Nosie Cancellation using Modified Error Data Normalized Step Size Algorithm

Shelly Garg
Assistant Professor ,Department of ECE,CGC Landran,Punjab.

Reecha Sood
Assistant Professor,Department of CSE,CGC Landran,Punjab.

Mandeep kaur
Assistant Professor,Department of CSE,CEC, Landran,Punjab.

Pankaj Palta
Assistant Professor,Department of ECE,CEC,Landran,Punjab.

Abstract –This paper presents a Modified Error Data Normalized Step Size (MEDNSS) algorithm in which time fluctuating step size relies on standardization of both error and data vector. An Adaptive Noise Canceller (ANC) is utilized to enhance the system performance in the presence of signal leakage components or signal crosstalk. This ANC comprises of three microphones and two adaptive filters that consequently modify their channel coefficients by utilizing MEDNSS algorithm. The first adaptive filter cancels the signal leakage elements and second adaptive filter cancels the noise.. The execution of the MEDNSS algorithm is broke down, recreated and contrasted with the Error Data Normalized Step Size (EDNSS) algorithm in stationary and non-stationary environments utilizing different noise power levels. Computer simulation results exhibit the noteworthy enhancements of the MEDNSS algorithm over the EDNSS calculation in minimizing the signal distortion, Excess Mean Square Error (EMSE) , low misadjustment variable furthermore enhance Signal to Noise Ratio (SNR).

Index Terms – Adaptive filter; Crosstalk reduction; MEDNSS algorithm; Noise cancellation; Stationary and non-stationary environments; EMSE; Misadjustment factor; SNR.

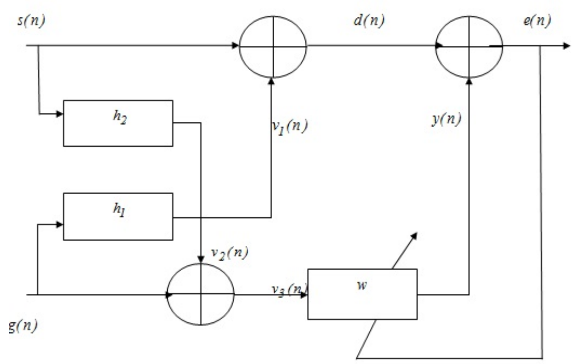
1. INTRODUCTION

A critical operation in voice communication frameworks includes the extraction of undesirable segments from the desired signal. This issue emerges as a rule, for example, helicopters, planes and vehicles where acoustic noise is added to discourse signal. In spite of the fact that the single microphone strategy for noise cancelation can be accomplished utilizing wiener and kalman sifting however two microphones approach utilizing adaptive filtering is an all the more capable method for this reason. The quality of the adaptive noise canceller lies in the way that it doesn't require earlier information of the discourse signal or the corrupted signal. Be that as it may, a connectionbetween the noise that defiles the speech signal and the noise in the reference input is important for the adjusting modified algorithm to expel the noise from the essential data signal. Numerous two microphone Adaptive Noise Canceller(ANCs) have been proposed in the literature[1]-[5] utilizing Least mean square(LMS) based algorithms that alter the step-size of the update equation to improve the tracking ability of the algorithm and its speed of convergence as well. In all these ANCs, it was accepted that there are no signal leakage components into the reference information. The presence of these signal leakage segments at the reference data is a down to earth concern since it causes cancelation of a part of the first discourse signal at the input of the ANC, and results in extreme signal distortion and low Signal to Noise Ratio (SNR) at the yield of the ANC. The extent of this contortion relies upon signal to noise ratio at the essential and reference inputs. A few procedures were proposed in the writing to enhance the framework execution for this situation of signal leakage [6], [7]. High computational complexity nature is connected with these strategies and calculations. This paper presents a Modified Error Data Normalized Step Size (MEDNSS) where the step size changes as indicated by the error and data vector standardization and connected to an ANC which comprises of three microphones and two adaptive filter.

