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Research Article

Comparative Analysis of various Adaptive Filtering Algorithms for Adaptive System Identification

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Abstract

System identification is one of the most interesting applications for adaptive filters, for this dissertation provides a comparison of LMS, VSSLMS,NLMS and TDLMS adaptive algorithms. This process provided the best suitable algorithm for usage in adaptive filters for system identification. This technique Based on the error signal, where filter's coefficients are updated and corrected, in order to adapt, so the output signal has the same values as the reference signal. Its applications include echo cancellation, channel equalization, interference cancellation, and so forth. Simulation results show that the proposed algorithms outperform the standard NLMS and TDLMS algorithms in both convergence rate and steady-state performance for sparse systems identification.

Keywords: *LMS, VSSLMS, NLMS and TDLMS Algorithms, Adaptive system identification.*

1. Introduction

During the last decades the adaptive filters have (W.B. Mikhael *et. al* 1989) attracted the attention of many researchers due to their property of self-designing. Adaptive filtering comprises two basic operations: the filtering process and the adaptation process. In the filtering process an output signal is generated from an input data signal using a digital filter, whereas the adaptation process consists of an algorithm which adjusts the coefficients of the filter to minimize a desired cost function. In applications where Identification is the procedure of specifying the unknown model in terms of the available experimental evidence (Y. Gu *et.al,* 2009) that is, a set of measurements of the input output desired response signals and an appropriately error that is optimized with respect to unknown model parameters.

2. Adaptive System Identification

System identification refers to the ability of an adaptive system to find the FIR filter that best reproduces the response of another system (Y.Chen *et.al,* 2009) whose frequency response is a priori unknown. The setup is shown in fig.1

When the adaptive system reaches its optimum value and the output (e) is zero. An FIR filter is obtained (Irina Dornean *et.al*, 2007) whose weights are the result of the adaptation process that is giving the same output as that of the 'unknown system' for the same input. In other words, the FIR filter reproduces the behavior of the 'unknown system.

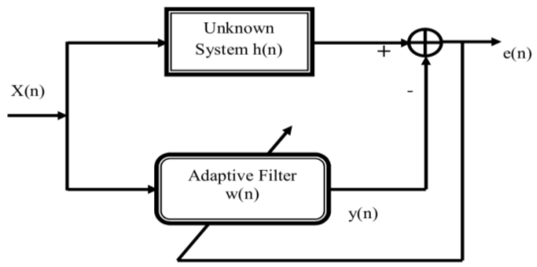

Fig.1 System Identification Model

2.1 Least Mean Square (LMS) Algorithm

The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff in 1959 through their studies of pattern recognition.(S. Haykins ,1996),) From there it has become one of the most widely used algorithms(V.J.Mathews *et.al*,1993) in adaptive filtering. Algorithm, the filter tap weights of the adaptive filter (Raymond H. Kwong *et.al*, 1992) are updated according to the following formula.

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (1)$$
$$e(n) = d(n) - y(n) \quad (2)$$
$$y(n) = w^T(n)x(n) \quad (3)$$

x(n) is the input vector of time delayed input values and vector w(n) is the weight vector defined as

$$x(n) = [x(n)x(n-1)..x(n-N+1)]^T \quad (4)$$
$$w(n)=[w_0(n)w_1(n)w_2(n) \ldots \ldots, w_{N-1}(n)]^T \quad (5)$$

$y(n)$ and $d(n)$ are,respectively, the filter output and the desired response , $e(n)$ denoted the feedback error and μ is the convergence factor.

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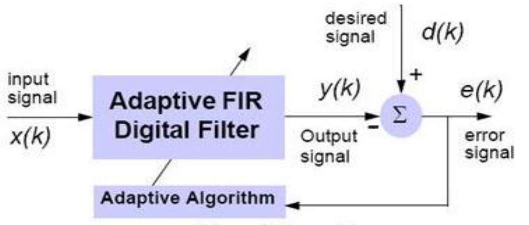

Fig.2 Block diagram of adaptive transversal filters employing adaptive algorithm.

