

COMPARISON ON PERFORMANCE OF NLMS AND OPTIMAL REGULARIZATION NLMS ALGORITHMS FOR SPEECH ENHANCEMENT

¹Anoosha.Ch, ²Yashoda.K, ³Nagamani.D

Assistant professor, Department of ECE, Anil Neerukonda Institute of Technology & Science, visakhapatnam

Abstract

The Adaptive noise cancellation algorithm is the popular technology for noise cancellation. There are different adaptive algorithms such as Least Mean Squares (LMS) algorithm, Normalized Least Mean Squares (NLMS), etc. all has their own merits and demerits, and their improvement algorithms are different. In practical applications, such as speech signal which is corrupted by high background noise need to be processed to extract useful signal and suppress noise. By studying the adaptive noise cancellation(ANC) principles, for speech enhancement this paper uses the optimal regularization NLMS algorithm to improve its application in noise cancellation and compares the simulation results with traditional NLMS algorithm. The performance of these techniques is compared with parameters such as SNR, true and estimated weights, and true and estimated noise. From simulation results both NLMS and the regularization NLMS can suppress noise but the regularization NLMS algorithm has a better ability to suppress noise and faster convergence.

Keywords—NLMS; the regularization NLMS; Adaptive filter

I.INTRODUCTION

Speech enhancement means to improve speech quality by using different algorithms[4]. The objective is improvement in intelligibility and overall perceptual quality of degraded speech signal using audio signal techniques. Enhancing of speech degraded by noise, or noise reduction, is the most important field of speech enhancement, and used for many applications such as mobiles, VoIP, teleconferencing systems, speech recognition and hearing aids. The most common problem in speech processing is the effect of interference noise in speech signals. Interference noise masks the speech signal and reduces its intelligibility. Interference noise can come from acoustical sources such as ventilation equipment, traffic, crowds and commonly, reverberation and echoes. It can also arise electronically from thermal noise, tape hiss or distortion products. If the sound system has unusually large peaks in its frequency response, the speech signal can even end up masking itself. Thus main aim is the enhancement of speech corrupted by noise in a non-stationary speech signal. However, due to the ever growing technology, today we have many adaptive algorithms for speech enhancement. LMS algorithm is the first one then there are many modified algorithms based on LMS among them NLMS algorithm is the algorithm that is used today mostly[4]. In order to further improve the performance

we regularize the NLMS algorithm[4]. For this purpose we are taking a random signal which is added with some random noise. Regularized NLMS algorithm is then applied on this distorted signal along with other traditional algorithms to observe the best algorithm for speech enhancement.

II.ADAPTIVE NOISE CANCELLATION

Adaptive filters adjust its transfer function according to an optimizing algorithm. Due to complexity of optimizing algorithms, most adaptive filters are digital filters. Adaptive filters perform digital signal processing and adapt their performance based on the input signal. Fig. 1 shows a typical adaptive noise cancellation system.

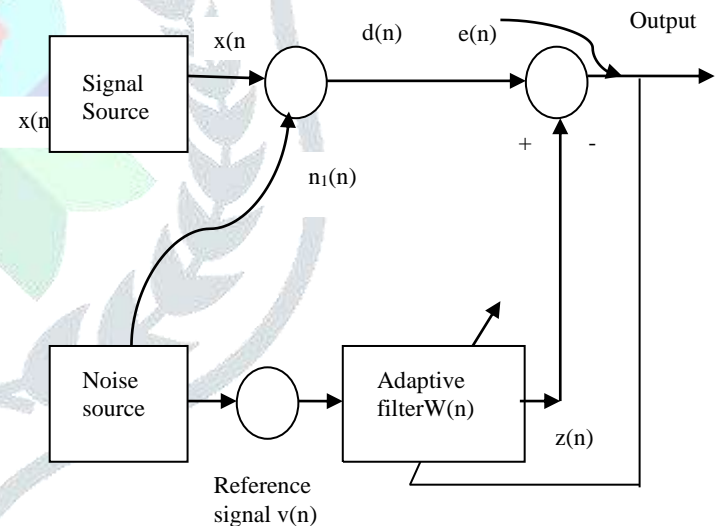


Fig.1 Adaptive noise cancellation block diagram

The Fig. 1 serves as a foundation for particular adaptive filter realizations, such as least mean square or normalized least mean squares. The idea behind figure is that a variable filter extracts an estimate of the desired signal. To start the discussion of the block diagram, we take the following assumptions.

The input signal is the sum of a desired signal $x(n)$ and interfering noise $n_1(n)$ [3]

$$d(n) = x(n) + n_1(n) \quad (1)$$

When noise reference signal $v(n)$ passes through the adaptive filter with weight coefficient $W(n)$, the output of adaptive filter can obtain an estimated $z(n)$, and $z(n)$ is close to noise interference $n_1(n)$.

