS.**

I. Introduction

Adaptive noise cancellation is the best possible solution for noise removal in a wide range of fields. A desired signal which is accidentally corrupted by some unwanted noise can often be recovered by an adaptive noise canceller using the least mean squares (LMS) algorithm. But the disadvantage in using LMS algorithm is its excess mean-squared error, or misadjustment which increases linearly with the desired signal power. This leads to deteriorating performance when the desired signal exhibits large power fluctuations and is a grave problem in many speech processing applications. From the standard point of performance, it is known [1] that the Recursive Least- Squares (RLS) algorithm offers fast convergence and good error performance in the presence of any noise. This criterion makes this algorithm beneficial for adaptive noise cancellation. In real time signal processing, where the computational power is considered, and at present as the computational power of devices increases, it is difficult to use RLS algorithm. The RLS algorithm is difficult to implement because of its computational complexity. The computation time of the algorithm scales with $O(M^2)$, where M is the filter order. This makes the computation of RLS in real-time nearly impossible especially when higher filter lengths are used. In this paper we provide a better alternative filter Fast transversal LMS (FT-LMS) filter. This filter is designed in such a manner that it provides the least squares solution to the given adaptive filtering problem which scales the computation time to O(M),which makes this feasible for real-time applications. The rest of the paper is organized in the following manner. Section II provides an overview of LMS algorithm. Section III briefs the RLS algorithm. Section IV gives an overview about FT-LMS algorithm. Section V will provide simulation results of FT-LMS, RLS and RLS filters and discusses about their performance in reducing noise. Section VI will provide conclusions on this work.

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II. LMS Algorithm

Least mean squares (LMS) algorithms are one of the class of adaptive filters used to produce a desired filter by finding the filter coefficients which produce 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 decent [2]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS follows an iterative procedure that makes successive corrections to the weight vector which eventually leads to the minimum mean square error

The LMS algorithm is a linear adaptive filtering algorithm, which consists of two basic processes:

1) A filtering process, which

a) Computes the output of a linear filter in response to an input signal and

b) Generates an estimation error by comparing this output with a desired response

2) An adaptive process, which adjusts 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:

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

$$e(n)=d(n)-y(n) \tag{2}$$

We assume that the signals involved are real valued the LMS algorithm changes (adapts) the filter tap weights to minimize the error e (n). 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.

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

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

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

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where,

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

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

Note that the i-th element of the gradient vector $\nabla e^2(n)$ is

$$\frac{\partial e^2}{\partial w_i} = 2e(n)\frac{\partial e(n)}{\partial w_i} \tag{4}$$

$$= -2e(n)x(n-1)$$

Then

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

Finally we obtain

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

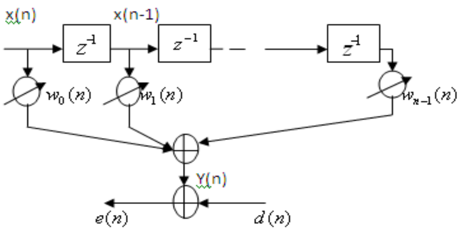


Fig. 1. Block diagram of LMS filtering scheme

III. RLS Algorithm

The Recursive least squares (RLS) adaptive filter [3] is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals [4]. This in contrast to other algorithms such as the least mean squares that aim to reduce the mean square error. For 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 :

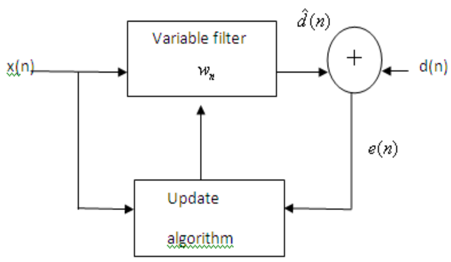


Fig. 2. Block diagram of RLS filtering scheme

The error implicitly depends on the filter coefficients through the estimate

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

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:

$$C(w_n) = \sum_{i=0}^{n} \lambda^{n-1} e^2(n) \tag{7}$$

This form can be expressed in terms of matrices as

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

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

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

We have

$$P(n) = R_x^{-1}(n)$$

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

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

$$w_n = p(n) r_{dx}(n)$$

$$w_n = w_{n-1} + g(n)[d(n) - x^T(n) w_{n-1}]$$

$$= w_{n-1} + \alpha(n) g(n) \tag{11}$$

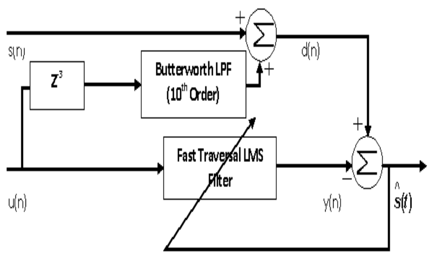
where $\alpha(n) = d(n) - x^T(n) w_{n-1}$ is a *priori* error. Compare this with the *a posteriori* error; the error calculated *after* the filter is updated

