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Direct Adaptive Approach to Multichannel Active Noise Control and Sound Reproduction

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***Abstract*— A new direct adaptive approach is proposed for general multichannel active noise control (ANC) when all of the sound path dynamics are uncertain and changeable. To reduce the canceling errors, two kinds of virtual errors are introduced and are forced into zero by adjusting three adaptive FIR matrix filters in an on-line manner, by which the convergence of the actual canceling errors to zero can be attained at the objective points. Unlike conventional approaches, the proposed algorithm can give an adaptive feedforward controller directly without need of explicit identification of the secondary path channels, and requires neither any dither signals nor the PE property of the source signals, which is a great advantage of the proposed approach. The proposed multichannel approach is also applicable to multichannel sound reproduction (SR), in which the SR controller can be directly tuned without explicitly identification of room sound transmission channels.**

I. Introduction

Active noise control (ANC) is a way of suppressing unwanted low frequency noises generated by primary sources by emitting artificial secondary sounds to objective points [1]–[3]. Sound reproduction (SR) using multiple loudspeakers and microphones is regarded as a special case of multichannel ANC [3][4]. Since the path dynamics cannot be precisely modeled and may be uncertainly changeable, adaptive tuning of the feedforward controller is essentially needed. A variety of filtered-x LMS algorithms have been proposed to attain the cancellation via the feedforward adaptation in uncertain situations. Stability assured filtered-x algorithms have also been investigated in [5]–[7].

To deal with a general case when the secondary path channels are uncertain and changeable, we can take two possible adaptive approaches: One is an indirect adaptive approach based on real-time identification of the secondary path dynamics, in which the secondary path model in the filtered-x algorithms is updated by the identified model [2][3][8] or the feedforward controller is also redesigned via the identified model [6][7]. For the precise identification of the secondary path channels, dither noises are needed to assure the persistently exciting (PE) condition for the identifiability. The other is a direct adaptive approach which can directly tune the feedforward controller without explicit identification of the channels. Few efficient direct adaptive algorithms have been proposed to treat with a general case in which all the path matrices are unknown.

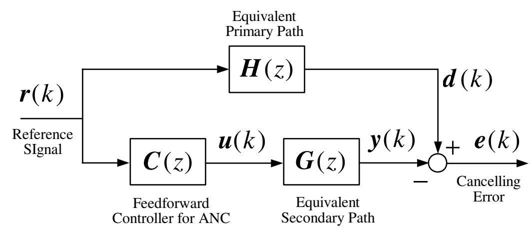

Fig. 1. Structure of equivalent multichannel ANC system

The purpose of this paper is to propose a new direct approach to a general multichannel case. To reduce the canceling errors, two virtual error vectors are introduced and are forced into zero by adjusting parameters in three adaptive matrix filters in an online manner. Unlike the ordinary indirect approaches, even if the source noises do not hold the PE property, the convergence of the two virtual errors to zero can assure the actual cancellation, and so neither any dither signals nor the PE property of the primary noises is needed. The proposed method is also different from the ordinary overall modeling approach [9][2] which also links the ordinary filtered-x algorithm with identification of the overall path models. The proposed approach does not employ ordinary filtered-x algorithms and the adaptive controller parameters are directly updated so that the two virtual errors can be minimized, which results in stable convergence. Sound reproduction (SR) problem using multiple loudspeakers and microphones are also formulated as a special case of the multichannel ANC problem. The proposed multichannel approach can also be applied to the sound field control, in which the sound controller can directly tuned without explicit identification of sound transmission dynamics in a room. Effectiveness of the proposed adaptive approach is examined in numerical simulations

II. Multichannel Sound Control Problems

An equivalent structure of multi-channel feedforward sound control systems is depicted by Fig.1. In ANC case, the signal $\boldsymbol{r}(k) \in \mathcal{R}^{N_r}$ detected by N_r reference microphones are the inputs to the $N_c \times N_r$ adaptive feedforward controller matrix $\hat{\boldsymbol{C}}(z,k)$, where N_c is the number of

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the secondary loudspeakers which produce artificial control sounds $\boldsymbol{u}(k) \in \mathcal{R}^{N_c}$ to cancel the primary source noises at the N_e objective points. The canceling errors are detected as $\boldsymbol{e}(k) \in \mathcal{R}^{N_e}$ by the N_e error microphones, which are expressed in terms of the accessible signals $\boldsymbol{r}(k)$ and $\boldsymbol{u}(k)$, as

$$\boldsymbol{e}(k) = \boldsymbol{H}(z)\boldsymbol{r}(k) - \boldsymbol{G}(z)\boldsymbol{u}(k) \tag{1}$$

where $\boldsymbol{H}(z) \in \mathcal{Z}^{N_e \times N_r}$ and $\boldsymbol{G}(z) \in \mathcal{Z}^{N_e \times N_c}$ are the equivalent primary and secondary path matrices respectively, which are uncertain and changeable. Thus, in the ANC in Fig.1, we cannot measure the signals $\boldsymbol{d}(k)$ and $\boldsymbol{y}(k)$ separately, but only measure the canceling error $\boldsymbol{e}(k)$, since the model of $\boldsymbol{G}(z)$ involves uncertainty. Thus, the multi-channel ANC problem is how to tune the inverse controller $\boldsymbol{C}(z)$ directly by using only accessible signals $\boldsymbol{r}(k)$, $\boldsymbol{u}(k)$ and $\boldsymbol{e}(k)$, even if the sound transmission matrices $\boldsymbol{H}(z)$ and $\boldsymbol{G}(z)$ are uncertain.

