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VIRTUAL ERROR APPROACH TO DIRECT MULTI-CHANNEL ADAPTIVE ACTIVE NOISE CONTROL

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Abstract
A new direct adaptive approach is proposed for general multichannel active noise control (ANC) when all of the sound channel dynamics are uncertain and changeable. To reduce the cancelling 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 cancelling errors to zero can be attained at the error 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. The proposed virtual error approach can be extended to the frequency-domain ANC.

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.

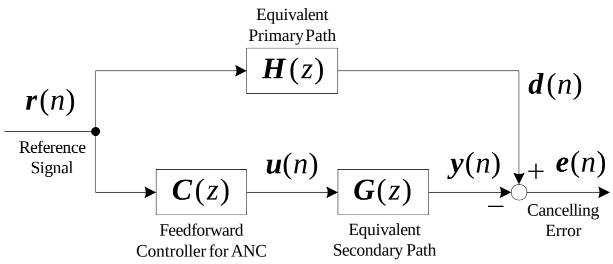


Fig.1 Schematic diagram of adaptive active noise control system

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 [2][9] which also combines 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. The proposed virtual error approach can also be extended to the frequency-domain ANC problem. Its effectiveness is examined in numerical simulations.

ADAPTIVE ACTIVE NOISE CONTROL PROBLEM

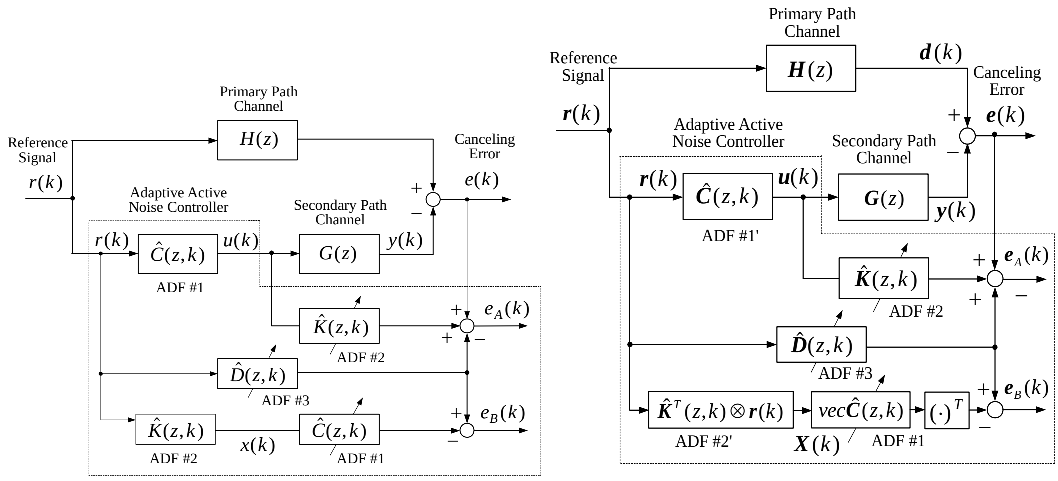
An equivalent structure of multi-channel feedforward sound control systems is depicted by Fig.1. In ANC case, the signal $\boldsymbol{r}(k) \in \mathcal{R}^{N_r}$ detected by N_r reference microphones are the inputs to the $N_c \times N_r$ adaptive feedforward controller matrix $\hat{\boldsymbol{C}}(z,k)$,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

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

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.

VIRTUAL ERROR APPROACH IN TIME DOMAIN

Fig.2 shows the schematic diagrams of the virtual error approach in time domain. 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. 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:



(a) Single channel case (b) Multichannel case

Fig.2 Virtual error method for time-domain multichannel ANC

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

$$\boldsymbol{e}_A(k) = \boldsymbol{e}(k) + \hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) - \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) \tag{3}$$

