Evaluation Of Noise Cancellation Using LMS And NLMS Algorithm

Niti Gupta, Dr. Poonam Bansal

Abstract: This paper is focused on the adaptive noise cancellation of speech signal using the least mean square (LMS) and normalized least mean square method (NLMS). Adaptive Noise Cancellation is an alternative way of cancelling noise present in a corrupted signal. In this technique, evaluation of distorted signal by additive noise or interference achieved with no a priori estimates of signal or noise. A comparative study is carried out using LMS and NLSM methods. Result shows that these methods has potential in noise cancellation and can be used for variety of applications.

Index Terms: NLMS, LMS, Noise Cancellation, Adaptive filtering, Convergence rate, Error rate, FIR,IIR

1 INTRODUCTION

In various application areas, such as digital communication [1], biomedical engineering [2] and radar the aim is to extract the valuable signal corrupted by interference and noise. In practical situation obtained acoustic signal corrupted due to finite precision in coding the transmitted wave or due to the background noise. The traditional method of additive noise removal is to use a filter that suppresses the noise and leaves the signal unchanged. These filters can be fixed or adaptive. An adaptive filter [3][4] requires no prior information of the signal or noise. Also, adaptive filter can adjust their parameter automatically whereas fixed filter based on prior knowledge of both signal and noise. Noise cancellation is the technique to reduce the unwanted signal from the speech by using the secondary signal which is specifically design to cancel the first. Noise problem in the environment is more pronounced due the technological growth that has led to more number of noisy engine, heavy machinery, high electromagnetic devices and other noise sources. Traditionally, passive techniques such enclosures, barriers, silencers are used to remove undesired signal in acoustic noise cancellation [5][6]. Silencers are highly useful in broad range of frequency but in low frequency band they are ineffective and costly. All communication devices are highly affected by the mechanical vibrations. The basic idea of signal processing is to the separate unwanted information from the signal by enhancing or extracting the useful information. Hence the signal processing tends to be application dependent. In the most of practical applications Adaptive filters are used and preferred over fixed digital filters because adaptive filters have the property on the other hand, have the ability to adjust their own parameters automatically **and their design requires little or no a priori knowledge of signal or noise characteristics. Adaptive filter can be realized as finite impulse response (FIR), infinite impulse response (IIR), lattice and transform domain filter [7]. There are different approaches used in adaptive filtering, the general form of adaptive filter is the transversal filter using least mean square (LMS) algorithm and NLMS algorithm. These algorithms by applies an individual convergence factor at each iteration and updates for each adaptive filter coefficient at every iteration** Here in Fig 1, the basic idea of noise cancellation is shown. Signal 's' which gets transmitted through a sensor is compounded with noise 'n_0' as it passes through and the primary input contains signal as well as noise which can be denoted as '$s+n_0$'. Another sensor gets a noise 'n_1' which does not have correlation with the signal which in turn acts as a reference input. The noise 'n_1' thus is filtered to produce an output 'y' which is similar to n_0.

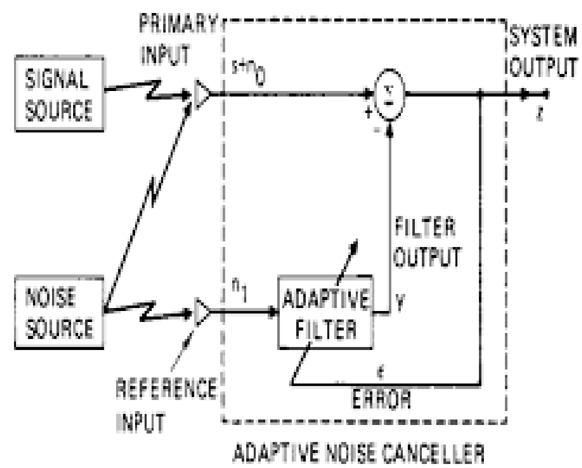

Figure 1: *Noise cancellation Technique*

The output of filter is subtracted from'$s+n_0$' so that output is of the for "$s+n_0$-y'. If we know the characteristic over which the signal is transmitted then a fixed filter can be designed with respect to primary and reference sensors. But transmission characteristic over the path are unknown and also they are not fixed, because of which fixed filter are not feasible. An adaptive filter which can adapt its own impulse response is necessary which can be done through some algorithm thus the filter can adapt to the changing condition and readjust to minimize error of signal. The objectives are to produce a system which can reduce the error rate in least iteration and hence reduce the operational cost. The objective is achieved by giving a feedback and adjusting the filter using Least Mean Square algorithm The shortcomings of LMS is solved by using another algorithm called Normalized least mean square algorithm.

