International Journal on Emerging Technologies **2**(1): 50-52(2011) **ISSN : 0975-8364**

Simulation of LMS Noise Canceller Using Simulink

Soni Changlani* and M.K. Gupta**

Department of Electronics and Communication Engineering
**Lakshmi Narain College of Technology, Bhopal, (MP)*
***Maulana Azad National Institute of Technology, Bhopal, (MP)*

(Received 11 January, 2011 Accepted 15 February, 2011)

ABSTRACT : This paper presents the simulation of noise canceller system which contains adaptive filter and using LMS adaptive algorithm. The objective of noise cancellation is to produce the estimate of the noise signal and to subtract it from the noisy signal and hence to obtain noise free signal. This work basically focuses on effect of step size on the convergence of LMS adaptive filter. We simulate the adaptive filter with MATLAB.

Keyword : Noise canceller; adaptive algorithm; LMS; step size

I. INTRODUCTION

Liner filtering is required in a variety of applications. A filter will be optimal only if it is designed with some knowledge about input data. If this information is not known, then adaptive filters [1] are used. An adaptive filter is essentially a digital filter with self-adjusting characterstics. It adapts, automatically, to changes in its input signals. In adaptive filtering, the adjustable filter parameters are to be optimized. The criteria arrived at for optimization should consider the filter performance and realisability. Adaptive algorithms are used to adjust the coefficient of the digital filter. Common algorithms that have found widespread applications are the least mean square (LMS), the recursive least square (RLS), and the kalman filter [3] algorithms.

II. LMS ADAPTIVE ALGORITHM

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 [2] is an adaptive algorithm. The least mean square (LMS) algorithm is widely used in applications to adaptive filtering due to its computational simplicity, unbiased convergence in the mean to the Wiener solution, and the existence of a proof of convergence in a stationary environment [3], it uses a gradient-based method of steepest decent [3]. The gradient is the del operator (partial derivative) and is applied to find the divergence of a function, which is the error with respect to the n^{th} coefficient in this case. The LMS algorithm approaches the minimum of a function to minimize error by taking the negative gradient of the function. The LMS algorithm is undoubtedly the most popular algorithm for adaptive signal processing. The popularity of the LMS algorithm is to a large extent due to its computational simplicity [4]. Furthermore, it is generally felt that its behavior is quite simple to understand and the algorithm appears to be very robust [3]. The desired signal $d(k)$ is tracked by adjusting the filter coefficients $w(k)$. The input reference signal $x(k)$ is a known signal that is fed to the FIR filter. The difference between $d(k)$ and $y(k)$ is the error $e(k)$. The error $e(k)$ is then fed to the LMS algorithm to compute the filter coefficients $w(k + 1)$ to iteratively minimize the error [3]. The LMS algorithm consist of two basic process.

1. **Filtering process:** In filtering processes, calculation of output of FIR filter by convolving input and taps and calculation of estimated error by comparing the output to desired signal.
2. **Adaptation process:** In adaptation process filter adjust tap weights based on the estimation error.

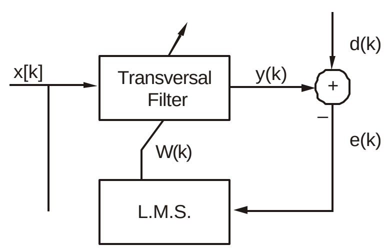

Fig. 1. LMS Implementation.

The coefficient vector updates equation for the LMS algorithm is given by

$$w(k + 1) = w(k) + 2\,\mu\, x(k)e(k) \qquad ...(1)$$

Where μ is the step size of the LMS filter. The LMS algorithm is convergent in the mean square if and only if the step-size parameter satisfy $(0< \mu < 2/l_{max})$, l_{max} is the largest eigenvalue of the correlation matrix of the input data. Larger values for step size Increases adaptation rate (faster adaptation) Increases residual mean-squared error.

III. ADAPTIVE NOISE CANCELLATION

The basic idea of an adaptive noise cancellation algorithm is to pass the noisy signal through a filter that tends to suppress the noise while leaving the signal unchanged. This process is an adaptive process, which means it can not require a priori knowledge of signal or noise characteristics. The technique adaptively adjusts a set of filter coefficients so as to remove the noise from the noisy signal. To realize the adaptive noise cancellation, we use two inputs and an adaptive filter. One input is the signal corrupted by noise (Primary Input, which can be expressed as (s(n) +N_o(n)). The other input contains noise related in some way to that in the main input but does not contain anything related to the signal (Noise Reference Input expressed as N_1(n). The noise reference input pass through the adaptive filter and output y(n) is produced as close a replica as possible of N_o(n). The filter readjusts itself continuously to minimize the error between N_o(n) and y(n) during this process. Then the output y(n) is subtracted from the primary input to produce the system output e= S+N_o -y, which is the denoised signal. Assume that S, N_0, N_1 and y are statistically stationary and have zero means. Suppose that S is uncorrelated with N_0 and N_1, but N_1 is correlated with N_0. We can get the following equation of expectations:

$$E[e^2] = E[s^2] + E[(N_o - y)^2] \quad \text{... (2)}$$

When the filter is adjusted so that $E[e^2]$ is minimized, $E[(N_o - y)^2]$ is also minimized. So the system output can serve as the error signal for the adaptive filter.