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{4}$$

$$\boldsymbol{u}(k) = \hat{\boldsymbol{C}}(z,k)\boldsymbol{r}(k) \tag{5}$$

$$\boldsymbol{X}(k) = \hat{\boldsymbol{K}}^T(z,k) \otimes \boldsymbol{r}(k) \tag{6}$$

where $vec[\boldsymbol{A}]$ denotes a row vector expansion of a matrix $\boldsymbol{A}$, and $\otimes$ denotes the Kronecker product. Then we consider the sum of two virtual errors in Fig.2(b) from (3) and (4) as

$$\boldsymbol{e}_A(k) + \boldsymbol{e}_B(k) = \boldsymbol{e}(k) + \hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) - [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{7}$$

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. It can be proved by showing the equality:

$$\hat{\boldsymbol{K}}(z,k)\boldsymbol{u}(k) = [vec[\hat{\boldsymbol{C}}(z,k)]\boldsymbol{X}(k)]^T \tag{8}$$

in sufficiently large k. 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.

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

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

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

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

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

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

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

$$= e_m(k) + \sum_{i=1}^{N_c} \boldsymbol{\omega}_{mi}^T(k)\hat{\boldsymbol{\theta}}_{K,mi}(k) - \sum_{i=1}^{N_r} \boldsymbol{\xi}_{mj}^T(k)\hat{\boldsymbol{\theta}}_{D,mj}(k)\,) \tag{10}$$

where $m = 1,\cdots,N_e$, $\boldsymbol{\omega}_{mi}^T(k) = (u_i(k-1),\cdots,u_i(k-L_{mi}^K))^T$, $\hat{\boldsymbol{\theta}}_{K,mi}(k) = (\hat{k}_{mi}^{(1)}(k),\cdots,\hat{k}_{mi}^{(L_{mi}^K)}(k))^T$, $\boldsymbol{\xi}_{mj}^T(k) = (r_j(k-1),\cdots,r_j(k-L_{mj}^D))^T$ and $\hat{\boldsymbol{\theta}}_{D,mj}(k) = (\hat{d}_{mj}^{(1)}(k),\cdots,\hat{d}_{mj}^{(L_{mi}^D)}(k))^T$. 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 $\hat{\boldsymbol{\theta}}_{D,mj}(k)$, we can derive the adaptive algorithm for updating these parameters as follows:

$$\hat{\boldsymbol{\theta}}_{K,mi}(k+1) = \hat{\boldsymbol{\theta}}_{K,mi}(k) - \gamma(k)\boldsymbol{\omega}_{mi}(k)e_{A,m}(k) \tag{11a}$$

$$\hat{\boldsymbol{\theta}}_{D,mj}(k+1) = \hat{\boldsymbol{\theta}}_{D,mj}(k) - \gamma(k)\boldsymbol{\xi}_{mj}(k)e_{A,m}(k) \tag{11b}$$

$$\gamma(k) = 2\alpha\|\boldsymbol{e}_A(k)\|^2 \Big/ \rho + \sum\nolimits_{m=1}^{N_e} e_{A,m}^2(k)\left(\|\boldsymbol{\omega}_m(k)\|^2 + \|\boldsymbol{\xi}_m(k)\|^2\right) \tag{11c}$$

where $\boldsymbol{\omega}_m(k) = (\boldsymbol{\omega}_{m1}^T(k),\cdots,\boldsymbol{\omega}_{mN_c}^T(k))^T$, $\boldsymbol{\xi}_m(k) = (\boldsymbol{\xi}_{m1}^T(k),\cdots,\boldsymbol{\xi}_{mN_r}^T(k))^T$, and $0<\alpha<1$, $\rho>0$ is a small constant. The algorithm (11) has a feature that the step size is not constant but is adjusted by the error vector $\boldsymbol{e}_A(k)$.

