



Modified Error Data Normalized Step Size algorithm Applied to Adaptive Noise Canceller

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Abstract: This paper introduces a Modified Error Data Normalized Step Size (MEDNSS) algorithm in which time varying step size depends upon normalization of both error and data vector. An Adaptive Noise Canceller (ANC) is used to improve the system performance in the presence of signal leakage components or signal crosstalk. This ANC consists of three microphones and two adaptive filters that automatically adjust their filter coefficients by using MEDNSS algorithm. The first adaptive filter cancels the signal leakage components and second adaptive filter cancels the noise. The performance of the MEDNSS algorithm is analyzed, simulated and compared to the Error Data Normalized Step Size (EDNSS) algorithm in stationary and non-stationary environments using different noise power levels. Computer simulation results demonstrate the significant improvements of the MEDNSS algorithm over the EDNSS algorithm in minimizing the signal distortion, Excess Mean Square Error (EMSE) and low misadjustment factor.

Keywords: Adaptive filter; Crosstalk reduction; MEDNSS algorithm; Noise cancellation; Stationary and non-stationary environments.

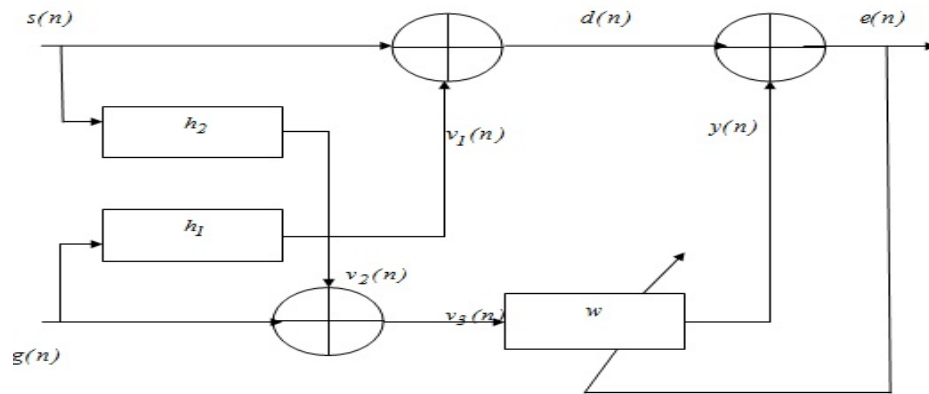
I. Introduction

An important operation in voice communication systems involves the extraction of unwanted components from the desired speech signal. This problem arises in many situations, such as helicopters, airplanes and automobiles where acoustic noise is added to speech signal. Although the single microphone method for noise cancellation can be achieved using wiener and kalman filtering but two microphone approach using adaptive filtering is a more powerful technique for this purpose. The strength of the adaptive noise canceller lies in the fact that it doesn't require prior knowledge of the speech signal or the corrupted signal. However, a correlation between the noise that corrupts the speech signal and the noise in the reference input is necessary for the adapting modified algorithm to remove the noise from the primary input signal. Many two microphone Adaptive Noise Canceller(ANCs) have been proposed in the literature[1]-[5] using Least mean square(LMS) based algorithms that changes 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 assumed that there are no signal leakage components into the reference input. The presence of these signal leakage components at the reference input is a practical concern because it causes cancellation of a part of the original speech signal at the input of the ANC, and results in severe signal distortion and low Signal to Noise Ratio (SNR) at the output of the ANC. The magnitude of this distortion depends on the signal to noise ratio at the primary and reference inputs. Several techniques were proposed in the literature to improve the system performance in this case of signal leakage [6], [7]. High computational complexity is associated with these techniques and algorithms. This paper introduces a Modified Error Data Normalized Step Size (MEDNSS) where the step size varies according to the error and data vector normalization and applied to an ANC which consists of three microphones and two adaptive filters.

