Adaptation for Active Noise Control

Fan Jiang, Hiroyuki Tsuji, Hiromitsu Ohmori, and Akira Sano

In active noise control, adaptive approaches play an essential role when dealing with uncertainties and changes in noise and control path dynamics of sound propagation. This article is concerned with two new adaptive schemes. One is a direct adaptive approach which can explicitly update a feedforward controller with guaranteed stability on the assumption that the control path dynamics are known *a priori*. The other is an indirect adaptive approach which is available when the both noise and control path dynamics are uncertain and changeable. The algorithm consists of on-line identification of two relevant transfer function models and real-time calculation of the corresponding feedforward controller. The two adaptive schemes are examined in experimental studies in an air duct system and their effectiveness is shown by the results.

Introduction

Based on the rapid progress of high-speed and low-cost computing devices such as digital signal processors (DSPs), active noise control has increasingly gained much attention in automotive vehicles, aerospace cabin systems, office and manufacturing environments, and other industrial settings because it can complement traditional passive technologies and attain better performance on attenuation of low-frequency sounds [1-4].

In the control methodology, feedforward control is an effective approach for attaining satisfactory canceling performance if the primary noise is measurable and the controller can be causal. Therefore, almost all active noise control applications are based on feedforward techniques up to now. An alternative approach is feedback control [5, 6]. Since the approach does not need measurement of the primary noise and deals with the controller causality problem, it has been gaining interest for development of applicable feedback algorithms. Owing to the properties of the noise problems, however, pure feedback control has seen relatively limited use in active noise control [7]. It is meaningful to explore the way of applying feedback control techniques and combining them with feedforward control techniques, for active noise applications. In this article, we mainly discuss the feedforward control schemes.

In actual noise control systems, because the path dynamics cannot be precisely obtained and may be changing due to the variations of the positions of both the noise source and objective point, a deterministic feedforward controller cannot be expected to attain satisfactory performance; therefore, adaptations should be introduced into the controller for dealing with these uncertainties and changes. In such adaptive approaches, the canceling error can be used to adjust the controller parameters, which is somewhat of feedback control; but since these methods require noise measurements, they are traditionally viewed as feedforward algorithms [6]. A variety of filtered-x type LMS adaptive algorithms are conventionally used to adjust the weights of a feedforward controller implemented by an FIR type of adaptive filter [8-13]. However, they sometimes display a serious problem of instability, dictating that the step size of the algorithms should be chosen carefully. Moreover, in the situation that the control path dynamics are uncertain and changeable, the identification of control path dynamics from the control loudspeaker to the error-detecting microphone will be performed simultaneously with the adjustment of controller parameters. Thus, additional models or microphones and loudspeakers should be introduced, and, since the identification of the control path dynamics need a converging process, the use of the dynamic parameters identified within this period will adversely affect adjustment of the controller parameters.

To cope with these problems, two new types of adaptive control schemes are considered in this article: a direct adaptive algorithm and an indirect adaptive algorithm. In the direct adaptive algorithm, the controller parameters are updated directly based on a strictly positive real (SPR) error model [14], which can ensure the convergence of the controller parameters and the boundedness of the canceling error, if the control path dynamics are known *a priori* and the disturbance is bounded. On the other hand, the indirect adaptive algorithm enables adaptation to uncertainties in both noise and control path dynamics. This fully adaptive algorithm consists of two steps: on-line identification of two transfer function models based on a stability guaranteed algorithm by using accessible signals, and real-time calculation of the feedforward controller by dividing the one identified model by the other. The algorithm does not need additional microphones and loudspeakers, and, although the error canceling performance will be affected by the accuracy of the dividing calculation, the stability of identification of the system models is independent of the output of the controller.

The work presented in this article is a one of continuous investigation of [15,16]. The two adaptive schemes are systematically summarized, and the theoretical conditions as well as practical applicability are extensively studied. A new robust adaptive algorithm, which can attain the tight boundedness, is proposed, and the algorithm of realizing the indirect controller is also given where the fast Fourier transform (FFT) approach is applied. Finally, the two algorithms are successfully applied to the noise cancellation in an air duct system.

Hiroyuki Tsuji is now at Communication Research Laboratory, Ministry of Posts and Telecommunications, 4-2-1 Nukuikitamachi, Koganei-shi 186, Japan. The other authors are with the Department of Electrical Engineering, Keio University, 3-14-1 Hiyoshi, Kohoku-ku, Yokohama 223, Japan. A version of this article was presented at the IEEE International Conference on Control Applications, Dearborn, MI, Sept. 15-18, 1996.

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Deterministic and Adaptive Aspects of Active Noise Control

Structure of Control System

The schematic diagram of an adaptive active noise control system is depicted in Fig. 1, in which the control objective is to cancel or attenuate the sound pressure level, mainly caused by primary source noise $s(k)$, at the objective point A. The cancellation is performed actively by producing an artificial secondary control sound from a loudspeaker located at point C. To construct an adaptive feedforward control system, a primary noise-detecting microphone, or reference microphone, and an error-detecting microphone, or error microphone, are introduced, located at point B and point A, respectively, to obtain the reference signal $r(k)$ and the canceling error $e(k)$. The two measured signals are fed to the adaptive feedforward controller $\hat{C}(z,k)$, which provides the control signal $u(k)$ for the secondary loudspeaker C. If the feedback controller $F(z)$ is employed, as indicated by the dotted line in Fig. 1(b), the problem becomes one which involves a design of the control system with two degrees of freedom. In that case, the control signal $v(k)$ is given by the sum of the feedforward and feedback controls as $v(k) = u(k) + w(k)$. The feedback controller $F(z)$ has two important roles: one is for control robust to unmodelled dynamics of the path dynamics and uncertain disturbance $n(k)$ [17], and the other is for stabilization of an adaptive algorithm robust to changes of the control path dynamics [15]. In the system, four path dynamics are involved, and here we denote the path dynamics of sound propagation from the primary noise $s(k)$ to the reference microphone and error microphone as $G_1(z)$ and $G_2(z)$, respectively, and that from the secondary control sound $v(k)$ to these two microphones as $G_3(z)$ and $G_4(z)$, respectively, as shown in Fig. 1. Thus, $G_1(z)$ and $G_2(z)$ are referred to as the primary or noise path dynamics, $G_3(z)$ and $G_4(z)$ as the secondary or control path dynamics, and the latters are used in this article.