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

$$\begin{aligned}
e_{B,m}(k) &= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) - [\hat{C}_{11}(z,k),\cdots,\hat{C}_{1N_r}(z,k),\cdots,\hat{C}_{N_c1}(z,k),\cdots,\hat{C}_{N_cN_r}(z,k)] \\
&\qquad \cdot[x_{m11}(k),\cdots,x_{m1N_r}(k),\cdots,x_{mN_c1}(k),\cdots,x_{mN_cN_r}(k)]^T \\
&= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) - (\bar{\boldsymbol{x}}_{m11}^T(k),\cdots,\bar{\boldsymbol{x}}_{m1N_r}^T(k),\cdots,\bar{\boldsymbol{x}}_{mN_c1}^T(k),\cdots,\bar{\boldsymbol{x}}_{mN_cN_r}^T(k)) \\
&\qquad (\hat{\boldsymbol{c}}_{11}^T(k),\cdots,\hat{\boldsymbol{c}}_{1N_r}^T(k),\cdots,\hat{\boldsymbol{c}}_{N_c1}^T(k),\cdots,\hat{\boldsymbol{c}}_{N_cN_r}^T(k))^T \\
&= \sum_{j=1}^{N_r} \hat{D}_{mj}(z,k)r_j(k) - \boldsymbol{\varphi}_{X,m}^T(k)\hat{\boldsymbol{\theta}}_C(k)
\end{aligned} \tag{12}$$

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

Thus, the second virtual error vectors are expressed by

$$\boldsymbol{e}_B(k) = \hat{\boldsymbol{D}}(z,k)\boldsymbol{r}(k) - \boldsymbol{\Phi}_X^T(k)\hat{\boldsymbol{\theta}}_C(k) \tag{13}$$

where

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

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

$$\hat{\boldsymbol{\theta}}_C(k+1) = \hat{\boldsymbol{\theta}}_C(k) + \gamma_c(k)\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k) \tag{14a}$$

$$\gamma_c(k) = 2\alpha\|\boldsymbol{e}_B(k)\|^2 \Big/ \rho_c + \|\boldsymbol{\Phi}_X(k)\boldsymbol{e}_B(k)\|^2 \tag{14b}$$

where $0<\alpha_c<1$, and $\rho_c>0$ is a small constant.

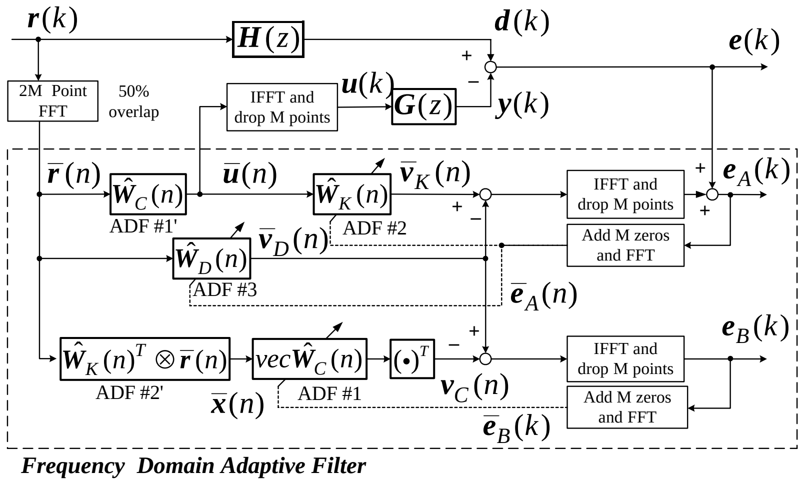


Fig.3 Virtual Error approach in frequency domain multichannel ANC

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 (13) and (16), we can generate the control inputs $\boldsymbol{u}(k)$ and the auxiliary signals $\boldsymbol{X}(k)$. As shown in Fig.2, there are no dynamics between the adaptive filters and the virtual errors, then the stability can be assured.

VIRTUAL ERROR APPROACH IN FREQUENCY DOMAIN

Fig.3 shows a new fully adaptive tuning algorithm in the frequency-domain for a multichannel ANC. We introduce two kinds of virtual error vectors $\boldsymbol{e}_A(k)$ and $\boldsymbol{e}_B(k)$, which are forced to zero by using two frequency-domain adaptive FIR filter matrices $\hat{\boldsymbol{W}}_C(n)$, $\hat{\boldsymbol{W}}_K(n)$ and $\hat{\boldsymbol{W}}_D(n)$. Let n refer to the block index, which is related to the original sampling time k as

$$k = nM + s, \quad s = 0,1,\cdots,M-1, \quad n = 1,2,\cdots$$

where M is the block length.