II. Adaptive Noise Canceller

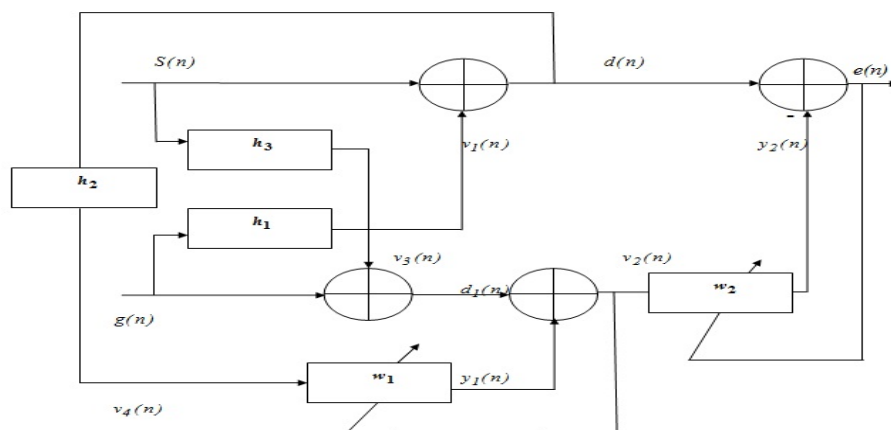
An adaptive noise canceller with signal leakage in the reference input is shown in the given Figure 1. The leakage signal is represented as an output of a low pass filter h_2 . This conventional ANC consists of two microphones and one adaptive filter. This adaptive filter is designed by using varying step-size algorithms. First microphone represents the speech signal $s(n)$ and the second microphone represents the reference noise input $g(n)$. The signal components leaking from the first microphone through a channel with impulse response h_2 and becomes $v_2(n)$. An estimate of $g(n)$ passes through a channel with impulse response h_1 becomes $v_1(n)$. The combination of $s(n)$ and $v_1(n)$ represented as $d(n)$. The combination of $g(n)$ and $v_2(n)$ represented as $v_3(n)$ which is used as an desired signal of first adaptive filter. These signal components cause distortion in the recovered speech. So, SNR output decreases as compared to input SNR. It shows that due to signal leakage components SNR degrades and gives output signal with some distortion.

Figure 1: Conventional ANC with signal leakage problem [13]



To solve this problem in conventional ANC we introduce a third microphone to provide a signal that is correlated with the signal components leaked from the primary input. This signal is processed by the first adaptive filter (w_1) to produce a crosstalk free noise at its output. This noisy signal, with almost no leakage components of the speech, is processed through the second adaptive filter to cancel the noise at its input and accordingly produces the recovered speech at the output of the ANC. The block diagram of ANC as shown in Figure 2. This ANC consists of three microphones and two adaptive filters. These two adaptive filters are designed by using varying step size algorithms. First microphone represents the speech signal $s(n)$ and the second microphone represents the reference noise input signal $g(n)$. The signal components leaking from the first microphone through a channel with impulse response h_3 and becomes $v_3(n)$. An estimate of $g(n)$ passes through a channel with impulse response h_1 becomes $v_1(n)$. The combination of $s(n)$ and $v_1(n)$ represented as $d(n)$. The combination of $g(n)$ and $v_3(n)$ represented as $d_1(n)$ which is used as an desired signal of first adaptive filter. These signal components cause distortion in the recovered speech. To solve this problem we introduce a third microphone to provide a signal $v_4(n)$, that is correlated with the crosstalk signal that leaks from the primary microphone into reference one. The transmission path between the third microphone and first adaptive filter is represented by the impulse response h_2 , and $d(n)$ passes through a channel with impulse response h_2 provides $v_4(n)$ signal which is used as the reference noise input signal for 1st adaptive filter. This signal is processed by the first adaptive filter (w_1) to produce a signal without leakage components at the output. This noisy signal $v_2(n)$, with almost no leakage components of the speech, is processed through the second adaptive filter to cancel the noise at its input, and accordingly produces the recovered speech $e(n)$ at the output of the ANC.

Figure 2: ANC for solving leakage problem [13]



The performance of ANC may be described in terms of the Excess Mean Square Error (EMSE) or misadjustment (M).