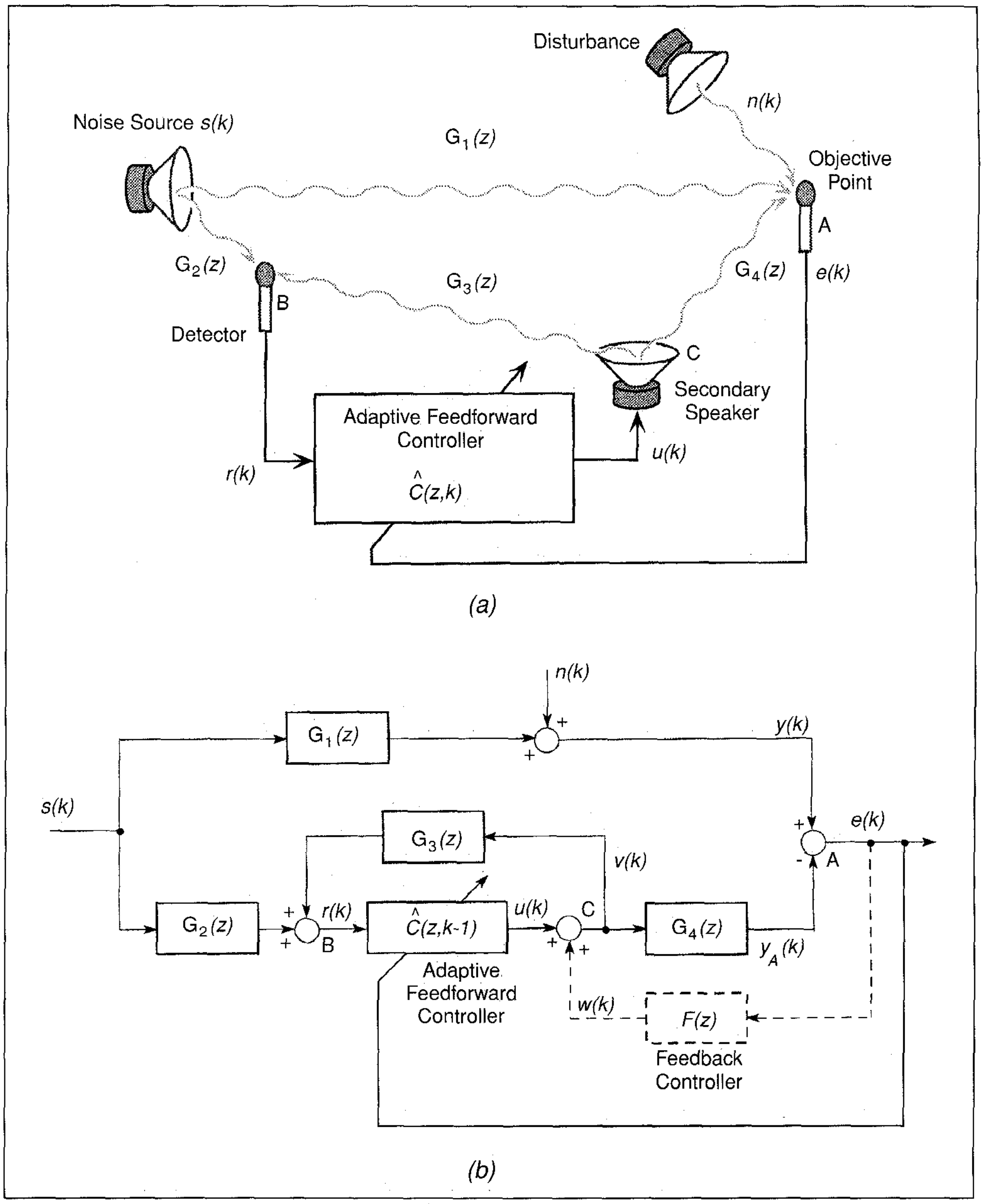

Fig. 1. Schematic diagram of the adaptive active noise control system.

Deterministic Aspect of Active Noise Control

By replacing the adaptive controller $\hat{C}(z,k)$ with a deterministic controller $C(z)$, we can describe the system in Fig. 1(b) by the following equations:

$$e(k) = G_1(z)s(k) - G_4(z)v(k) + n(k)\,, \tag{1}$$

$$r(k) = G_2(z)s(k) + G_3(z)v(k)\,, \tag{2}$$

$$v(k) = C(z)r(k) + F(z)e(k)\,. \tag{3}$$

Eliminating $v(k)$ and $r(k)$ from (1), (2), and (3), we can express the canceling error signal $e(k)$ at the point A as

$$e(k) = \frac{G_1(z) - [G_1(z)G_3(z) + G_2(z)G_4(z)]C(z)}{1 - G_3(z)C(z) + G_4(z)F(z)}s(k) + \frac{1 - G_3(z)C(z)}{1 - G_3(z)C(z) + G_4(z)F(z)}n(k)\,. \tag{4}$$

If all of the path dynamics $G_1(z)$, $G_2(z)$, $G_3(z)$, and $G_4(z)$ are known *a priori* and there is no disturbance, i.e., $n(k) = 0$, and the closed-loop transfer function in (4) is asymptotically stable, then the perfect cancellation of the primary noise at the objective point can be attained by selecting the feedforward controller $C(z)$ as

$$C(z) = \frac{G_1(z)}{G_1(z)G_3(z) + G_2(z)G_4(z)} \equiv C^*(z) , \tag{5}$$

which does not depend on the feedback controller $F(z)$.

Since the control scheme discussed here is a feedforward one, the realizable or causal problem of the controller caused by the microphone/loudspeaker placement, which does not need to be dealt with in feedback control approaches [5-7], will be touched upon. Let d_1, d_2, d_3, and d_4 denote the delay of path dynamics $G_1(z)$, $G_2(z)$, $G_3(z)$, and $G_4(z)$, respectively, then from (5) the condition that the controller $C^*(z)$ is causal can be obtained without difficulty as

$$d_2 + d_4 < d_1 , \tag{6}$$

which suggests that the reference microphone will be set close to the primary noise source and the control loudspeaker to the objective point. In practical applications, although the noise source or/and the objective point may be changeable, in general the change ranges of the noise source and objective point can be roughly known, so a set of placement points can be found to make the controller causal by considering these changes. In fact, the condition (6) is not too severe since it can be satisfied in most of actual active noise control systems.

When the perfect canceling controller $C^*(z)$ given by (5) is causal, in the presence of disturbance $n(k)$, if $C(z)$ is chosen as $C^*(z)$ in (5), (4) becomes

$$e(k) = \frac{G_2(z)}{G_2(z) + [G_1(z)G_3(z) + G_2(z)G_4(z)]F(z)} n(k) . \tag{7}$$

It can easily be seen that the cancellation error $e(k)$ will be reduced by an appropriate design of the feedback controller $F(z)$ by taking into account the effects of the disturbance $n(k)$ [17]. In the following discussion, we assume that the disturbance $n(k)$ is bounded, i.e.,

$$|n(k)| < \beta . \tag{8}$$

It should be noticed that due to the feedforward control property, if $C(z) = C^*(z)$ either $C(z)$ or the closed-loop subsystem composed by $C(z)$ and the feedback path dynamics $G_3(z)$ will contain the inverse terms of the feedforward path dynamics $G_2(z)$ and $G_4(z)$. Therefore, if exact $C^*(z)$ is applied to attain the perfect canceling performance, the feedforward path dynamics $G_2(z)$ and $G_4(z)$ should be minimum phase functions. If they are not, to construct a stable control system the controller should be realized approximately, which is usually done in actual applications by using a stable FIR filter. When such an approximate controller is adopted, the effect of the primary noise cannot be canceled perfectly. The situation is the same in the adaptive aspect and the minimum phase conditions discussed in the later sections are done merely from the adaptive algorithm viewpoint.

