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RESEARCH PAPER

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Effect of White Noise for Online Secondary Path Modeling and Noise Reduction in Multichannel ANC System

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Abstract: In practical cases for active noise control (ANC), the secondary path may be time varying .For these cases, the secondary path should be estimated online. Several approaches have been introduced for online secondary path modeling (OSPM) in single- channel feed forward ANC systems .In these systems additive random noise as a training signal is injected to achieve secondary path modeling during online operation .This paper investigates the issue of reducing noise and secondary path modeling in multichannel active noise control by not continually injection of white noise during system operation. The existing methods in multichannel have concentrated on online secondary path modeling. This paper uses the advantages of white noise with larger variance to model the secondary path, but the injection is stopped at the optimum point to increase the performance of the system. It is shown that the proposed method has better performance in reducing residual noise and also it has better convergence rate in online secondary path modeling in multichannel ANC system.

Keywords: Multichannel active noise control; online secondary path modeling (OSPM); Adaptive filter

I. INTRODUCTION

ANC is a technique that cancels the primary unwanted noise by introducing a canceling anti-noise of equal amplitude but opposite phase, that resulting in an attenuated residual noise [1].The most popular adaption algorithm used for active noise control (ANC) application is filtered-x LMS (FXLMS) algorithm which is a modified version of the LMS algorithm [3].The block diagram of a feed forward FXLMS algorithm is shown in Figure1. Here $P(z)$ is the primary path, the acoustic response from the reference noise source to the error sensor and $S(z)$ is secondary path.
$\hat{S}(z)$ Is estimation of the secondary path $S(z)$ and $W(z)$ is a adaptive FIR filter. The secondary path may be time varying and it should be estimated online when the ANC is in operation [4,6] . For solving this problem the basic additive random noise technique for online secondary path modeling in ANC systems is proposed by Eriksson et el. [5]. As shown in Figure2 this system comprises two processes: a noise control process and secondary path modeling process. Another methods that have been proposed after Eriksson, were Bao's, Zhang's and Akhtar's methods [6-11]. Bao and Zhang have used another adaptive filter that lead to increasing computational complexity but Akhtar's method has better performance in secondary path modeling and also it has lower computational complexity [9]. In an enclosure or a large-dimention duct, it is desirable to cancel noise at several location, so, it is generally necessary to use a multichannel ANC system with several secondary sources, error sensors, and perhaps even several reference sensors [1,2]. Figure3 shows structure of a multichannel $(I \times J \times K)$ acoustic ANC system with I reference inputs, J secondary sources, and K error sources.

The $J \times K$ secondary paths may be time varying, and they need to be estimated online during system operation. In this paper we investigate various methods for online secondary path modeling and reduction noise in multichannel $(I \times J \times K)$ ANC system, where $I = 1, J = 2$ and $K = 2$, with one reference microphone, two secondary loadspeakers and two error microphones. Existing online SPM techniques in $1 \times 2 \times 2$ ANC system use white noise with a low variance to model the secondary path. Since injecting white noise increases residual noise and it is undesirable, here we use white noise with larger variance in modeling the secondary path which cause to better convergence speed for OSPM filters that is a extension of Davari's method [13] to multichannel $(1 \times 2 \times 2)$ ANC system . To prevent the undesirable effect raised by the larger white noise (increasing residual noise) , the variable step size (VSS) LMS algorithm that is used to adapt the modeling filter of the secondary path, is stopped at the optimum point[13].This algorithm has two benefits; one using white noise with larger variance that improves convergence speed for OSPM filters and the other stopping injection white noise that increases noise attenuation. In practical cases, it is possible that the secondary path change suddenly and it lead to divergence of the OSPM filter. To prevent this problem, white noise is injected again to remodel the secondary path. The organization of the rest paper is as the follows: section 2 describes Eriksson's[5] and Akhtar's methods[9] for online SPM in multichannel ANC system ,and section 3 describes the proposed method that is extension of a method for single channel [13] to multichannel ANC system. Section4 gives details of simulation results and finally, section 5 contains concluding remarks.

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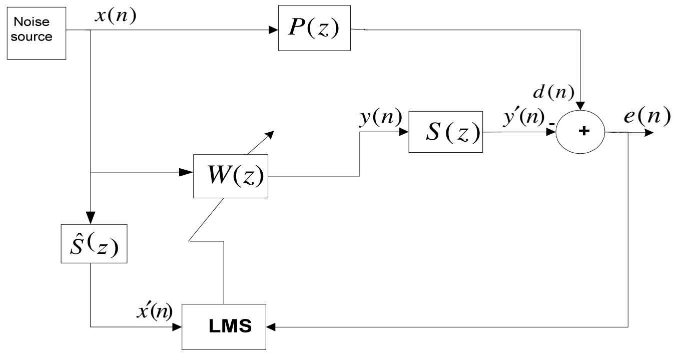

Figure1. Block diagram of feed forward ANC system using FXLMS algorithm.

