NEW DIRECT ADAPTIVE ALGORITHM FOR MULTICHANNEL ACTIVE NOISE CONTROL AND SOUND REPRODUCTION

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ABSTRACT

A new direct adaptive algorithm is proposed for multichannel active noise control (ANC) and sound reproduction (SR) when primary and secondary path dynamics are all uncertain and changeable. To attenuate the canceling errors or reproduction errors, two kinds of virtual error vectors are introduced and are forced into zero by adjusting three adaptive FIR matrix filters in an on-line manner. It is shown that the convergence of the canceling or reproduction errors to zero can be attained at the objective points. The proposed algorithm can tune an inverse controller matrix 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 for the identifiability.

1. INTRODUCTION

Active noise control (ANC) for suppressing unwanted low frequency noises from primary sources is attained by emitting control sounds from secondary loudspeakers to realize cancellation at objective points [1][2]. Sound reproduction (SR) using multiple loudspeakers and microphones is regarded as a special case of multichannel ANC [3][4]. Since the path channels cannot be precisely modeled and may be uncertainly changeable, adaptive tuning of the feedforward inverse controller is essentially needed [2]. When the secondary path channels are uncertain, the filtered-x adaptive algorithms are performed jointly with identification of the secondary path channels [2]–[8]. The on-line identification sometimes needs dither noises for assuring the persistently exciting (PE) property of the reference signals to attain the identifiability of the path channel models.

The purpose of this paper to propose a new adaptive algorithm which can directly tune the multichannel inverse controller without explicit identification of the channels unlike the ordinary filtered-x algorithms using the identified secondary path models. To reduce the canceling errors, two virtual error vectors are introduced and are forced into zero by adjusting parameters in three adaptive FIR matrix filters in an online manner. It is shown that the convergence of the canceling error vector to zero can be attained if the parameters are adjusted and converge to any constants so that the two virtual error vectors can become zero. Unlike the ordinary filtered-x algorithms, the proposed approach can tune an inverse controller matrix 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 for the identifiability.

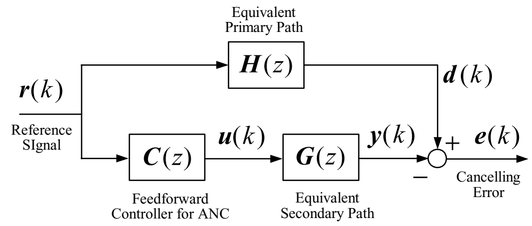


Fig. 1. Structure of equivalent multichannel ANC system

2. MULTICHANNEL SOUND CONTROL PROBLEM

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 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 multichannel 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 $N_c \geq N_r$ [9]. 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.

3. VIRTUAL ERROR METHOD

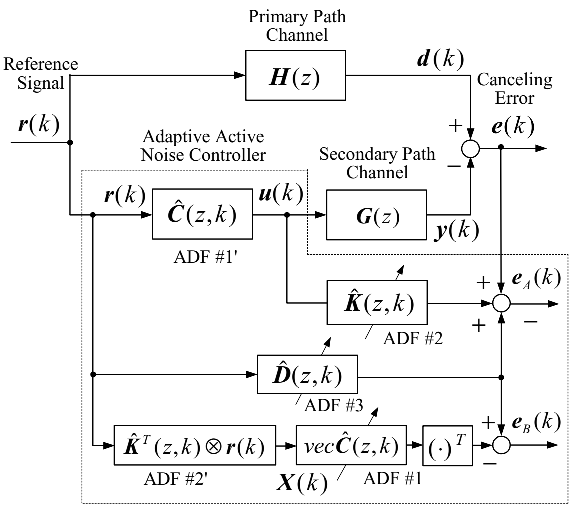


Fig. 2. Virtual error method for multichannel case

The proposed controller structure is illustrated in Fig.2. Compared to a single channel case [10], the algorithm becomes complicated since the exchange of product of two matrices gives a different result. 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 $\hat{\boldsymbol{D}}(z,k)$. The relations of the error vectors are given as

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

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

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{2c}$$

where

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

$$\boldsymbol{X}(k) = \hat{\boldsymbol{K}}^T(z,k) \otimes \boldsymbol{r}(k) \tag{4}$$

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.2, which is given from (2b) and (2c) as

$$\begin{aligned}\boldsymbol{e}_A(k) + \boldsymbol{e}_B(k) = \boldsymbol{e}(k) &+ \hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) \\ &-[vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T\end{aligned} \tag{5}$$