Adaptive Aspect of Active Noise Control

When part or all of the path dynamics are uncertain and changing, control adaptation will be required for tuning the deterministic feedforward controller to adapt to these uncertain factors so that canceling performance can be maintained. Therefore, the adaptive feedforward controller $\hat{C}(z, k)$ is structured such that it is generally implemented by using an IIR or FIR type of adaptive filter described by

$$\hat{C}(z, k) = \frac{\hat{b}_1(k)z^{-1} + \hat{b}_2(k)z^{-2} + \ldots + \hat{b}_m(k)z^{-m}}{1 + \hat{a}_1(k)z^{-1} + \hat{a}_2(k)z^{-2} + \ldots + \hat{a}_n(k)z^{-n}} , \tag{9a}$$

$$\hat{C}(z, k) = \hat{c}_1(k)z^{-1} + \hat{c}_2(k)z^{-2} + \ldots + \hat{c}_L(k)z^{-L} ; \tag{9b}$$

respectively. We take the IIR structure in (9a) for a moment to discuss the capability of the proposed stability-assured adaptive algorithm in a general framework. By using this form of adaptive filter, the adaptive feedforward control $u(k)$, the output of the adaptive filter, can be expressed as

$$u(k) = \hat{C}(z, k-1)r(k) = \hat{\theta}^T(k-1)\varphi(k-1) , \tag{10}$$

where

$$\hat{\theta}(k-1) \equiv \begin{pmatrix} \hat{a}_1(k-1), \hat{a}_2(k-1), \ldots, \\ \hat{a}_n(k-1), \hat{b}_1(k-1), \hat{b}_2(k-1) \ldots, \hat{b}_m(k-1) \end{pmatrix}^T ,$$

$$\varphi(k-1) \equiv \begin{pmatrix} -u(k-1), -u(k-2), \ldots, \\ -u(k-n), r(k-1), r(k-2), \ldots, r(k-m) \end{pmatrix}^T .$$

Eliminating $s(k)$ and $v(k)$ from (1), (2), and (3), we can rewrite the canceling error $e(k)$ in terms of the accessible signal $r(k)$, and obtain the error model as

$$\begin{aligned} e(k) &= W(z)\left(\frac{\overline{G_1}(z)}{\overline{G_4}(z)} - \hat{C}(z, k-1)\right)r(k) + \xi(k) \\ &= W(z)\left[C^*(z) - \hat{C}(z, k-1)\right]r(k) + \xi(k) \\ &= W(z)\left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right] + \xi(k) , \end{aligned} \tag{11}$$

where

$$\overline{G_1}(z) = \frac{G_1(z)}{G_2(z)} , \tag{12a}$$

$$\overline{G_4}(z) = G_4(z) + \frac{G_1(z)G_3(z)}{G_2(z)} , \tag{12b}$$

$$\begin{aligned} \xi(k) &= \frac{1}{1 + \overline{G_4}(z)F(z)} n(k) \\ &= \frac{G_2(z)}{G_2(z) + [G_1(z)G_3(z) + G_2(z)G_4(z)]F(z)} n(k) , \end{aligned} \tag{12c}$$

$$W(z) = \frac{\overline{G_4}(z)}{1+\overline{G_4}(z)F(z)}$$
$$= \frac{G_1(z)G_3(z)+G_2(z)G_4(z)}{G_2(z)+\left[G_1(z)G_3(z)+G_2(z)G_4(z)\right]F(z)}, \tag{12d}$$

and θ^* is the true parameter vector corresponding to the perfect canceling controller $C^*(z)$ in (5). It can be confirmed that $\overline{G_1}(z)/\overline{G_4}(z) = C^*(z)$. The error model (11) expresses the dynamical relation of the canceling error $e(k)$ with the parameter error $\theta^* - \hat{\theta}(k-1)$. It can be seen from (11) and (12d) that the error system dynamics $W(z)$ include all the uncertain path dynamics.

Table 1 categorizes various actual cases according to the prior knowledge on the path dynamics, for which adaptive schemes will be discussed later. In Case 1 where both the control path dynamics $G_4(z)$ and $G_3(z)$ are known, we can give a stability-assured robust adaptive algorithm in which the parameters of $\hat{C}(z,k)$ are directly adjusted according to available signals, as presented in the next section. The direct adaptive algorithm can be extended to Case 2 where $G_1(z)$ to $G_3(z)$ are unknown and Case 3 where all of the path dynamics are unknown, although rather restricted assumptions are needed. In Case 4, we present an indirect fully adaptive algorithm which is based on the on-line identification of two input-output models and real-time calculation of a corresponding feedforward controller.

Direct Adaptive Algorithms

Stability-Assured Algorithm in Case 1

On the assumption that the control path dynamics $G_4(z)$ and $G_3(z)$ are known *a priori*, a stability-guaranteed adaptive algorithm for adjusting $\hat{C}(z,k)$ directly can be given. Since $G_3(z)$ indicates the feedback acoustic path effect from the secondary loudspeaker to the reference microphone, while the feedback path effect can be canceled by subtracting $G_3(z)v(k)$ from the reference signal $r(k)$, the assumption that $G_3(z)$ is known is equivalent to assuming that $G_3(z) = 0$. Thus, it follows from (12b) that $\overline{G_4}(z) = G_4(z)$, then the error system (11) is reduced to

$$e(k) = W(z)\left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right] + \xi(k), \tag{13}$$

where $W(z) = G_4(z)/(1+G_4(z)F(z))$, and $\xi(k) = \left(1+G_4(z)F(z)\right)^{-1} n(k)$. In addition, since $W(z)$ is known, the upper bound of $\xi(k)$ can be assessed by $|\xi(k)| < \bar{\beta} = \left|1+G_4(e^{j\omega})F(e^{j\omega})\right|^{-1}\beta$, where the upper bound β of $n(k)$ has been given by (8).