In sound reproduction (SR) systems, $\boldsymbol{r}(k) \in \mathcal{R}^{N_r}$ is the recorded signal vector to be reproduced at the object points. $\boldsymbol{C}(z)$ is an inverse controller matrix which determines the control sound vector $\boldsymbol{u}(k) \in \mathcal{R}^{N_c}$ emitted from the loudspeakers. These sounds are transmitted via the listening room space to reproduce the desired sounds $\boldsymbol{y}(k)$ at the locations of listener's ears, where $N_r = N_e$ in SR case. The transmission paths from the N_c loudspeaker to the N_e microphones are expressed by the channel matrix $\boldsymbol{G}(z)$. $\boldsymbol{C}(z)$ is determined so that the reproduced signals $\boldsymbol{y}(k)$ can be equal to the delayed recorded signals $\boldsymbol{d}(k) = \boldsymbol{H}(z)\boldsymbol{r}(k)$, where $\boldsymbol{H}(z) = \text{diag }[z^{-\Delta_1}, \cdots, z^{-\Delta_{N_r}}]$ and $N_c \geq N_r$ [12]. Unlike the ANC problem, $\boldsymbol{H}(z)$ is known and specified a priori. Thus the SR problem is how to decide and update the sound reproduction controller $\boldsymbol{C}(z)$ directly, even if the sound transmission matrix $\boldsymbol{G}(z)$ is uncertain.

Thus, the purpose of this paper is to give a new adaptive algorithm to update the controller $\boldsymbol{C}(z)$ directly without explicit identification of the unknown channel matrices $\boldsymbol{H}(z)$ and $\boldsymbol{G}(z)$ ($\boldsymbol{G}(z)$ only in SR case), unlike conventional approaches.

III. Direct Adaptive Approach

A. Virtual Error Method: Single Channel Case

We give a new direct adaptive approach which does not need explicit identification of the secondary path dynamics, unlike the ordinary filtered-x algorithms using the identified model of $G(z)$. The basic structure of the proposed adaptive feedforward control algorithm is illustrated in Fig.2, where $e(k)$, $e_A(k)$ and $e_B(k)$ can be expressed as:

$$e(k) = H(z)r(k) - G(z)u(k) \tag{2a}$$

$$e_A(k) = e(k) + \hat{K}(z,k)u(k) - \hat{D}(z,k)r(k) \tag{2b}$$

$$e_B(k) = \hat{D}(z,k)r(k) - \hat{C}(z,k)x(k) \tag{2c}$$

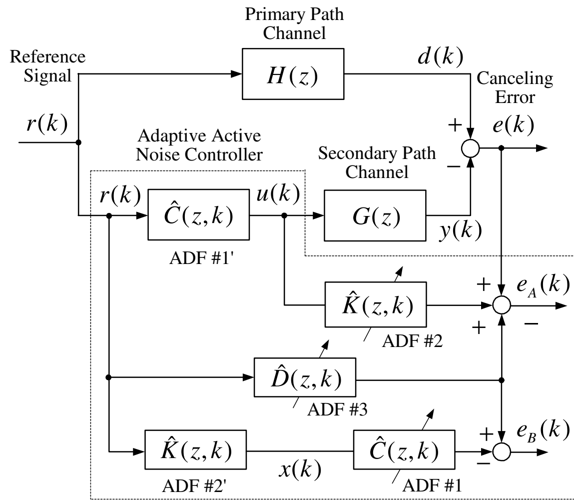


Fig. 2. Virtual error method for single channel case

where $H(z)$ and $G(z)$ are equivalent primary and secondary paths respectively, and the control input $u(k)$ and the auxiliary signal $x(k)$ are also defined as

$$u(k) = \hat{C}(z,k)r(k) \tag{3}$$

$$x(k) = \hat{K}(z,k)r(k) \tag{4}$$

The feature of the proposed approach is that two virtual errors $e_A(k)$ and $e_B(k)$ are introduced and forced to zero by three adaptive filters, and the structure does not need any filtered-x type of adaptive algorithms. It follows from Fig.2

$$\begin{aligned} e_A(k) + e_B(k) &= [e(k) + \hat{K}(z,k)u(k) - \hat{D}(z,k)r(k)] \\ &\quad + [\hat{D}(z,k)r(k) - \hat{C}(z,k)x(k)] \\ &= e(k) + \hat{K}(z,k)\hat{C}(z,k)r(k) - \hat{C}(z,k)\hat{K}(z,k)r(k) \end{aligned} \tag{5}$$

Thus, if $e_A(k)$ and $e_B(k) \to 0$ (for $k \to \infty$) is satisfied and the FIR parameters of $\hat{C}(z,k)$ and $\hat{K}(z,k)$ converge to any constants, then the second and third terms in the right hand side of (5) can be cancelled, then by the relation $e_A(k) + e_B(k) = e(k)$, thus it can also be attained that $e(k) \to 0$.

