Performance Analysis of Gradient Adaptive LMS Algorithm

Harjeet Kaur, Dr. Rahul Malhotra, Anjali Patki

Abstract- Tracking speed and stability of adaptive gradient filtering algorithms represented by least mean square (LMS) are restricted for non-stationary environment. The noise cancellation simulation results testified that the algorithm could get stabilized only after 20 iterative operations and provide stronger ability to boost SNR of weak signal compared with LMS/NLMS/Variable size/sign LMS filter. All the performances indicates that tracking ability and convergence stability are superior to other algorithm in the same environment.

Index Terms- adaptive filter, least mean-square (LMS) algorithm, noise cancellation system

I. Introduction

Filtering is the technique or practice leading to accepting selected signal from the band of spectrum of the incoming wavelengths to the system. In the process of digital signal processing, often to deal with some unforeseen signal **,** noise or time varying signals, if only by a two FIR and IIR filter of fixed coefficient cannot achieve optimal filtering. Under such circumstances, we must design adaptive filters, to track the changes of signal and noise. Adaptive filter is that it uses the filter parameters of the moment ago to automatically adjust the filter parameters of the present moment to adapt to the statistical properties that signal and noise unknown or random change, in order to achieve optimal filter. based on in depth study of adaptive filter, based on LMS algorithm and RLS algorithm are applied to adaptive filter technology to the noise and through the simulation results prove that its performance is usually much better than using conventional methods designed to filter fixed

II. Adaptive Filter

The principle of an adaptive filter is its time-varying, self-adjusting characteristics. An adaptive filter usually takes on the form of an FIR filter structure, with an adaptive algorithm that continually updates the filter coefficients, such that an error signal is minimized according to some criterion. The error signal is derived in some way from the signal flow diagram of the application, so that it is a measure of how close the filter is to the optimum. Most adaptive algorithms can be regarded as approximations to the Wiener filter, which is therefore central to the understanding of adaptive filters.

$$y[n] = \sum_{k=0}^{N-1} c_k^*[n] x[n-k]$$

Here, the $c_k[n]$ are time dependent filter coefficients (we use the complex conjugated coefficients ck[n] so that the derivation of the adoption algorithm is valid for complex signals, too).

Adaptive filters are designed as compare to FIR and IIR filter because in this filter coefficients are to be varied. According to taps adapt the filter by doing iterations. In this filter using a weight control mechanism or transversal filter in which weights are to be updated.

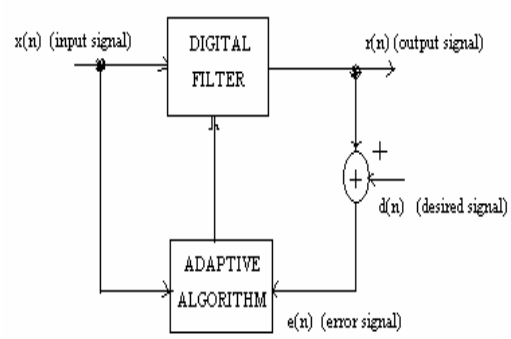


Figure 1: Block diagram of adaptive filter

III. Algorithm of Adaptive Filter

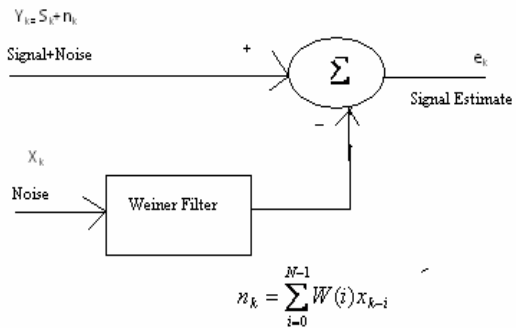
Adaptive filters are designed to remove the problem of wiener filter. In wiener filters the processed data will be matched with the prior information for designing. Adaptive filter is totally based on stochastic approach. This approach is totally based on Steepest Descent Algorithm which is to be solved the Weiner-Hopf equation. In this method the weights are adjusted iteratively in the direction of the gradient. The error performance surface used by the SD method is not always known a priori. We can use the estimated values. Thus LMS algorithm belongs to the family of stochastic gradient algorithm. Then define NLMS, Variable Step LMS, and Sign LMS.

A. Wiener Filter Theory

The starting point for deriving the equations for the adaptive filter is to define very clearly what we mean by an optimum filter. The Wiener filter is probably the most common definition in use,

$$e_k = y_k - \hat{n} = y_k - \sum_{i=0}^{N-1} w(i).x_{k-i}$$

it requires the prior information about the data to be processed and filter is optimum where $w(i)$ is the ith coefficient of the Wiener filter. Since we are dealing with discrete values, the input signal and Wiener filter coefficients can be represented in matrix notation.



$$n_k = \sum_{i=0}^{N-1} W(i) x_{k-i}$$

Figure2: Weiner filter

B. Least Mean Square Algorithm (LMS)

The error performance surface used by the SD method is not always known a priori. We can use estimated values. The estimates are RVs and thus this leads to a stochastic approach. We will use the following instantaneous estimates.

$$W(n+1) = W(n) + \frac{1}{2}\mu[-\nabla(j(n))]$$

$$W(n+1) = W(n) + \mu X(n) e^*(n)$$

Thus LMS algorithm belongs to the family of stochastic gradient algorithms. The update is extremely simple while the instantaneous estimates may have large variance; the LMS algorithm is recursive and effectively averages these estimates. The simplicity and good performance of the LMS algorithm make it the benchmark against which other optimization algorithms are judged.