Now we will consider how to update the controller parameters in a stable manner on the above assumptions. To derive a stability-assured adaptive algorithm based on the error system (13), the requirement that $W(z)$ is a SPR transfer function should be satisfied, but since $W(z)$ possesses the dynamics of sound propagation which contains the time delay, it is not SPR. In order to make the error system (13) be a SPR function, we introduce the auxiliary variable $e_a(k)$ and the extended error $\varepsilon(k)$ as

$$e_a(k) = \hat{\theta}^T(k)\left[W(z)\varphi(k-1)\right] - W(z)\left[\hat{\theta}^T(k-1)\varphi(k-1)\right], \tag{14}$$

$$\varepsilon(k) = e(k) - e_a(k), \tag{15}$$

respectively. Then by using (14) and (15), the error system (13) can be transformed to

$$\varepsilon(k) = \left(\theta^* - \hat{\theta}(k)\right)^T \psi(k-1) + \xi(k), \tag{16}$$

where $\psi(k-1) = W(z)\varphi(k-1)$. It can be seen that the obtained model possesses the SPR property.

LMS type of robust adaptive algorithm. Based on the new error system (16) an LMS type of basic adaptive algorithm can be given as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \gamma_0 \psi(k-1)\varepsilon(k), \tag{17a}$$

where $\gamma_0 > 0$ is the step size of the algorithm. Because $\varepsilon(k)$ includes $\hat{\theta}(k)$, the recursive calculation given by (17a) cannot be carried out directly; therefore, $\varepsilon(k)$ is revised by substituting 17(a) into (14) and then rewriting (15) as

$$\varepsilon(k) = \frac{\eta(k)}{1+\gamma_0 \psi^T(k-1)\psi(k-1)}, \tag{17b}$$

$$\eta(k) = e(k) + W(z)u(k) - \hat{\theta}^T(k-1)\psi(k-1). \tag{17c}$$

It can be easily shown that the algorithm (17) can assure the convergence of the error signal $\eta(k)$, theoretically for an arbitrarily large value of the step size γ_0. Considering the existence of the disturbance $n(k)$, on the basis of the above result we can give an LMS-type of robust adaptive algorithm as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \gamma(k)\psi(k-1)\varepsilon(k), \tag{18a}$$

$$\varepsilon(k) = \frac{\eta(k)}{1+\gamma(k)\psi^T(k-1)\psi(k-1)}, \tag{18b}$$

$$\eta(k) = e(k) + W(z)u(k) - \hat{\theta}^T(k-1)\psi(k-1), \tag{18c}$$

$$\gamma(k) = \begin{cases} \gamma_0 & |\eta(k)| \ge 2\bar{\beta} \\ \gamma_k & 2\bar{\beta}/\sqrt{3} \le |\eta(k)| < 2\bar{\beta} \\ 0 & |\eta(k)| < 2\bar{\beta}/\sqrt{3} \end{cases}, \tag{18d}$$

$$\gamma_k \le \frac{3\eta^2(k) - 4\bar{\beta}^2}{d + \left(4\bar{\beta}^2 - \eta^2(k)\right)\psi^T(k-1)\psi(k-1)}, \tag{18e}$$

where step size $\gamma_0 > 0$ is an arbitrarily large number and $d > 0$ is a sufficiently small number to prevent zero division. It can be proved via the Lyapunov approach that $\hat{\theta}(k)$ converges to a constant weight vector, and that the canceling error is bounded by

$$\lim_{k\to\infty} \sup |e(k)| = 2\bar{\beta}/\sqrt{3} \tag{19}$$

Table 1. Partially and Fully Adaptive Control Algorithms

Case	Noise Path Dynamics	Control Path Dynamics		Feedback Controller	Error System Dynamics	Adaptivity	Algorithm
	$G_1(z)$ $G_2(z)$	$G_3(z)$	$G_4(z)$	$F(z)$	$W(z)$		
Case 1	Unknown	Known ($G_3(z)=0$)	Known	$F(z) \neq 0$ (or $F(z)=0$)	$W(z)=\dfrac{G_4(z)}{1+G_4(z)F(z)}$	Partially Adaptive	Direct Adaptive
Case 2	Unknown	Unknown	Known	$F(z) \neq 0$ (or $F(z)=0$)	$W(z)=G_4(z)$	Partially Adaptive	Direct Adaptive
Case 3	Unknown	Unknown	Unknown	$F(z) \neq 0$	$W(z)=\dfrac{1}{F(z)}$	Fully Adaptive	Direct Adaptive
Case 4	Unknown	Unknown	Unknown	$F(z) \neq 0$ (or $F(z)=0$)	$W(z)=1$ (in Identification)	Fully Adaptive	Indirect Adaptive

In (18), the extended error $\eta(k)$ is used as the error signal for adjusting the controller parameters rather than the real error $e(k)$, but which will not influence the convergence of the canceling error $e(k)$, because $\eta(k)$ will converge to $e(k)$ when the controller parameters converge, as will be discussed later. From (19) it can be known that the upper bound β of the disturbance $n(k)$ will finally determine the upper bound of the canceling error, if its choice is overly conservative, although the stability margin is increased, the canceling error will be increased. Therefore, from the viewpoint of reducing the canceling error, the upper bound β should be selected reasonably small, which also indicates that this robust adaptive algorithm is different from the ordinary ones. The proposed algorithm is slightly more complicated than ordinary robust adaptive algorithms, but the upper bound of the canceling error can be successfully attained by the tighter bound.

Remark 1: It should be pointed out that if $G_3(z) = 0$, from (5) it can be known that to make the perfect canceling controller $C^*(z)$ exist, both $G_2(z)$ and $G_4(z)$ should be minimum phase transfer functions, but since the effect of $G_3(z)$ cannot be canceled perfectly or we can purposely retain its effect in a certain degree, the minimum phase requirements can be eliminated, while the effect of this remaining factor to stability can be compensated by reasonably increasing the dead zone of the algorithm, as will be discussed in Case 2. Moreover, from the expression (12d) of the error system dynamics $W(z)$ it can be seen that if $F(z) = 0$, the condition that $G_2(z)$ should be a minimum phase transfer function is still needed; therefore, to avoid this problem the feedback controller $F(z)$ should be applied. A way to prevent $G_2(z)$ from non-minimum phase is to place the reference microphone to the noise source as close as possible, which may be acceptable in some active noise control applications. In addition, since the dead zone exists, $\hat{C}(z, k)$ will not exactly approach $C^*(z)$, which may weaken the minimum phase condition.

Comparison with ordinary filtered-x algorithm. Almost all of the conventional adaptive active noise cancellation algorithms employ a variation of the filtered-x algorithm [7], which is typically expressed in this setup as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \gamma\psi(k-1)e(k), \tag{20}$$

where $\psi(k-1) = W(z)\varphi(k-1)$ and $\gamma > 0$ is a positive step size. Since the stability of the algorithm can not be guaranteed, the step size γ should be chosen carefully to attain convergence.