The reference data which is detected in j-th reference microphone for n-th block is thus defined by the set $\{r_j(nM+s)\}_{s=0}^{M-1}$, where $\boldsymbol{r}_j(n) = (r_j(nM),\cdots,r_j(nM+M-1))^T$. The j-th frequency-domain reference vector $\bar{\boldsymbol{r}}_j(n)$ of size $N = 2M$ are calculated applying FFT's on the corresponding time-domain signal vectors as

$$\bar{\boldsymbol{r}}_j^T(n) = [\boldsymbol{r}_j^T(n-1), \boldsymbol{r}_j^T(n)]_{FFT} = (\bar{r}_j^{(0)}(n),\cdots,\bar{r}_j^{(l)}(n),\cdots,\bar{r}_j^{(N-1)}(n))^T$$

where l denotes l-th frequency bin with $\omega_l = l\pi/NT_s$ and T_s is the sampling interval.

We introduce three adaptive filter weights in frequency domain $\hat{\boldsymbol{w}}_{C,ij}(n)$, $\hat{\boldsymbol{w}}_{D,mj}(n)$ and $\hat{\boldsymbol{w}}_{K,mj}(n)$ as $\hat{\boldsymbol{w}}_{C,ij}(n) = (\hat{w}_{C,ij}^{(0)}(n),\cdots,\hat{w}_{C,ij}^{(l)}(n),\cdots,\hat{w}_{C,ij}^{(N-1)}(n))^T$, $\hat{\boldsymbol{w}}_{K,mi}(n) = (\hat{w}_{K,mi}^{(0)}(n),\cdots,\hat{w}_{K,mi}^{(l)}(n),\cdots,\hat{w}_{K,mi}^{(N-1)}(n))^T$ and $\hat{\boldsymbol{w}}_{D,mj}(n) = (\hat{w}_{D,mj}^{(0)}(n),\cdots,\hat{w}_{D,mj}^{(l)}(n),\cdots,\hat{w}_{D,mj}^{(N-1)}(n))^T$, where $i = 1,\cdots,N_c$, $j = 1,\cdots,N_r$, $m = 1,\cdots,N_e$ and $l = 0,\cdots,N-1$. Then, the i-th frequency domain control input $\bar{\boldsymbol{u}}_i(n)$ is defined as

$$\bar{\boldsymbol{u}}_i^T(n) = \sum_{j=1}^{N_r} \hat{\boldsymbol{w}}_{C,ij}^T(n) * \bar{\boldsymbol{r}}_j(n), \qquad \text{where} \quad \boldsymbol{a}^T * \boldsymbol{b} \equiv \boldsymbol{a}^T \cdot Diag[\boldsymbol{b}]$$

where $Diag[\boldsymbol{b}]$ denotes a diagonal matrix rearranging elements of the vector $\boldsymbol{b}$ diagonally. The auxiliary signal vector $\bar{\boldsymbol{x}}_{mij}(n)$ given by the Kronecker product between $\hat{\boldsymbol{w}}_{K,mi}(n)$ and $\bar{\boldsymbol{r}}_j(n)$, and $\bar{\boldsymbol{x}}_m(n)$ are defined as

$$\bar{\boldsymbol{x}}_{mij}{}^T(n) = \hat{\boldsymbol{w}}_{K,mi}(n)^T * \bar{\boldsymbol{r}}_j(n), \text{ where } \bar{\boldsymbol{x}}_m(n) = [\bar{\boldsymbol{x}}_{m11}{}^T(n), \bar{\boldsymbol{x}}_{m12}{}^T(n), \cdots, \bar{\boldsymbol{x}}_{mN_cN_r}{}^T(n)]^T$$