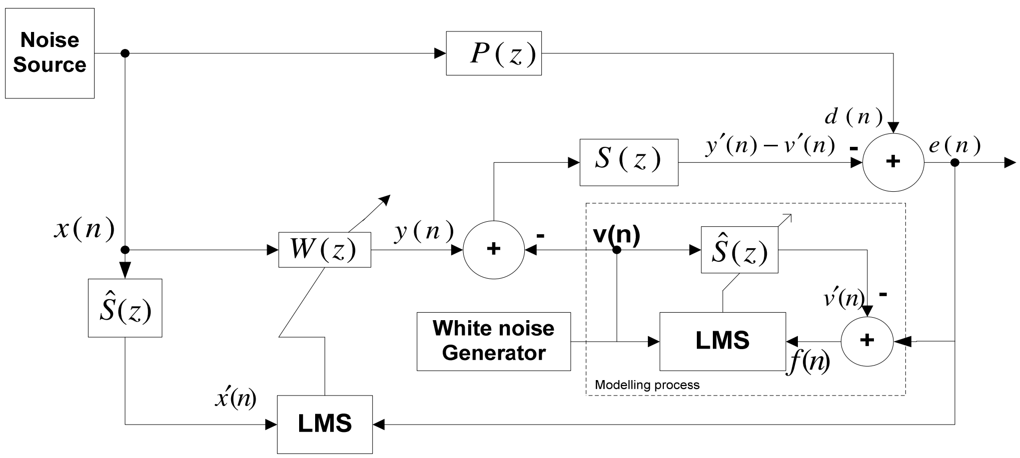

Figure2. Eriksson's method for ANC system with online secondary path modeling

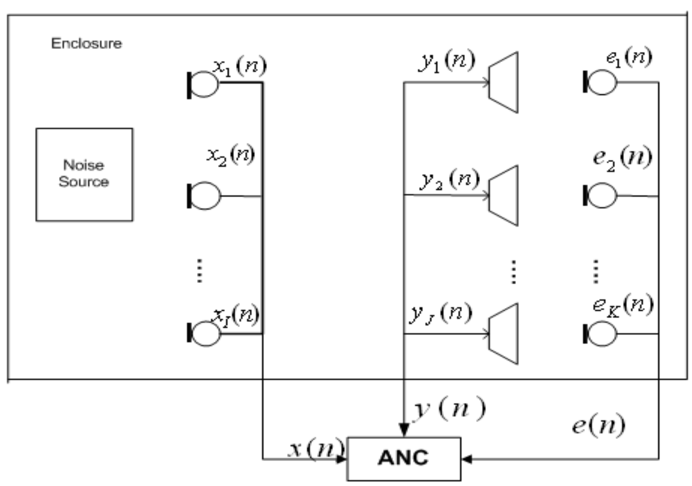

Figure3.stucture of a multichannel with I reference inputs, J secondary sources and K error sensors

II. SUMMARY OF EXISTING METHODS FOR ONLINE SPM

A. Eriksson's method

As mentioned before, the basic additive random noise technique is proposed by Eriksson et el. [5].In Figure4 has been shown the extension of this method to the case of 1×2×2 ANC system. $S_{kj}(z)$, where k=1, 2 and j=1,2, are the secondary path transfer functions from the jth canceling signal $y_j(n)$ to kth microphone $e_k(n)$ and also $P_{11}(z)$ and $P_{21}(z)$ represent primary paths tween noise source $x(n)$ and two error microphones $e_1(n)$ and $e_2(n)$,respectively. $\hat{S}_{kj}(z)$ Are the secondary path estimates that initially are estimated by offline modeling and during system operation are modeled online. This method uses additive random noise $v_1(n)$ for online secondary path modeling and $z^{-\Delta}$ is inter-channel decoupling delay unit used to generate uncorrelated excitation signal $v_2(n)$[1].

The secondary signals $y_1(n)$ and $y_2(n)$ are generated by adaptive filters $W_1(z)$ and $W_2(z)$and are combined with $v(n)$ to derive the secondary sources, so we have:

$$y_i(n) = w_j^T(n)x(n) \qquad (1)$$

$w_j(n)$ is coefficients vector for jth control filters $W_j(z)$ of length L and $x(n)$is reference signal at time n , that are represented as:

$w_j(n) = [w_{j0}(n)\ w_{j1}(n) \dots\ w_{jL-1}(n)]^T$ and $x(n) = [x(n)\ x(n-1) \dots\ x(n-L+1)]^T$.

The residual noise is expressed as:

$$e_k(n) = d_k(n) - [y'_{k1}(n) + y'_{k2}] + [v'_{k1}(n) + v'_{k2}(n)] \quad (2)$$

$d_k(n)$ Is the primary noise signal at kth microphone and $[y'_{k1}(n) + y'_{k2}]$, $[v'_{k1}(n) + v'_{k2}(n)]$ are secondary noise components .The signal $y'_{kj}(n) - v'_{kj}(n)$, is generated by filtering $(y_j(n) - v_j(n))$ through the secondary path $S_{kj}(z)$ as follow:

$$y'_{kj}(n) - v'_{kj}(n) = s_{kj}(n) * (y_j(n) - v_j(n) \qquad (3)$$

where $*$ denotes linear convolution and $s_{kj}(n)$ is impulse response of secondary path $S_{kj}(z)$.

The coefficients of two adaptive control filters are adjusted by multiple-error FXLMS (MeFXLMS) algorithm as:

$$w_j(n+1) = w_j(n+1) + \mu_w[\hat{x}'_{j1}(n)e_1(n) + \hat{x}'_{j2}(n)e_2(n))] \qquad (4)$$

$$\hat{x}'_{jk}(n) = \hat{s}_{kj}(n) * x(n) \qquad (5)$$

where μ_w is step- size for control filters and $\hat{s}_{kj}(n)$ is the model of secondary path $s_{kj}(n)$ that is convolved with reference noise to generate filtered signal $\hat{x}'_{jk}(n)$.Error signal for OSPM filters is $f_k(n)$, that is expressed as :

$$f_k(n) = e_k(n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k2}(n)] = d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] + [v'_{k1}(n) - \hat{v}'_{k1}(n)] + [v'_{k2}(n) - \hat{v}'_{k2(n)}] \qquad (6)$$

