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A Simplified Method for Online Secondary Path Modeling in Multichannel ANC Systems

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***Abstract*— In single-channel feedforward active noise control (ANC) systems, the additive random noise-based method are often applied to achieve secondary path modeling during online operation of ANC systems. This paper investigates the issue of online secondary path modeling (OSPM) in multichannel ANC systems. It is shown that the application of existing methods for OSPM in multichannel ANC systems, greatly increases the computational complexity. This paper is an extension of our previous work for OSPM in ANC systems. It is shown that Authors' method has reduced computational complexity as compared with the other methods. The computer simulations are carried out which demonstrate the effectiveness of the proposed method.**

I. Introduction

Active noise control (ANC) is based on the principle of destructive interference of propagating acoustic waves. The most popular adaptation algorithm used for ANC applications is the FxLMS algorithm [1]. The basic method for ANC systems with online secondary path modeling (OSPM) is proposed by Eriksson et. al [2]. As shown in Fig. 1, the ANC filter $W(z)$ is updated using FxLMS algorithm, where the reference signal, $x(n)$, is filtered through the model of the secondary path, $S(z)$, following the adaptive filter $W(z)$. The OSPM filter $\hat{S}(z)$ is used to model $S(z)$, and is updated using LMS algorithm. The main problem with this system is the intrusion between the control process and modeling process, which degrades the overall performance of the ANC system. Improvements in the Eriksson's method have been proposed in [3]–[5]. These improved methods introduce another adaptive filter into the ANC system of Fig. 1, and hence result in an increased computational complexity.

In this paper we investigate various methods for OSPM in multichannel ANC systems. In particular, we consider $1\times2\times2$ ANC system comprising one reference signal, two secondary loudspeakers and two error microphones, with the presumption that study can be extended to general $I\times J\times K$ ANC systems. Section II describes extension of Eriksson's method [2], and Zhang's cross-updating method [5] for OSPM in multichannel ANC systems. Section III explains the proposed method, which is extension of authors' previous work [7] for single-channel ANC systems. The main idea is to have structure similar to Eriksson's method and to achieve performance as comparable to that of Zhang's method. Thus we intend to achieve improved performance yet keeping the computational complexity low. Section IV presents the computer simulations and concluding remarks.

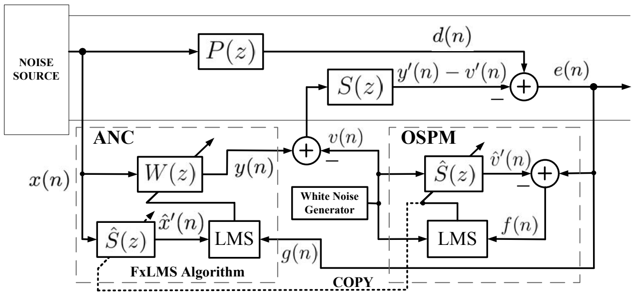

Fig. 1. Eriksson's method for OSPM in single-channel ANC systems.

II. Online Secondary Path Modeling in $1\times2\times2$ ANC Systems

A. Eriksson's Method

As shown in Fig. 1, the Eriksson's method for OSPM in ANC systems add an LMS algorithm-based modeling filter to identify the secondary path $S(z)$. Extending this method to the case of $1\times2\times2$ ANC system, we need four modeling filters $\hat{s}_{kj}(n)$ to identify the secondary paths $s_{kj}(n)$, $j=1,2$, $k=1,2$. This method is shown in Fig. 2. Here $P_{11}(z)$ and $P_{21}(z)$ represent primary paths between noise source and two error microphones $e_1(n)$ and $e_2(n)$, respectively; $W_1(z)$ and $W_2(z)$ are two adaptive filters generating the canceling signals $y_1(n)$ and $y_2(n)$, respectively for two error microphones; and $S_{kj}(z)$ represent secondary path between kth microphone $e_k(n)$ for $k=1,2$ and jth canceling signal $y_j(n)$ for $j=1,2$. Here $v_1(n)$ is the internally generated random noise that is uncorrelated with $d_1(n)$, $d_2(n)$, $y_1(n)$, and $y_2(n)$; and $z^{-\Delta}$ is inter-channel decoupling delay unit used to generate uncorrelated excitation signal $v_2(n)$ [1].