The coefficients for a adaptive filter [3]of order ρ are defined as

$$W_n = [w_n(0), w_n(1), \dots, w_n(\rho)]^T \tag{2}$$

Finally the error signal or cost function is the difference between the desired and the estimated signal

$$e(n) = x(n) + n_1(n) - z(n) \tag{3}$$

Where $e(n)$ is the system final output of speech signal by constantly updating the adaptive filter weights to make the estimated signal close to $n_1(n)$.

III. THE REGULARIZATION NLMS ALGORITHM

The stability of the basic NLMS is controlled by a fixed step-size This parameter also governs the rate of convergence, speed of tracking ability and the amount of steady-state excess mean-square error (MSE)[1]. In practical applications, the step-size is divided by sum of the squared norm of the input vector and a positive regularization parameter ϵ which is also called the ϵ -NLMS algorithm, to solve an ill-conditioned problem. An adaptive filter will behave poorly if it is not properly regularized.

The adaptive filter input data is

$$v(n) = [v(n), v(n-1), \dots, v(n-L+1)]^T \tag{4}$$

Where L denotes the length of the filter, and the corresponding weight vector is

$$w(n) = [w(n), w(n-1), \dots, w(n-L+1)]^T \tag{5}$$

The coefficient update equation of traditional NLMS algorithm is expressed as

$$w(n+1) = \mu[\epsilon + v^T(n)v(n)]^{-1}v(n)e(n); 0 < \mu < 2 \tag{6}$$

$$e(n) = d(n) + v^T(n)w(n) \tag{7}$$

Where $d(n)$ is a given desired signal, $e(n)$ is the error signal.

The adaptive step size μ is a scalar, ϵ is a small positive number. $\mu[\epsilon + v^T(n)v(n)]^{-1}$ controls both the convergence rate and steady state[1] which a higher value results in a faster rate of convergence and less stable, vice versa. This realizes the regularization for adaptive filter by optimizing the value of ϵ and also deduces regularization NLMS algorithm. From (5) can be written as

$$w(n+1) = B(n)w(n) - \mu\bar{w}(n) \tag{8}$$

$$B(n) = \mu[\epsilon + v^T(n)v(n)]^{-1}v(n)v(n)^T \tag{9}$$

$$\bar{w}(n) = [\epsilon + v^T(n)v(n)]^{-1}v(n)d(n) \tag{10}$$

In fact $\bar{w}(n)$ is one of the solutions of $\bar{e}(n) = d(n) - v(n)^T\bar{w}(n)$

So the NLMS filter can realize regularization by computing the constraint equation[5]

$$\min\{[d(n) - v(n)^T\bar{w}(n)]^2 + \epsilon\|\bar{w}(n)\|^2\}$$

In ANC system, if $\bar{e}(n) = d(n)$, the impact of the speech signal on noise signals estimation can be eliminated as

$$E\{\bar{e}^2(n)\} = \partial_s^2 \tag{11}$$

$$E\{[d(n) - v(n)^T\bar{w}(n)]^2\} = \partial_s^2 \tag{12}$$

Where ∂_s^2 is the variance of speech signal $s(n)$, In order to solve the regularization parameter, let ≥ 1 , and the input noise signal $v(n)$ is stable. Then

$$v^T(n)v(n) \sim L\partial_x^2 \tag{13}$$

Where ∂_x^2 is the noise variance of $v(n)$, Substitute (12) in

$$[1 - L\partial_x^2[\epsilon + L\partial_x^2]^{-1}]^2 = \frac{\partial_s^2}{d^2(n)} \tag{14}$$

When the estimated amount of the reference channel noise $y(n)$ is infinitely close to the noise signal component n_1 of noisy speech. We can see that:

$$d(n) = v^T(n)w(n) + s(n) \tag{15}$$

Since $s(n)$ and $x(n)$ is not relevant, then[5]

$$E[d^2] = E[s^2] + w^T E[v^T(n)]w \tag{16}$$

$$\partial_d^2 = \partial_s^2 + w^T \partial_x^2 w \tag{17}$$

Assuming $NSR = \frac{w^T \partial_x^2 w}{\partial_s^2}$ and substitute in (13)

$$\epsilon^2 - 2 \frac{L\partial_x^2}{NSR} \epsilon - \frac{L\partial_x^2}{NSR} = 0 \tag{18}$$

Solving

$$\epsilon = \frac{L(1+\sqrt{(1+NSR)})}{NSR} \partial_x^2 \tag{19}$$

$$\gamma_{NLMS} = \frac{L(1+\sqrt{(1+NSR)})}{NSR} \partial_x^2 \tag{20}$$

$$\epsilon = \frac{L(1+\sqrt{(1+NSR)})}{NSR} \partial_x^2 = \gamma_{NLMS} \tag{21}$$

Where ϵ is regularization parameter, γ_{NLMS} is the normalized

regularization parameter[1] and NSR is the ratio of the energy of output estimation noise and input clean speech signal.