The difference between the proposed algorithm (18) and the filtered-x algorithm (20) lies in the fact that they use different error signals. The proposed algorithm (18) uses the extended error $\eta(k)$, while the filtered-x algorithm (20) uses the actual error $e(k)$. For more detailed inspection, we have rewritten $\eta(k)$ in (18c) by use of (10) as

$$\eta(k) = e(k) + W(z)\left[\hat{\theta}^T(k-1)\varphi(k-1)\right] - \hat{\theta}^T(k-1)\left[W(z)\varphi(k-1)\right]. \tag{21}$$

From (21) we can see that it is the existence of the second and third terms in (21) that makes the difference between $\eta(k)$ and $e(k)$, and these two terms are not the same in the transient phase of adaptation, so it can be recognized that they play an important role in assuring the stability. On the other hand, in steady state, when $\hat{\theta}(k-1)$ converges to a constant, the second and third terms

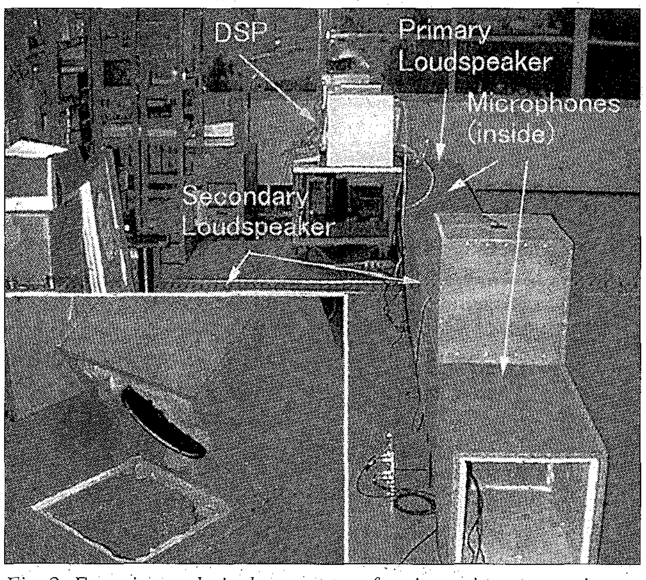

Fig. 2. Experimental air duct system of active noise attenuation.

in (21) will be canceled because the operator $W(z)$ can be exchanged with the converged constant parameter vector, indicating that $\eta(k)$ approaches $e(k)$. Therefore, regardless of its robust property, the proposed algorithm (18) approaches a kind of normalized filtered-x algorithm described by

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{\gamma_0 \psi(k-1) e(k)}{1 + \gamma_0 \psi^T(k-1)\psi(k-1)} . \tag{22}$$

Extensions of Robust Adaptive Algorithm

Extension to Case 2. If we have a model $\hat{G}_3(z)$ of the feedback path dynamics $G_3(z)$, we can reduce the feedback effect by subtracting $\hat{G}_3(z)v(k)$ from the reference signal $r(k)$, and which can be perfectly canceled if $\hat{G}_3(z) = G_3(z)$. However, in practice the model $\hat{G}_3(z)$ involves a modeling error, and it may also be varying; therefore, we should deal with the remaining feedback effect due to $G_3'(z) = G_3(z) - \hat{G}_3(z)$. For a general discussion, we categorize this case as Case 2 where $G_3(z)$ or $G_3'(z)$ is unknown. In this case, although the error system dynamics $W(z)$ in (12d) depends on all of the unknown path dynamics $G_1(z)$, $G_2(z)$, and $G_3(z)$, we can deal with the feedback path effect of $G_3(z)$ by including it into the uncertain disturbance term and rewrite the error system (11) as

$$e(k) = W'(z)\left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right] + \xi'(k) , \tag{23}$$

where

$$W'(z) = \frac{G_4(z)}{1 + G_4(z)F(z)} , \tag{24a}$$

$$\xi'(k) = \frac{G_1(z)G_3(z)\left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right]}{\left[1 + G_4(z)F(z)\right]\left[G_2(z) + \left(G_1(z)G_3(z) + G_2(z)G_4(z)\right)F(z)\right]} + \xi(k) . \tag{24b}$$

Since $G_1(z)G_3(z)/G_2(z)$ has a long delay time and large attenuation, and the feedback effect $G_3(z)$ may be reduced to $G_3'(z)$, we can expect that the magnitude of $\xi'(k)$ is reduced regardless of $\xi(k)$. Thus, if $|\xi'(k)| < \bar{\beta}'$, the adaptive algorithm similar to (18) is also applicable. Actually, due to the properties of $G_1(z)G_3(z)/G_2(z)$, even if the effect of $G_3(z)$ is not taken into consideration, in many actual applications, the robust algorithm based on (23) can get good convergence for a considerablely large step size γ_0.

Extension to Case 3. Next we consider a fully adaptive case in which all the path dynamics $G_1(z)$, $G_2(z)$, $G_3(z)$, and $G_4(z)$ are unknown and varying. In this case, by choosing $F(z) \neq 0$ properly, it follows from (11) and (12) that the error model can be rewritten as

$$e(k) = W''(z)\left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right] + \xi''(k) , \tag{25}$$

where $W''(z) = F^{-1}(z)$, $\xi''(k) = \left[\left(1 + \overline{G}_4(z)F(z)\right)F(z)\right]^{-1} \left[\left(\theta^* - \hat{\theta}(k-1)\right)^T \varphi(k-1)\right] + \xi(k)$. Thus a direct adaptive algorithm similar to (18) can also be applicable if $|\xi''(k)| < \bar{\beta}''$ is satisfied, where $\bar{\beta}''$ is an upper bound. Furthermore, according to (4) and (25), we should assume that $F(z)$ is a minimum-phase transfer function with zero relative degree and which can robustly stabilize the closed-loop system, i.e., the poles of $\left[1 + \overline{G}_4(z)F(z)\right]^{-1}$ can remain inside the unit circle within a specified range of changes of dynamics $G_i(z)$ for $i = 1, 2, 3$, and 4, and all the poles of $[1 - G_3(z)C^*(z) + G_4(z)F(z)]^{-1}$ are inside the unit circle. The design of $F(z)$ with the specifications can be formulated into a robust control problem.

A simulation example of the algorithm based on the error system (25), comparing with the ordinary filtered-x algorithm and the stability-assured algorithm available when $G_4(z)$ is given *a priori*, was given in [15], which shows that the fully adaptive algorithm can be applied to some cases and adapt to the changes in all the path dynamics.