We proposed a single channel adaptive algorithms for updating the FIR parameters in $\hat{K}(z,k)$, $\hat{D}(z,k)$ and $\hat{C}(z,k)$ [10][11]. In the following, a more practical algorithm is given to update the FIR the parameters defined by

$$\hat{K}(z,k) = \sum_{i=1}^{L_k} \hat{k}_i(k) z^{-i}$$

$$\hat{D}(z,k) = \sum_{j=1}^{L_d} \hat{d}_j(k) z^{-j}$$

$$\hat{C}(z,k) = \sum_{n=1}^{L_c} \hat{c}_n(k) z^{-n}$$

Let the parameter vectors denoted by $\hat{\boldsymbol{\theta}}_K(k) = [\hat{k}_1(k), \ldots, \hat{k}_{L_K}(k)]^T$, $\hat{\boldsymbol{\theta}}_D(k) = [\hat{d}_1(k), \ldots, \hat{d}_{L_D}(k)]^T$ and

$\hat{\boldsymbol{\theta}}_C(k) = [\hat{c}_1(k), \ldots, \hat{c}_{L_C}(k)]^T$, and let the regressor signal vectors denoted by $\boldsymbol{\zeta}(k) = [u(k-1), \ldots, u(k-L_K)]^T$, $\boldsymbol{\xi}(k) = [r(k-1), r(k-2), \ldots, r(k-L_D)]^T$ and $\boldsymbol{\varphi}(k) = [x(k-1), \ldots, x(k-L_C)]^T$. Then a simplified adaptive algorithm is expressed by

$$\hat{\boldsymbol{\theta}}_K(k+1) = \hat{\boldsymbol{\theta}}_K(k) - \gamma_K \boldsymbol{\zeta}(k)\varepsilon_A(k) \tag{6a}$$

$$\hat{\boldsymbol{\theta}}_D(k+1) = \hat{\boldsymbol{\theta}}_D(k) + \gamma_D \boldsymbol{\xi}(k)\varepsilon_A(k) \tag{6b}$$

$$\hat{\boldsymbol{\theta}}_C(k+1) = \hat{\boldsymbol{\theta}}_C(k) + \gamma_C \boldsymbol{\varphi}(k)\varepsilon_B(k) \tag{6c}$$

$$\varepsilon_1(k) = \frac{e_A(k)}{1 + \gamma_D\|\boldsymbol{\xi}(k)\|^2 + \gamma_K\|\boldsymbol{\zeta}(k)\|^2}$$

$$\varepsilon_B(k) = \frac{e_B(k)}{1 + \gamma_C\|\boldsymbol{\varphi}(k)\|^2}$$

Then by replacing the old parameters of $\hat{\boldsymbol{\theta}}_C(k)$ and $\hat{\boldsymbol{\theta}}_K(k)$ in ADF#1' and ADF#2' in Fig.2 with the updated parameters in (6(a))(6(b)), we can generate the control input $u(k)$ and auxiliary signal $x(k)$.

B. Virtual Error Method: Multichannel Case

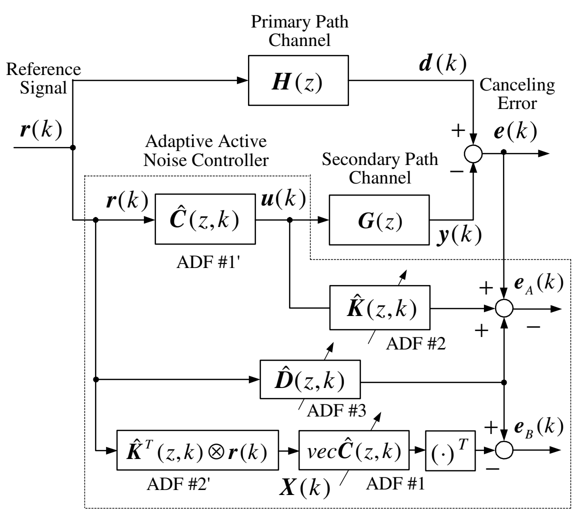


Fig. 3. Virtual error method for multichannel case

In a multichannel case, since the exchange of product of two matrices gives a different result, the key idea in the single channel case cannot be applied in a straightforward way. Fig.3 shows a new direct adaptive tuning algorithm for a multichannel case. Similarly we introduce two kinds of virtual error vectors $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$, which are forced to zero by using three adaptive FIR matrix filters $\hat{\boldsymbol{C}}(z,k)$, $\hat{\boldsymbol{K}}(z,k)$ and $\hat{\boldsymbol{D}}(z,k)$. It is seen that $\boldsymbol{e}_B(k)$ is generated in a different way from the single channel case. Thus we can give the expression of the errors as:

$$\boldsymbol{e}(k) = \boldsymbol{H}(z)\boldsymbol{r}(k) - \boldsymbol{G}(z)\boldsymbol{u}(k) \tag{7a}$$

$$\boldsymbol{e}_A(k) = \boldsymbol{e}(k) + \hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) - \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) \tag{7b}$$

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{7c}$$

where

$$\boldsymbol{u}(k) = \hat{\boldsymbol{C}}(z,k)\boldsymbol{r}(k) \tag{8}$$

$$\boldsymbol{X}(k) = \hat{\boldsymbol{K}}^T(z,k) \otimes \boldsymbol{r}(k) \tag{9}$$

where $vec[\boldsymbol{A}]$ denotes a row vector expansion of a matrix $\boldsymbol{A}$, and $\otimes$ denotes the Kronecker product, which are explained later in two channel case.