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2 METHODOLOGY

2.1 LMS Algorithm

Least mean squares (LMS) algorithms are class of adaptive filter uses least mean squares of the error signal (difference between the desired and the actual signal) to calculate filter coefficients. It is a stochastic gradient descent method in which filter is only adapted depending on the current time error. The basic notion behind the LMS filter is to update the filter weights (1) such that to converge to the optimal filter weights. At the beginning it assumes small or zero weight, after that in each iteration weights are updated based on the gradient of least mean square error. Positive MSE-gradient indicates, the error would keep increasing positively, whereas same weight is used in iterations, implies that we need to decrease the weights. In case if the gradient is negative, weights should be decreased. Weight update equation can be describe in (1) as

$$K_{n+1} = k_n - \mu \Delta \varepsilon[n] \quad (1)$$

Where, ε represent mean-square error, and negative sign implies that weight should be change opposite to slope of gradient.

The kth order LMS algorithm can be summarized in (2) to (5)

Parameters:
k = filter order
μ = step size

$$\text{Initialization: } \hat{H}(0) = 0 \quad (2)$$

Computation:
For n = 0, 1, 2...

$$Z(n) = [z(n), z(n-1), \ldots, z(n-k+1)]t \quad (3)$$

$$e(n) = d(n) - \hat{H}\, h(n)\, Z(n) \quad (4)$$

$$\hat{H}(n+1) = \hat{H}(n) + e^*(n)\, Z(n) \quad (5)$$

In LMS algorithm the weight would not reach the optimal value because the exact value of expectation is not used. However, convergence is possible in mean. If step size is not chosen properly convergence in mean would be misleading due to the large variance. To void this problem upper bound on step size is needed which can be given in (6)

$$0 < \mu < 2/\lambda_{max} \quad (6)$$

Here λmax is autocorrelation matrix, whose Eigen values are positive. The system becomes unstable if the condition is not full filled. If μ is very small then the convergence is very slow but system would be slow. So maximum convergence can be achieved for condition (7)

$$\mu = 2\, \lambda\, 555 + \lfloor 555 \quad (7)$$

In (7) λmin has smallest Eigen value, the convergence speed is determined by λmin. LMS algorithm has its limitation as it is sensitive to the input which makes choosing the learning rate 'μ' harder, which guarantees stability of the algorithm. So a variant of LMS algorithm [8] which is called as Normalized least mean squares NLMS algorithm [9][10] can be used which can solve the problem.

2.2 NLMS Algorithm

NLMS solves the problem by normalizing from the power of input.

Algorithm Summary:
The algorithm can be summarized in

Parameter: k=filter order
μ =Step size

$$\text{Initialization: } \hat{H}(0) = 0 \quad (8)$$

Computation:
For n = 0, 1, 2...

$$Z(n) = [z(n), z(n-1), \ldots, z(n-k+1)]^\wedge t \quad (9)$$

$$e(n) = d(n) - \hat{H}h(n)\, Z(n) \quad (10)$$

$$\hat{H}(n+1) = \hat{H}(n) + (\mu e^*(n)\, Z(n)/Z^\wedge h(n)\, Z(n)) \quad (11)$$

In case there is no interference then the optimal learning rate is independent of input and the impulse response. But this is only possible in ideal situation and in general case this is not possible and hence the optimal learning rate given by

$$\mu opt = (E[|y\, n - y\, n|)/(E[|e(n)|2]) \quad (12)$$

2.3 Computational methodology

The experiment was computed with x (n) as a input signal which is composed of signal s(n) with noise signal $n_1(n)$. The desired system output was d (n) with y (n) being the Adaptive noise cancellation output . We have used w(n) as the weight vector with e(n) as the error signal .The desired equation are shown in (13)-(17).

$$x(n)=s(n)+n_1(n) \quad (13)$$

$$d(n)=x(n) \quad (14)$$

$$y(n)=w^T(n)+x'(n) \quad (15)$$

$$e(n)=d(n)-y(n) \quad (16)$$

$$w(n+1)=w(n)+2\mu e(n)x'(n) \quad (17)$$

3 RESULTS

Figure 2 shows the result by using LMS algorithm. Parameter μ was chosen as 0.0002 with filter length of 5 . We can see the original signal s(n) depicted in green with the input signal containing noise in blue , the performance of LMS algorithm can be seen in red.