2. ADAPTIVE NOISE CANCELLER

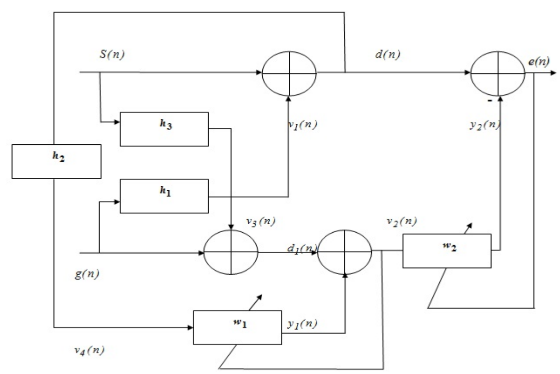
An adaptive noise canceller with signal leakage in the reference information is appeared in the given Figure 1. The leakage signal is spoken to as a yield of a low pass channel h_2 .This traditional ANC comprises of two receivers and one versatile channel. This versatile channel is planned by utilizing varying step-size algorithms. In the first microphone speaks to the discourse signal $S(n)$ and the second amplifier speaks to the reference noise input $g(n)$. The signal parts leaking from the main amplifier through a channel with impulse response h_2 and turns into $v_2(n)$ .An assessment of $g(n)$ goes through a channel with impulse response h_1 turns into $v_1(n)$ .The mix of $S(n)$ and $v_1(n)$ represented as $d(n)$ .The combination of $g(n)$ and $v_2(n)$ spoke to as $v_3(n)$ which is utilized as a desired signal of first versatile channel. These signal parts cause distortion in the recovered speech. Along these lines, SNR yield diminishes when contrasted with information SNR. It demonstrates that because of signal leakage parts SNR degrades and gives yield signal with somedistortion.

Figure 1: Conventional ANCwith signal leakage problem [13]



To take care of this issue in customary ANC we introduce a third microphone to provide a signal that is related with the signal segments leaked from the essential information. This signal is handled by the primary versatile channel (w_1) to create a crosstalk free noise at its yield. This noisy signal, with no spillage parts of the discourse, is prepared during that time versatile channel to wipe out the noise at its data and as needs be produces the recovered speech at the yield of the ANC.The block diagram of ANC as appeared in Figure2. This ANC comprises of three microphones and two versatile channels. These two versatile channels are composed by utilizing differing step size algorithms. To start with amplifier speaks to the discourse signal $S(n)$ and the second microphone speaks to the reference noise information signal $g(n)$. The signal segments leaking from the first microphone through a channel with impulse response h_3 and turns into $v_3(n)$ .An appraisal of $g(n)$ goes through a channel with impulse response h_1 turns into $v_1(n)$ .The mix of $S(n)$ and $v_1(n)$ spoke to as $d(n)$ .The combination of $g(n)$ and $v_3(n)$ spoke to as $d_1(n)$ which is utilized as a desired signal of first versatile channel. These signal parts cause distortion in the the recovered speech. To take care of this issue we acquaint a third microphone with give a signal $v_4(n)$, that is corresponded with the crosstalk signal that breaks from the essential amplifier into reference one. The transmission way between the third microphone and first versatile channel is spoken to by the impulse response h_2 ,and $d(n)$ goes through a channel with impulse response h_2 gives $v_4(n)$ signal which is utilized as the reference commotion information signal for first versatile channel. This signal is prepared by the principal versatile channel (w_1) to create a signal without leakage segments at the yield. This noisy signal $v_2(n)$, with no spillage parts of the discourse, is prepared during that time versatile channel to wipe out the noise at its input, and as needs be produces the recovered discourse $e(n)$ at the yield of the ANC..

Figure 2: ANC for solving leakage problem [13]



The execution of ANC may be depicted as far as the Excess Mean Square Error (EMSE) or misadjustment (M). The EMSE at the n^{th} iteration is characterized by

$$EMSE(n)=\frac{1}{L}\sum_{j=0}^{L-1}\left|e_1(n-j)\right|^2 \tag{1}$$

Where, $e_1(n)=e(n)-s(n)$ is the excess (residual) error , n is the the iteration number and L is the number of samples used to assess the EMSE. The impact of L is just to smooth the plot of EMSE.