We can show that the canceling error vector $\boldsymbol{e}(k)$ converges to zero, if the coefficient parameters in the three adaptive FIR filter matrices $\hat{\boldsymbol{C}}(z,k)$, $\hat{\boldsymbol{K}}(z,k)$ 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 these filter parameters converge to any constant values. To prove this property, we should show that

$$\hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) = [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{6}$$

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 (6) is

$$\begin{aligned}
&\hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) = \hat{\boldsymbol{K}}(z,k)\hat{\boldsymbol{C}}(z,k)\boldsymbol{r}(k) \\
&= \begin{bmatrix} \hat{K}_{11}(z) & \hat{K}_{12}(z) \\ \hat{K}_{21}(z) & \hat{K}_{22}(z) \end{bmatrix} \begin{bmatrix} \hat{C}_{11}(z) & \hat{C}_{12}(z) \\ \hat{C}_{21}(z) & \hat{C}_{22}(z) \end{bmatrix} \begin{bmatrix} r_1(k) \\ r_2(k) \end{bmatrix} \\
&= \left[\begin{array}{l} (\hat{K}_{11}(z)\hat{C}_{11}(z) + \hat{K}_{12}(z)\hat{C}_{21}(z))r_1(k) \\ (\hat{K}_{21}(z)\hat{C}_{11}(z) + \hat{K}_{22}(z)\hat{C}_{21}(z))r_1(k) \end{array}\right. \\
&\qquad \left.\begin{array}{l} +(\hat{K}_{11}(z)\hat{C}_{12}(z) + \hat{K}_{12}(z)\hat{C}_{22}(z))r_2(k) \\ +(\hat{K}_{21}(z)\hat{C}_{12}(z) + \hat{K}_{22}(z)\hat{C}_{22}(z))r_2(k) \end{array}\right]
\end{aligned} \tag{7}$$

where k in the adaptive filter matrices is omitted for the simplicity of notation.

On the other hand, the right hand side of (6) can be rewritten from (4) for sufficiently large k, as

$$\begin{aligned}
&[vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T = [vec[\hat{\boldsymbol{C}}(z,k)]\hat{\boldsymbol{K}}^T(z,k) \otimes \boldsymbol{r}(k)]^T \\
&= \left[\begin{bmatrix} \hat{C}_{11}(z) & \hat{C}_{12}(z) & \hat{C}_{21}(z) & \hat{C}_{22}(z) \end{bmatrix}\right. \\
&\qquad \left. \cdot \begin{bmatrix} \hat{K}_{11}(z)r_1(k) & \hat{K}_{21}(z)r_1(k) \\ \hat{K}_{11}(z)r_2(k) & \hat{K}_{21}(z)r_2(k) \\ \hat{K}_{12}(z)r_1(k) & \hat{K}_{22}(z)r_1(k) \\ \hat{K}_{12}(z)r_2(k) & \hat{K}_{22}(z)r_2(k) \end{bmatrix}\right]^T \\
&= \left[\begin{array}{l} (\hat{C}_{11}(z)\hat{K}_{11}(z) + \hat{C}_{21}(z)\hat{K}_{12}(z))r_1(k) \\ (\hat{C}_{11}(z)\hat{K}_{21}(z) + \hat{C}_{21}(z)\hat{K}_{22}(z))r_1(k) \end{array}\right. \\
&\qquad \left.\begin{array}{l} +(\hat{C}_{12}(z)\hat{K}_{11}(z) + \hat{C}_{22}(z)\hat{K}_{12}(z))r_2(k) \\ +(\hat{C}_{12}(z)\hat{K}_{21}(z) + \hat{C}_{22}(z)\hat{K}_{22}(z))r_2(k) \end{array}\right]
\end{aligned} \tag{8}$$

If the parameters in the all adaptive filters converge to any constants, we can exchange the product of two polynomials $\hat{C}_{ij}(z)$ and $\hat{K}_{kl}(z)$ in (7) and (8), and then it follows that (7) is equal to (8) in sufficiently large time. Then, it gives from (5) that the convergence of $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$ to zero assures the convergence of $\boldsymbol{e}(k)$ to zero. It is noticed that the controller parameters do not need to true values but only constants which make $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$ zero.