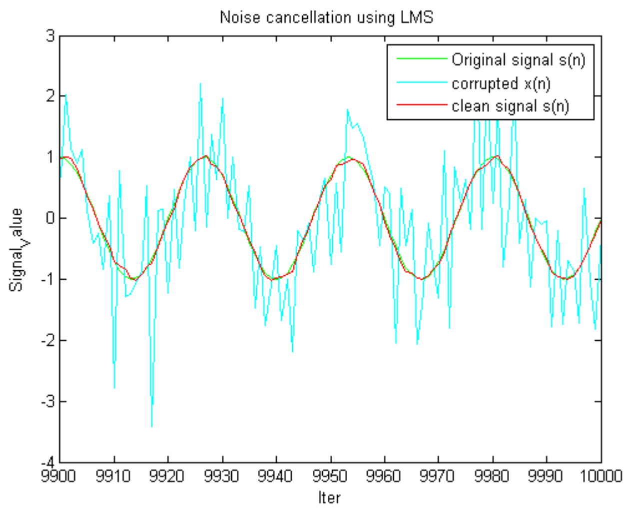

Figure 2. *Noise Cancellation using LMS Algorithm*

Under close observance we find that LMS algorithm does not have a very good response in denoising and in Figure 3 we can observe that LMS presents a convergence but takes many number of iteration until the error value reaches its to the minimum

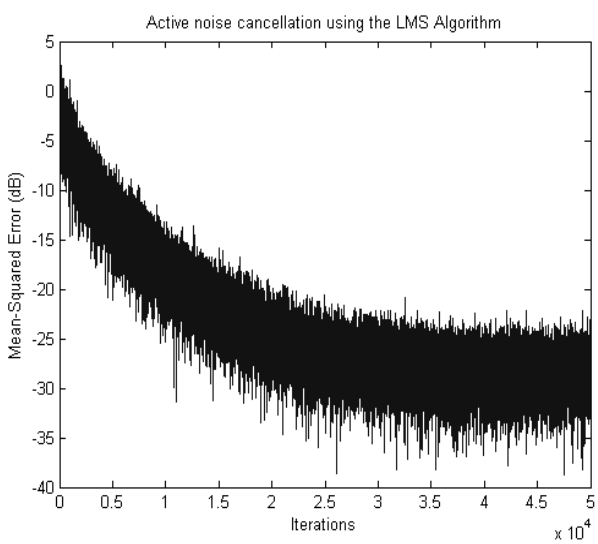

Figure 3. *Convergence rate for LMS*

Under the NLMS algorithm the same approach is followed but μ, the LMS parameter will be replaced by a new value given by (18)

$$\mu=(\mu'/\delta + ||x(n)||^2) \quad (18)$$

Taking a small positive constant δ =3.2 the step size parameter is μ =0.005. and the output can be observed in figure 2 where blue represents the input signal is green , the signal with noise is represented by blue and the clean signal with red .

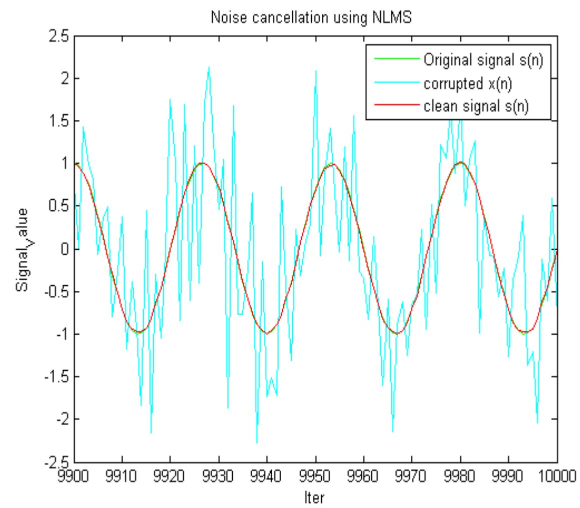

Figure 4. *Noise cancellation using NLMS algorithm*

It can be noticed that the algorithm has better response than the LMS algorithm. Figure 5 shows that the noise converges in close to about 9000 iterations making the computation time very less

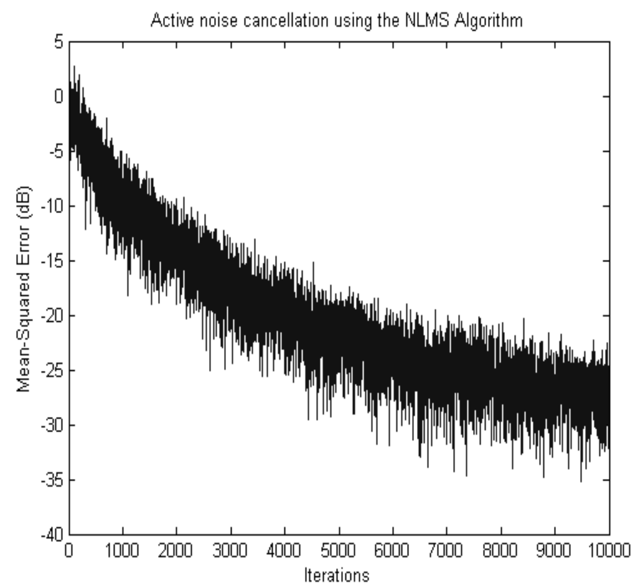

Figure 5: *Convergence rate for NLMS*

Figure 6 and Figure 7 describes the result of adaptive system for LMS and NLMS respectively