The steady state EMSE assessed by averaging EMSE in above mathematical statement over n after the calculation has achieved steady state condition is characterized by

$$EMSE_{ss}=\left(\frac{1}{M-F}\right)\sum_{n=F}^{M-1}EMSE(n) \tag{2}$$

Where, M is the total number of samples of the speech signal and F is the number of samples after which the algorithm achieves enduring state condition. The misadjustment (M) is characterized as the ratio of the steady state excess MSE to the minimum MSE.

$$M=\frac{EMSE_{ss}}{MSE_{min}} \tag{3}$$

Where MSE_{min} equivalents to the the power of the original clean speech signal S, arrived at averaged over samples at which the algorithm is in steady state isgiven by

$$MSE_{min} = \left(\frac{1}{M-F}\right)\sum_{n=F}^{M-1}|S(n)|^2 \tag{4}$$

3. MODIFIED EDNSS ALGORITHM

Numerous variable step-size LMS based calculations have been proposed in the literature[8]-[12] with the point of modifying the step size of the update mathematical statement to enhance the essential tradeoff between convergence and least Mean Square Error(MSE).A new time-differing step-size was recommended in[10] based on the estimate of the square of a time-averaged autocorrelation function between e(n) and e(n-1).The step size is balanced based on the energy of the instantaneous error [11]. The execution of this algorithm corrupts within the sight of measurement noise in a system modeling application [10]. The step size in [12] is expected to fluctuate as indicated by the evaluated estimation of the standardized absolute error. The standardization was made with respect to the desired signal. The vast majority of these algorithms don't perform exceptionally well if an unexpected change occurs to the system impulse response .In light of regularization Newton's recursion [8], we can compose

$$w(n+1) = w(n) + \mu(n)[\varepsilon(n)I + R_X]^{-1}[p - R_X w(n)] \tag{5}$$

where : n =iteration number, w =An $N\times1$ vector of adaptive filter weights, $\varepsilon(n)$ =An iteration-dependent regularization parameter, $\mu(n)$ = An iteration dependent step-size, I = The $N\times N$ identity matrix, $p(n) = E[d(n)X(n)]$ is the cross-correlation vector between the desired signal $d(n)$ and the input signal $x(n)$, $R_X(n) = E[X(n)X^T(n)]$ is the autocorrelation matrix of $X(n)$. Writing (5) in the LMS form by replacing p and R_X by their instantaneous approximation $d(n)\ X(n)$ and $X(n)X^T(n)$, respectively, with appropriate proposed weights, we obtain

$$w(n+1) = w(n) + \mu\gamma[\alpha\|e_L(n)\|^2 I + \gamma X(n)X^T(n)]^{-1}x(n)e(n) \tag{6}$$

Where: μ = A positive constant step size, α and γ = Positive constants, $e(n)$ is the system output error

And

$$\|e_L(n)\|^2 = \sum_{i=0}^{L-1}|e(n-i)|^2 \tag{7}$$

Equation (7) is the squared norm of the error vector, $e(n)$, estimated over its last L values. Now expanding equation (6) and applying the matrix inversion formula:

$$[A+BCD]^{-1} = A^{-1} - A^{-1}B[C^{-1} + DA^{-1}B]DA^{-1} \tag{8}$$

With:

$A = \alpha\|e_L(n)\|^2 I, B = X(n), C = \gamma, and, D = X^T(n)$

We obtain:

$$[\alpha\|e_L(n)\|^2 I + \gamma X(n)X^T(n)]^{-1} = \alpha^{-1}\|e_L(n)\|^{-2} I - \alpha^{-1}\|e_L(n)\|^{-2} IX(n) \times \frac{X^T(n)\alpha^{-1}\|e_L(n)\|^{-2}}{\gamma^{-1} + X^T(n)\alpha^{-1}\|e_L(n)\|^{-2}X(n)} \tag{9}$$

Multiplying both sides of (9) by $X(n)$ from right, and rearranging the equation, we have

$$[\alpha\|e_L(n)\|^2 I + \gamma X(n)X^T(n)]^{-1}X(n) = \frac{X(n)}{\alpha\|e_L(n)\|^2 + \gamma\|X(n)\|^2} \tag{10}$$

Substituting (12) in (6), we obtain Modified Error Data Normalized Step Size (MEDNSS) algorithm:

$$w(n+1) = w(n) + \frac{\mu(1-\alpha)}{\alpha\|e_L(n)\|^2 + (1-\alpha)\|X(n)\|^2}X(n)e(n) \tag{11}$$