4. ADAPTIVE ALGORITHMS FOR ANC AND SR

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

$$\hat{C}_{ij}(z,k) = \hat{c}_{ij}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{ij}^{(L_{ij}^C)}(k)z^{-L_{ij}^C} \tag{9a}$$

$$\hat{K}_{mi}(z,k) = \hat{k}_{mi}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{mi}^{(L_{mi}^K)}(k)z^{-L_{mi}^K} \tag{9b}$$

$$\hat{D}_{mi}(z,k) = \hat{d}_{mj}^{(1)}(k)z^{-1} + \cdots + \hat{c}_{mj}^{(L_{mj}^D)}(k)z^{-L_{mj}^D} \tag{9c}$$

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

4.1. Adaptive Algorithm for attenuation of $\boldsymbol{e}_A$

It follows from Fig.2 that the first virtual error vector $\boldsymbol{e}_A(k)$ is expressed by

$$\begin{aligned}
e_{A,m}(k) &= e_i(k) + \sum_{i=1}^{N_c} \hat{K}_{mi}(z,k)u_i(k) - \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) \\
&= e_m(k) + \sum_{i=1}^{N_c} \boldsymbol{\omega}_{mi}^T(k)\hat{\boldsymbol{\theta}}_{K,mi}(k) - \sum_{j=1}^{N_r} \boldsymbol{\xi}_{mj}^T(k)\hat{\boldsymbol{\theta}}_{D,mj}(k)
\end{aligned}$$

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:

$$\hat{\boldsymbol{\theta}}_{K,mi}(k+1) = \hat{\boldsymbol{\theta}}_{K,mi}(k) - \gamma(k)\boldsymbol{\omega}_{mi}(k)e_{A,m}(k) \tag{10a}$$

$$\hat{\boldsymbol{\theta}}_{D,mj}(k+1) = \hat{\boldsymbol{\theta}}_{D,mj}(k) + \gamma(k)\boldsymbol{\xi}_{mj}(k)e_{A,m}(k) \tag{10b}$$

$$\gamma(k) = \frac{2\alpha\|\boldsymbol{e}_A(k)\|^2}{\rho + \sum_{m=1}^{N_e} e_{A,m}^2(k)\left(\|\boldsymbol{\omega}_m(k)\|^2 + \|\boldsymbol{\xi}_m(k)\|^2\right)} \tag{10c}$$

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 (10) has a feature that the step size is not constant but is adjusted by the error vector $\boldsymbol{e}_A(k)$.

4.2. Adaptive Algorithm for attenuation of e_B

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

$$\begin{aligned}
e_{B,m}(k) &= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) \\
&-[\hat{C}_{11}(z,k), \cdot\cdot, \hat{C}_{1N_r}(z,k), \cdots, \hat{C}_{N_c1}(z,k), \cdot\cdot, \hat{C}_{N_cN_r}(z,k)] \\
&\cdot [x_{m11}(k), \cdot\cdot, x_{m1N_r}(k), \cdot\cdot, x_{mN_c1}(k), \cdot\cdot, x_{mN_cN_r}(k)]^T \\
&= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) \\
&-(\boldsymbol{x}_{m11}^T(k), \cdot\cdot, \boldsymbol{x}_{m1N_r}^T(k), \cdot\cdot, \boldsymbol{x}_{mN_c1}^T(k), \cdot\cdot, \boldsymbol{x}_{mN_cN_r}^T(k)) \\
&\cdot[\hat{\boldsymbol{c}}_{11}(k), \cdots, \hat{\boldsymbol{c}}_{1N_r}(k), \cdots, \hat{\boldsymbol{c}}_{N_cN_r}(k)]^T \\
&= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) - \boldsymbol{\varphi}_{X,m}^T(k)\hat{\boldsymbol{\theta}}_C(k)
\end{aligned} \tag{11}$$

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

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - \boldsymbol{\Phi}_X^T(k)\hat{\boldsymbol{\theta}}_C(k) \tag{12}$$

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:

$$\hat{\boldsymbol{\theta}}_C(k+1) = \hat{\boldsymbol{\theta}}_C(k) + \gamma_c(k)\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k) \tag{13a}$$

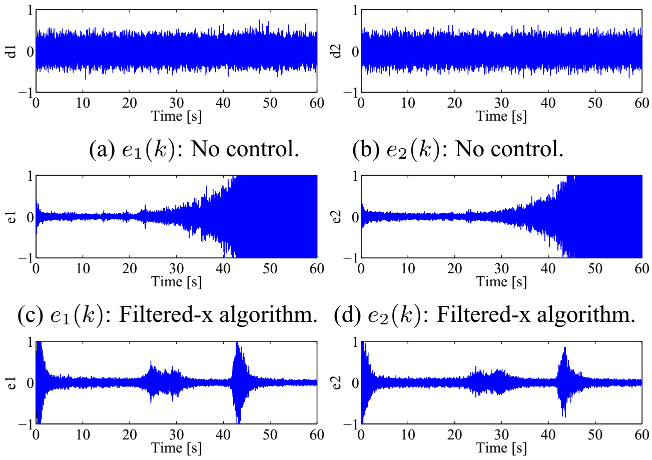
$$\gamma_c(k) = \frac{2\alpha_c\|\boldsymbol{e}_B(k)\|^2}{\rho_c + \|\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k)\|^2} \tag{13b}$$

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.2 by the new adjusted parameters in (10) and (13), we can generate the control inputs $\boldsymbol{u}(k)$ and the auxiliary signals $\boldsymbol{X}(k)$.