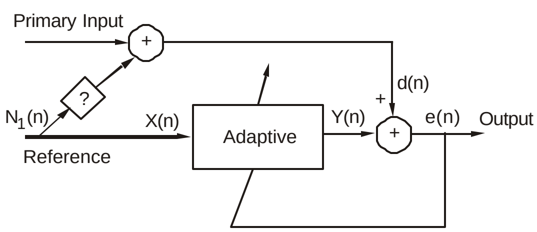

Fig. 2. Adaptive noise canceller.

IV. SIMULATION AND RESULTS

In this section we evaluate the performance of LMS algorithms in noise cancellation [5] setup Fig. 2. Input signal is speech signal whereas Gaussian noise was used as noise signal. The two signals were added and subsequently fed into the simulation of LMS adaptive filter. The order of the filter was set to M = 10. The parameter *m* is varied. Various output is obtained for various step size *i.e.* μ = 0.005, 0.01, 0.02, 0.05, 0.075, 0.075, 0.1, 0.5. Comparision are work out in form of figures, which show the input and output signals from the filters.

The LMS filtered output is shown in Fig. 4 (*a* to *g*), for various step size. The analysis is done with 128 iteration. The step size m control the performance [6] of the algorithm. If step is too small, Fig. (4*a*), filter gives slow response and it takes time to follow the input. And if step size m is 0.02, Fig. (4), output takes 100 evaluation steps to follow the input.

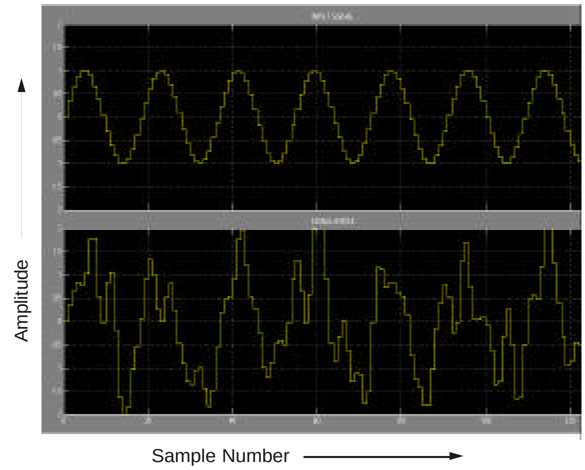

Fig 3 Input Signal and Noisy Signal

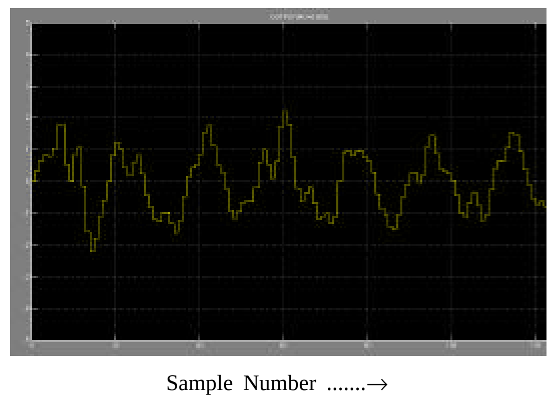

Fig. 4*a*. Filter output for LMS adaptive filter for step size μ = 0.005.