Where, γ is replaced by $(1-\alpha)$ in eq. (11) without loss of simplification. The fragmentary amount in eq. (10) may be seen as a period varying step-size $\mu(n)$ of the MEDNSS algorithm. Obviously, $\mu(n)$ is controlled by standardization of both error and input information vectors. This algorithm is subject to standardization of both data and error. The parameters α, L, μ are suitably accomplished the best tradeoff amongst convergence and low final mean square error. It differs from the NLMS algorithm in the additional term $\|e_L(n)\|^2$ with a relative consistent. For the situation when L=n, this additional term will expand the denominator of the time -changing step-estimate (the fractional quantity of (11)), and thus a bigger estimation of μ ought to be utilized as a part of this calculation to accomplish quick rate of convergence at the early phases of adaptation. As n increases (with L=n), $\mu(n)$ diminishes aside from conceivable here and there varieties because of measurable changes in the input signal energy $\|X(n)\|^2$. Expansion of the parameter $(1-\alpha)$ enhances the system performance when contrasted with the EDNSS calculation. To compute (7) with negligible computational intricacy, the error value created in the principal emphasis is squared and put away. The error value in the second iteration is squared and added to the previous stored value. At that point, the outcome is put away with a specific end goal to be utilized as a part of the following emphasis and soon. A sudden change in the system response will marginally expand the denominator of $\mu(n)$, however will bring about an altogether larger numerator. In this way, the estimation of step-size will increment before endeavoring to meet once more. The step size $\mu(n)$ ought to vary between two predetermined hard points of confinement [14]. The lower esteem ensures the ability of the calculation to react to an unexpected change that could happen at a huge estimation of cycle number n, while the greatest worth keeps up the stability of the algorithm. Note that setting α =0 in this mathematical statement results in the standard NLMS calculation.

4. SIMULATION AND RESULTS

A correlation of the MEDNSS with EDNSS calculations are depicted utilizing Adaptive Noise Cancelation as appeared in Figure 1 and 2 separately. The simulations are done utilizing a male native speech tested at a frequency of 11.025 kHz. The quantity of bits per test is 8 and the aggregate number of tests is 33000. The simulation results are exhibited for stationary and non stationary situations. For the stationary case, the noise $g(n)$ was thought to be zero white Gaussian with three distinct variances as appeared in Table1. For non stationary case, the noise was thought to be zero mean white Gaussian with difference that expansions straightly from $\sigma^2_{g_{min}}$ =0.00001 to three distinctive most extreme values, $\sigma^2_{g_{max}}$ for example, 0.0001, 0.001, 0.01 as showed in Table 2. In ordinary ANC the accompanying estimations of parameters were utilized : N=12, L= 20N, $\mu = 0.03$ and $\alpha = 0.7$,where N,L, μ, and α are the comparing parameter of the EDNSS calculation and utilized as a part of the versatile filter(w)shown in Figure 1. ANC in Figure 2 the accompanying estimations of parameters were utilized:

$N_1 = N_2 = 12$, $L_1 = L_2 = 20N$ $\mu_1 = 0.15, \mu_2 = 0.03, \alpha_1 = 0.9,$ and $\alpha_2 = 0.7$ where $N_1, L_{1,} \mu_1$ and α_1 are channel length, mistake vector length, step size parameter and corresponding steady, separately, of the MEDNSS calculation and in addition EDNSS calculation utilized as a part of the main versatile channel (w_1)appeared in Fig.2. So N_2, L_2, μ_2 also, and α_2 are comparing parameters of the MEDNSS calculation and additionally EDNSS calculation utilized as a part of the second versatile channel (w_2) appeared in Fig.2. The estimation of α were chosen as a trade off between fast rate of convergence and great following capacity with most concern to have a high rate of convergence in the first adaptive filter and good tracking capability in the second adaptive filter .The impulse responses of the three autoregressive (AR) low pass channels utilized as a part of the recreations are h_1 =[1.5 - 0.5 0.1], h_2 =[2 - 1.5 0.3] and h_3 =[3 - 1.2 0.3].Figure 3 delineates the execution of traditional ANC for the non-stationary case in which $\sigma^2_{g\,max}$ =0.01 as appeared in Table 4. It indicates high Excess error. From Top to Bottom, it demonstrates original speech signal S (n), combination of noise and speech signal d (n), recovered signal e (n) and excess error signal e (n)- S (n). Figure 4 represents the execution of MEDNSS and algorithm of an ANC for the non-stationary case in which $\sigma^2_{g\,max}$ =0.01 as appeared in Table 3. MEDNSS calculation gives low EMSE and misadjusment variable when contrasted with EDNSS calculation. The adaptation constants of the algorithm utilized as a part of both ANCs were chosen to accomplish a trade off between low EMSE and high initial rate of convergence for an extensive variety of noise variances. From these tables, change of up to 34dB in EMSEss utilizing MEDNSS calculation for ANC when contrasted with routine ANC. It is beneficial to note that if the noise variance increases, the execution of the traditional ANC turns into somewhat better as showed in Table 1 and 2. This is normal in light of the fact that expanding noise power level results in a less huge impact of the signal leakage at the reference data. This sign leakage gives low SNR in customary ANC. So an ANC is utilized to improve the SNR rate utilizing MEDNSS and EDNSS calculation.