The EMSE at the n^{th} iteration is defined by

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

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

The steady state EMSE estimated by averaging EMSE in above equation over n after the algorithm has reached steady state condition is defined by

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

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

$$M = \frac{EMSE_{ss}}{MSE_{min}} \quad (3)$$

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

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

III. Modified EDNSS algorithm

Many variable step-size LMS based algorithms have been proposed in the literature[8]-[12] with the aim of altering the step-size of the update equation to improve the fundamental trade-off between speed of convergence and minimum Mean Square Error(MSE). A new time-varying step-size was suggested 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 adjusted based on the energy of the instantaneous error[11]. The performance of this algorithm degrades in the presence of measurement noise in a system modeling application [10]. The step-size in [12] is assumed to vary according to the estimated value of the normalized absolute error. The normalization was made with respect to the desired signal. Most of these algorithms do not perform very well if an abrupt change occurs to the system impulse response. Based on regularization Newton's recursion [8], we can write

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

where : n =iteration number, w =An $N \times 1$ 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

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

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

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

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:

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

With:

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

We obtain:

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

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

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

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

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

Where, γ is replaced by $(1-\alpha)$ in eq. (11) without loss of generality. The fractional quantity in eq. (10) may be viewed as a time-varying step-size $\mu(n)$ of the MEDNSS algorithm. Clearly, $\mu(n)$ is controlled by normalization of both error and input data vectors. This algorithm is dependent on normalization of both data and error. The parameters α, L, μ are appropriately chosen to achieve the best tradeoff between convergence and low final mean square error. It differs from the NLMS algorithm in the added term $\|e_L(n)\|^2$ with a proportional constant. For the case when $L=n$, this added term will increase the denominator of the time-varying step-size $\mu(n)$ (the fractional quantity of (11)), and hence a larger value of μ should be used in this algorithm to achieve fast rate of convergence at the early stages of adaptation. As n increases (with $L=n$), $\mu(n)$ decreases except for possible up and down variations due to statistical changes in the input signal energy $\|X(n)\|^2$. Addition of the parameter $(1-\alpha)$ improves the system performance as compared to the EDNSS algorithm. To compute (7) with minimal computational complexity, the error value produced in the first iteration is squared and stored. The error value in the second iteration is squared and added to the previous stored value. Then, the result is stored in order to be used in the next iteration and soon. A sudden change in the system response will slightly increase the denominator of $\mu(n)$, but will result in a significantly larger numerator. Thus, the value of step-size will increase before attempting to converge again. The step-size $\mu(n)$ should vary between two predetermined hard limits [14]. The lower value guarantees the capability of the algorithm to respond to an abrupt change that could happen at a very large value of iteration number n , while the maximum value maintains the stability of the algorithm. Note that setting $\alpha=0$ in this equation results in the standard NLMS algorithm.

IV. Simulations and Results

A comparison of the MEDNSS with EDNSS algorithms are described using Adaptive Noise Cancellation as shown in Figure 1 and 2 respectively. The simulations are carried out using a male native speech sampled at a frequency of 11.025 kHz. The number of bits per sample is 8 and the total number of samples is 33000. The simulation results are presented for stationary and non stationary environments. For the stationary case, the noise $g(n)$ was assumed to be zero mean white Gaussian with three different variances as shown in Table 1. For non stationary case, the noise was assumed to be zero mean white Gaussian with variance that increases linearly from $\sigma_{g_{min}}^2 = 0.00001$ to three different maximum values $\sigma_{g_{max}}^2$ such as 0.0001, 0.001, 0.01 as demonstrated in

Table 2. In conventional ANC the following values of parameters were used : $N=12, L=20N, \mu=0.03$ and $\alpha=0.7$, where N, L, μ , and α are the corresponding parameter of the EDNSS algorithm and used in the adaptive filter(w) shown in Figure 1. ANC in Figure 2 the following values of parameters were used: $N_1=N_2=12, L_1=L_2=20N, \mu_1=0.15, \mu_2=0.03, \alpha_1=0.9$, and $\alpha_2=0.7$ where N_1, L_1, μ_1 and α_1 are filter length, error vector length, step size parameter and proportional constant, respectively, of the MEDNSS algorithm as well as EDNSS algorithm used in the first adaptive filter (w_1) shown in Fig.2. Similarly, N_2, L_2, μ_2 and α_2 are corresponding parameters of the MEDNSS algorithm as well as EDNSS algorithm used in the second adaptive filter (w_2) shown in Fig.2. The value of α were selected as a compromise between fast rate of convergence and good tracking capability 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 filters used in the simulations 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 illustrates the performance of conventional ANC for the non-stationary case in which $\sigma_{g_{max}}^2=0.01$ as shown in

