A New Time-Varying LMS Adaptive Filtering Algorithm in noise Cancellation System

Siddappaji¹, K.L. Sudha²

¹BMS College of Engg, Bangalore-19 ²DSCE, Bangalore-78

Abstract: A number of variable step size LMS algorithms are used to improve the performance of the conventional Least Mean Square (LMS) algorithm. This paper presents a new Time varying LMS (NTVLMS) algorithm by making use of a nonlinear function to get the variable step size parameter μ . The algorithm has been tested for adaptive noise cancellation in the case of stationary signal corrupted by additive white Gaussian noise. The simulation results show that the performance is better compared to conventional LMS, Robust variable step size LMS (RVSSLMS) and Time varying LMS (TVLMS) algorithm.

1. INTRODUCTION

One of the most popular algorithm in adaptive signal processing is the least-mean-square (LMS) algorithm and it was developed by Widrow [1] [2] [3]. It is still used in adaptive signal processing for its simplicity, less computation, ease of implementation and having good convergence property. The LMS algorithm is described by the equation (1) and (2)

$$e(n) = d(n) - X^{T}(n)W(n)$$
(1)

$$w(n+1) = w(n) + 2\mu X(n)e(n)$$
(2)

Where w(n) is filter coefficient at time n, μ is step size, e(n) is adaptation error, d(n) is the desired signal and x(n) is the filter input respectively. Equation (1) shows that LMS algorithm uses an adaptation error and a step size parameter to update the filter coefficients. In this algorithm, the step size parameter μ is constant. The choice of this parameter μ is very important to the convergence and stability of the algorithm. The stability of the convergence of LMS algorithm requires the step size parameter μ has to satisfy the condition in equation(3)

$$0 \le \mu \le \frac{1}{tr(R)} \le \frac{1}{\lambda_{max}} \tag{3}$$

Where tr(R) is the trace of the autocorrelation matrix of input x and λ_{max} is the maximum eigenvalue of R.

In general a smaller step size leads to a small steady state misadjustment (SSM) but a slower convergence rate. While a

larger step size gives faster convergence but a large SSM. That is the drawback of the LMS algorithm. But it is still far from optimum trade-off between SSM and convergence rate. Then RVSSLMS algorithm and TVLMS algorithm were proposed to solve this problem. In RVSSLMS algorithm, the step size of the algorithm is adjusted according to the square of the time averaged estimate of the auto correlation of error function e(n) and e(n-1). The TVLMS algorithm uses a suitable step size in the initial stage to speed up the convergence and the step size is adjusted to a smaller value gradually during the convergence. This algorithm has been developed by making use of a nonlinear function. In section 2, the RVSSLMS and TVLMS are discussed. In section 3, the new TVLMS algorithm is presented. In section 4, the presented algorithms are applied to noise cancellation system and simulation results are presented. Finally draws the conclusion.

2. RVSSLMS AND TVLMS ALGORITHMS

The Robust variable step size (RVSS) LMS algorithm [6] was developed to overcome the drawbacks of LMS and variable step size LMS algorithms [4][5]. The Variable step size LMS (VSSLMS) algorithm [5] provides better performance over LMS algorithm but its performance is degraded in the presence of uncorrelated noise. Then the above said algorithm was developed to overcome the limitation. In this algorithm, the step size parameter is adjusted according to the square of the time averaged estimate of the auto correlation of error function e(n) and e(n-1). The estimate is a time average of e(n) and e(n-1) that is described as in equation(4)

$$p(n) = \beta p(n-1) + (1-\beta)e(n)e(n-1)$$
(4)

Here, p(n) is used to achieve two things: The error autocorrelation is a good measure of the proximity to the optimum, and it rejects the effect of uncorrelated noise sequence while updating the step size. The step size update expression is given by equation(5)

$$\mu(n+1) = \alpha \mu(n) + \gamma p^2(n) \tag{5}$$

where $0 < \alpha < 1$ and $\gamma > 0$ as on [5]. In the early stages of the algorithm $\mu(n)$ is large due to high error autocorrelation estimate $p^2(n)$. As we approach optimum, error autocorrelation approaches zero, providing smaller step size.

The Time-Varying LMS (TVLMS) algorithm [7] [8] works in the same manner as the conventional LMS algorithm except the time dependent convergence parameter $\mu(n)$. In TVLMS algorithm the step size parameter is found out by using the equation (6)

$$\mu(n) = \alpha(n)\mu_o \tag{6}$$

where μo is the value of step size parameter in the conventional LMS algorithm. This μo is used to update $\mu(n)$ in this algorithm. $\alpha(n)$ is a decaying factor. We will consider the decaying law as in equation(7)

$$\alpha(n) = C^{\frac{1}{(1+an^b)}} \tag{7}$$

Where C, a, b are positive constants that will determine the magnitude and the rate of decrease for $\alpha(n)$. According to the above law, C has to be a positive number larger than 1. When C = 1, $\alpha(n)$ will be equal to 1 and the TVLMS algorithm will be the same as that of conventional LMS algorithm. As $\alpha(n)$ decreases with respect to time, the convergence parameter $\mu(n)$ decreases and rate of convergence increases compared to LMS algorithm with increased computational complexity.