Remark 2: Generally, the design issue of $F(z)$ is relatively complicated. But it can be noticed that, in the pro-

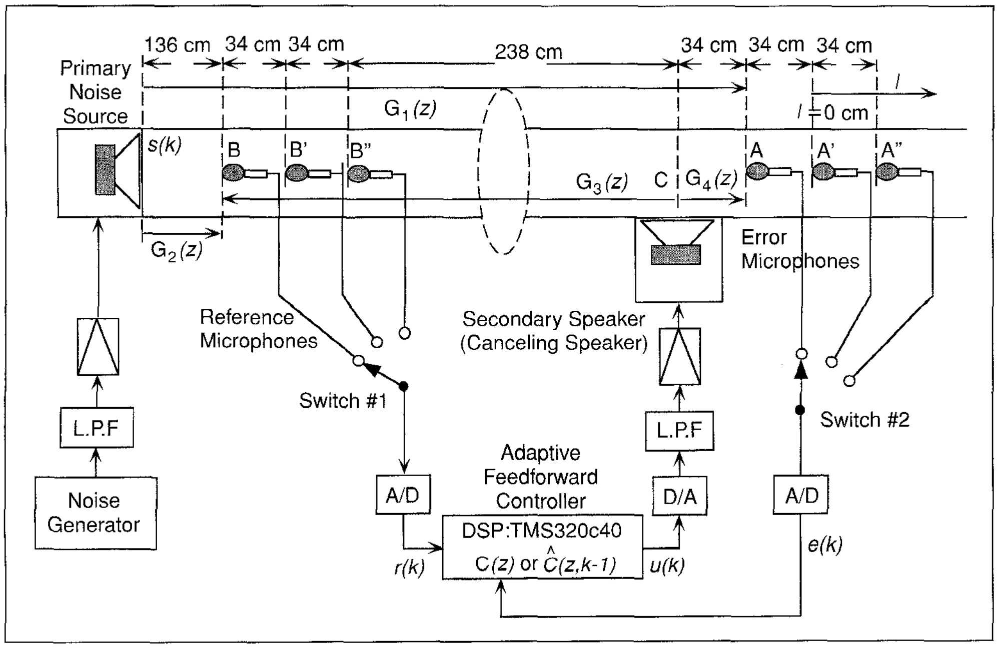

Fig. 3. Schematic diagram of the experimental air duct system of active noise attenuation.

posed scheme, the noise cancellation is mainly completed by the adaptive feedforward controller $\hat{C}(z,k)$, not the feedback controller $F(z)$. Furthermore, since the concern here is robust stability, not robust performance, if the robust controller, designed according to the change range of $G_1(z)$ to $G_4(z)$, is not a minimum phase controller, it is allowable to deviate the optimum design so long as all the requirements are satisfied, which will decrease the complexity of the design. Of course, the design of the robust feedback controller is still an important consideration in the algorithm.

Remark 3: Since $\xi''(k)$ contains $\hat{\theta}(k-1)$, we do not know whether $\xi''(k)$ is bounded by an acceptable β'' or not. Therefore, the application of this algorithm is rather limited. What we want to propose here is an idea by which a direct fully adaptive algorithm can be realized. If a stability-guaranteed adaptive algorithm can be derived based on (25) by dealing with the uncertain term of the parameter estimation errors directly, but not combining it with the disturbance term, then a direct fully adaptive approach will finally be attained.

Indirect Adaptive Algorithm

Deterministic Aspect

In Cases 1 to 3, the parameters of $\hat{C}(z,k)$ are directly adjusted by using accessible signals. An alternative approach for dealing with changes in all of the path dynamics is an identification-based indirect adaptive algorithm which will be investigated in this section.

Rewriting (11) and (12) gives

$$e(k)=\frac{\overline{G}_1(z)}{1+\overline{G}_4(z)F(z)}r(k)-\frac{\overline{G}_4(z)}{1+\overline{G}_4(z)F(z)}u(k)+\xi(k)$$
$$=\overline{H}_1(z)r(k)-\overline{H}_2(z)u(k)+\xi(k)\,, \qquad (26)$$

where $\overline{G}_1(z)$ and $\overline{G}_4(z)$ are already defined by (12a) and (12b), respectively, and $\overline{H}_1(z)$ and $\overline{H}_2(z)$ are defined by

$$\overline{H}_1(z)=\frac{\overline{G}_1(z)}{1+\overline{G}_4(z)F(z)}\,, \qquad (27a)$$

$$\overline{H}_2(z)=\frac{\overline{G}_4(z)}{1+\overline{G}_4(z)F(z)}\,, \qquad (27b)$$

respectively. It can be seen from (11), (12), and (27) that dividing $\overline{H}_1(z)$ by $\overline{H}_2(z)$ can give the perfect canceling controller $C^*(z)$,

$$\frac{\overline{H}_1(z)}{\overline{H}_2(z)}=\frac{\overline{G}_1(z)}{\overline{G}_4(z)}=C^*(z)\,, \qquad (28)$$

which implies that the perfect cancellation controller $C^*(z)$ can be obtained by identifying the two transfer functions $\overline{H}_1(z)$ and $\overline{H}_2(z)$ and then dividing $\overline{H}_1(z)$ by $\overline{H}_2(z)$ in an on-line manner. This is the principle of the proposed indirect algorithm.

Indirect Fully Adaptive Algorithm

Identification of two overall transfer function models. From the simplicity of practical implementation, we identify the

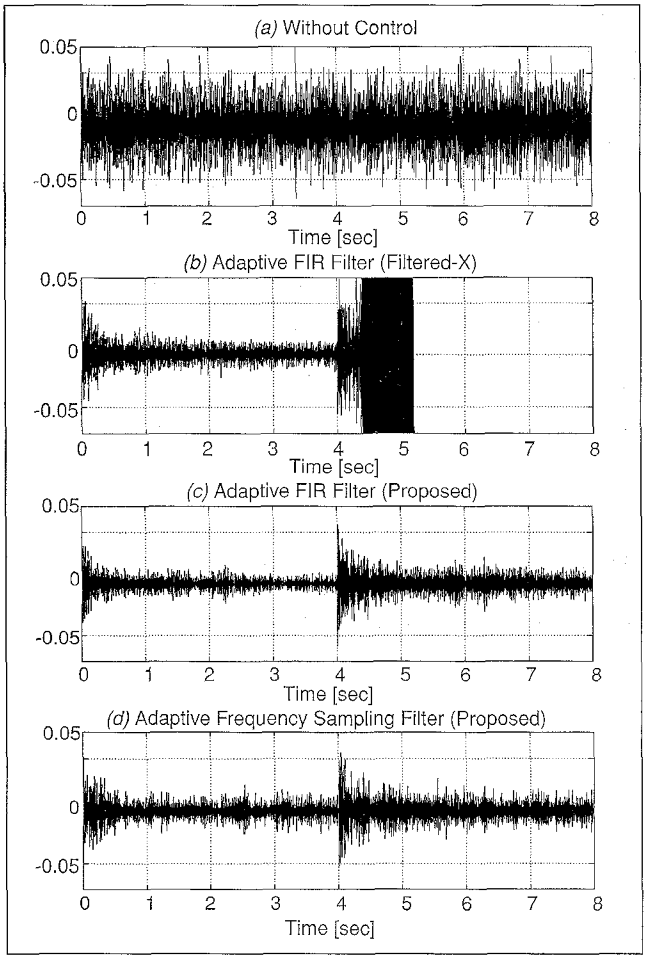

Fig. 4. Canceling error when $G_4(z)$ is known and constant, obtained by (b) filtered-x algorithm, (c) proposed stability-assured direct partially adaptive algorithm, and (d) direct partially adaptive algorithm in frequency domain [16].