2.2 Variable Step Size LMS (VSSLMS) Algorithm

The VSSLMS algorithm overcomes the conflicting requirements of the step size parameter (P.Sristi *et al*. 2001) i.e. a large step size is needed for faster convergence and a small step size is needed to reduce misadjustment (R. Harris *et al* 1986).

The VSSLMS algorithm first introduced by Kwong and Johnston in uses the following update formula for the adaptive filter coefficients:

$$w(n+1) = w(n) + \mu_i(n) g_i(n) \quad (6)$$

$$g(n) = e(n)x(n)$$

$$\mu_i(n) = \mu_i(n-1) + \rho g_i(n) g_i(n-1) \quad (7)$$

Where g is a vector comprised of the gradient terms, $g_i(n)$=e(n)x(n-i), i=0.N-1, the length corresponds to the order of the adaptive filter. The values for μ(n)can be calculated in either of the methods expressed in equation (7). Here ρ is a small positive constant (V. J. Mathews *et al* 1993)optionally used to control the effect of the gradient terms on the update procedure.

2.3 Normalized LMS (NLMS) Algorithm

A subclass of least mean square algorithms that is very commonly used is called the Normalized Least Mean Square (NLMS). These algorithms are upgrades (B. Farhang et.al 1998) to the standard LMS algorithms, and it is intended to increase convergence speed, and stability of the algorithms. to increase the algorithm's performance while increasing the stability.

This is achieved (S. Haykins ,1996)by normalizing the step size μ with an estimate of the input signal power, such that,

$$\mu(n) = \frac{\mu}{\gamma + \|X(n)\|^2} \quad (8)$$

Where $\|X(n)\|^2$ the squared norm of input signal vector, and γ is is a small positive constant used to insure that if $\|X(n)\|^2$ is zero or close to it, the instability due to division by zero is avoided. Therefore from equation (1) the weight update equation for NLMS is given by

$$w(n+1) = w(n) + 2\frac{\mu}{\gamma + \|X(n)\|^2} e(n)X(n) \quad (9)$$

2.4 Transform Domain LMS (TDLMS) Algorithm

The convergence of the time domain VSSLMS algorithms is still slow for correlated inputs (B.F. Boroujeny *et al* 1992) and it was found that the TDLMS can improve the convergence using the decorrelation of the input sequence. This normalization is applied only in the update formula of the adaptive filter coefficients (D. I. Kim *et al* 2000) which for the i^{th} filter coefficient can be written as follows:

$$w_i(n+1) = w_i(n) + \frac{\mu}{\epsilon + \sigma_{s_i}(n)^2} s_i(n)e(n) \quad (10)$$

Where $\sigma_{si}{}^2(n)$ is the power estimate of the i^{th} transform coefficients s_i(n) and ϵ is a small constant which eliminates the numerical instability when σ $_{si}$ (n) is close to zero.

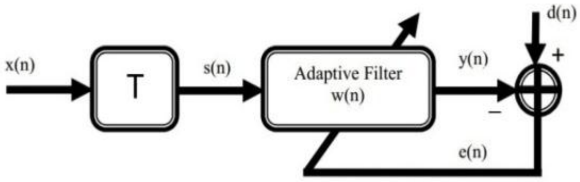

Fig.4: The block diagram of the transform domain Adaptive FIR filter

3. Simulation Results and Discussion

Set up a simulation to compare the performance of proposed sparsity-aware LMS, VSSLMS with the NLMS and TDLMS algorithms.

Firstly, we compare the steady-state MSE of different adaptive algorithm with different filter length ,and no. of iteration with ,input signal is i.e. gaussian.