Where $\hat{v}_{kj}(n) = s_{kj}(n) * v_j(n)$. Coefficients of modeling filters $\hat{s}_{kj}(n)$ are updated as follow:

$$\hat{s}_{kj}(n+1) = \hat{s}_{kj}(n) + \mu_s v_j(n) f_k(n) \qquad (7)$$

Where μ_s is step size parameter for modeling filters. The additive random noise algorithm is an invasive approach because it appears at control zone and increases residual noise, so a low level of random noise $v(n)$ is required .Considering (6) and (2), $d_k(n) - \left[y'_{k1}(n) + y'_{k2}(n)\right]$ acts as a disturbance for the online SPM filters especially at the start because $y'_{k1}(n)$ and $y'_{k2}(n)$ are zero, and $\left[v'_{k1}(n) + vk2'n\right.$ acts as a disturbance for control filters, but since the level of white noise is low, this disturbance is negligible.

B. Akhtar's Method

In order to reducing disturbance for the online SPM filters in Eriksson's method, Akhtar proposed variable step size-LMS algorithm (VSS-LMS) for online SPM [5-6] . The extension of this method to the case of $1 \times 2 \times 2$ ANC system is shown in Figure5. Initially this disturbance is very large, but as ANC system convergences, this disturbance reduces towards zero. This allows to use initially a small step size and gradually increases the step size as the ANC system start to converge. For more details on theory of this algorithm reader may refer to [9]. In this method, $f_k(n)$ is used as error signal for control filters which decreases disturbance factor for convergence of control filters because as the modeling process convergences($S_{kj}(z) \to \hat{S}_{kj}(z)$), $[\ v'_{k1}(n) -$ Error! Bookmark not defined. $\hat{v}'_{k1}(n)]$ and $[\ v'_{k2}(n) - \hat{v}'_{k2}(n)]$ reduce toward zero and disturbance factor is deleted gradually.

Here μ_s is function of variable $\rho_k(n)$ and varies between μ_{smin} and μ_{smax} . $\rho_k(n)$ depends on powers of error signals f_k and e_k, and is defined as:

$$\rho_k(n) = P_{fk}(n) / P_{ek}(n) \qquad (8)$$

$$\rho_k(0) \approx 1 \quad , \quad \lim_{n\to\infty} \rho_k(n) \to 0$$

The powers of error signals $e_k(n)$ and $f_k(n)$ obtained as:

$$P_{ek}(n) = \lambda P_{ek}(n-1) + (1-\lambda)e_k^2(n)$$

$$(9)$$

$$P_{fk}(n) = \lambda P f_k(n-1) + (1-\lambda) f_k^2(n$$

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Where λ is the forgetting factor $(0.9 < \lambda < 1)$.

Now, the step size for online SPM filters $\hat{S}_{k1}(z)$ and $\hat{S}_{k2}(z)$ is calculated as:

$$\mu_{sk}(n) = \rho_k(n)\mu_{smin} + (1 - \rho_k(n))\mu_{smax} \qquad (10)$$

Where μ_{smin} and μ_{smax} and λ are determined experimentally. The coefficients for control filters are updated using MeFXLMS algorithm as:

$$w_j(n+1) = w_j(n) + \mu_w[\hat{x}'_{j1}(n)f_1(n) + \hat{x}'_{j2}(n)f_2(n)] \qquad (11)$$

VSS-LMS algorithm increases modeling accuracy and improve performance system.

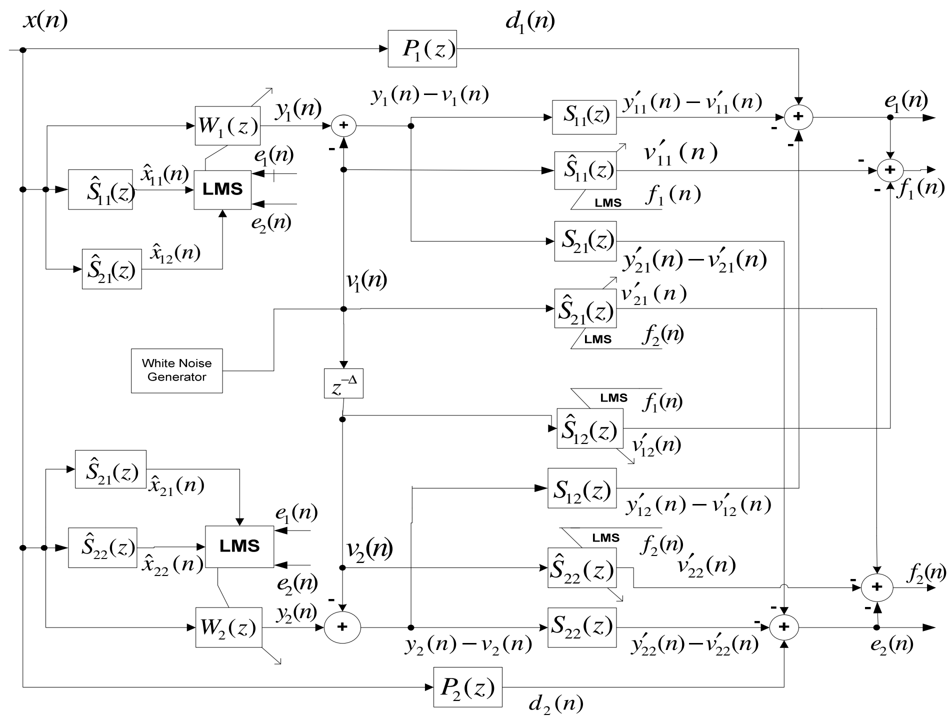

Figure4. Eriksson's method for online secondary path modeling (SPM) in multichannel (1×2×2) ANC systems