Then we consider the sum of two virtual errors in Fig.3 from (7b) and (7c) as

$$\boldsymbol{e}_A(k) + \boldsymbol{e}_B(k) = \boldsymbol{e}(k) + \hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) - [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{10}$$

If the coefficient parameters in the three adaptive FIR filters $\hat{\boldsymbol{C}}(z,k)$, $\hat{\boldsymbol{K}}(z,k)$ and $\hat{\boldsymbol{D}}(z,k)$ can be updated so that the error vectors $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$ may become zero, and the filter parameters converge to constant values, we can show that the canceling error $\boldsymbol{e}(k)$ can also converge to zero. To prove this property, we should show that

$$\hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) = [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{11}$$

in sufficiently large k. For the simplicity, the proof is done in a case with $N_r = N_c = 2$. The left hand side of (11) is

$$\begin{aligned}
\hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) &= \hat{\boldsymbol{K}}(z,k)\hat{\boldsymbol{C}}(z,k)\boldsymbol{r}(k) \\
&= \begin{bmatrix} \hat{K}_{11}(z) & \hat{K}_{12}(z) \\ \hat{K}_{21}(z) & \hat{K}_{22}(z) \end{bmatrix} \begin{bmatrix} \hat{C}_{11}(z) & \hat{C}_{12}(z) \\ \hat{C}_{21}(z) & \hat{C}_{22}(z) \end{bmatrix} \begin{bmatrix} r_1(k) \\ r_2(k) \end{bmatrix} \\
&= \begin{bmatrix} (\hat{K}_{11}(z)\hat{C}_{11}(z) + \hat{K}_{12}(z)\hat{C}_{21}(z))r_1(k) \\ (\hat{K}_{21}(z)\hat{C}_{11}(z) + \hat{K}_{22}(z)\hat{C}_{21}(z))r_1(k) \end{bmatrix. \\
&\qquad \begin{matrix} +(\hat{K}_{11}(z)\hat{C}_{12}(z) + \hat{K}_{12}(z)\hat{C}_{22}(z))r_2(k) \\ +(\hat{K}_{21}(z)\hat{C}_{12}(z) + \hat{K}_{22}(z)\hat{C}_{22}(z))r_2(k) \end{matrix} \Bigg]
\end{aligned} \tag{12}$$

where k in the adaptive filter matrices is omitted for the simplicity of notation. On the other hand, we have

$$\begin{aligned}
[vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T &= [vec[\hat{\boldsymbol{C}}(z,k)]\hat{\boldsymbol{K}}^T(z,k) \otimes \boldsymbol{r}(k)]^T \\
&= \Bigg[\begin{bmatrix} \hat{C}_{11}(z) & \hat{C}_{12}(z) & \hat{C}_{21}(z) & \hat{C}_{22}(z) \end{bmatrix} \\
&\qquad \cdot \begin{bmatrix} \hat{K}_{11}(z)r_1(k) & \hat{K}_{21}(z)r_1(k) \\ \hat{K}_{11}(z)r_2(k) & \hat{K}_{21}(z)r_2(k) \\ \hat{K}_{12}(z)r_1(k) & \hat{K}_{22}(z)r_1(k) \\ \hat{K}_{12}(z)r_2(k) & \hat{K}_{22}(z)r_2(k) \end{bmatrix}\Bigg]^T \\
&= \Bigg[\begin{matrix} (\hat{C}_{11}(z)\hat{K}_{11}(z) + \hat{C}_{21}(z)\hat{K}_{12}(z))r_1(k) \\ (\hat{C}_{11}(z)\hat{K}_{21}(z) + \hat{C}_{21}(z)\hat{K}_{22}(z))r_1(k) \end{matrix} \\
&\qquad \begin{matrix} +(\hat{C}_{12}(z)\hat{K}_{11}(z) + \hat{C}_{22}(z)\hat{K}_{12}(z))r_2(k) \\ +(\hat{C}_{12}(z)\hat{K}_{21}(z) + \hat{C}_{22}(z)\hat{K}_{22}(z))r_2(k) \end{matrix} \Bigg]
\end{aligned} \tag{13}$$

If the parameters in the all adaptive filters converge to constants, we can exchange the product of two polynomials $\hat{C}_{ij}(z)$ and $\hat{K}_{kl}(z)$ in (13), and then we can establish that (12) is equal to (13) in sufficiently large time. Then, we can assure the convergence of $\boldsymbol{e}(k)$ to zero through the convergence of $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$ to zero.