Table 4. It shows high Excess error. From Top to Bottom, it shows 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 illustrates the performance of MEDNSS and EDNSS algorithm of an ANC for the non-stationary case in which $\sigma_{g_{max}}^2=0.01$ as shown in Table 3. MEDNSS algorithm provides low EMSE and misadjustment factor as compared to EDNSS algorithm. The adaptation constants of the algorithm used in both ANC were selected to achieve a compromise between small EMSE and high initial rate of convergence for a wide range of noise variances. From these tables, improvement of up to 34dB in EMSEs using MEDNSS algorithm for ANC as compared to conventional ANC. It is worthwhile to note that if the noise variance increases, the performance of the conventional ANC becomes a little better as illustrated in Table 1 and 2. This is expected because increasing noise power level

results in a less significant effect of the signal leakage at the reference input. This signal leakage provides low SNR in conventional ANC. So an ANC is used to enhance the SNR rate using MEDNSS and EDNSS algorithm.

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

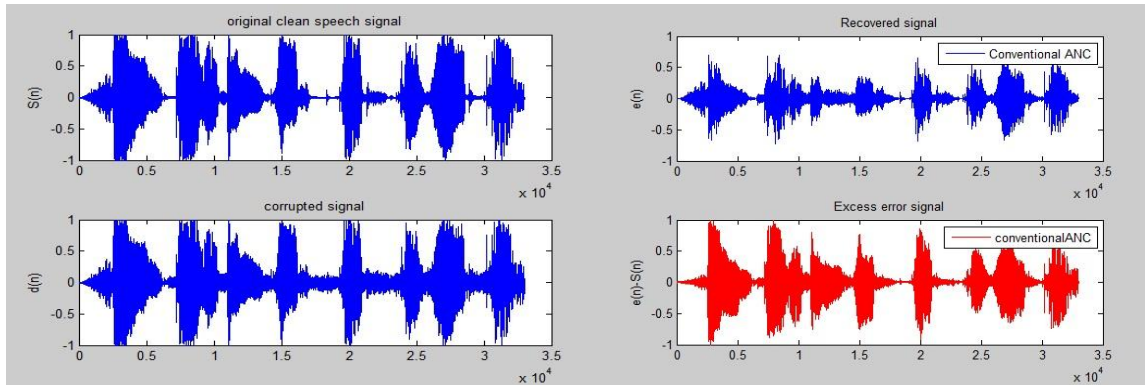


Figure 4: Performance Comparison between the MEDNSS and EDNSS algorithm of ANC in non-stationary noise environment ($\sigma_{g_{max}}^2=0.01$, Table 4)

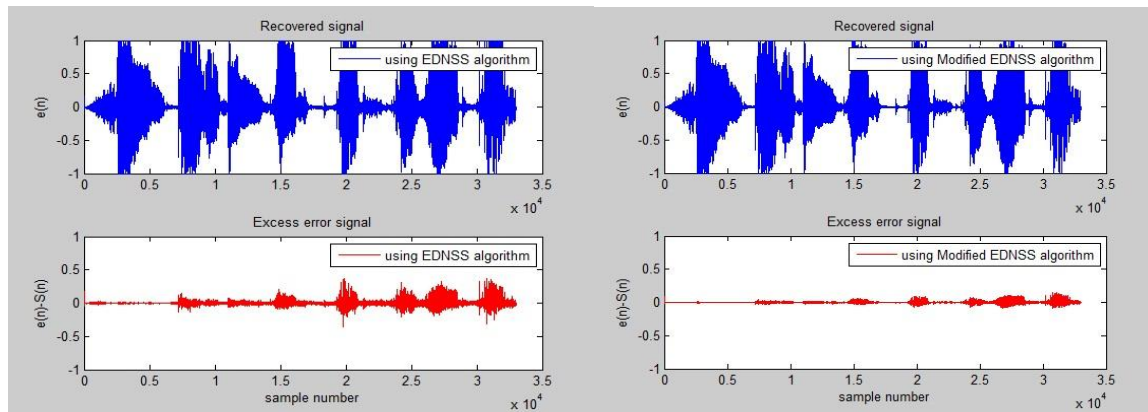


Figure 5: EMSE in dB of the conventional ANC ($\sigma_g^2=0.001$, Table1), EDNSS algorithm and MEDNSS algorithm using ANC in stationary noise environment ($\sigma_g^2=0.001$, Table3)