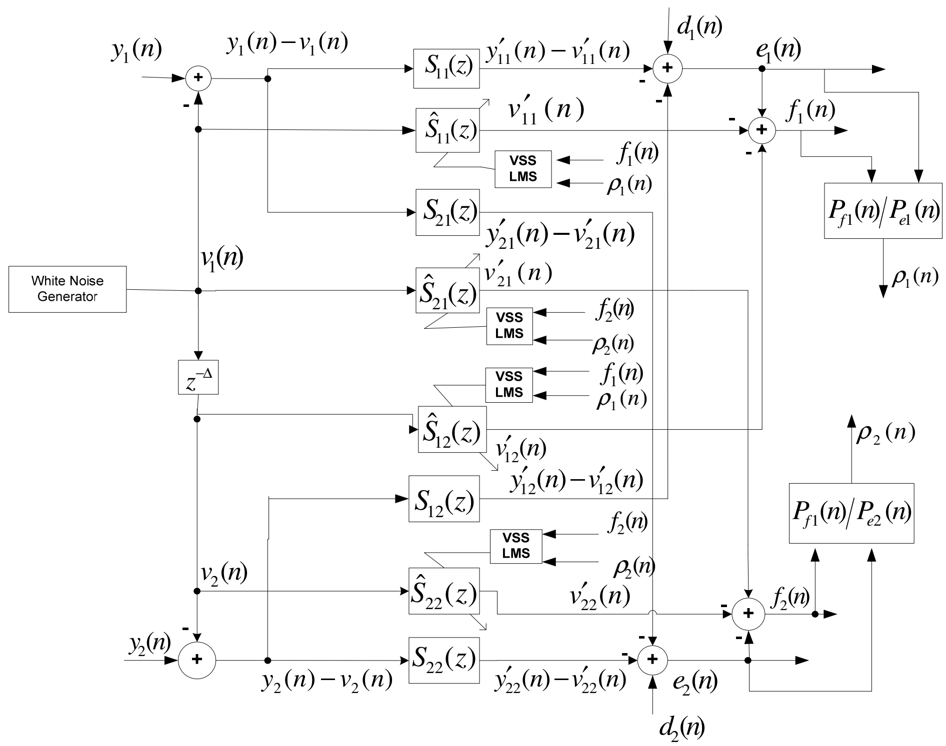

Figure5.Akhtar's method for online SPM in $1 \times 2 \times 2$ ANC system

III. PROPOSED METHOD FOR ONLINE SECONDARY PATH MODELING AND REDUCING NOISE IN $1 \times 2 \times 2$ ANC SYSTEMS

Here we extend Davari's work in single channel [13] to the $1 \times 2 \times 2$ ANC system. This method has the structure similar to Akhtar's method and follows VSS-LMS algorithm. It uses white noise with larger variance in modeling the secondary path that improves convergence rate for OSPM filters. This method has two stages: in first stage white noise with larger variance (compared to existing method) is used that increases convergence speed for OSPM filters but decrease residual noise attenuation, which is undesirable, because the main purpose in ANC is noise reduction. To prevent this effect, in stage two, injection white noise and VSS-LMS algorithm is stopped at the optimum point. Stopping injection white noise increase noise attenuation because in order to (3), $v(n)$ is deleted. VSS-LMS algorithm is initially set to small step size and during the process, $\mu_{sk}(n)$ increases and $f_k(n)$ decreases .Increasing $\mu_{sk}(n)$ corresponds to a faster convergence and decreasing $f_k(n)$ corresponds to a good estimation for $\hat{S}_{kj}(z)$ and injection of white noise is stopped at the optimum point when:

$$\mu_{smax} - \mu_{sk} < \alpha_k \quad , 10^{-5} \leq \alpha_k < 5 \times 10^{-4} \qquad (12)$$

If during stage two, the secondary path suddenly changes, system will diverge. To prevent this effect, $\hat{S}(z)$ needs to be updated. So the algorithm is design in such a way that it can control the secondary path changes by the following expression [13]:

$$20 \log 10 f(n) < 0 \qquad (13)$$

The above inequality is traced after stopping white noise and if it does not satisfy, the system injects white noise again to remodel $\hat{S}(z)$.

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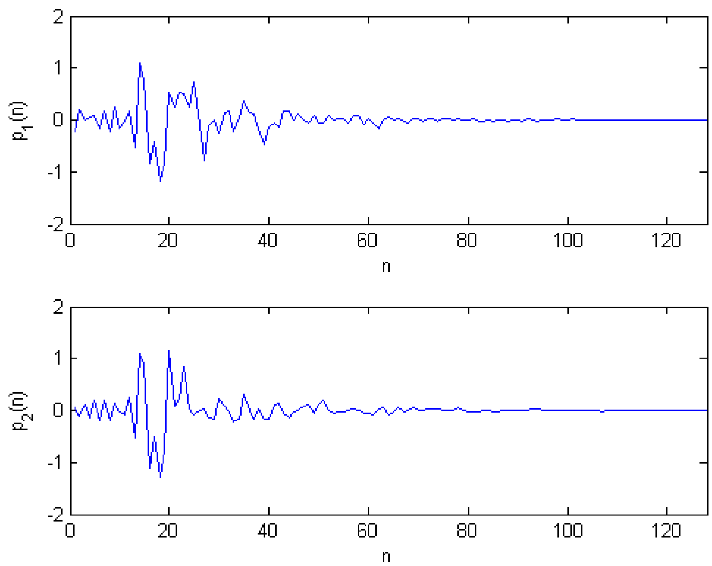