C. Adaptation for Multichannel Active Noise Control

We express the three adaptive matrix filters $\hat{\boldsymbol{C}}(z,k)$, $\hat{\boldsymbol{K}}(z,k)$ and $\hat{\boldsymbol{D}}(z,k)$ as

$$\hat{C}_{ij}(z,k) = \hat{c}_{ij}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{ij}^{(L_{ij}^C)}(k)z^{-L_{ij}^C} \tag{14a}$$

$$\hat{K}_{mi}(z,k) = \hat{k}_{mi}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{mi}^{(L_{mi}^K)}(k)z^{-L_{mi}^K} \tag{14b}$$

$$\hat{D}_{mi}(z,k) = \hat{d}_{mj}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{mj}^{(L_{mj}^D)}(k)z^{-L_{mj}^D} \tag{14c}$$

where $i = 1, \cdots, N_c$, $j = 1, \cdots, N_r$ and $m = 1, \cdots, N_e$.

(1) *Adaptation for Minimization of* $\boldsymbol{e}_A(k)$

It follows from Fig.3 that the first virtual error vector $\boldsymbol{e}_A(k)$ is expressed by

$$e_{A,m}(k) = e_i(k) + \sum_{i=1}^{N_c} \hat{K}_{mi}(z,k)u_i(k) - \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k)$$

$$= e_m(k) + \sum_{i=1}^{N_c} \boldsymbol{\omega}_{mi}^T(k)\hat{\boldsymbol{\theta}}_{K,mi}(k) - \sum_{j=1}^{N_r} \boldsymbol{\xi}_{mj}^T(k)\hat{\boldsymbol{\theta}}_{D,mj}(k)$$

where $m = 1, \cdots, N_e$, $\boldsymbol{\omega}_{mi}(k) = (u_i(k-1), \cdots, u_i(k - L_{mi}^K))^T$, $\hat{\boldsymbol{\theta}}_{K,mi}(k) = (\hat{k}_{mi}^{(1)}(k), \cdots, \hat{k}_{mi}^{(L_{mi}^K)}(k))^T$, $\boldsymbol{\xi}_{mj}(k) = (r_j(k-1), \cdots, r_j(k-L_{mj}^D))^T$ and $\hat{\boldsymbol{\theta}}_{D,mj}(k) = (\hat{d}_{m1}^{(1)}(k), \cdots, \hat{d}_{mj}^{(L_{mj}^D)}(k))^T$.

Then from the minimization of the instantaneous squared error norm $\|\boldsymbol{e}_A(k)\|^2$ with respect to $\hat{\boldsymbol{\theta}}_{K,mi}(k)$ and $\hat{\boldsymbol{\theta}}_{D,mi}(k)$, we can derive the adaptive algorithm for updating these parameters as follows:

$$\hat{\boldsymbol{\theta}}_{K,mi}(k+1) = \hat{\boldsymbol{\theta}}_{K,mi}(k) - \gamma(k)\boldsymbol{\omega}_{mi}(k)e_{A,m}(k) \tag{15a}$$

$$\hat{\boldsymbol{\theta}}_{D,mj}(k+1) = \hat{\boldsymbol{\theta}}_{D,mj}(k) + \gamma(k)\boldsymbol{\xi}_{mj}(k)e_{A,m}(k) \tag{15b}$$

$$\gamma(k) = \frac{2\alpha\|\boldsymbol{e}_A(k)\|^2}{\rho + \sum_{m=1}^{N_e} e_{A,m}^2(k)\left(\|\boldsymbol{\omega}_m(k)\|^2 + \|\boldsymbol{\xi}_m(k)\|^2\right)} \tag{15c}$$

where $\boldsymbol{\omega}_m(k) = (\boldsymbol{\omega}_{m1}^T(k), \cdots, \boldsymbol{\omega}_{mN_c}^T(k))^T$, $\boldsymbol{\xi}_m(k) = (\boldsymbol{\xi}_{m1}^T(k), \cdots, \boldsymbol{\omega}_{mN_r}^T(k))^T$, and $0 < \alpha < 1$, $\rho > 0$ is a small constant. The algorithm (15) has a feature that the step size is not constant but is adjusted by the error vector $\boldsymbol{e}_A(k)$.

(2) *Adaptation for Minimization of* $\boldsymbol{e}_B(k)$

On the other hand, the second virtual error is given by

$$e_{B,m}(k) = \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k)$$

$$-[\hat{C}_{11}(z,k), \cdot\cdot, \hat{C}_{1N_r}(z,k), \cdots, \hat{C}_{N_c1}(z,k), \cdot\cdot, \hat{C}_{N_cN_r}(z,k)] \cdot [x_{m11}(k), \cdot\cdot, x_{m1N_r}(k), \cdot\cdot, x_{mN_c1}(k), \cdot\cdot, x_{mN_cN_r}(k)]^T$$

