Active Noise Cancellation Headset

Say-Wei Foo[1] ,T N Senthilkumar[1], and Charles Averty[2]
[1]School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore.
[2] ST Microelectronics Asia Pacific Ltd.

Abstract **--In this paper, a new design for headset with active noise cancellation capability is presented. For the proposed headset, a Variable-Step-Size Normalized Least-Mean-Square (VSS-NLMS) algorithm is adopted in the combined audio and feedback active noise cancellation system. Experimental results show that for the same set of signals, the average noise reduction using the proposed adaptive algorithms is 38dB compared with 36dB using Normalized Least-Mean-Square algorithm and 14 dB using the Least-Mean-Square algorithm. The speed of convergence using the proposed approach is also faster compared with the other two cases. Informal listening tests also favor the adoption of the proposed VSS-NLMS adaptive algorithm.**

Index Terms— **active noise cancellation, audio signal, headset, signal processing**

I. INTRODUCTION

With the advances in consumer electronics, more and more people listen to high quality pre-recorded music on the move using a headset. However, if this is done in a noisy environment such as in a flying aircraft or in a subway train, listening fatigue would soon set in when the noise level is high. Research has been ongoing to develop noise cancellation systems to reduce the noise level while preserving the music level of the audio wave presented to the eardrums.

For one such active noise cancellation (ANC) system, a microphone is placed together with the loudspeaker inside the ear-cup of the headset and a combined audio and feedback system is introduced between the audio source and the special headset as illustrated in Fig.1.

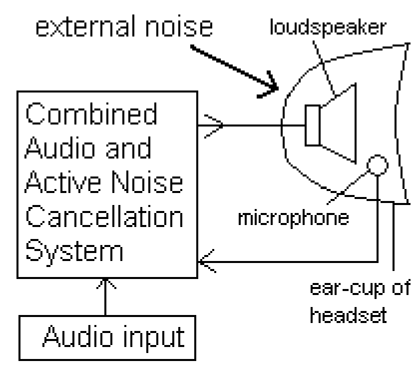

Fig. 1 Combined audio and ANC headset

The block diagram of a combined audio ANC system is depicted in Fig.2. The essential operation of the feedback system is to produce a signal that will nullify the external noise in the ear-cup of the headset. For the system to work properly, it is assumed that the external noise and the desired signal are uncorrelated and the magnitude of the external noise entering the ear-cup should be less than what the loudspeaker in the ear-cup can produce.