Figure6.impulse response of primary paths $P_1(z)$ and $P_2(z)$

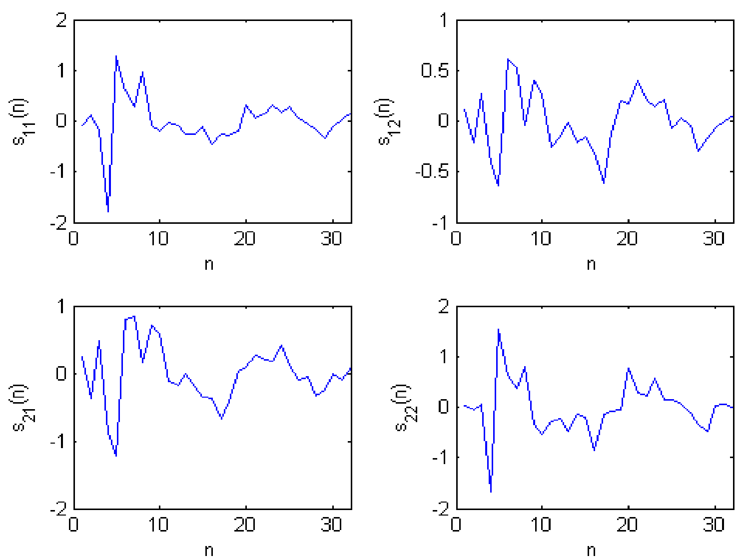

Figure7. impulse response of secondary paths $S_{11}(z)$,$S_{12}(z)$,$S_{21}(z)$ and $S_{22}(z)$

IV. SIMULATION RESULTS

In this section the proposed ANC system is simulated and primary and secondary paths are shown in Figure6 and7. Lengths of modeling filters $\hat{S}_{kj}(z)$ and control filters $W_j(z)$ are 32 and 64, respectively. The initial coefficients for $\hat{S}_{kj}(z)$ are estimated by offline modeling, which is stopped when the modeling error (14) has been reduced to -5dB [1].All the results shown are average of 10 realizations and a sampling frequency of 4 kHz is used. The situations in case1 are the same as [12] and α_k and step sizes for case2 and case3 are obtained by trial and error, for fast and stable convergence and also for better noise reduction.

used the data provided with [1], the primary and secondary acoustic paths are considered as FIR filters of tap-weight length 128 and 32, respectively. The impulse responses of

The results are simulated on the basis of relative modeling error $(\Delta S(dB))$ for $S_{21}(z)$ and $S_{22}(z)$ and noise reduction$(R(dB))$ that are defined as:

$$\Delta S_{kj}(dB) = 10\log_{10}\left(\frac{\sum_{i=0}^{M-1}\left[s_{kj}(n) - \hat{s}_{kj}(n)\right]}{\sum_{i=0}^{M-1} s_{kj}(n)}\right)$$

$$R_k = -10\log_{10}\left[\frac{\sum e_k^2(n)}{\sum d_k^2(n)}\right] \tag{14}$$

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Where M is the length of OSPM filter

A. Cas1

In this case, x(n) is considered as a narrowband signal comprising frequencies of 150 Hz,300Hz,and 450Hz and it's variance is adjusted to 2 and a zero mean white noise is added with SNR of 30dB. Signal v(n) is a zero-mean white Gaussian noise of variance 0.05 for Eriksson's and Akhtar's method and variance 0.24 for proposed method. The parameters for the Eriksson's and Akhtar's and proposed method are adjusted as follow: Eriksson's method: $\mu_w = 1 \times 10^{-5}$, $\mu_s = 2 \times 10^{-4}$, Akhtar's method: $\mu_w = 1 \times 10^{-5}$, $\mu_{smin} = 7.5 \times 10^{-4}$, $\mu_{smax} = 7.5 \times 10^{-3}$, proposed method: $\mu_w=1\times10^{-5}$, $\mu_{smin} = 7.5 \times 10^{-4}$, $\mu_{smax} = 7.5 \times 10^{-3}$,$\alpha_1=\alpha_2=2\times10^{-5}$ and $10^{-5} \leq \alpha_k < 5 \times 10^{-4}$.

Simulation results for case1 are shown in s 8 and 9. As shown in Figure8, the proposed method has better convergence speed for OSPM filters.Figure9. shows the curves of step size and noise reduction . As can be seen in Figure9(b), initially, the step sizes are set to small value but during system operation ,they increase toward maximum value. The step size μ_{s1} for proposed method increase faster to maximum value which lead to faster convergence for OSPM filters and when it reaches to optimum point, injection of white noise is stopped and according to fig9(a), noise reduces more than Eriksson's and Akhtar's method..

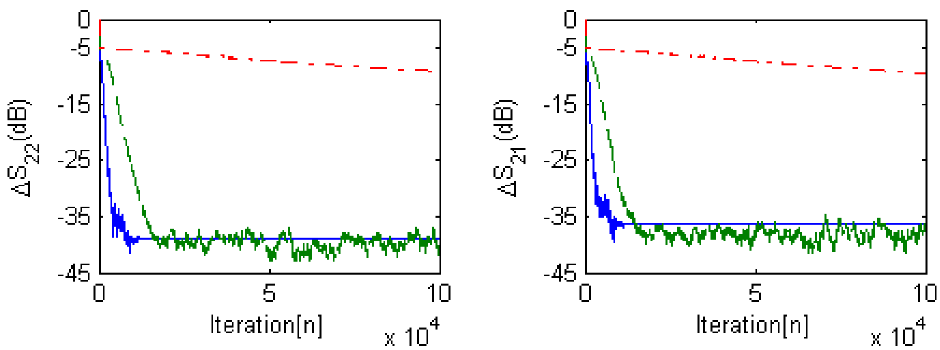

Figure8. Secondary path modeling error for $\hat{S}_{22}(z)$,$\hat{S}_{21}(z)$ (Eriksson's method (dash-dot line),Akhtar's method(dashed line),Proposed method(solid line)) in case1