The simulation result describing the MSE against the number of iterations is shown in Fig

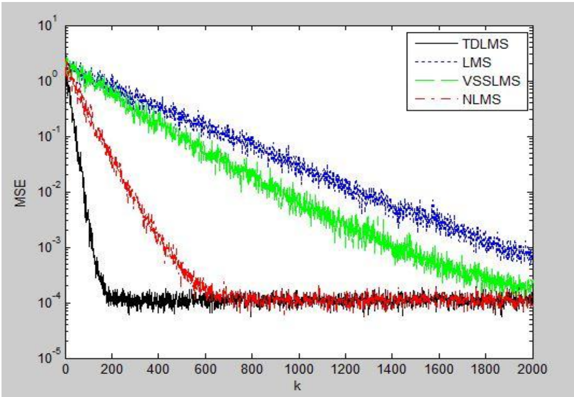

Fig. 4: MSE learning Curve for filter length 10 with No. of iteration = 2000

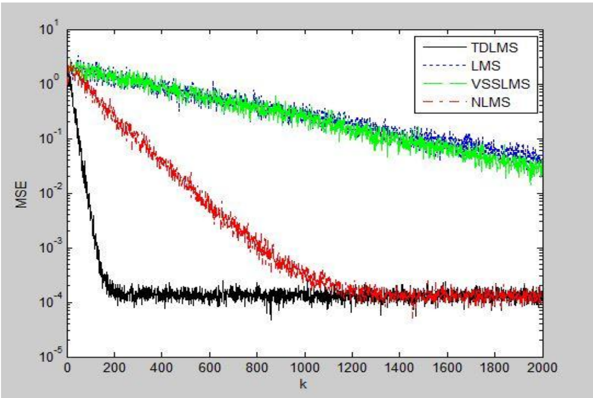

Fig. 5: MSE learning Curve for filter length 20 With no. of iteration = 2000

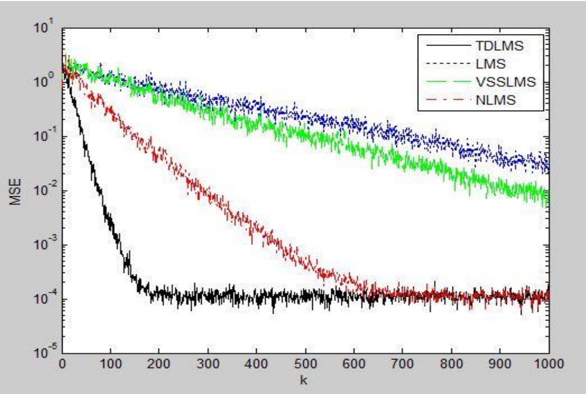

Fig. 6: MSE learning Curve for filter length 10 with no. of iteration = 1000

As we can see from the MSE results, at different filter length and no. of iteration the LMS algorithm has poor convergence rate and mean square error (MSE), but. the VSSLMS, which is a improved variation of the LMS, has a better convergence rate and MSE than the LMS algorithm but it still does not achieve a better steady-state performance than our proposed both algorithms NLMS and TDLMS . Both of our proposed NLMS and TDLMS algorithm get the best steady-state performance especially performance of the TDLMS is best out of three algorithms.

When we consider on the basis of computational complexity of adaptive algorithms i.e. LMS required 2N+1 computation, NLMS required 3N+1 computation, VSSLMS required 4N+1 computation TDLMS required 15N computations. It shows LMS is most computational simplicity algorithm and TDLMS is least computational simplicity algorithm.

Conclusions

1) In this paper it was shown. How the various adaptive algorithms applied for system identification technique on the basis of their steady state performance, and computational complexity.
2) Simulation results have been carried out to compare the LMS, VSSLMS, NLMS and TDLMS algorithms.
3) As we can see from the results of simulations, the TDLMS and NLMS algorithms possess a faster convergence rate and a better steady-state performance than conventional algorithms i.e. LMS and VSSLMS.
4) But This paper does not claim that the conventional algorithms is outdated because when we consider on the basis of computational complexity LMS algorithm is most simple relatively to other algorithms that's why It is relatively easy to be implemented in software and hardware.

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