$$= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k)$$

$$-(\boldsymbol{x}_{m11}^T(k), \cdot\cdot, \boldsymbol{x}_{m1N_r}^T(k), \cdot\cdot, \boldsymbol{x}_{mN_c1}^T(k), \cdot\cdot, \boldsymbol{x}_{mN_cN_r}^T(k)) \cdot [\hat{\boldsymbol{c}}_{11}(k), \cdots, \hat{\boldsymbol{c}}_{1N_r}(k), \cdots, \hat{\boldsymbol{c}}_{N_cN_r}(k)]^T$$

$$= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) - \boldsymbol{\varphi}_{X,m}^T(k)\hat{\boldsymbol{\theta}}_C(k) \tag{16}$$

where $\boldsymbol{x}_{mij}^T(k) = (x_{mij}(k-1), \cdots, x_{mij}(k - L_{ij}^C))^T$, $\hat{\boldsymbol{c}}_{ij}(k) = (\hat{c}_{ij}^{(1)}(k), \cdots, \hat{c}_{ij}^{(L_{ij}^C)}(k))^T$, $\boldsymbol{\varphi}_{X,m}^T(k) = (\boldsymbol{x}_{m11}^T(k), \cdots, \boldsymbol{x}_{m1N_r}^T(k), \cdots, \boldsymbol{x}_{mN_c1}^T(k), \cdots, \boldsymbol{x}_{mN_cN_r}^T(k))$, $\hat{\boldsymbol{\theta}}_C(k) = (\hat{\boldsymbol{c}}_{11}^T(k), \cdots, \hat{\boldsymbol{c}}_{1N_r}^T(k), \cdots, \hat{\boldsymbol{c}}_{N_c1}^T(k), \cdots, \hat{\boldsymbol{c}}_{N_cN_r}^T(k))^T$.

Thus, the second virtual error vectors are expressed by

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - \boldsymbol{\Phi}_X^T(k)\hat{\boldsymbol{\theta}}_C(k) \tag{17}$$

where

$$\boldsymbol{\Phi}_X^T(k) \equiv \begin{bmatrix} \boldsymbol{\varphi}_{X,1}^T(k) \\ \boldsymbol{\varphi}_{X,2}^T(k) \\ \vdots \\ \boldsymbol{\varphi}_{X,N_e}^T(k) \end{bmatrix}$$

Then, we can give the adaptive algorithm for updating the parameters in $\hat{\boldsymbol{C}}(z,k)$ as follows:

$$\hat{\boldsymbol{\theta}}_C(k+1) = \hat{\boldsymbol{\theta}}_C(k) + \gamma_c(k)\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k) \tag{18a}$$

$$\gamma_c(k) = \frac{2\alpha_c\|\boldsymbol{e}_B(k)\|^2}{\rho_c + \|\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k)\|^2} \tag{18b}$$

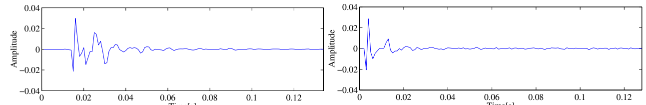
where $0 < \alpha_c < 0$, and $\rho > 0$ is a small constant.

Then by updating the old parameters of $\hat{\boldsymbol{\theta}}_C(k)$ and $\hat{\boldsymbol{\theta}}_K(k)$ in ADF#1' and ADF#2' in Fig.3 by the new adjusted parameters in (15) and (18), we can generate the control inputs $\boldsymbol{u}(k)$ and the auxiliary signals $\boldsymbol{X}(k)$.

IV. Simulation Results

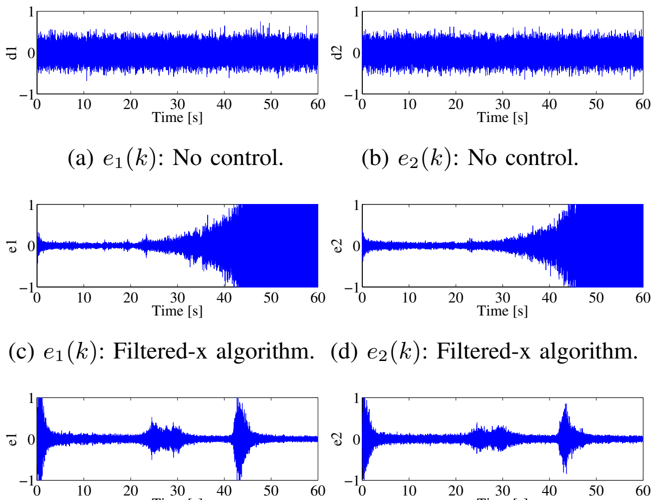
A. Multichannel Active Noise Control

The effectiveness of the proposed direct adaptive algorithm is examined in two channel ANC in a room. The setup is same as used in our previous experimental study [7], in which $N_r = N_c = N_e = 2$. In the simulation we used the path models which were obtained experimentally. Fig.4 illustrates examples of the obtained impulse responses of the primary path $H_{11}(z)$ and secondary path $G_{11}(z)$, which are used as unknown in the simulation. Let the sampling interval be 1 ms. We consider two types of the primary source noises: One is random noise in low frequency range from 50 Hz to 400 Hz, or the other is periodic signals with unknown frequencies which do not satisfy the PE condition. The length of all the adaptive filters are chosen as $L_c = L_d = L_k = 70$, and $\alpha = \alpha_c =$