3. NEW TV LMS ALGORITHM

Based on the performance of LMS, RVSSLMS and TVLMS algorithm, a New TVLMS algorithm is presented. This algorithm can improve the convergence rate with respect to LMS, RVSSLMS and TVLMS algorithms and computational complexity is large compared to LMS algorithm and less compared to RVSSLMS and TVLMS algorithm. The proposed algorithm updates the step size by

$$\mu(n) = d + \mu_o tan^{-1}(-fn + g)$$
(8)

where d, f and g are positive constants select suitably. μ_0 is the value of step size parameter in conventional LMS algorithm. This μ_0 is used to update $\mu(n)$ in this algorithm. The proposed algorithm gives good result for additive white Gaussian noise with variable input signal power

4. APPLICATION TO THE ADAPTIVE NOISE CANCELLATION SYSTEM

The basic adaptive noise cancelling system is shown in figure 1.



Fig. 1. Block diagram of adaptive noise cancellation system[2]

A signal is transmitted over a channel and is received by the receiver i.e., Primary Sensor (PS) with uncorrelated noise $x_0(n)$. The signal s(n) and noise $x_0(n)$ combine to form the desired signal $d(n) = s(n) + x_0(n)$. A second signal input to the adaptive filter received by the secondary sensor (SS) is noise x(n), which is uncorrelated with the signal but correlated in some unknown way with noise $x_0(n)$. In this setup, we model the noise path from the noise source to secondary sensor as known as unknown FIR channel $w_C(n)$. The noise x(n) applied as an input to the adaptive filter to produce an output y(n), which is close enough to the replica of $x_0(n)$.

In this system the signal x(n) is processed by the filter that automatically adjust its weights through the above mentioned algorithms with respect to the error signal e(n).

$$y(n) = \sum_{i=0}^{N-1} w(i) x(n-i) = W^{T}(n) X(n) \dots \dots$$
(9)

Here,

$$X(n) = [x(n), x(n-1), \dots, x(n-N+1)]^T$$

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

Where N is the order of the filter, w_i is the filter coefficient.

To implement LMS based adaptive noise cancellation system, it is very important to choose the following parameters such as filter order, initial values of the filter coefficients, and value of the step size parameter.

5. SIMULATION RESULTS

The simulation results of the four algorithms are given as follows.

- 1. The condition of simulation is:
- 2. The order of the adaptive filter is 2
- 3. Initial values of the filter coefficients are set be zeros.
- 4. The input signal is continuous wave of sine signal.
- 5. The noise is a white Gaussian noise

6. The amplitude of the sine signal is 0.01 and 0.2, corresponding to SNR -43 dB and -17dB.

The algorithm was implemented for 200 iterations for each case.

In this paper performance of the algorithms are analysed under three different conditions:

1. FIR channel function $w_C(n)$ is $\delta(n)$

Signal amplitude 0.01



Signal amplitude 0.2



Fig. 5 Error curve

mse curve for LMS

FIR CHANNEL FUNCTION W_C(N) IS DELAYED 6. AND ATTENUATED

Signal amplitude 0.01



Signal amplitude 0.2

7. FIR CHANNEL FUNCTION W_c(N) IS FINITE IMPULSE RESPONSE

Signal amplitude 0.01



Signal amplitude 0.2



Fig. 13) Error curve

From Figure 2, 3, 4 and Figure 5,

- 1. The proposed algorithm has faster convergence rate
- 2. The steady error of the proposed algorithm is less compared to LMS RVSSLMS and TVLMS algorithms in case of both low signal-to noise ratios (SNR) and high signal-to noise ratios (SNR).

From Figure 6, 7, 8 and Figure 9,

- 1. The proposed algorithm has faster convergence rate
- 2. The steady error of the proposed algorithm is less compared to LMS RVSSLMS and TVLMS algorithms in case of both low signal-to noise ratios (SNR) and high signal-to noise ratios (SNR). The RVSSLMS algorithm exhibits more steady state error compare to remaining three algorithms for low and high SNR.

From Figure 10, 11, 12 and Figure 13,

- 1. The proposed algorithm has faster convergence rate
- 2. The steady error of the proposed algorithm is less compared to LMS RVSSLMS and TVLMS algorithms in case of both low signal-to noise ratios (SNR) and high signal-to noise ratios (SNR).

From the above analysis, we came to know that performance of NTVLMS algorithm is better compared to remaining algorithms. The performance of RVSSLMS algorithm is degraded if the correlation of the noise is decreased. Finally, this system will work for highly correlated noise sequences.

8. CONCLUSION

The New TVLMS algorithm shows improved performance over the conventional LMS, RVSSLMS and TVLMS algorithms under white Gaussian noise environment in all conditions. The concept of this paper is useful for the enhancement of speech signal in communication system, implementation of Radar communication system for the cancellation of jamming signal, interference cancellation in case of Digital communication and it is useful to other automation fields.

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