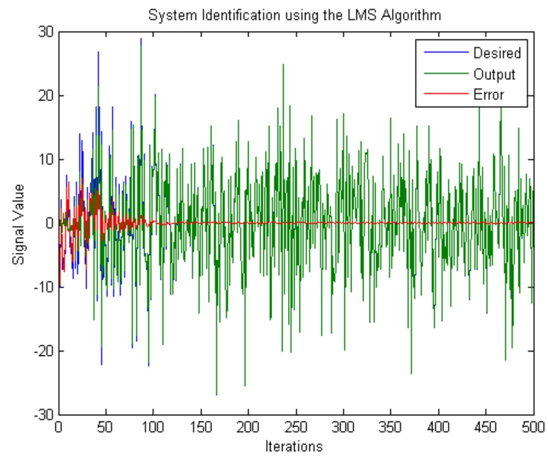

***Figure 6**. Required signal with filter output and error rate of the LMS algorithm*

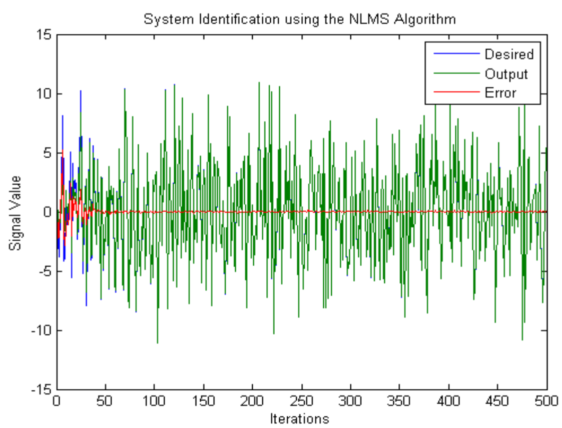

***Figure 7** Required signal with filter output and Error rate of the NLMS algorithm*

The desired output, filter output and the estimation error varies with iteration. The filter starts tracking the error from about 125 iteration after which filter attains a good tracking and after which error reaches zero value. Under Fig 7 we can observe that the optimal value is reached in 40-50 iteration.

4 CONCLUSION

The aim of the paper was to describe an application where the use of LMS and NLMS adaptive filter can be studied upon. The main goal was to see comparatively which algorithm holds well for Nosie cancellation application. Both LMS and NLMS are good but Error rate prediction for NLMS algorithm is better as it takes less number of Iteration whereas complexity of NLMS is more with system being more stable

REFERENCES

[1] Khanna, V. K., Digital Signal Processing, S. Chand and Company Limited, New Delhi. 2009

[2] Husn-Hsien Chang Jose M.F. Moura " Biomedical Signal Processing,"ed. Myer Kutz, in Biomedical Engineering and Design Handbook, 2nd Edition , Volume 1, McGraw Hill.2010, Chapter 22, pp 559-579.

[3] Widrow, B.; Walach, E., "Adaptive LMS Filters," in Adaptive Inverse Control, Reissue Edition:A Signal Processing Approach , 1, Wiley-IEEE Press,2008,pp.59-87

[4] Widrow, B.; Walach, E., "Appendix A: Stability and Misadjustment of the LMS Adaptive Filter," in Adaptive Inverse Control, Reissue Edition:A Signal Processing Approach , 1, Wiley-IEEE Press, 2008, pp.339-348

[5] Adaptive Filter Theory by Simen Haykin: 3rd edition, Pearson Education Asia.LPE.

[6] Y. Adaptive Signal Processing by John G Proakis, 3rd edition, Perntice Hall of India

[7] Adaptive Signal Processing by Bernard Widrow and Samuel D.Stearns; PearsonEducationAsia,LPE.

[8] Górriz, J.M.; Ramírez, J.; Cruces-Alvarez, S.; Puntonet, C.G.; Lang, E.W.; Erdogmus, D., "A Novel LMS Algorithm Applied to Adaptive Noise Cancellation", IEEE Signal Processing Letters, VOL. 16, NO. 1, January2009.

[9] Bai, L.; Yin, Q., "A modified NLMS algorithm for adaptive noise cancellation," IEEE International Conference on Acoustics Speech and Signal Processing, 2010, ICASSP, vol., no., pp.3726-3729, 14-19 March 2010.

[10] Sayed, A., "Robust Adaptive Filters," in Adaptive Filters , 1, Wiley-IEEEPress,2008,pp.718-734.