(a) Primary path $H_{11}(z)$. (b) Secondary path $G_{11}(z)$

Fig. 4. Examples of FIR of primary and secondary paths

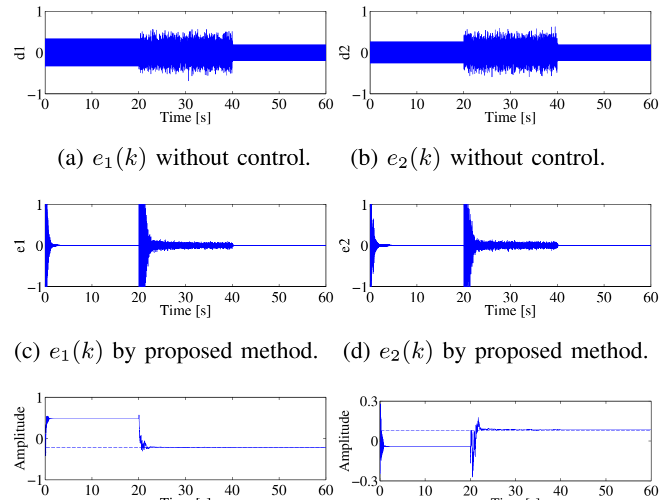


(a) $e_1(k)$: No control. (b) $e_2(k)$: No control.

(c) $e_1(k)$: Filtered-x algorithm. (d) $e_2(k)$: Filtered-x algorithm.

(e) $e_1(k)$: Proposed algorithm. (f) $e_2(k)$: Proposed algorithm.

Fig. 5. Comparison of control results between the filtered-x algorithm and the proposed fully direct adaptive algorithm



(a) $e_1(k)$ without control. (b) $e_2(k)$ without control.

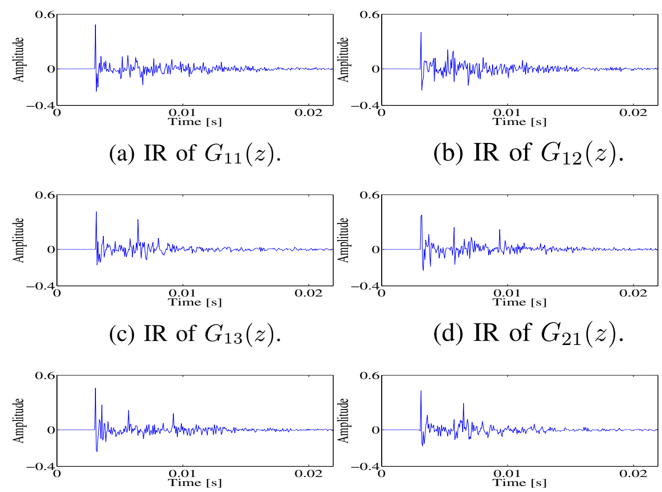
(c) $e_1(k)$ by proposed method. (d) $e_2(k)$ by proposed method.

(e) Controller parameter $\hat{c}_{11}^{(10)}$. (f) Controller parameter $\hat{c}_{11}^{(19)}$.

Fig. 6. Control results for source signals without PE property

First we consider a scenario in which the location of the two error microphones is moved by 34 cm instantaneously from the original positions to the primary sources by using the switches at 20 s after the start of control, and the location is again moved by 68cm to the control loudspeakers from the sources at 40 s. Figs.5(a) and 5(b) show the canceling errors $e_1(k)$ and $e_2(k)$ in a case without control. As shown in Figs.5(c) and 5(d), the filtered-x type of algorithm could not keep stable attenuation performance [7] at the first switched time, since it cannot adapt to uncertain changes of the secondary paths. On the other hand, the proposed method could still attain the stable control performance even if the channels changed rapidly as given in Figs.5(e) and 5(f).

Next, Figs. 6(a) to 6(f) show the control results in a case when the two primary source noises are periodic and consist of sinusoid with unknown frequencies 150 Hz and 250 Hz respectively in the time interval (0s, 20s), and both 400 Hz in the interval (40s, 60s). The primary noises in the interval (20s,40s) are the outputs of lowpass filters with passband (50Hz, 400Hz) for white noise inputs. Even when the primary source noises like sinusoids have no PE property, the proposed algorithm can give very nice canceling performance still in the interval (0s, 20s). During the interval, the adaptive algorithm updates only few number of parameters required for reducing the canceling errors. During the interval (20s, 40s), the primary source noises have sufficient PE property and then almost all of the parameters of the adaptive filters are updated and converge to their true values (for instance, the profiles of parameters converging to their true values are given by the dotted lines in Figs .6(e) and 6(f)). During the interval (40s, 60s) the primary source noises are sinusoids again, however,



(a) IR of $G_{11}(z)$. (b) IR of $G_{12}(z)$.

(c) IR of $G_{13}(z)$. (d) IR of $G_{21}(z)$.