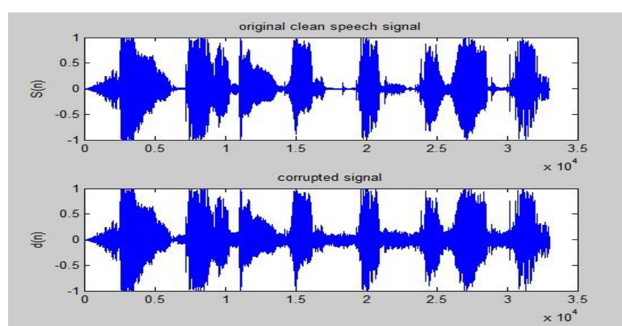
Signal to Noise Ratio (SNR): The signal-to-noise ratio is used to measure the amount of desired signal level with the noise level. The ideal method for calculating the SNR is the amount of speech energy over the noise energy after the enhancement method. The input SNR and output SNR are calculated as below:

$$SNR_{in} = 10\,log10 \frac{s(n)^2}{d(n)^2} \Big/ n \tag{12}$$

$$SNRout = 10\log 10 \frac{s^2_{out}}{n^2_{out}} \Big/ n \tag{13}$$

Where s_{out} and n_{out} are the filtered outputs of the Wiener beam former i.e. pure speech signal *s(n)* and pure noise signal *d(n)* separately and also '*n*' is the length of the speech and noise signals. [15]

Figure 3: Performance of Conventional ANC in non-stationary noise environment ($\sigma^2_{g\,max}$ =0.01, Table 2)



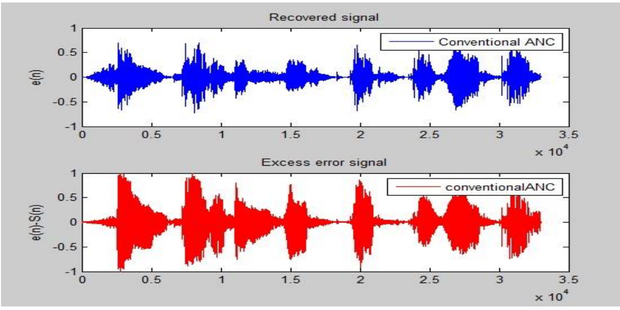


Figure 4: Performance Comparison between the MEDNSS and EDNSS algorithm of ANC in non-stationary noise environment ($\sigma^2_{g\,max}$ =0.01, Table 4)

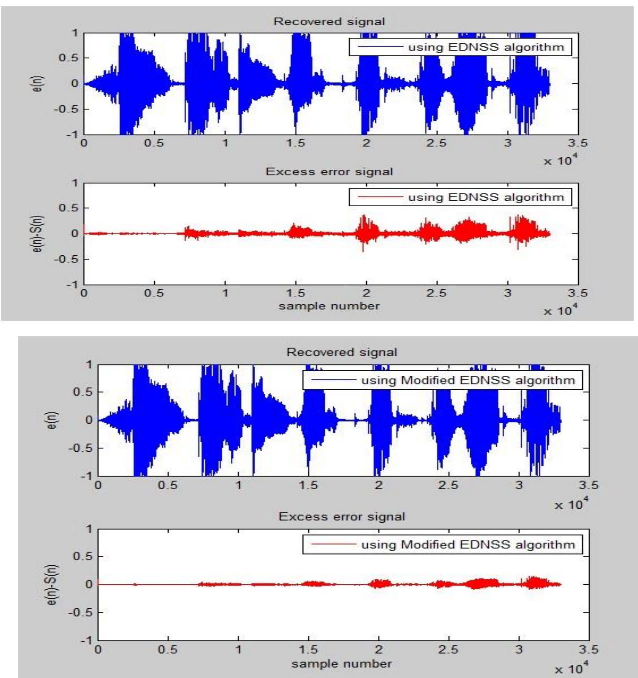
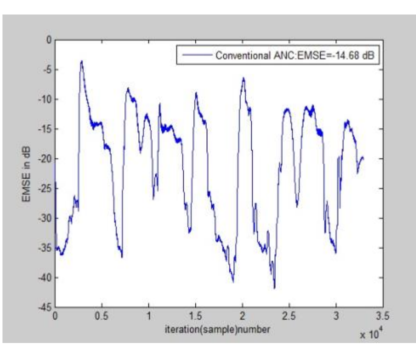