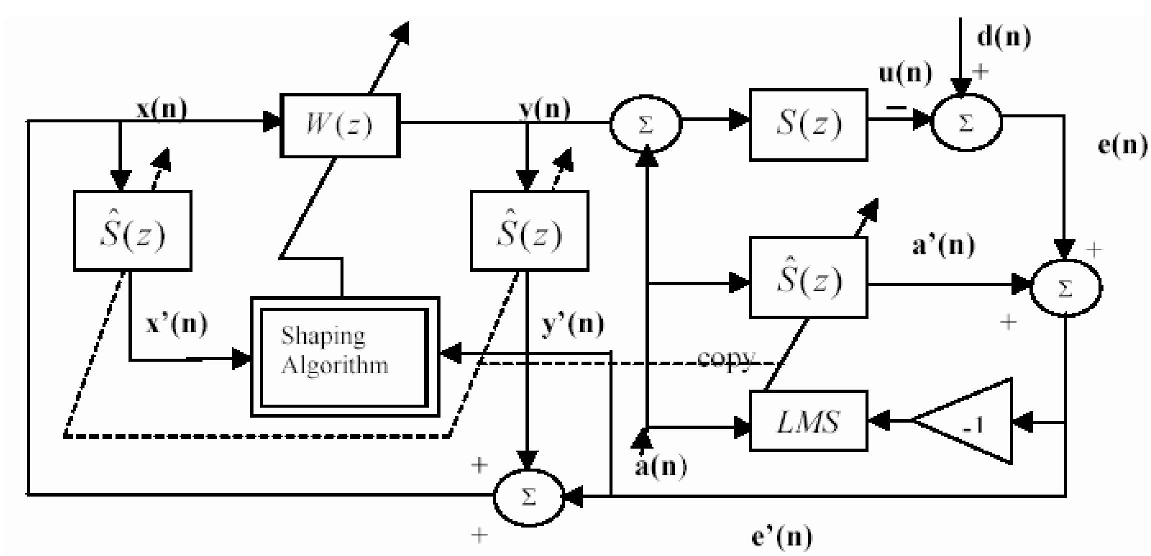

Fig.2 Block diagram of a generic combined audio and feedback ANC system

In Fig.2, S(z) simulates the headset model. d(n) denotes the external noise. The output signal, e(n), contains both the residual noise and the desired audio signal, it is the signal presented to the eardrum and hence should be as close to the desired audio signal as possible. The residual noise e'(n) is separated from the output e(n), by adding the filtered audio signal a'(n) from $\hat{S}(z)$. The audio signal is used as a reference signal in the adaptive filter $\hat{S}(z)$. The adaptive filter $\hat{S}(z)$ is called the audio interference cancellation filter, since it is used to remove the audio signal from e(n). Estimate of the secondary path model filter $\hat{S}(z)$ is made offline using a white noise input. The estimate of the noise, e'(n) is obtained by mixing e(n) with the desired audio signal a'(n). The reference noise signal x(n) is extracted from e'(n). This reference noise signal and the residual noise signal are fed to the Shaping Algorithm, which computes the weights of the ANC filter denoted by *W(z)* in the block diagram.

For ease of analysis, we shall assume that the audio signal a(n) is of persistent excitation and uncorrelated with the primary noise d(n) and that the audio interference cancellation filter $\hat{S}(z)$ models the secondary path filter $S(z)$. The following derivations of the ANC system can be made after convergence of the adaptive filter $\hat{S}(z)$ [1].

$$E'(z) = E(z) + \hat{S}(z)A(z) \tag{1}$$

$$E(z) = D(z) - U(z)S(z) \tag{2}$$

Substituting (2) into (1), we get

$$E'(z) = D(z) - U(z)S(z) + \hat{S}(z)A(z) \tag{3}$$

As $U(z) = A(z) + Y(z)$, (3) can be written as

$$E'(z) = D(z) - (A(z) + Y(z))S(z) + \hat{S}(z)A(z) \tag{4}$$

If $\hat{S}(z)$ is a perfect model of the secondary path, represented by the filter $S(z)$, that is, $\hat{S}(z) = S(z)$, then (4) becomes,

$$E'(z) = D(z) - Y(z)S(z) \tag{5}$$

D(z) represents the primary noise signal and the term $Y(z)S(z)$ represents the anti-noise signal. Hence $E'(z)$ represents the residual error signal of the ANC system.

The z-transform of the input reference noise signal, x(n), can be written as,

$$X(z) = E'(z) + Y(z)\hat{S}(z) \tag{6}$$

By substituting (5) into (6), we have

$$\begin{aligned} X(z) &= D(z) - Y(z)S(z) + Y(z)\hat{S}(z) \\ &= D(z) + Y(z)(\hat{S}(z) - S(z)) \end{aligned} \tag{7}$$

If $\hat{S}(z) = S(z)$, then $D(z) = X(z)$. Thus, the reference noise signal x(n) is identical to the external noise d(n).

II. THE SHAPING ALGORITHM

For the Shaping Algorithm as shown in Fig.2, Woon S. Gan and Sen M. Kuo in their paper [1] investigated the case using Least Mean Square (LMS) algorithm. However, the gain and step-size for the LMS algorithm are fixed resulting in suboptimal performance when the environment changes. Furthermore, unstable conditions may arise when the noise level is high. To overcome these drawbacks, we propose the adoption of a Variable Step-Size Normalized LMS (VSS-NLMS) algorithm as the Shaping Algorithm. The basic principle of operation of VSS-NLMS algorithm is that when the filter coefficients are close to the optimum solution, a small step size is used; otherwise a large step size is applied. For the experiments mentioned in this paper, time-varying step-size parameter is changed in such a way that the change is proportional to the negative of the gradient of the squared estimation error with respect to the convergence parameter. This algorithm reduces the trade-off between speed of convergence and steady-state error.

Mathematically, the weights are adjusted according to the following expression [2],

$$W_{k+1} = W_k + \mu_k \frac{e_k X_k}{\|X_k\|^2 + \beta} \tag{8}$$

where μ_k is the time-varying step-size and the error signal e_k is defined as,

$$e_k = d_k - X_k^T W_k \tag{9}$$

The step-size sequence μ_k will be adapted using the following expression,

$$\mu_k = \mu_{k-1} - \frac{\rho}{2} \frac{\partial e_k^2}{\partial \mu_{k-1}} \tag{10}$$

which can be transformed after, substituting (8) and (9) into (10), into the following form.

$$\mu_k = \mu_{k-1} + \rho e_k e_{k-1} \frac{X_k^T X_{k-1}}{\|X_{k-1}\|^2 + \beta} \tag{11}$$

where ρ is a small positive constant that controls the behavior of the step-size sequence μ_k.