Then, $\bar{\boldsymbol{v}}_{K,m}(n)$ and $\bar{\boldsymbol{v}}_{C,m}(n)$ which correspond to m-th error microphone are expressed by

$$\bar{\boldsymbol{v}}_{K,m}{}^T(n) = \sum_{i=1}^{Nc} \hat{\boldsymbol{w}}_{K,mi}{}^T(n) * \bar{\boldsymbol{u}}_i(n) = \sum_{i=1}^{Nc} \hat{\boldsymbol{w}}_{K,mi}{}^T(n) * (\sum_{j=1}^{Nr} \hat{\boldsymbol{w}}_{C,ij}{}^T(n) * \bar{\boldsymbol{r}}_j^{(l)})^T \quad (15)$$

$$\bar{\boldsymbol{v}}_{C,m}{}^T(n) = [vec(\hat{\boldsymbol{W}}_C(n))]\bar{\boldsymbol{x}}_m(n) = (\hat{\boldsymbol{w}}_{C,11}{}^T(n), \hat{\boldsymbol{w}}_{C,12}{}^T(n), \cdots, \hat{\boldsymbol{w}}_{C,N_cN_r}{}^T(n))\bar{\boldsymbol{x}}_m(n)$$

$$= \sum_{i=1}^{Nc}\sum_{j=1}^{Nr} \hat{\boldsymbol{w}}_{C,ij}(n) * \hat{\boldsymbol{x}}_{mij}(n) = \sum_{i=1}^{Nc}\sum_{j=1}^{Nr} \hat{\boldsymbol{w}}_{C,ij}(n) * (\hat{\boldsymbol{w}}_{K,mi}{}^T(n) * \bar{\boldsymbol{r}}_j^{(l)})^T \quad (16)$$

Thus, the auxiliary signals of the l-th frequency bin at the n-th time block are written as

$$\bar{v}_{K,m}^{(l)}(n) = \sum_{i=1}^{Nc}\sum_{j=1}^{Nr} \hat{w}_{K,mi}^{(l)}(n)\hat{w}_{C,ij}^{(l)}(n)\bar{r}_j^{(l)}(n), \quad \bar{v}_{C,m}^{(l)}(n) = \sum_{i=1}^{Nc}\sum_{j=1}^{Nr} \hat{w}_{C,ij}^{(l)}(n)\hat{w}_{K,mi}^{(l)}(n)\bar{r}_j^{(l)}(n)$$

where $\hat{\boldsymbol{w}}_{K,mi}(n)$, $\hat{\boldsymbol{w}}_{C,ij}(n)$, $\bar{r}_j^{(l)}$ are the weight of the each l-th frequency bin respectively. Since they are scalar values, we can exchange the product of two $\hat{\boldsymbol{w}}_{K,mi}(n)$ and $\hat{\boldsymbol{w}}_{C,ij}(n)$ in (15) and (16), and then we can establish that (15) is equal to (16).

The noise canceling error at m-th error microphone is expressed by

$$e_m(nM+s) = d_m(nM+s) - y_m(nM+s)$$

where $s = 0,1,\cdots,M-1$, $m = 1,\cdots,N_e$, and the m-th virtual errors are also expressed by

$$\boldsymbol{e}_{A,m}(n) = \boldsymbol{e}_m(n) + \{\boldsymbol{v}_{K,m}(n) - \boldsymbol{v}_{D,m}(n)\}_- \text{ and } \boldsymbol{e}_{B,m}(n) = \boldsymbol{e}_m(n) + \{\boldsymbol{v}_{D,m}(n) - \boldsymbol{v}_{C,m}(n)\}_-$$

where, $\{\boldsymbol{z}\}_-$ denotes the last M elements of $\mathrm{IFFT}\{\boldsymbol{z}\}$. Then we consider the sum of two virtual errors in Fig.3 from above equations as

$$\boldsymbol{e}_{A,m}(n) + \boldsymbol{e}_{B,m}(n) = \boldsymbol{e}_m(n) + \{\boldsymbol{v}_{K,m}(n) - \boldsymbol{v}_{C,m}(n)\}_- = \boldsymbol{e}_m(n)$$

If the coefficient parameters in the two adaptive filters $\hat{\boldsymbol{W}}_C(n)$ and $\hat{\boldsymbol{W}}_K(n)$ converge so that the errors $\boldsymbol{e}_A(n)$ and $\boldsymbol{e}_B(n)$ may become zero, the reconstruction error vector $\boldsymbol{e}(n)$ can also converge to zero.