The adaptive filters $W_1(z)$ and $W_2(z)$ take the reference signal $x(n)$ to generate the canceling signals as

$$y_j(n) = \boldsymbol{w}_j^T(n)\boldsymbol{x}(n) \tag{1}$$

where $\boldsymbol{w}_j(n) = [w_{j0}(n), w_{j1}(n), \cdots, w_{jL-1}(n)]^T$ is tap-weight vector for jth control filter $W_j(z)$, L is the tap-weight length of $W_j(z)$, $\boldsymbol{x}(n) = [x(n), x(n-1), \cdots, x(n-L+1)]^T$ is tap-input vector, and $j=1,2$. The signal $y_j(n)-v_j(n)$ is filtered through the secondary path $S_{kj}(z)$ to generate the

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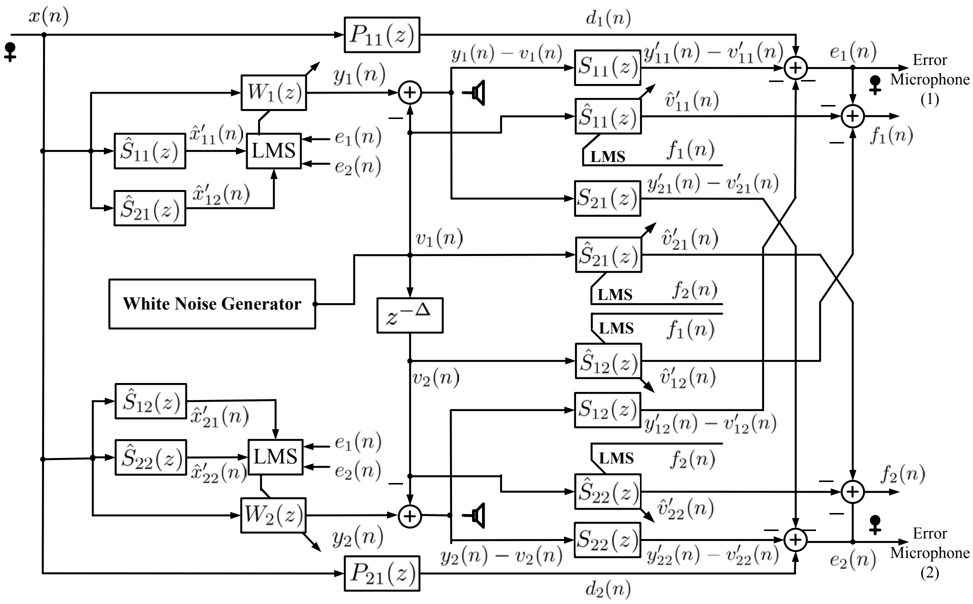

Fig. 2. Eriksson's method for online secondary path modeling (OSPM) in multichannel (1 × 2 × 2) ANC systems.

canceling signal $y'_{kj}(n) - v'_{kj}(n)$ as

$$y'_{kj}(n)y'_{kj}(n) - v'_{kj}(n) = s_{kj}(n) * y_j(n) \tag{2}$$

where $s_{kj}(n)$ is impulse response of secondary path $S_{kj}(z)$ between kth error microphone and jth control filter, and $*$ denotes linear convolution. Now error signal at kth microphone is give as

$$e_k(n) = d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] + [v'_{k1}(n) + v'_{k2}(n)]. \tag{3}$$

where $d_k(n) = p_{k1} * x(n)$ is the primary noise signal at kth microphone. The jth adaptive filter is updated using MeFxLMS algorithm as

$$\boldsymbol{w}_j(n+1) = \boldsymbol{w}_j(n) + \mu_w[\hat{\boldsymbol{x}}'_{j1}(n)e_1(n) + \hat{\boldsymbol{x}}'_{j2}(n)e_2(n)] \tag{4}$$

where μ_w is step-size for control filters, and $\hat{\boldsymbol{x}}'_{jk}(n)$ is the filtered reference signal obtained as