In addition to VSS-NLMS, the performance of the Normalized LMS (NLMS) algorithm is also investigated. The NLMS algorithm was first introduced by Nagumo and Noda [3]. In its simple form, the algorithm can be represented as follows.

$$y(k) = W^T(k)X(k) \tag{12}$$

$$e(k) = d(k) - y(k) \tag{13}$$

$$W(k+1) = W(k) + \frac{\alpha\, e(k)X(k)}{\gamma + X^T(k)X(k)} \tag{14}$$

The term α is the normalized adaptation factor, its value is chosen between 0 and 2. γ is a small positive term included to ensure that the update term does not become excessively large when the signal power $X^T(k)X(k)$ becomes small.

III. EXPERIMENTS AND PERFORMANCE COMPARISON

Experiments were carried out to assess the performance of the LMS, NLMS and VSS-NLMS algorithms under different noisy environments. For the noise control adaptive filter W(z), 128 taps are used whereas the order of the secondary path adaptive filter is 75 taps. The initial step size value chosen for NLMS is α = 0.004 and the value of γ is chosen to be 0.05. The initial step size value chosen for VSS-NLMS is 0.001 and the optimal value for constants ρ and β is 0.3. The values for ρ and β are critical. It is found that inappropriate selection of these values will result in system instability. For the case with subway train noise, the system is unstable when LMS algorithm is adopted. The output waveforms when the ANC is off and when the ANC is on using the NLMS and VSS-NLMS algorithms are shown in Fig.A1 to Fig.A3 in Appendix A. The residual noise for the two cases is shown in Fig.A4 and Fig.A5. The magnitudes of noise reduction and the convergence rates for the three algorithms under different noise environments are summarized in Tables 1 and 2. For subway train noise, the performance of the system using LMS algorithm is unstable and hence no values are given.

It can be observed that the VSS-NLMS algorithm efficiently attenuates the noise signals by more than 37.6 dB compared to an average of 36dB using NLMS and 14.2 dB using LMS. The convergence rate of the VSS-NLMS algorithm is also much faster. Informal listening tests also reveal that the quality of the audio signal received is significantly better.

TABLE I
NOISE ATTENUATION (dB)

	LMS	**NLMS**	**VSS-NLMS**
Helicopter noise	24	35	38
Jet air noise	12	31	33
Propeller air noise	20	37	38
Subway train noise	Unstable	34	37
Car noise	10	39	41
Air hammer noise	5	38	38
Average (excluding train noise)	14.2	36.0	37.6

TABLE II
RATE OF CONVERGENCE (No. of iterations)

	LMS	**NLMS**	**VSS-NLMS**
Helicopter noise	22000	2470	1500
Jet air noise	120000	1350	1200
Propeller air noise	78000	750	640
Subway train noise	Unstable	1700	1180
Car noise	240000	950	800
Air hammer noise	250000	270	150

The power spectral density of the noise present in the corresponding frame of the signals shown in Figs.A1,A2 and A3 are shown in Fig.3. From the figure, it can be observed that VSS-NLMS gives the highest noise reduction.

IV. CONCLUSION

In this paper, a new algorithm is proposed for active noise cancellation headset. The performance of the new algorithm, Variable Step-Size Normalized LMS is compared with that of the LMS and NLMS under different noisy environments. Results show that not only the convergence of the VSS-NLMS is faster, but it also gives significantly much better noise reduction under all the noisy conditions tested. Informal listening tests also confirm the superiority of the proposed algorithm.

ACKNOWLEDGEMENT

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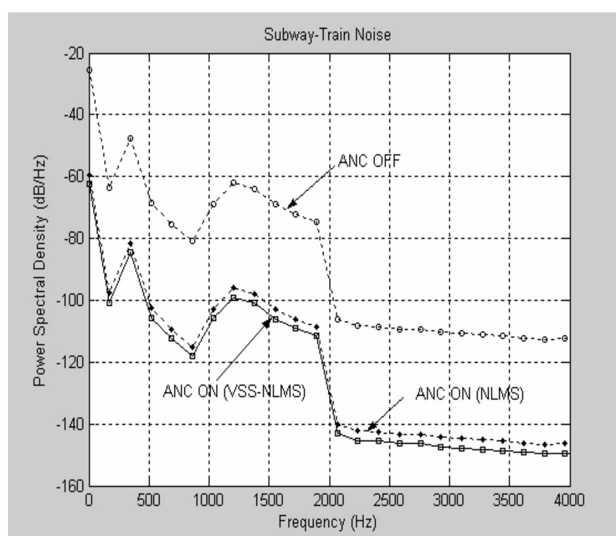

Fig.3 Spectrum showing noise reduction using NLMS and VSS-NLMS algorithms (Subway train noise)

APPENDIX A: WAVEFORMS OF SIGNALS (NOISE: SUBWAY TRAIN SOUND)