C. Normalized LMS Algorithm

In the standard LMS algorithm the correction is proportional to m $\mathbf{x}(n)e^*(n)$. If $\mathbf{x}(n)$ is large, the update suffers from gradient noise amplification.

The normalized LMS algorithm seeks to avoid gradient noise amplification. The step size is made time varying, m(n), and optimized to minimize error.

$$W(n) + \mu(n)[p - RW(n)]$$

D. LMS Algorithm with Sign Algorithms

In high speed communication the time is critical, thus faster adaptation processes is needed

$$\text{sgn}(a) = \begin{cases} 1 & a > 0 \\ 0 & a = o \\ -1 & a < 0 \end{cases}$$

The Sign algorithm (other names :pilot LMS, or sign Error)

$$w(n+1) = w(n) + \mu u(n)\,\text{sgn}(e(n))$$

IV. IMPLEMENTATION OF ALGORITHM

A. Adaptive Noise Canceling Applied to a sinusoidal interference

The traditional method of suppressing a sinusoidal interference corrupting an information bearing signal is to use a fixed notch filter tuned to the frequency of the interference. To design the filter, we naturally need to know the precise frequency of the interference. But if the notch is required to be very sharp and the sinusoidal signal is known to drift slowly, clearly, then we have a problem which calls for adaptive solution. One such solution is provided by the use of adaptive noise canceling, an application that is different. Figure shows the block diagram of a dual port input adaptive noise canceller. The primary input supplies an information bearing signal and a sinusoidal interference that are uncorrelated to each other. The reference input supplies a correlated version of the sinusoidal interference. For the adaptive filter, we may use a transversal filter whose tap weights are adapted by means of the LMNS algorithm. The filter uses the reference input to provide (at its output) an estimate of the sinusoidal interfering signal contained in the primary input. Thus, by subtracting the adaptive filter output from the primary input, the effect of the sinusoidal interference is diminished. In particular, an adaptive noise canceller using the LMS algorithm has two important characteristics

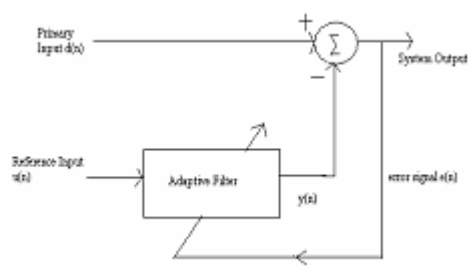


Figure3: Adaptive Noise Canceling Applied to a sinusoidal interference

1. The canceller behaves as an adaptive notch filters whose null point id determined by the angular frequency w_0 of the sinusoidal interference. Hence, the canceller is tunable, and the tuning frequency moves with w_0
2. The notch in the frequency response of the canceller can be made very sharp at precisely the frequency of the sinusoidal interference by choosing a small enough value for the step size parameterμ.

V. OBSERVATION AND ANALYSIS

The simulation results show that LMS and RLS algorithm in the area to cancel the noise has very good results, LMS filtering gives good results when length of filter is short, it has a simple structure but shortcomings of LMS algorithm convergence rate is slow but the convergence speed and noise vector there is a contradiction, accelerate the convergence speed is quicker at the same time noise vector has also increased. Convergence of the adaptive for the choices of gain constant μ is very sensitive. The noise signal and signal power when compared to larger, LMS filter output is not satisfactory, but RLS algorithm convergence rate is faster than the LMS algorithm, the convergence is unrelated with the spectrum of input signal, filter performance is superior to the least mean squares algorithm, but its each iteration is much larger operation than LMS. The required storage capacity is large, is not conducive to achieving a timely manner, the hardware is also relatively difficult to achieve. The simulation results show that more than LMS algorithm and RLS algorithm in the area to cancel the noise has very good results, to complete the task of noise reduction.

A. Output of LMS algorithm on various step sizes (0.0075, 0.0025, 0.025, and 0.075)

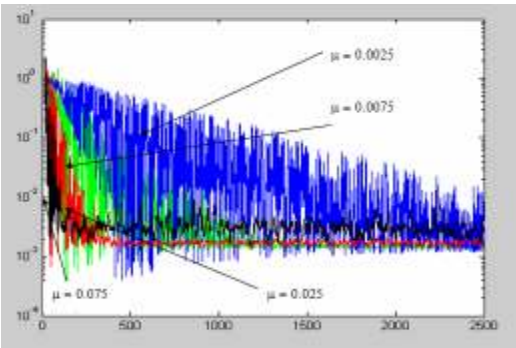


Figure 4: Graph of MSE V/S number of iterations for LMS algorithm

For smallest step sizes, μ= .0075, the convergence is the slowest, and the best steady state average squared error. The convergence time is about 2300 iterations. The steady state average squared error is about 0.001.For large step size, μ = 0.075, the convergence is the fastest, and the worst steady state average squared error. The convergence time is about 100 iterations. The steady state average squared error is about 0.005.