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

where $\hat{s}_{kj}(n)$ is model of the secondary path $s_{kj}(n)$. Using the outputs of OSPM filters $\hat{s}_{k1}(n)$ and $\hat{s}_{k2}(n)$, the error signal for LMS equation of $\hat{s}_{k1}(n)$ and $\hat{s}_{k2}(n)$ is generated as

$$\begin{aligned} f_k(n) &= e_k(n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k2}(n)] \\ &= d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] \\ &\quad +[v'_{k1}(n) - \hat{v}'_{k1}(n)] + [v'_{k2}(n) - \hat{v}'_{k2}(n)] \end{aligned} \tag{6}$$

where $\hat{v}'_{kj}(n) = \hat{s}_{kj}(n) * v_k(n)$ is an estimate of $v'_{kj}(n)$. Now the OSPM filters $\hat{s}_{kj}(n)$ are adapted using LMS algorithm as

$$\hat{\boldsymbol{s}}_{kj}(n+1) = \hat{\boldsymbol{s}}_{kj}(n) + \mu_s \boldsymbol{v}_j(n) f_k(n) \tag{7}$$

where μ_s is step size and $\boldsymbol{v}_j(n)$ is data buffer, for OSPM filters $\hat{s}_{kj}(n)$. Here $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ acts as a disturbance for the OSPM filters. Due to presence of strong disturbance, the convergence of the OSPM filters is greatly frustrated and in the worst case (especially at start when canceling signals $y'_{k1}(n)$ and $y'_{k2}(n)$ are zero), the adaptation may become unstable.

B. Zhang's Cross-updated Method

In order to reduce mutual intrusion of control and OSPM filters, Zhang's *et. al.* has proposed a cross-updated ANC system in [5]. The application of this method for OSPM in $1 \times 2 \times 2$ ANC systems is shown in Fig. 6. Here, we give a very briefly description of this method and for details the reader is referred to [5]. The basic idea is to process the kth error signal $e_k(n)$ such that the component $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ can be removed form (7). This is done by introducing an adaptive noise cancelation filter (ADNC) $H_k(z)$ excited by the reference signal $x(n)$. As shown in Fig. 6., the desired response for $H_k(z)$ is generated by subtracting the outputs of $\hat{S}_{k1}(z)$ and $\hat{S}_{k2}(z)$ from the error signal $e_k(n)$, and is given as

$$\begin{aligned} g_k(n) &= e_k(n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k2}(n)] \\ &= d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] \\ &\quad +[v'_{k1}(n) - \hat{v}'_{k1}(n)] + [v'_{k2}(n)] - \hat{v}'_{k2}(n)]. \end{aligned} \tag{8}$$

Since $H_k(z)$ is excited by $x(n)$, its output $u_k(n)$ would converge to $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ being correlated with $x(n)$. This signal $u_k(n)$ is used to generate desired response for the OSPM filters. Thus the outputs of OSPM filters $\hat{S}_{kj}(z)$ and ADNC filters $H_k(z)$ are used to generated desired response for each other, and hence the name "cross-updating". Now the error signals for LMS algorithm-based OSPM filters $\hat{S}_{kj}(z)$ are generated as

$$f_{k1}(n) = e_k(n) - u_k(n) - \hat{v}'_{k1}(n) - \hat{v}'_{k2}(n) \tag{9}$$

$$f_{k2}(n) = e_k(n) - u_k(n) - \hat{v}'_{k1}(n) - \hat{v}'_{k2}(n) \tag{10}$$

where $k = 1, 2$. After convergence of the OSPM filters, the signals $g_k(n)$ converges to $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$, and hence can be used in adaptation of the control filter, as

$$\boldsymbol{w}_j(n+1) = \boldsymbol{w}_j(n) + \mu_w[\hat{\boldsymbol{x}}'_{j1}(n)g_1(n) + \hat{\boldsymbol{x}}'_{j2}(n)g_2(n)]. \tag{11}$$