5. SIMULATION RESULTS

5.1. Multichannel Active Noise Control



(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.

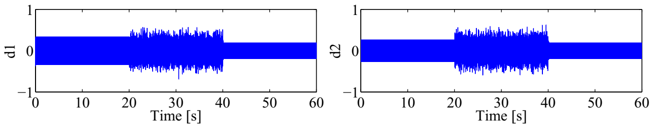
(e) $e_1(k)$: Proposed algorithm. (f) $e_2(k)$: Proposed algorithm.

Fig. 3. Comparison of control results between the filtered-x algorithm and the proposed fully direct adaptive algorithm

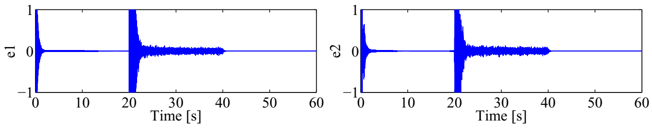
The effectiveness of the proposed direct adaptive algorithm is examined in two channel ANC in a room. The setup is same as used in our previous experimental study [6], in which $N_r = N_c = N_e = 2$. In the simulation we used the path models which were obtained experimentally. Let the sampling interval be 1 ms. We consider two typed 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 $\alpha = \alpha_c = 0.9(< 1)$, $\rho = \rho_c = 0.01$.

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.3(a) and 3(b) show the canceling errors $e_1(k)$ and $e_2(k)$ in a case without control. As shown in Figs.3(c) and 3(d), the filtered-x type of algorithm could not keep stable attenuation performance [6] 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.3(e) and 3(f).

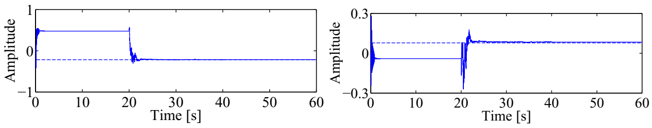
Next, Figs. 4(a) to 4(f) show the control results in a case when the two primary source noises are periodic and consist of sinusoid with unknown frequencies 150 Hz and 250 Hz respectively in the time interval (0s, 20s), and both 400 Hz in the interval (40s, 60s). The primary noises in the interval (20s,40s) 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



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

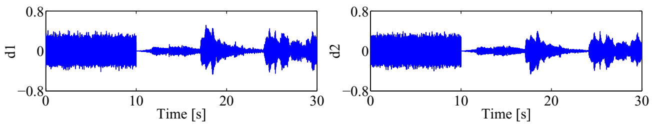


(c) $e_1(k)$ by proposed method. (d) $e_2(k)$ by proposed method.

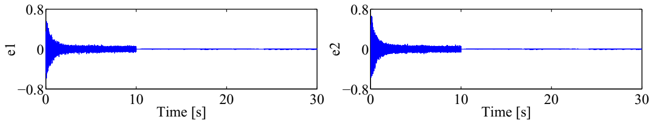


(e) Controller parameter $\hat{c}_{11}^{(10)}$. (f) Controller parameter $\hat{c}_{11}^{(19)}$.

Fig. 4. Control results for source signals without PE property

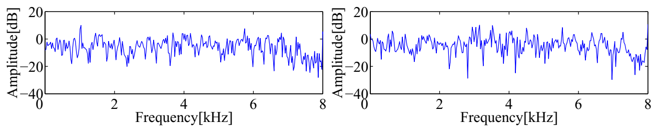


(a) Recorded signal $d_1(k)$. (b) Recorded signal $d_2(k)$.



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

Fig. 5. Sound reproduction results.



(a) Frequency response of $C_{11}(z)$. (b) Frequency response of $C_{31}(z)$.

Fig. 6. Examples of frequency response of $\boldsymbol{C}(z)$.

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 .4(e) and 4(f)). During the interval (40s, 60s) the primary source noises are sinusoids again, however, 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.

5.2. 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, which are uncertain in the simulation. Since $\boldsymbol{H}(z)$ is specified 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.5 shows the sound reproduction results, where the sampling frequnecy 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. 5(c) and 5(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.6 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 [11].

6. CONCLUSION

We have presented the new direct adaptive algorithm for tuning the feedforward inverse controller in multichannel cases, which is effective even when the all path matrices are uncertain. The proposed algorithm does not need explicit identification of the uncertain secondary paths and is different from the ordinary filtered-x algorithms.

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