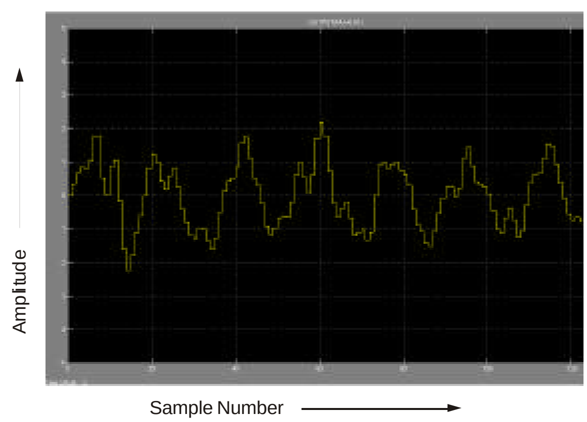

Fig 4b: Filter Output for LMS adaptive filter for step size μ = 0.1

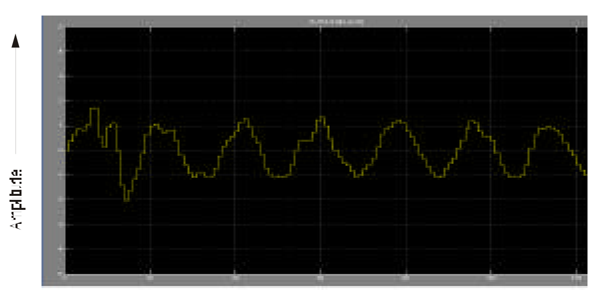

Fig 4c: Filter output for LMS adaptive filter for step size μ = 0.02

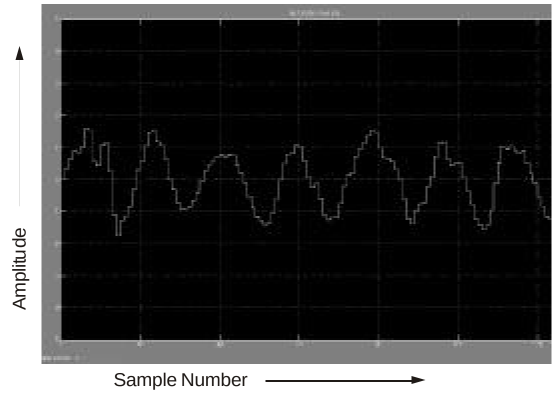

Fig 4d: filter output for L.M.S adaptive filter for step size μ = 0.05

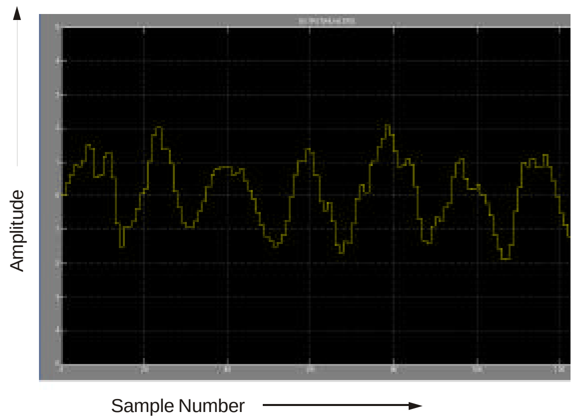

Fig 4e : Filter output for LMS adaptive filter for step size m = 0.075

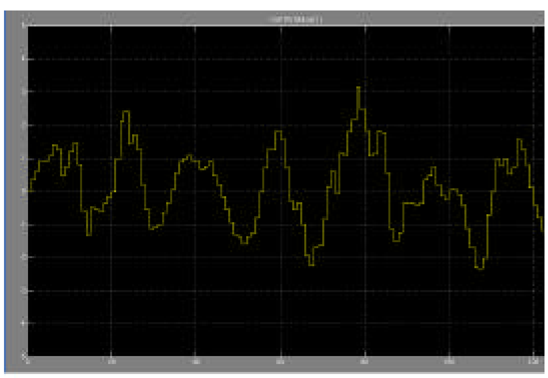

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Fig. 4*f*. Filter output for LMS adaptive filter step size μ = 0.1.

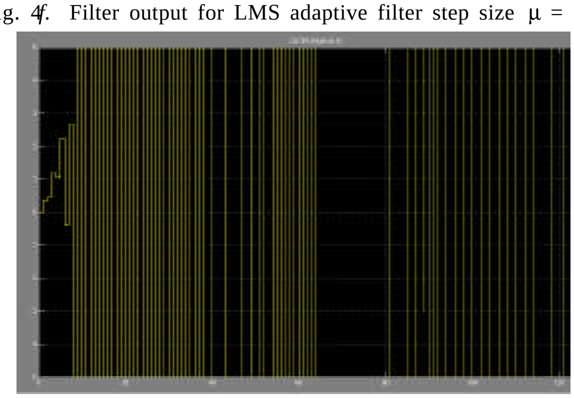

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Fig. 4*g*. Filter output for LMS adaptive filter step size μ = 0.5.

If Step size μ is between (0.02-0.075), output will follow the input within the evaluation steps fig (4c to 4e) convergence speed is improve , but filter output is smooth in this case. If step size is too large, Fig. (4g), the filter response is converging fast, but filtering is not proper.

IV. CONCLUSION

The conclusion of above results is that, If LMS filter is used for noise cancellation and complexity reduction are main criteria, and if the "Step size (μ)" is increased, LMS algorithm converges more quickly, but at the expense of granularity – the LMS Filter Output is not as smooth. Step size is not too small it takes time to converge, and step size is not too large, filter response is not converging in case of large step size.

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