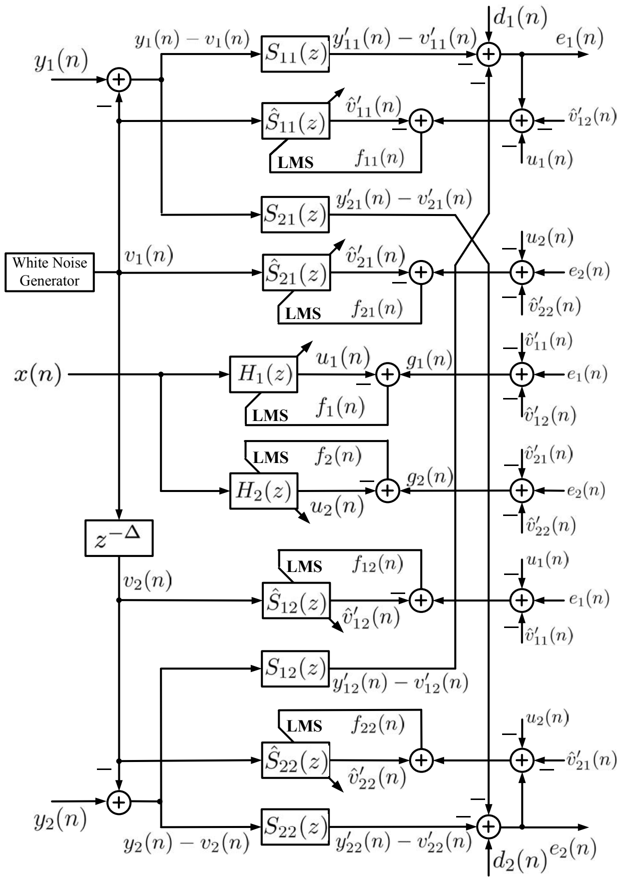

Fig. 3. Zhang's method for OSPM in $1 \times 2 \times 2$ ANC systems.

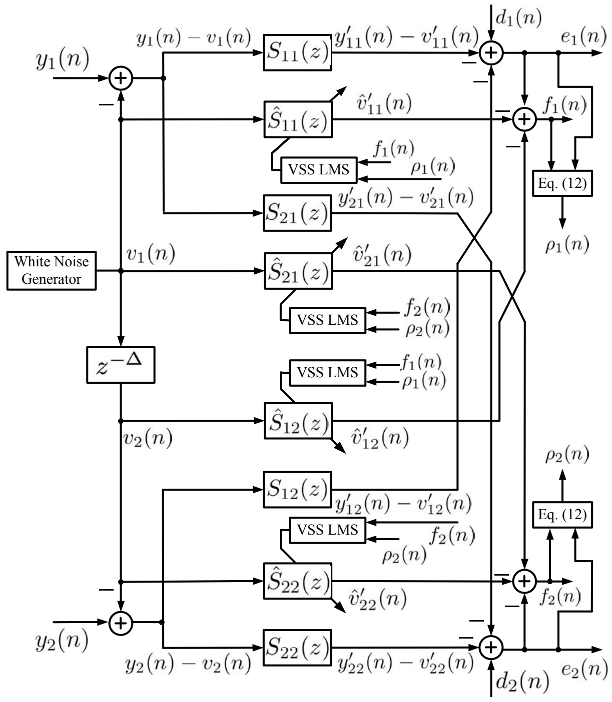

Fig. 4. Proposed method for OSPM in $1 \times 2 \times 2$ ANC systems.

In Zhang's method the adaptive filters are adapted using disturbance free error signals, and hence the performance of this method is better than the Eriksson's method. The price to be paid is introduction of ADNC filters, and this increases the computational complexity of the ANC system. Note that we need as many ADNC filters, as the number of error microphones. Thus for a $1 \times J \times K$ ANC system with K error microphones, where OSPM may be needed due to changing environment, we need K additional adaptive filters just to generate "nice" signals for control filters and OSPM filters. In such case the computational complexity of the Zhang's method will be substantially high.

III. Proposed Method for Online Secondary Path Modeling in $1 \times 2 \times 2$ ANC Systems

Here we present the extension of our previous work [7] to the $1 \times 2 \times 2$ ANC system. Consider (7) which gives the error signals $f_k(n)$ for OSPM filters in Eriksson's method. As stated earlier, here $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ acts as a disturbance signal for OSPM filters. Initially this disturbance is very large, but as ANC system converges, this disturbance reduces towards zero. Thus error signal in OSPM filter is corrupted by a disturbance which is decreasing in nature. This allows us to use initially a small step size for OSPM modeling, and when ANC system start converging we gradually increase the step size. The procedure to vary the step-size is explained below.