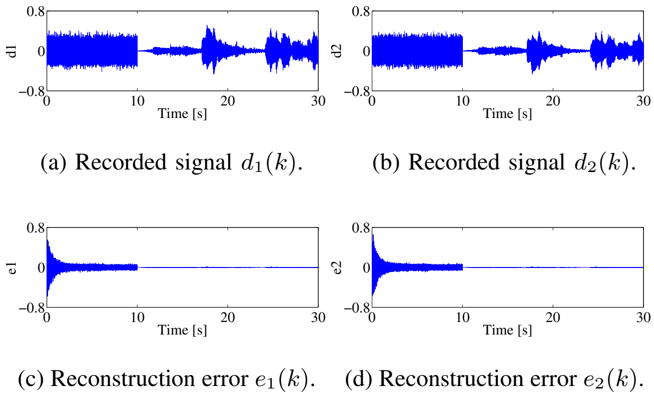
(e) IR of $G_{22}(z)$. (f) IR of $G_{23}(z)$.

Fig. 7. Impulse response of listening room $\boldsymbol{G}$(z).

since the adjustment of almost all adaptive parameters has been completed, then no parameters are required to be updated. Thus, the proposed direct adaptive scheme is also very robust to the insufficiency of the PE property of the primary source noises, while the conventional indirect adaptive approaches need dither noises for attaining the identifiability of the secondary paths.

B. Two Channel Sound Reproducrion

We applied the proposed approach to direct tuning of the inverse controller for stereophonic SR system with $N_c = 3$ and $N_r = N_e = 2$. Experimentally obtained impulse responses were used to describe the room transmission path dynamics, all of which are illustrated in Fig.7, which are uncertain in the simulation. Since $\boldsymbol{H}(z)$ is specified

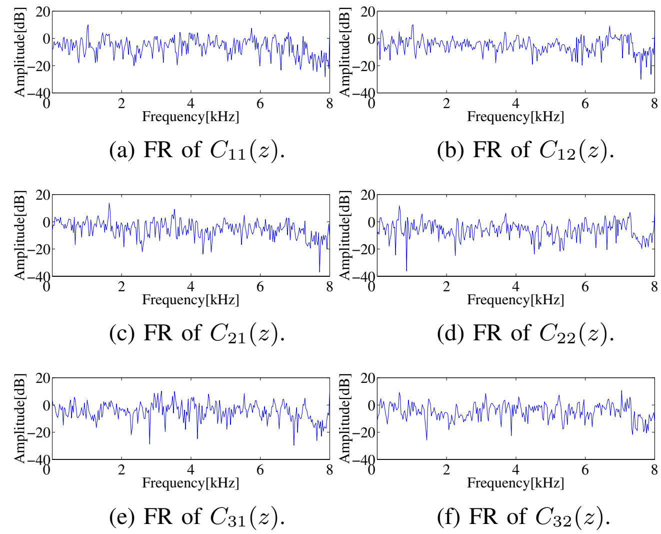


(a) Recorded signal $d_1(k)$. (b) Recorded signal $d_2(k)$.

(c) Reconstruction error $e_1(k)$. (d) Reconstruction error $e_2(k)$.

Fig. 8. Sound reproduction results.

a priori, the corresponding adaptive filter matrix $\hat{\boldsymbol{D}}(z,k)$ can be replaced by $\boldsymbol{H}(z)$. Then only $\hat{\boldsymbol{K}}(z,k)$ and $\hat{\boldsymbol{C}}(z,k)$ are to be updated. In this simulation, the inverse controller was directly tuned by using white noise as $\boldsymbol{r}(k)$ for first 10 seconds and then by using the stereophonic signals as $\boldsymbol{r}(k)$. Fig.8 shows the sound reproduction results, where the sampling frequncy is 32kHz, and the numbers of taps of $\hat{\boldsymbol{K}}(z,k)$ and $\hat{\boldsymbol{C}}(z,k)$ are 350 and 605. As shown in Figs. 8(c) and 8(d), after 10s the two music signals are almost perfectly reconstructed. One of the advantages of the proposed method is that the inverse controller parameters can be directly tuned, without using the ordinary filtered-x algorithms. Fig.9 shows some examples ofthe frequency response of the tuned controller $\hat{\boldsymbol{C}}(z,k)$, and they are very flat over the wide range adaptively, while the flat characteristics cannot be easily obtained by the conventional methods [13]. In the proposed approach, the magnitude of the controllers in the frequency domain can automatically suppressed since the controller parameters can be adjusted so that the reconstruction errors are directly minimized.



(a) FR of $C_{11}(z)$. (b) FR of $C_{12}(z)$.

(c) FR of $C_{21}(z)$. (d) FR of $C_{22}(z)$.

(e) FR of $C_{31}(z)$. (f) FR of $C_{32}(z)$.

Fig. 9. Frequency response of obtained $\boldsymbol{C}(z)$.

V. Conclusion

We have presented the new direct adaptive algorithm for tuning the feedforward sound controller in multichannel cases, which is effective even when the all path matrices are uncertain. The proposed algorithm need neither explicit identification of the uncertain secondary paths nor the addtional input of the dither noises for assuring the PE condition of the primary source noises. The effectiveness of the proposed approach has been validated in the simulation of two channel active noise control system, and the sound reproduction with two sources and three control loudspeakers.

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