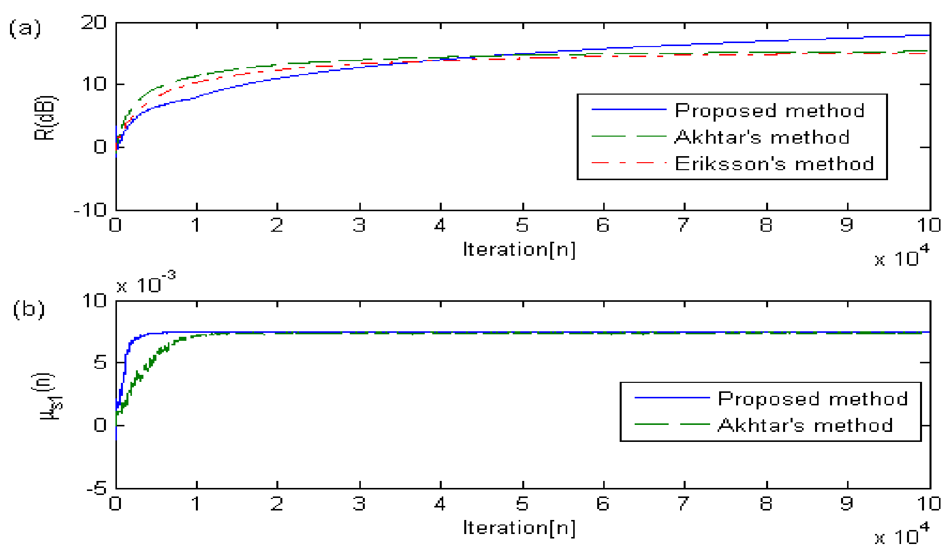

Figure9. Simulation results for case1: (a) noise reduction R(dB) for error microphone1; and (b) step size μ_{s1} for Akhtar's and proposed method.

B. Case2

Here we consider x(n) a narrowband signal comprising frequencies of 0.1-0.9 *KHz* with the step of 100 Hz. Its variance is adjusted to 2, and a white noise with SNR of 30 dB is added. As in case1, $v(n)$ is a zero-mean white Gaussian noise of variance 0.05 for Eriksson's and Akhtar's method and variance 0.24 for proposed method The step size parameters are adjusted as: Eriksson's method: $\mu_w=1\times10^{-5}$, $\mu_s=5\times10^{-4}$, Akhtar's method: $\mu_w=9\times10^{-5}$, $\mu_{smin}=5\times10^{-4}$, $\mu_{smax}=7.5\times10^{-3}$, proposed method: $\mu_w=9\times10^{-5}$, $\mu_{smin}=5\times10^{-4}$, $\mu_{smax}=7.5\times10^{-3}$, $\alpha_1 = \alpha_2 = 4 \times 10^{-5}$ and $10^{-5} \leq \alpha_k < 5 \times 10^{-4}$. The simulation results are shown in Figure10 and Figure11 **.**We conclude from these simulations

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that the proposed method has better performance in both convergence speed and noise reduction.

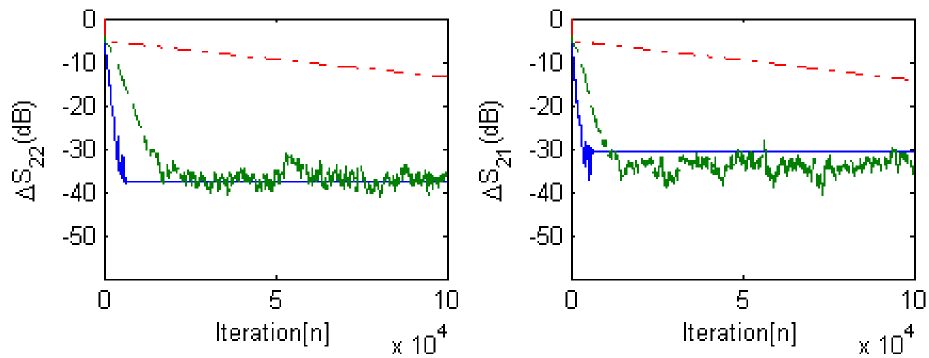

Figure10 .Secondary path modeling error for $\hat{S}_{22}(z)$,$\hat{S}_{21}(z)$ (Eriksson's method (dash-dot line),Akhtar's method(dashed line),Proposed method(solid line)) in case 2.