We apply the FFT to the first virtual error vector $\boldsymbol{e}_{A,m}(k)$ to obtain $\bar{\boldsymbol{e}}_{A,m}(n)$ expressed in the frequency-domain as $\bar{\boldsymbol{e}}_{A,m}(n) = [\boldsymbol{0}, \boldsymbol{e}_{A,m}(n)]_{FFT}$, where $\boldsymbol{0}$ is the 1-by-M null vector. Then, the power spectral density of the reference signal for updating the weights $\hat{\boldsymbol{W}}_K(n)$ and $\hat{\boldsymbol{W}}_D(n)$ in the l-th frequency bin at the n-th iteration are expressed each as

$$\hat{P}_{K,l}^{(n)} = \gamma\hat{P}_{K,l}^{(n-1)} + (1-\gamma)\sum_{i=1}^{N_c}|u_i^{(l)}(n)|^2, \text{ where } \hat{\boldsymbol{Q}}_{K,ij}^{(n)} = \mathrm{Diag}[(\hat{P}_{K,0}^{(n)})^{-1}, \cdots, (\hat{P}_{K,N-1}^{(n)})^{-1}]$$

$$\hat{P}_{D,l}^{(n)} = \gamma\hat{P}_{D,l}^{(n-1)} + (1-\gamma)\sum_{j=1}^{N_r}|r_i^{(l)}(n)|^2, \text{ where } \hat{\boldsymbol{Q}}_{D,ij}^{(n)} = \mathrm{Diag}[(\hat{P}_{D,0}^{(n)})^{-1}, \cdots, (\hat{P}_{D,N-1}^{(n)})^{-1}]$$

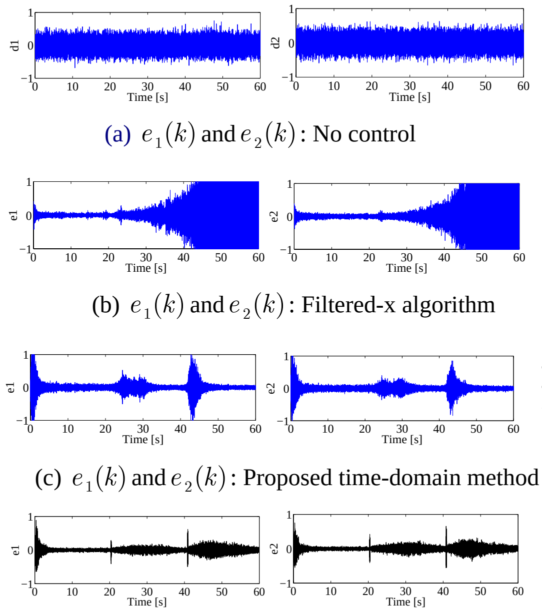
$$\hat{P}_{C,ij,l}^{(n)} = \gamma\hat{P}_{C,ij,l}^{(n-1)} + (1-\gamma)\sum_{m=1}^{N_e}|\bar{x}_{mij}^{(l)}(n)|^2, \text{ where } \hat{\boldsymbol{Q}}_{C,ij}^{(n)} = \mathrm{Diag}[(\hat{P}_{C,0}^{(n)})^{-1}, \cdots, (\hat{P}_{C,N-1}^{(n)})^{-1}]$$

where $l = 0,\cdots,N-1$ and γ is forgetting factor. Thus, the weights of two adaptive filters are updated by the frequency- domain LMS algorithm as

$$\hat{\boldsymbol{w}}_{K,mi}(n+1) = \hat{\boldsymbol{w}}_{K,mi}(n) - \alpha_K[\{\hat{\boldsymbol{Q}}_K^{(n)}\bar{\boldsymbol{u}}_i^H(n) * \bar{\boldsymbol{e}}_{A,m}(n)\}_+, \boldsymbol{0}]_{FFT} \quad (17a)$$