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

Thus we have correction factor as

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

IV. Fast- Transversal Least Mean Squares



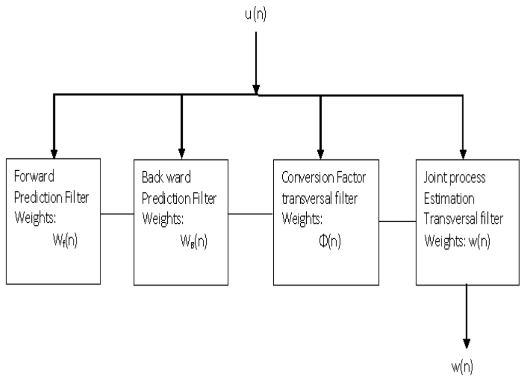


Fig. 3. Block diagram of Fast Transversal LMS Filter

The Fast Transversal LMS (FT-LMS) filter [5]-[6] is designed to provide the solution to the filtering problem with efficient performance. In addition, the FT-LMS filter provides this solution with reduced computational burden which scales linearly with the filter order. This makes it a very attractive solution in real time noise cancellation applications [7]-[11]. The FT-LMS development is based on the derivation of lattice-based least-squares filters. The four transversal filters used for forming the update equations are:

A. *Forward Prediction:*

The forward prediction transversal filter computes the forward filter weights in such a manner that minimizes the prediction error (in the least squares sense) of the next input sample based on the previous input samples.

B. *Backward Prediction:*

The backward prediction transversal filter computes backward filter weights in such a manner that minimizes the prediction error (in the least squares sense) of the $u(n-M)$ sample using the input vector input $u_b(n)=[u(n),u(n-1).....u(n-M+1)]^T$

C. *Conversion Factor:*

The gain computation transversal filter is used to recursively compute a gain vector which is used to updating the forward, backward and joint process estimation filter weights.

D. *Joint-Process Estimation:*

The joint-process estimation transversal filter computes filter weights in such a manner that the error between the estimated signal and the desired input signal (d(n)) is minimized. It is the joint process estimation weights that are equivalent to filter weights in other adaptive filtering algorithms. The structural diagram of the FT-LMS using the subcomponent transversal filters is shown in Figure 3.

V. Results and Discussions

In order to compare the performance of FT-LMS, LMS and RLS filters, respective filter algorithms were implemented in MATLAB [12] in an adaptive noise cancellation system.

In fig. 4 Performance of different adaptive filters is observed by varying the order of the adaptive filters from 1 to 32 .The improvement in the PSNR can be observed from RLS to FT-LMS filters. The highest PSNR is observed for FT-LMS for any given order.

In fig. 6 analysis for denoising of speech signals of LMS, RLS and FT-LMS filters is performed. For a given input speech signal improvement in PSNR of denoise signal from LMS to FT-LMS filters is observed.

These results show that FT-LMS filter performs better than LMS and RLS filters and is most suitable in noise removal applications. The waveforms for FT-LMS filter for a given speech signal can be observed in fig.5 and fig.7

In fig. 8 Performance of FT-LMS, RLS and LMS in CPU time is done by considering different orders. The FT-LMS filter takes less time to compute when compared with LMS and RLS filters for any given order.

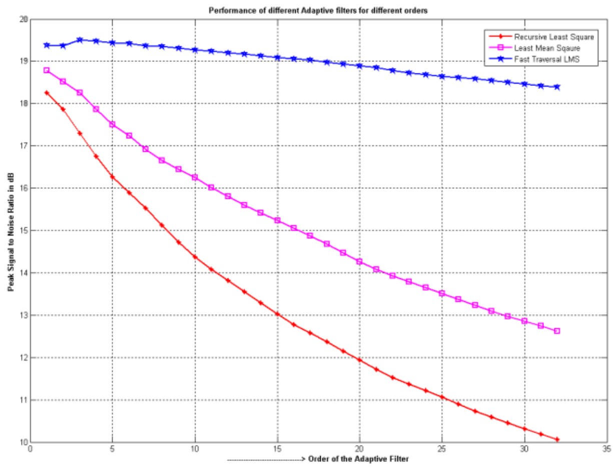


Fig. 4. Performance of adaptive filters for different orders

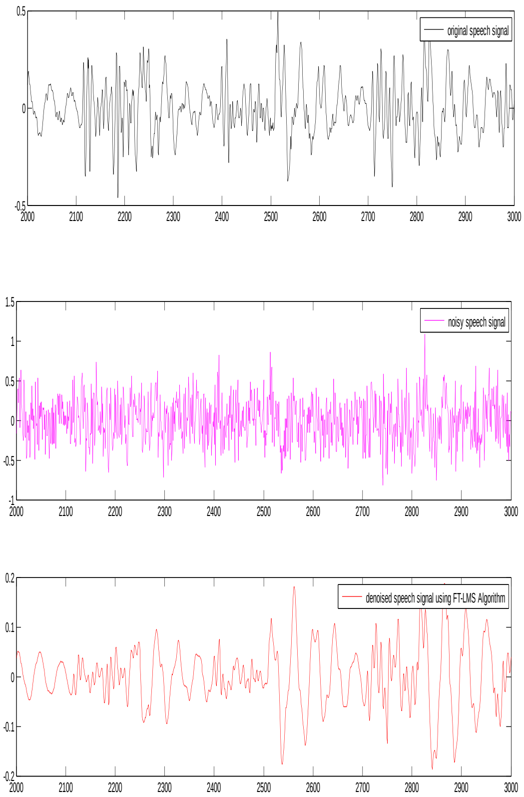


Fig. 5. Original, noisy speech signals and denoised Speech signal using FT-LMS Adaptive filter of length 1000 fom 2001 to 3000 samples.