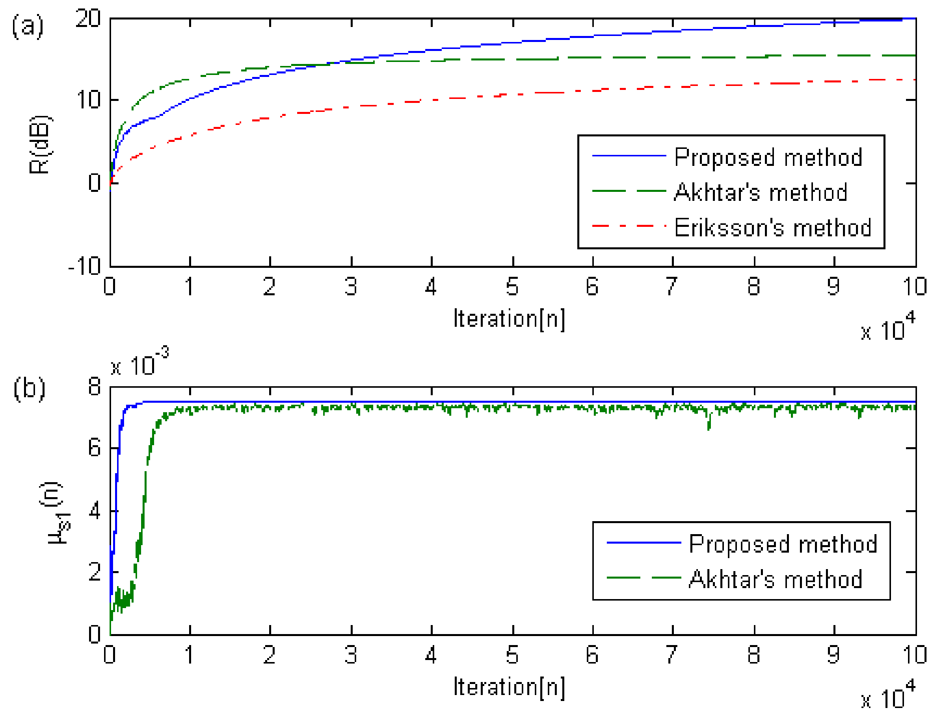

Figure11. Simulation results in case2: (a) noise reduction R(dB) for error microphone 1, and (b) step size μ_{s1} for Akhtar's and proposed method.

C.Case3

Here we assume x(n) a zero mean white Gaussian noise of unit variance that is filtered through a bandpass filter with the passband 100-400 Hz and it's variance is adjusted to 2.v(n) is the same as case 1 and 2. The step size parameters are adjusted as : Eriksson's method: $\mu_w=9\times10^{-5}$, $\mu_s=7\times10^{-4}$, Akhtar's method: $\mu_w=9\times10^{-5}$, $\mu_{smin}=9\times10^{-4}$, $\mu_{smax}=9\times10^{-3}$, proposed method: $\mu_w=9\times10^{-5}$, $\mu_{smin}=9\times10^{-4}$, $\mu_{smax}=9\times10^{-3}$,$\alpha_1=\alpha_2=1\times10^{-4}$ and $10^{-5}\leq \alpha_k <5\times10^{-4}$. The simulation results are given in Figure12 and Figure13 .Similar to the previous cases ,in proposed method, OSPM filters converge faster and noise is reduced more than Eriksson's and Akhtar's method.

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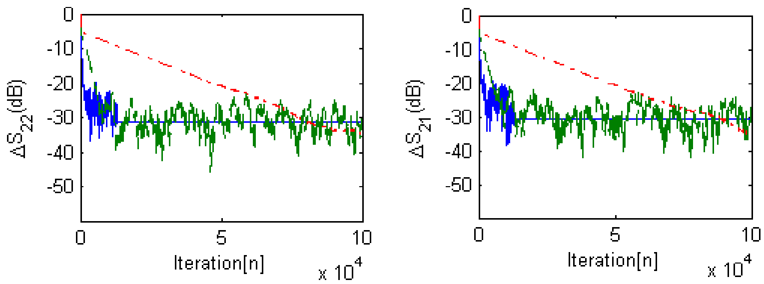

Figure12 .Secondary path modeling error for $\widehat{S_{22}}(z)$,$\hat{S}_{21}(z)$ (Eriksson's method (dash-dot line), Akhtar's method (dashed line), Proposed method (solid line)) in case 3.

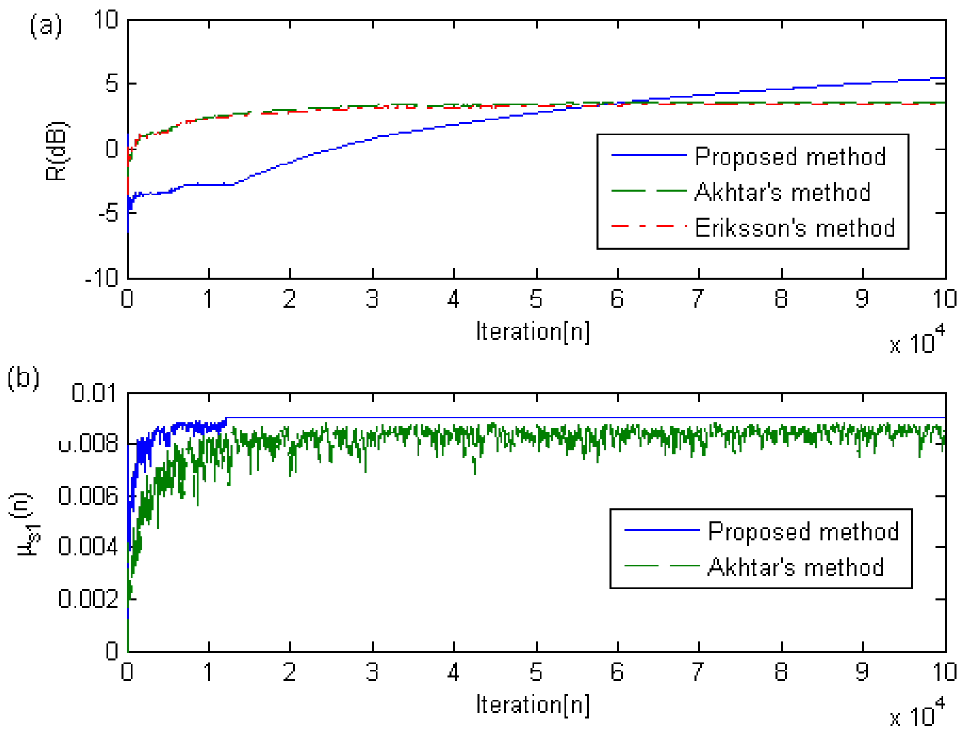

Figure13. Simulation result in case 3: (a) noise reduction R(dB) for error microphone 1, and (b) step size μ_{s1} for Akhtar's and proposed method.