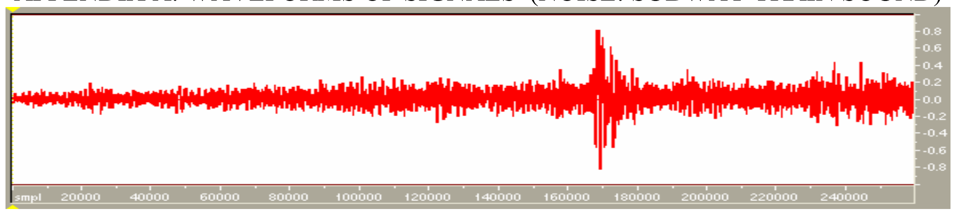

Fig.A1 Noise signal

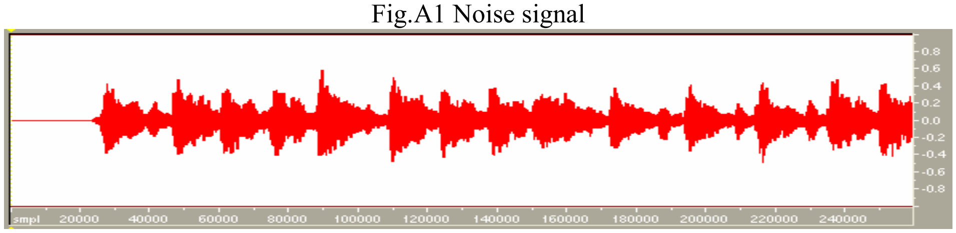

Fig A2 Music signal

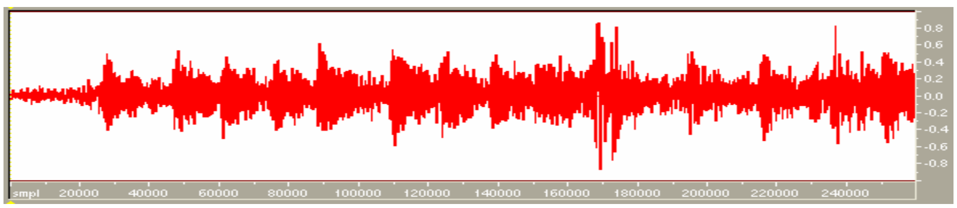

Fig A3 Output when ANC is OFF

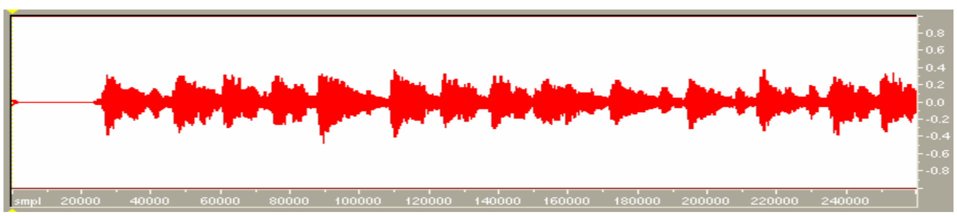

Fig.A5 Output when ANC is ON (VSS-NLMS)

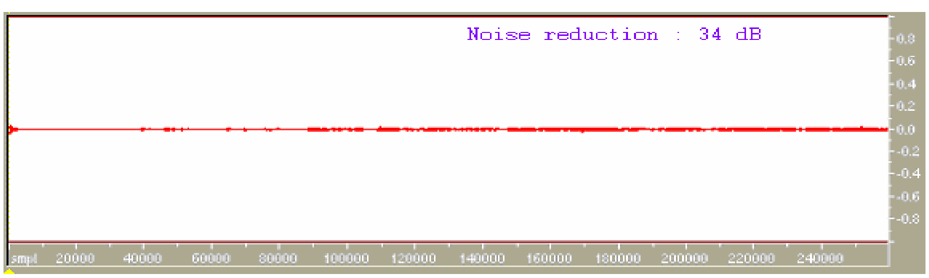

Fig A6 Residual noise (NLMS)

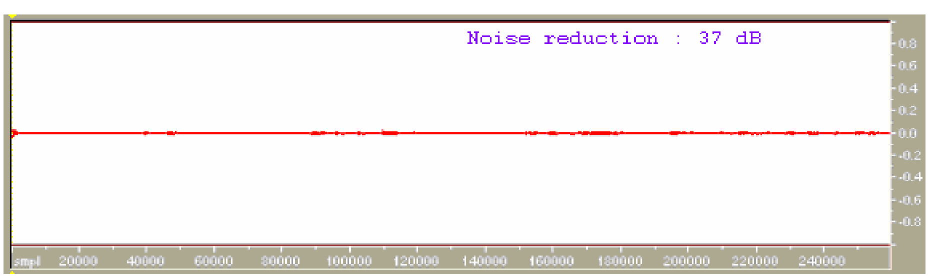

Fig.A7 Residual noise (VSS-NLMS)