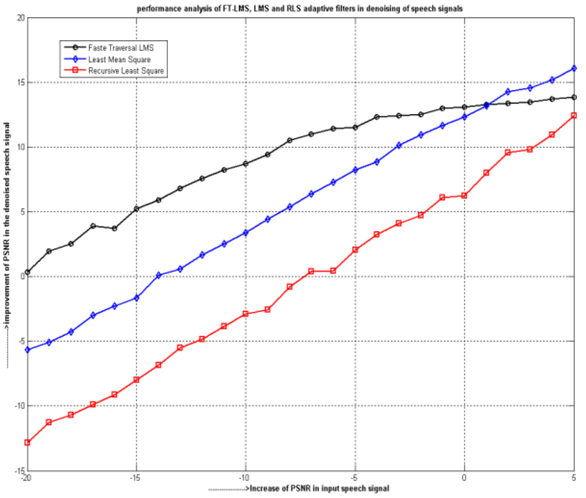


Fig. 6. Performance of Adaptive filters in denoising of speech signals

TABLE I: IMPROVEMENT OF PSNR FOR DIFFERENT ADAPTIVR FILTERS.

i/p PSNR	LMS	RLS	FT- LMS
-20	-12.86	-5.651	0.336
-16	-9.124	-2.294	3.6947
-12	-4.829	1.6626	7.5431
-8	-0.79345	5.39003	10.5161
-4	3.24463	8.86239	12.303
0	6.25552	12.317	13.0894
1	8.01129	13.1972	13.2573
2	9.54221	14.278	13.3491
3	9.80992	14.5499	13.4443
4	10.9615	15.18	13.7099
5	12.418	16.0804	13.8183

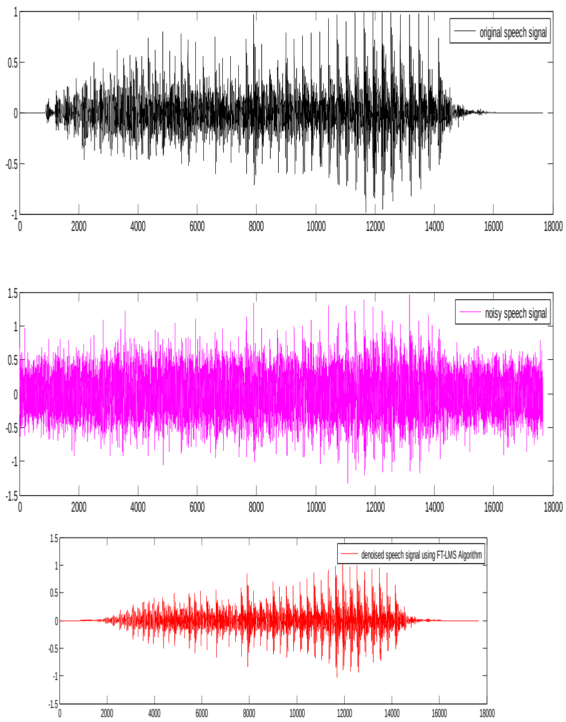


Fig. 7. Original, noisy speech signals and denoised Speech signal using FT-LMS Adaptive filter

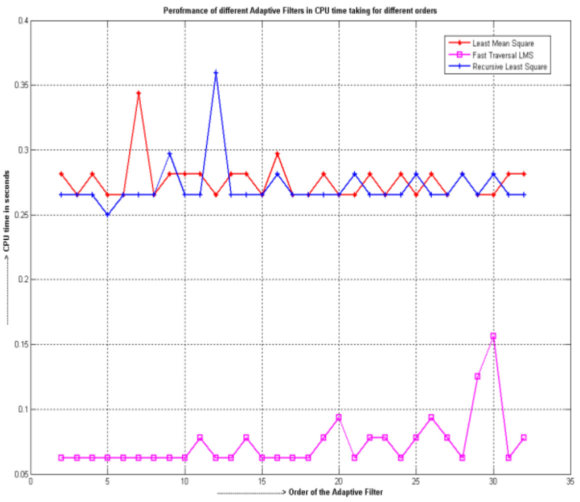


Fig. 8. Performance of adaptive filters in CPU time for different orders

VI. CONCLUSIONS

In this paper, the superiority of FT-LMS algorithm over LMS and RLS algorithm was provided. Simulations are done in order to compare the performance of these filters for acoustic noise cancellation. After thorough simulations, it is clear that the FT-LMS algorithm is a highly suitable solution for adaptive filtering applications where a large filter order is required without delaying the performance offered by the standard RLS algorithm in the presence of any noise. Future work should examine the feasibility of a real time hardware implementation of the FT-LMS algorithm.

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