IV PERFORMANCE COMPARISON

In this section , shown the simulation results on performance of traditional NLMS and optimal regularization NLMS algorithm on a speech signal. In this paper speech signal is consider as a sinusoidal signal to this a random noise is added. This noisy sinusoidal signal is applied to a adaptive filter to remove noise and to observe the performance of NLMS algorithms.

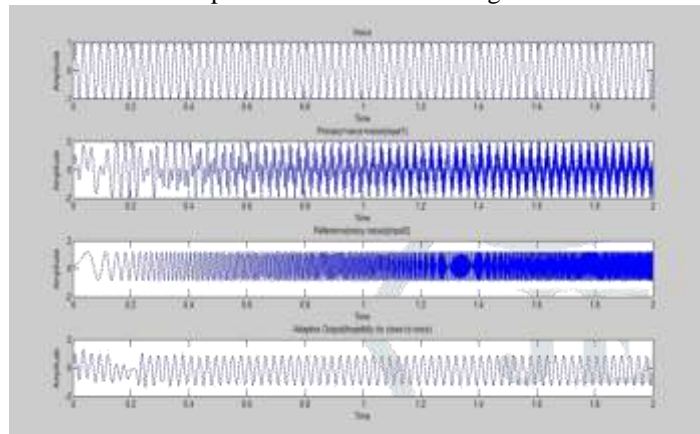


Fig. 2 Input and output of adaptive cancellation system. (a)Input speech signal (b)Noisy speech signal (c) Reference noise signal (d)Output of adaptive filter

In Fig. 2 we can see that a sinusoidal signal is given as speech signal. Then, random noise is added to this speech signal. We had take a reference signal which is correlated to the noise added to the speech. Then applied adaptive algorithm to these signals and obtained the output which is almost similar to the input speech signal.

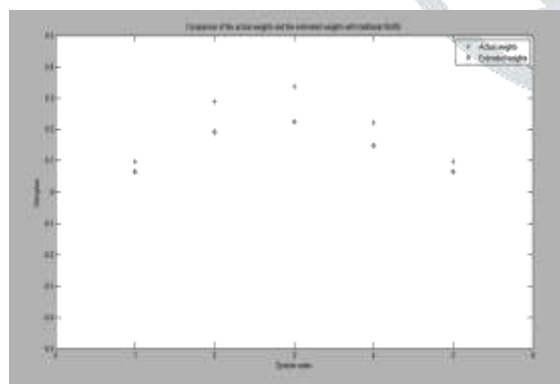


Fig. 3 Comparison of the Actual weights and the Estimated Weights with traditional NLMS

Actual weights and Estimated weights for traditional NLMS algorithm			
System order	Actual Weights	Estimated Weights	Difference between weights
1	0.0976	0.06507	0.03253
2	0.2873	0.1915	0.0958
3	0.336	0.224	0.112
4	0.221	0.1473	0.0737
5	0.0964	0.06427	0.03213

Table 1 Shown the values Of Actual weights and the Estimated Weights with traditional NLMS

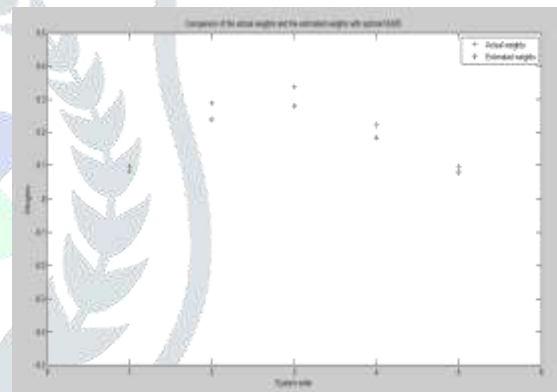


Fig. 4 Comparison of the Actual weights and the Estimated Weights with optimal regularization NLMS

Actual weights and Estimated weights for optimal regularization NLMS algorithm			
System order	Actual Weights	Estimated Weights	Difference between weights
1	0.0976	0.08133	0.01627
2	0.2873	0.2394	0.0479
3	0.336	0.28	0.056
4	0.221	0.1842	0.0368
5	0.0964	0.08033	0.01607

Table 2 Shown the values Of Actual weights and the Estimated Weights with regularization NLMS