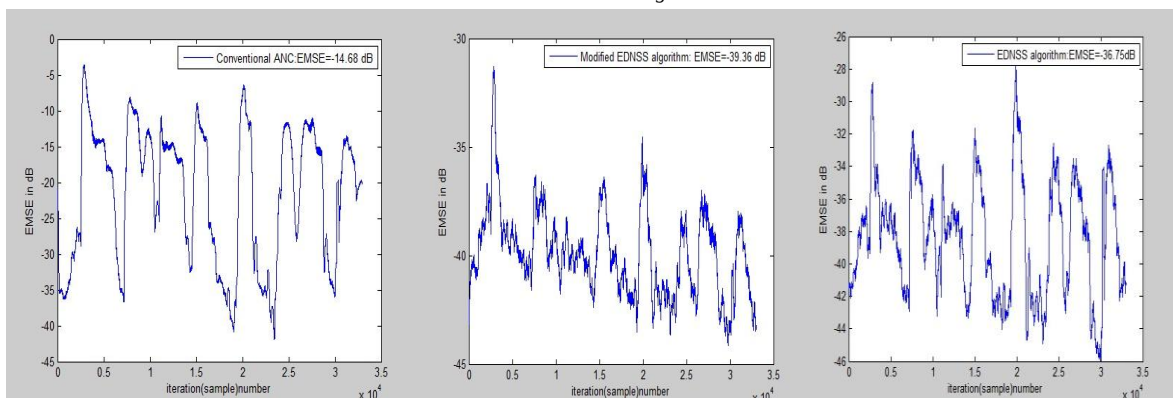


Table 1: EMSE_{ss} and M of the conventional ANC for stationary case

Stationary case		Conventional ANC	
Gaussian white	zero-mean noise, $g(n)$	Steady state EMSE (dB)	Misadjustment (M %)
	$\sigma_g^2=0.0001$	-13.6	103.4
	$\sigma_g^2=0.001$	-14.68	82.4
	$\sigma_g^2=0.01$	-14.94	77.5

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

Non-Stationary Case	Conventional ANC	
Gaussian Noise $g(n)$ $\sigma_{g_{min}}^2 = 0.00001$	Steady State EMSE(dB)	Misadjustment (M %)
$\sigma_{g_{max}}^2 = 0.0001$	-13.59	105.9
$\sigma_{g_{max}}^2 = 0.001$	-13.96	97.3
$\sigma_{g_{max}}^2 = 0.01$	-14.76	80.92

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%
$\sigma_g^2 = 0.0001$	-45.14	0.074	-46.6	0.05
$\sigma_g^2 = 0.001$	-36.75	0.5	-39.36	0.28
$\sigma_g^2 = 0.01$	-23.24	11.47	-24.9	7.7

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

Non-Stationary Case	ANC			
Gaussian Noise $g(n)$ $\sigma_{g_{min}}^2 = 0.00001$	EDNSS Algorithm		MEDNSS Algorithm	
	EMSE steady state (dB)	M%	EMSE steady state (dB)	M%
$\sigma_{g_{max}}^2 = 0.0001$	-47.67	0.04	-48.12	0.03
$\sigma_{g_{max}}^2 = 0.001$	-40.51	0.21	-43.09	0.11
$\sigma_{g_{max}}^2 = 0.01$	-30.10	2.36	-35.6	0.66

V. Conclusion

In this paper, a new Modified Error Data Normalized Step Size (MEDNSS) Algorithm is proposed to improve the system performance as compared to EDNSS Algorithm. Computer Simulations, using a new adaptive algorithm based on normalization of both error and data, show performance superiority of an ANC in decreasing signal distortion and producing small values of EMSE and Misadjustment factor.

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