We define a ratio $\rho_k(n)$ as

$$\rho_k(n) = \frac{P_{f_k}(n)}{P_{e_k}(n)} \tag{12}$$

where $P_{f_k}(n)$ and $P_{e_k}(n)$ are power of error signal $f_k(n)$ and $e_k(n)$ associated with the kth error microphone. These powers can be estimated by using low pass estimators, as:

$$P_\gamma(n) = \lambda P_\gamma(n-1) + (1-\lambda)\gamma^2(n) \tag{13}$$

where λ is the forgetting factor ($0.9 < \lambda < 1$). Using (6) $P_{f_k}(n)$ can be expressed as

$$\begin{aligned} P_{f_k}(n) \;\; &= \;\; P_{d_k(n)-[y'_{k1}(n)+y'_{k2}(n)]} \\ &\quad + P_{[v'_{k1}(n)-\hat{v}'_{k1}(n)]+[v'_{k2}(n)]-\hat{v}'_{k2}(n)]}. \end{aligned} \tag{14}$$

Similarly from (3) $P_{e_k}(n)$ can be expressed as

$$P_{e_k}(n) = P_{d_k(n)-[y'_{k1}(n)+y'_{k2}(n)]} + P_{[v'_{k1}(n)+v'_{k2}(n)]}. \tag{15}$$

At $t = 0$, when the ANC system is started, the canceling signals are $y'_{k1}(n)$ and $y'_{k2}(n)$ are zero (it is customary to initialize adaptive filters by null vectors), and $\rho_k(n)$ at $t = 0$ is given as

$$\rho_k(0) \approx \frac{P_{d_k(n)} + P_{[v'_{k1}(n)-\hat{v}'_{k1}(n)]+[v'_{k2}(n)]-\hat{v}'_{k2}(n)]}}{P_{d_k(n)} + P_{[v'_{k1}(n)+v'_{k2}(n)]}} \tag{16}$$

Since $v'_{kj}(n)$ are generated from a low-level random noise signal; $P_{d_k(n)} \gg P_{[v'_{k1}(n)+v'_{k2}(n)]}$, and hence $\rho_k(0) \approx 1$. When ANC system converges: $[y'_{k1}(n) + y'_{k2}(n)] \to d_k(n)$, and $\hat{v}'_{kj}(n) \to v'_{kj}(n)$, and hence $P_{f_k}(n) \to 0$. The numerator in (12) converges to 0 and the denominator is non-zero due to presence of term $P_{[v'_{k1}(n)+v'_{k2}(n)]}$. Thus when ANC system converges $\rho_k(n)$ approaches 0. We see that $\rho_k(n) \approx 1$ indicates that $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ is very large, and

$\rho_k(n) \approx 0$ indicates that $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ is very small, and ANC system is converging. On the basis of this observation initially when $\rho_k(n) \approx 1$ we use small step size for OSPM filters, and increase the step-size for OSPM filter in accordance with decrease in $\rho_k(n)$. The step size for OSPM filters $\hat{s}_{k1}(n)$ and $\hat{s}_{k2}(n)$ is calculated as

$$\mu_{s_k}(n) = \rho_k(n)\mu_{s_{\min}} + (1 - \rho_k(n))\mu_{s_{\max}} \qquad (17)$$

where $\mu_{s_{\min}}$ and $\mu_{s_{\max}}$ are the experimentally determined values for lower and upper bounds of the step size. Now the OSPM filters are adapted by same equation as (7) except for the difference of variable step size computed by using (12), (13) and (17).

When the OSPM filters converge, $\hat{v}'_{kj}(n) \to v'_{kj}(n)$, and hence (6) is free of any modeling noise, and is better suited for adaptation of control filters. Hence the control filters are updated using MeFxLMS algorithm as

$$\boldsymbol{w}_j(n+1) = \boldsymbol{w}_j(n) + \mu_w[\hat{\boldsymbol{x}}'_{j1}(n)f_1(n) + \hat{\boldsymbol{x}}'_{j2}(n)f_2(n)]. \quad (18)$$

The proposed method is shown in Fig. 7, and as shown, the structure of the proposed method is similar to that the Eriksson's method, except for the difference of few computations required in variable-step-size LMS (VSS LMS) algorithms in OSPM modeling.