D. *Case4*

In this case we have the reference signal and parameters in case1 and assume that the secondary paths change suddenly at n=50000. α_k , before and after sudden change is set to 1×10^{-5} and 2×10^{-5}, respectively. In proposed method, before sudden change in secondary path, injection of white noise is stopped and during this time, we trace equation (13). At n=50000, equation (13) does not satisfy and we inject white noise again.

As can be seen in Figure14 and Figure15 (b), the proposed method remodel the secondary path at n=50000 and step size decreases at this time and gradually increases. In this case, the proposed method gives better performance in modeling the secondary paths.

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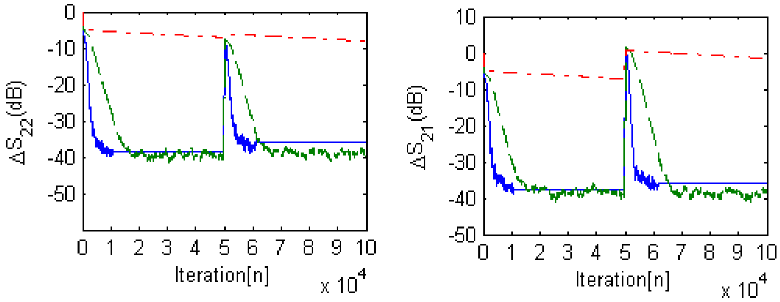

Figure14. Secondary path modeling error for $\hat{S}_{22}(z)$,$\hat{S}_{21}(z)$ (Eriksson's method (dash-dot line), Akhtar's method (dashed line), proposed method (solid line)) in case4

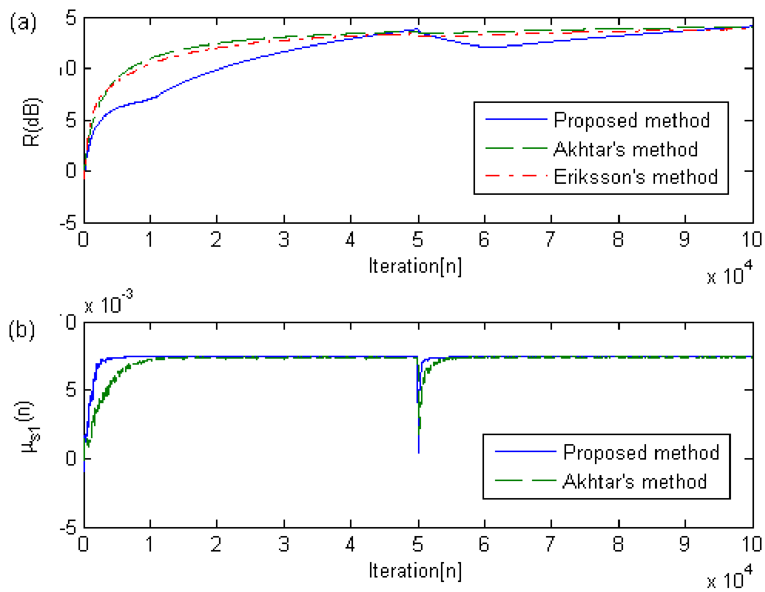

Figure15. Simulation results in case4: (a) noise reduction R(dB) for error microphone 1, and (b) step size μ_{s1} for Akhtar's and proposed method

E. .Case5

In this experiment we want to investigate the advantages of using white noise with larger variance in proposed method compared to Eriksson's and Akhtar's method. Here we consider x(n) and parameters similar to case1, expect that all methods use white noise with variance 0.24. According to simulation results in Figure16 and Figure9(a) , the proposed method can use the advantages of larger variance and achieve better performance in noise reduction , but in Eriksson's and Akhtar's method, should be used white noise with lower level for decreasing disturbance factor for control filters.

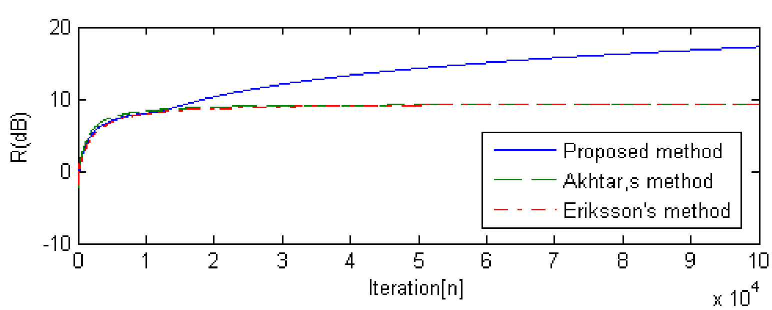

Figure16. Simulation result in case5: noise reduction $R(dB)$ for error microphone 1

V. CONCLUSION

In this paper, we have investigated three methods for online secondary path modeling and noise reduction in multichannel 1×2×2 ANC system. According to simulation results on various reference signals, from among three methods, the proposed method has faster convergence rate for OSPM filters and more noise reduction. It achieves faster

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convergence rate by using white noise with larger variance and more noise reduction due to stopping injection of white noise. It is also robust against sudden change in secondary paths.

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