Figure 5: EMSE in dB of the conventional ANC (σ^2_g =0.001, Table1), EDNSS algorithm and MEDNSS algorithm using ANC in stationary noise environment (σ^2_g =0.001, Table3)



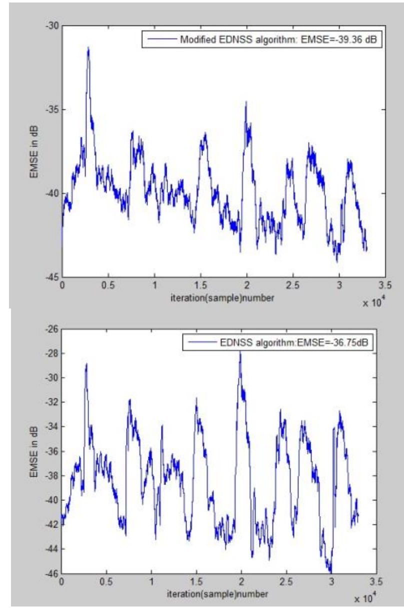


Table 1: $EMSE_{ss}$ and M of the conventional ANC for stationary case

Stationary case	Conventional ANC	
Gaussian white zero-mean noise, *g(n)*	Steady state EMSE (dB)	Misadjustment (M %)
σ^2_g =0.0001	-15.08	95.18
σ^2_g =0.001	-16.55	67.96
σ^2_g =0.01	-16.6	67.04

Table 2: $EMSE_{ss}$ and M of the conventional ANC for non-stationary case

Non-Stationary Case	Conventional ANC	
Gaussian Noise *g(n)* $\sigma^2_{g_{min}}$ =0.00001	Steady State EMSE(dB)	Misadjustment (M %)
$\sigma^2_{g_{max}}$ =0.0001	-14.9	98.5
$\sigma^2_{g_{max}}$ =0.001	-15.53	85.8
$\sigma^2_{g_{max}}$ =0.01	-16.5	68.54

Table 3: Comparison of EDNSS and MEDNSS algorithm of ANC for Stationary case

Stationary Case	ANC			
Gaussian white zero mean noise $g(n)$	EDNSS Algorithm		MEDNSS Algorithm	
	EMSE steady state (dB)	M%	EMSE steady state (dB)	M%
σ_g^2 =0.0001	-45.86	0.07	-47.19	0.05
σ_g^2 =0.001	-37.94	0.4	-40.4	0.27
σ_g^2 =0.01	-20.88	25.07	-24.7	10.23

Table 4: Comparison of EDNSS and MEDNSS algorithm of ANC for Non- stationary case

Non- Stationary case	EDNSS algorithm		MEDNSS algorithm	
Gaussian Noise g(n) $\sigma^2_{g_{min}}$ =0.00001	EMSE steady state (dB)	M%	EMSE steady state (dB)	M%
$\sigma^2_{g_{max}}$ =0.0001	-48.4	0.04	-48.7	0.039
$\sigma^2_{g_{max}}$ =0.001	-41.5	0.2	-43.4	0.13
$\sigma^2_{g_{max}}$ =0.001	-31.3	2.2	-35.1	0.94

Table 5: Comparison of EDNSS and MEDNSS algorithms based on SNR in stationary case.

Stationary case	Conventional ANC		ANC EDNSS algorithm	ANC MEDNSS algorithm
Gaussian white zero mean noise $g(n)$	SNR_{in}	SNR_{out}	SNR_{out}	SNR_{out}
σ_g^2 =0.0001	25.21	-17.46	28.27	37.58
σ_g^2 =0.001	15.21	-4.99	18.32	29.11
σ_g^2 =0.01	5.21	-4.15	8.86	11.63

Table 6: Comparison of EDNSS and MEDNSS algorithms based on SNR in non-stationary case

Non-Stationary case	Conventional ANC		ANC EDNSS algorithm	ANC MEDNSS algorithm
Gaussian noise $g(n)$ $\sigma^2_{g_{min}}$ =0.00001	SNR_{in}	SNR_{out}	SNR_{out}	SNR_{out}
$\sigma^2_{g_{max}}$ =0.0001	28.6	-21.2	31.6	37.7
$\sigma^2_{g_{max}}$ =0.001	19.14	-11.65	22.24	34.9
$\sigma^2_{g_{max}}$ =0.01	9.2	-4.80	12.5	24.17