transfer functions $\overline{H}_1(z)$ and $\overline{H}_2(z)$ as FIR models. Thus we have

$$\overline{H}_1(z)=H_1(z)+\Delta H_1(z)\,, \qquad (29a)$$

$$\overline{H}_2(z)=H_2(z)+\Delta H_2(z)\,, \qquad (29b)$$

where

$$H_1(z)=h_{12}z^{-2}+h_{13}z^{-3}+\ldots+h_{1\overline{m}}z^{-\overline{m}}\,, \qquad (29c)$$

$$H_2(z)=h_{21}z^{-1}+h_{22}z^{-2}+\ldots+h_{2\overline{n}}z^{-\overline{n}}\,, \qquad (29d)$$

and $\Delta H_1(z)$ and $\Delta H_2(z)$ denote the truncation error terms. Then the error model (26) can be expressed in a compact form as

$$e(k)=\boldsymbol{h}^T\varphi(k-1)+\zeta(k)\,, \qquad (30)$$

where

$$h^T = (h_{21}, h_{22}, \ldots, h_{2\bar{n}}, h_{12}, h_{13}, \ldots, h_{1\bar{m}}) = (h_2^T, h_1^T),$$

$$\varphi(k-1) = \begin{matrix}(-u(k-1), -u(k-2), \ldots, -u(k-\bar{n}),\\ r(k-2), r(k-3), \ldots, r(k-\bar{m}))^T\end{matrix},$$

and $\zeta(k)$ includes the disturbance term $\xi(k)$ and the truncation errors $\Delta H_1(z)$ and $\Delta H_2(z)$. Let $\hat{H}_1(z,k)$ and $\hat{H}_2(z,k)$ denote the estimates of $H_1(z)$ and $H_2(z)$, respectively, and correspondingly, $\hat{h}(k)$ denotes the estimate for the parameter vector h. Then the adaptive algorithm of LMS type is given as follows:

$$\hat{h}(k) = \hat{h}(k-1) + \gamma(k)\varphi(k-1)\varepsilon(k), \tag{31a}$$

$$\varepsilon(k) = \frac{\eta(k)}{1+\gamma(k)\varphi^T(k-1)\varphi(k-1)}, \tag{31b}$$

$$\eta(k) = e(k) - \hat{h}^T(k-1)\varphi(k-1), \tag{31c}$$

$$\gamma(k) = \begin{cases}\gamma_0 & |\eta(k)| \ge 2\bar{\beta}\\ \gamma_k & 2\bar{\beta}/\sqrt{3} \le |\eta(k)| < 2\bar{\beta}\\ 0 & |\eta(k)| < 2\bar{\beta}/\sqrt{3}\end{cases}, \tag{31d}$$

$$\gamma_k \le \frac{3\eta^2(k) - 4\bar{\beta}^2}{d + \left(4\bar{\beta}^2 - \eta^2(k)\right)\varphi^T(k-1)\varphi(k-1)}, \tag{31e}$$

where it is assumed that $|\zeta(k)| < \bar{\beta}$.

It can be noticed that the stability of identification of the system models $\hat{H}_1(z,k)$ and $\hat{H}_2(z,k)$ does not depend on the output of the controller provided it is bounded. Moreover, no additional loudspeakers and microphones are needed to perform this fully adaptive algorithm.

Remark 4: In this indirect adaptive algorithm, the minimum phase issues encountered in the direct adaptive algorithm also exist and can be coped with as discussed in Remark 1.

Calculation of corresponding controller. By using the identified parameter vector $\hat{h}(k)$, the adaptive controller can be constructed as follows:

$$\hat{C}(z,k) = \frac{\hat{H}_1(z,k)}{\hat{H}_2(z,k)} = \frac{\hat{h}_{12}(k)z^{-2} + \hat{h}_{13}(k)z^{-3} + \ldots + \hat{h}_{1\bar{m}}(k)z^{-\bar{m}}}{\hat{h}_{21}(k)z^{-1} + \hat{h}_{22}(k)z^{-2} + \ldots + \hat{h}_{2\bar{n}}(k)z^{-\bar{n}}}$$
$$\cong \hat{c}_1(k)z^{-1} + \hat{c}_2(k)z^{-2} + \ldots + \hat{c}_L(k)z^{-L}, \tag{32}$$

from which it can be noticed that $\{\hat{c}_i(k)\}$ are given by the deconvolution of the two estimated polynomials identified based on (31). A computational procedure for obtaining $\{\hat{c}_i(k)\}$ is summarized in the next four steps:

Step 1: Calculate the FFT of the two sequences $\{\hat{h}_{12}(k), \hat{h}_{13}(k), \ldots, \hat{h}_{1\bar{m}}(k)\}$ and $\{\hat{h}_{21}(k), \hat{h}_{22}(k), \ldots, \hat{h}_{2\bar{n}}(k)\}$, and denote them by $\{\hat{H}_1(e^{j2\pi i/L}, k) : i = 0, 1, \ldots, L-1\}$ and $\{\hat{H}_2(e^{j2\pi i/L}, k) : i = 0, 1, \ldots, L-1\}$, respectively.