B. Comparison of LMS and variable size LMS

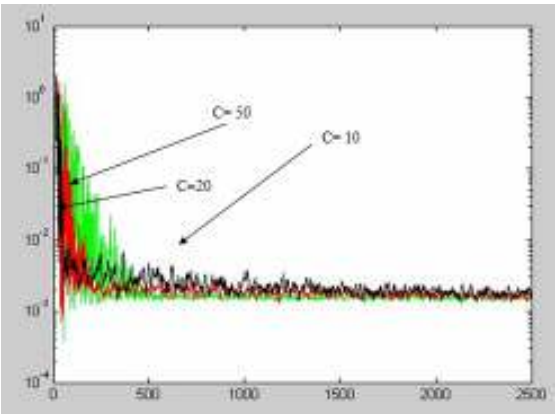


Figure 5: Comparison of LMS and variable size LMS steady state error will finally decrease

C. Comparison of LMS and Sign LMS

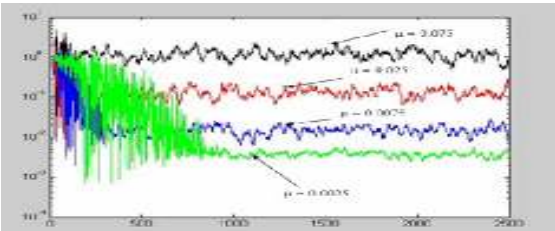


Figure 6: Graph of MSE V/S number of iterations for Sign LMS algorithm.

The steady state error will increase the convergence rate decreases.

D. Comparison of LMS and NLMS

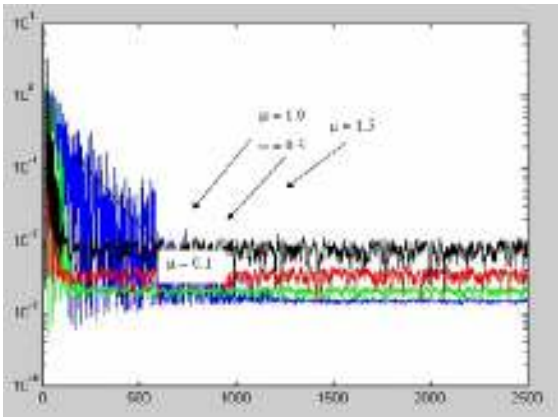


Figure 7: Graph of MSE V/S number of iterations for NLMS algorithm.

The convergence rate may decrease.

E. LMS output Spectrograms

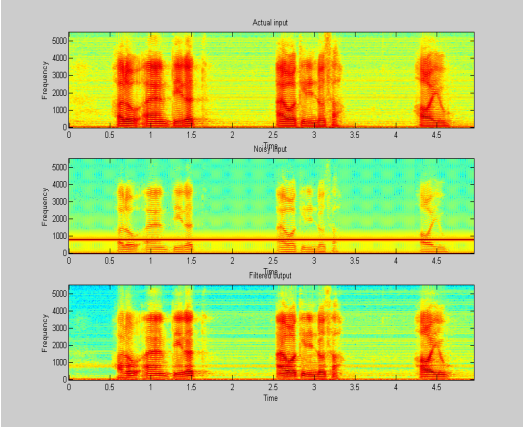


Figure 8: LMS output Spectrum for taps =32

Reducing the number of taps leaves a faint touch of noise component.

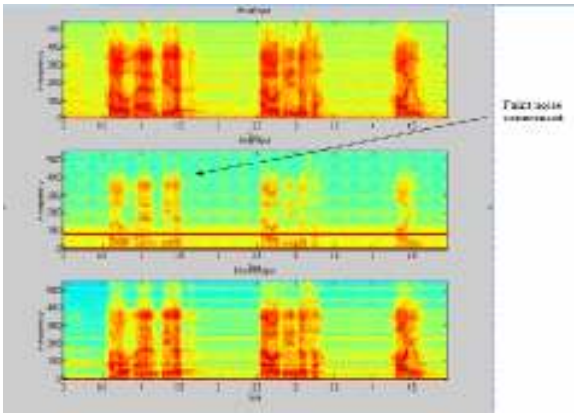


Figure 9: LMS output Spectrum for taps =16

Reducing the number of taps leaves a faint touch of noise component.

VI. CONCLUSION

Decide which algorithm is better as compare to other basis on values of step size and tap weights & check whose performance is better and which convergence graph is better by varying all these parameters. For that taken different – different values of step size parameter and get a result that are from 2500 iterations graph is stable at 20 iterations. So conclude that convergence rate is 20 and draw this graph between MSE and iterations. Same in case of spectrogram take different values of step size and vary the taps getting different results for all algorithms. This spectrogram has to shown three results one is input that is recorded, noise as a input and gives the final result by comparing that on the basis of particular algorithm.

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