Fig. 3, 4 and Table 1 and 2 shows the comparison of actual weights[2] and estimated weights with traditional NLMS also with Optimal NLMS. It can be observed that the estimated weights are close to actual weights in optimal NLMS process when compared to traditional NLMS. Thus, we can say

that optimal NLMS algorithm is better in terms of estimating weights

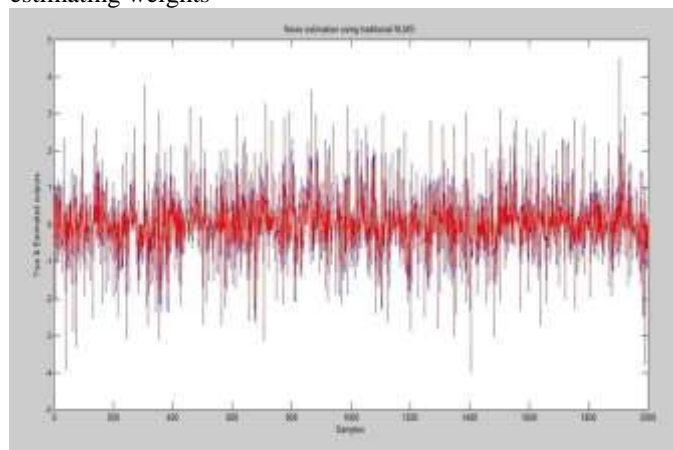


Fig. 5 Noise Estimation using Traditional NLMS

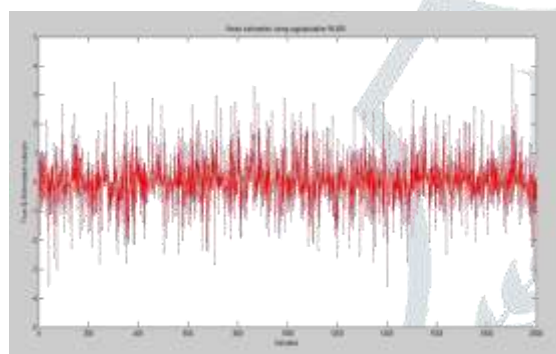


Fig. 6 Noise Estimation Using Regularization NLMS

Fig 5, 6 shows the true and estimated outputs with respect to samples using traditional and optimal NLMS respectively. It can be observed that optimal NLMS algorithm is better in estimating the noise when compared to traditional NLMS

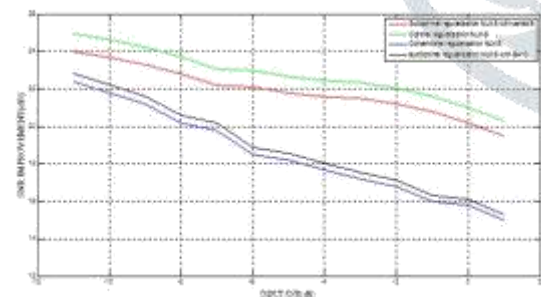


Fig. 7 The variation of output SNR value

Fig. 7 shows the variation of output SNR value with respect to input SNR value for traditional NLMS, optimal NLMS, suboptimal with varied beta and suboptimal with beta=10. It can be observed that SNR is highest for optimal NLMS, followed by suboptimal NLMS. Traditional NLMS has the least SNR. So optimal NLMS is good to suppress the noise and estimate the output..

INPUT SNR	OUTPUT SNR	
	Optimal regularization NLMS	Traditional NLMS
-10	24.65	21.8
-8	23.71	20.2
-6	22.98	18.5
-4	22.46	17.7
-2	22.05	16.8
0	21.01	15.8

Table 3. Comparison of SNR values of optimal regularized NLMS algorithm and traditional NLMS algorithm

V CONCLUSION

This paper verifies the regularized and traditional NLMS algorithm to suppress the noise in speech signal. The comparison has done on the basis of actual weights and estimated weights, noise estimation and SNR improvement. It is proven that the regularization in the NLMS algorithm improves the signal to noise ratio of speech signal which is corrupted by noise also the estimated weights are near to actual weights and have a faster convergence.

REFERENCES

- [1] Siqi Li, Shouhao Wu, Yongjie Wang, Wenxiu Guo and Youling Zhou "An improved NLMS algorithm based on speech enhancement", Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2015 IEEE.
- [2] Adaptive Filter Theory by Simen Haykin: 3rd edition, Pearson Education Asia. LPE.
- [3] Adaptive Signal Processing by John G Proakis, 3rd edition, Perntice Hall of India.
- [4] B. Widrow, "Adaptive noise canceling: principles and applications", Proceedings of the IEEE, vol. 63, pp. 1692-1716, 1975.
- [5] Benesty J, Paleologu C, Ciochina S. On Regularization in Adaptive filtering [J], IEEE transaction on Audio, Speech, and laungauge processing, 2011, 19(6):1734-1742