$$\hat{\boldsymbol{w}}_{D,mi}(n+1) = \hat{\boldsymbol{w}}_{D,mi}(n) + \alpha_D[\{\hat{\boldsymbol{Q}}_D^{(n)}\bar{\boldsymbol{r}}_i^H(n) * \bar{\boldsymbol{e}}_{A,m}(n)\}_+, \boldsymbol{0}]_{FFT} \quad (17b)$$

$$\hat{\boldsymbol{w}}_{C,ij}(n+1) = \hat{\boldsymbol{w}}_{C,ij}(n) + \alpha_C[\{\hat{\boldsymbol{Q}}_{C,ij}^{(n)}\bar{\boldsymbol{x}}_{mij}^H(n) * \bar{\boldsymbol{e}}_{B,m}(n)\}_+, \boldsymbol{0}]_{FFT} \quad (17c)$$



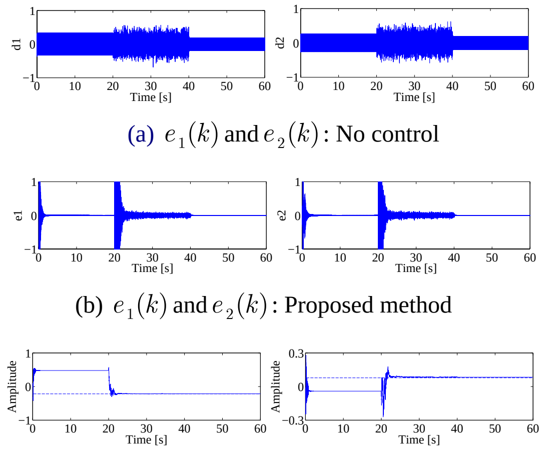
(a) $e_1(k)$ and $e_2(k)$: No control

(b) $e_1(k)$ and $e_2(k)$: Filtered-x algorithm

(c) $e_1(k)$ and $e_2(k)$: Proposed time-domain method

(d) $e_1(k)$ and $e_2(k)$: Proposed frequency-domain method

Fig.4 Comparison of control results between the filtered-x algorithm and the proposed fully direct adaptive algorithm



(a) $e_1(k)$ and $e_2(k)$: No control

(b) $e_1(k)$ and $e_2(k)$: Proposed method

(c) $\hat{c}_{11}^{(10)}$ and $\hat{c}_{11}^{(19)}$: Controller parameters

Fig.5 Control results for source signals without PE property

where, $\{\mathbf{z}\}_+$ denotes first block of $\mathrm{IFFT}\{\mathbf{z}\}$ and α_K, α_D, α_C are stepsizes.

Computational complexity can be evaluated by the number of multiplications needed in the time-domain and frequency domain approaches. For the simplicity, let N_c, N_r, N_e be set to a . In the time-domain approach, $(2a^3+3a^2)M$ and $(4a^3+6a^2)M+4a+6$ multiplications are executed in calculation of filter outputs and updating parameters. In the frequency domain approach, total number of multiplications is evaluated as $13a^3+28a^2+\ 12a(a+1)\log_2 M$. Then, in a case of $a=2$ and $M=1024$, the reduction of computational quantity can be obtained by almost $1/100$ in the frequency-domain approach.

SIMULATION RESULTS

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. 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 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 control loudspeakers by using the switches at 20 [s] after the start of control, and then the location is again moved by 68 [cm] apart from the control loudspeakers at 40 [s]. Fig.4(a) shows the canceling errors $e_1(k)$ and $e_2(k)$ in a case without control. As shown in Figs.4(b), 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 methods in time-domain and frequency-domain could still attain the stable control performance even if the channels changed rapidly as given in Figs. 4(c) and 4(d).

Next, Figs. 5(a) to 5(c) show the control results in a case when the two primary source noises are periodic and consist of sinusoids 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 Fig. 5(c). 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.

CONCLUSION

We have proposed the new direct adaptive algorithms in both time-domain and frequency-domain for tuning the feedforward sound controller in multichannel cases, which is effective even when the all path matrices are uncertain. The algorithms need neither explicit identification of the uncertain secondary paths nor the additional input of the dither noises for assuring the PE condition of the primary source noises.

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