IV. Simulation Results and Concluding Remarks

This section presents the simulation experiments performed to verify the effectiveness of the proposed method. The relative modeling error between $\hat{S}_{kj}(z)$ and $S_{kj}(z)$ is used as the performance measure and is defined as

$$\Delta S_{kj}(n) = (\|\hat{\boldsymbol{s}}_{kj}(n) - \boldsymbol{s}_{kj}(n)\| / \|\boldsymbol{s}_{kj}(n)\|) \qquad (19)$$

Using data provided with [1], the primarily and secondary acoustic paths are modeled as FIR filters of tap-weight lengths 128 and 32, respectively. The ANC filters $W_j(z)$, and the ADNC filters $H_k(z)$ are FIR filters of tap-weight lengths 64 and are initialized by null vectors of appropriate orders. The OSPM filters $\hat{S}kj(z)$ are FIR filters of tap-weight lengths 32, and are initialized by offline modeling that is stopped when the modeling error has been reduced to -5 dB. A sampling frequency of 4 kHz is used. The reference signal $x(n)$ is a narrowband signal comprising frequencies of 150 Hz, 300 Hz, and 450 Hz. Its variance is adjusted to 2 and a zero-mean white noise is added with SNR of 30 dB. The modeling excitation signal $v(n)$ is a zero-mean white Gaussian noise of constant variance 0.05. The step size parameters for various adaptive filters are adjusted by trial-and-error, for fast and stable convergence, and are found to be, Eriksson's method: $\mu_w = 1 \times 10^{-5}$, $\mu_s = 1 \times 10^{-4}$, Zhang's method: $\mu_w = 1 \times 10^{-5}$, $\mu_s = 5 \times 10^{-3}$, $\mu_h = 2.5 \times 10^{-3}$, Proposed method: $\mu_w = 1 \times 10^{-5}$, $\mu_{s_{\min}} = 7.5 \times 10^{-4}$, $\mu_{s_{\max}} = 7.5 \times 10^{-3}$. All the results shown below are average of 10 realizations.

The simulation results are presented in Fig. 5. Here Figures (a)–(d) show the secondary path modeling errors in OSPM filters $\hat{S}kj(z)$, and Figs. (e), (f) show the residual noise at error microphone 1. We see that the proposed method gives

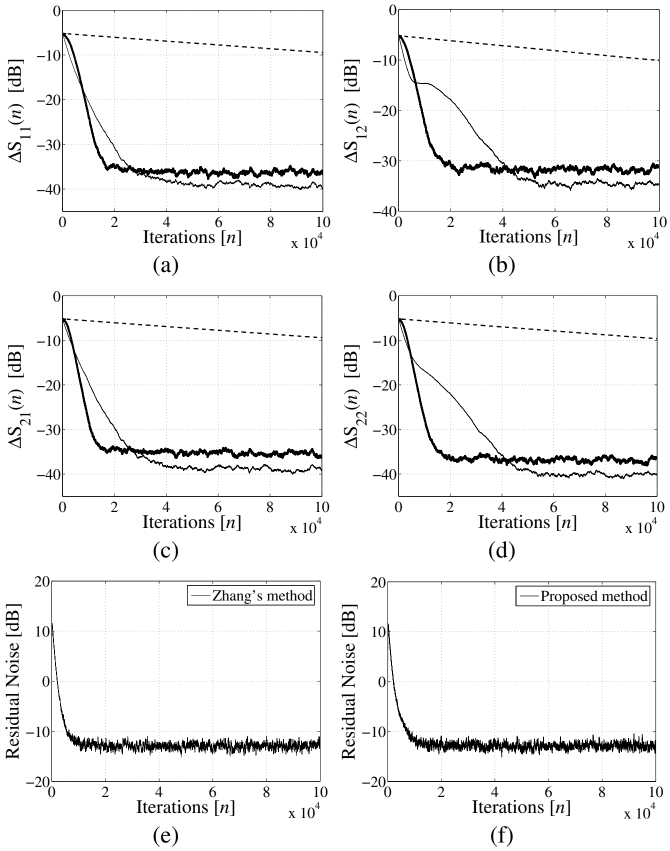

Fig. 5. Simulation results for narrowband signal of $150 + 300 + 450$ Hz. (a)–(d) Secondary path modeling error: Eriksson's method (dashed line), Zhang's method (thin solid line), and Proposed method (thick solid line). (e),(f) Residual noise at error microphone 1.

the better convergence speed in OSPM, and comparable noise reduction performance to that of the Zhang's method. It is worth mentioning that this performance is achieved at reduced computational cost due to the simple structure of the proposed method. A detailed computational complexity analysis, the results for broadband noise signals, and extension of method to general $I \times J \times K$ ANC systems will be presented in future publication.

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