Table 5 and Table 6 shows the comparison of EDNSS and MEDNSS algorithms based on SNR in stationary case and non- stationary case respectively. The presence of signal leakage provides low signal to noise ratio (SNR) in conventional ANC. A new ANC is used to enhance the SNR rate using MEDNSS and EDNSS algorithm in the presence of signal leakage components. These tables show that the MEDNSS algorithm provides high SNR as compared to EDNSS algorithm.

5. CONCLUSION

In this paper, another Modified Error Data Normalized Step Size (MEDNSS) Algorithm is proposed to enhance the system performance when contrasted with EDNSS Algorithm. Computer Simulations, utilizing another adaptive algorithm based on normalization of both error and data, show execution predominance of an ANC in diminishing signal distortion and creating small value of EMSE and Misadjustment component furthermore enhance SNR.

REFERENCES

[1] S. Ikeda and A. Sugiyama, "An adaptive noise canceller with low signal distortion for speech codecs," *IEEE Trans. On Signal, Processing,* vol. 47, March 1999, pp 665-674.

[2] J. E. Greenberg "Modified LMS algorithms for speech processing with an adaptive noise canceller," *IEEE Trans. On Speech and AudioProcessing,* vol. 6, July 1998, pp 338-351.

[3] W.A.Harrison, J S.Lim,and E. Singer, "A new application of adaptive noise cancellation," *IEEE Trans. Acoust.., Speech, Signal Processing,* vol. 34, Jan. 1986, pp. 21-27,.

[4] M.J. Al-Kindi and J. Dunlop, "A low distortion adaptive noise cancellation structure for real time applications," in *Proc. IEEE ICASSP,* 1987, pp. 2153-2156.

[5] S. F. Boll and D. C. Publisher, "Suppression of acoustic noise in speech using two microphone adaptive noise cancellation," *IEEE Trans.Acoust.,, Speech, Signal Processing*, vol.28, 1980, pp. 752-753.

[6] G. Mirchandani. R. L.Zinser, and J. B.Evans, "A new adaptive noise cancellation scheme in the presence of crosstalk," *IEEE Trans. CircuitsSyst..,* vol. 39,1992, pp. 681-694.

[7] V. Parsa, P. A. Parker, and R. N. Scott,"Performance analysis of a crosstalk resistant adaptive noise canceller," *IEEE Trans. CircuitsSyst.,* vol. 43, 1996, pp. 473-482.

[8] A.H. Sayed, "Fundamentals of Adaptive Filtering.1st Edn.," Wiley-*IEEE Press, Hoboken,* NJ,2003, pp: 1168.

[9] S.C. Douglas, and T.H.Y. Meng, "Normalized data nonlinearities for LMS adaptation" *IEEE Trans. Signal Processing,* vol.42, 1994, pp.1352-1365.

[10]] T. Aboulnasr, and K. Mayyas, "A robust variable step-size LMS-type algorithm: Analysis and simulations" *IEEE Trans. Signal. Processing* vol.45, 199, pp 631-639.

[11] R.H. Kwong, and E.W. Johnston, " A variable step-size LMS algorithm"*IEEE Trans. Signal Processing* vol.40 ,1992, pp.1633-1642.

[12] D.W. Kim, H.B. Kang, M.S. Eun and J.S. Choi, "A variable step-size algorithm using normalized absolute estimation error" *IEEE Xplore Press,* Rio de Janeiro, Brazil,Aug. 13-16, 1995, pp: 979-982.

[13] Z.M.Ramadan,"A Three Microphone Adaptive Noise Canceller for Minimizing Reverberation and Signal Distortion", *American Journal of Applied Sciences*, vol.5, 2008, , pp.320-327.

[14] Z.Ramadan, "Error Vector normalized adaptive algorithm applied to adaptive noise canceller and system identification" *American Journal of Applied Sciences,* vol.3, 2010, pp.710-717.

[15] S.F.Boll and D. C. Publisher, "Suppression of acoustic noise in speech using two microphone adaptive noise cancellation*", IEEE Transcations on Acoustics, Speech, and Signal Processing*,vol. ASSP-28,no.6,1980, pp.752-753.