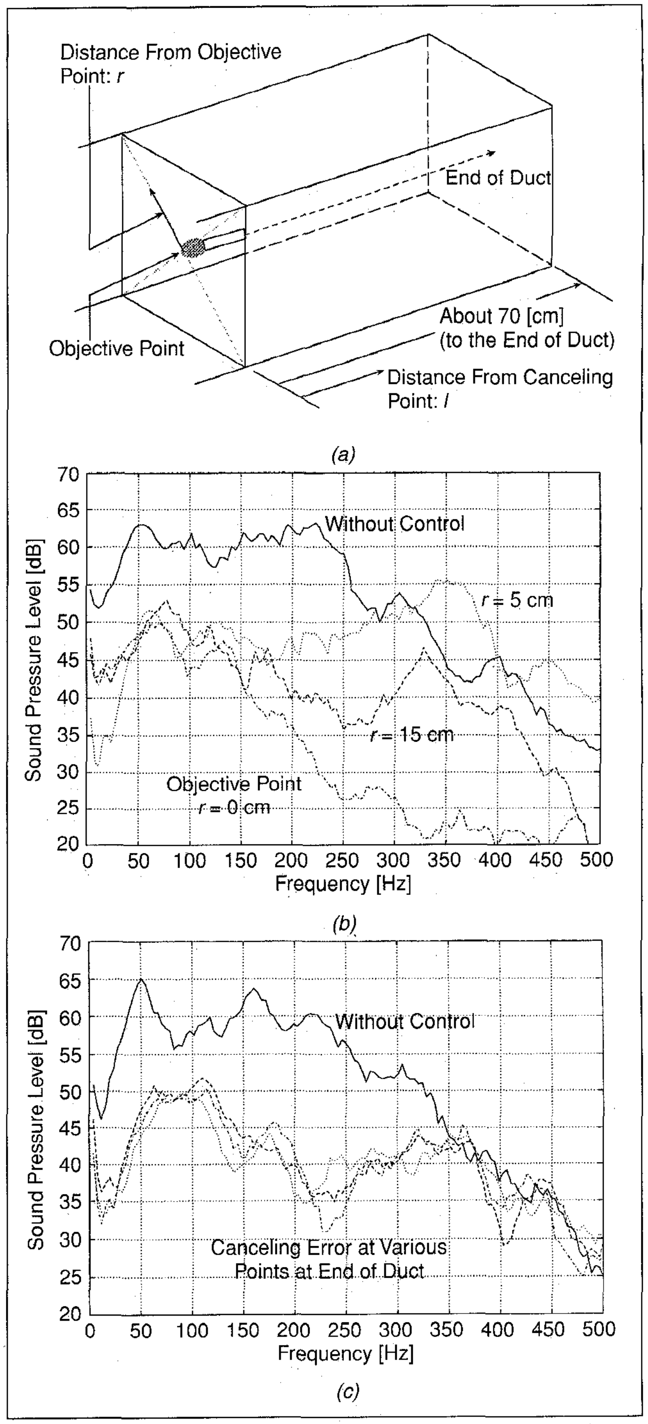

Fig. 5. Steady-state canceling performance in frequency domain of the proposed direct partially adaptive algorithm at different points in the air duct.

Step 2: Divide $\hat{H}_1(e^{j2\pi i/L}, k)$ by $\hat{H}_2(e^{j2\pi i/L}, k)$ for i = 0, 1, ..., L - 1, and denote the result as $\{C(e^{j2\pi i/L}, k) : i = 0, 1, \ldots, L-1\}$.

Step 3: Take the inverse FFT of $\{C(e^{j2\pi i/L}, k)\}$ to obtain the controller parameters $\{\hat{c}_i(k) : i = 1, 2, \ldots, L\}$ in $\hat{C}(z,k)$.

Step 4: Calculate the adaptive control input producing the secondary sound as

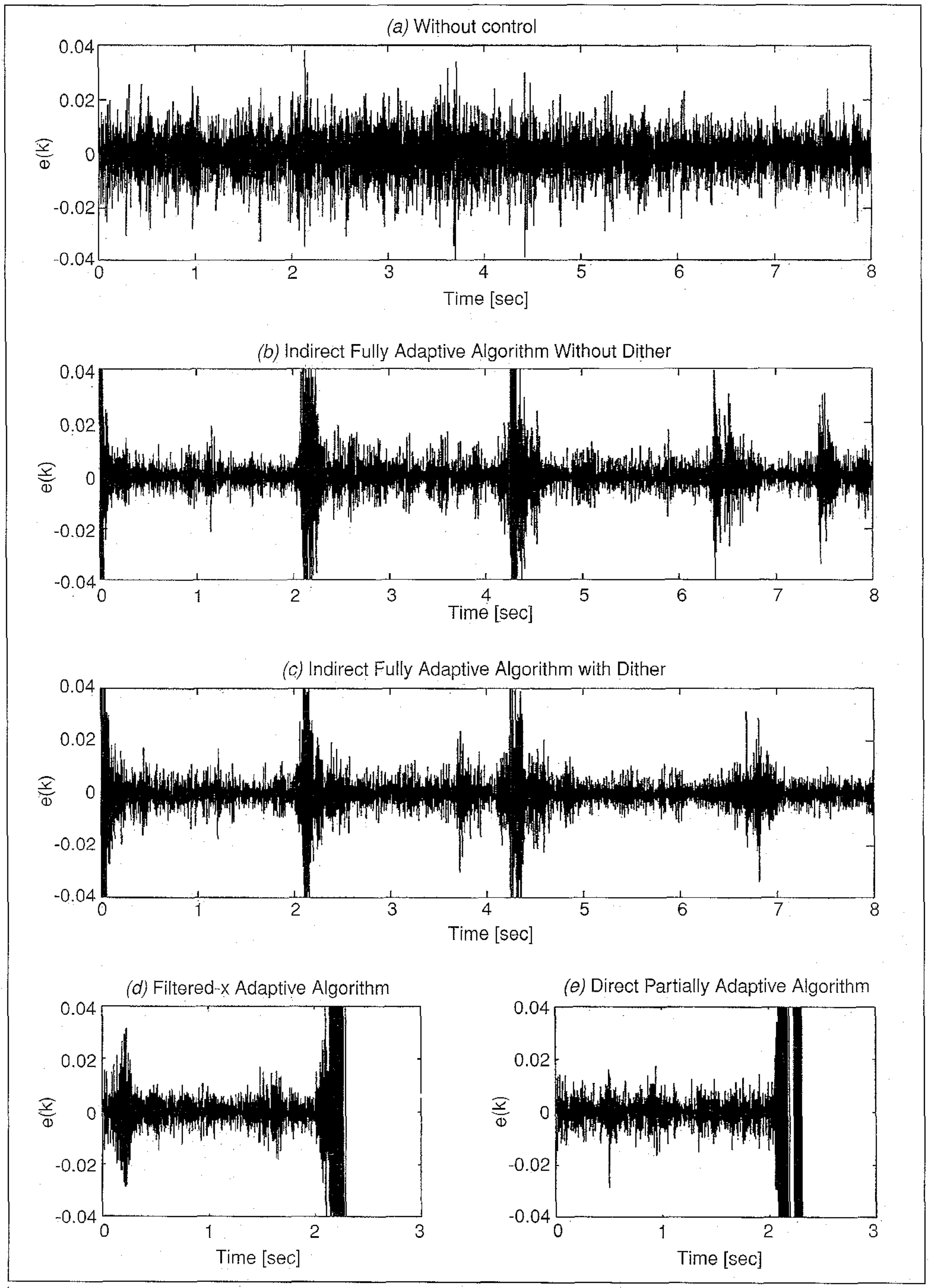

Fig. 6. Canceling error when $G_4(z)$ is changing, obtained by (b) and (c) proposed indirect fully adaptive algorithm without and with dither signal, (d) filtered-x algorithm, and (e) direct partially adaptive algorithm.

$$u(k+1) = \hat{C}(z,k)r(k+1) = \sum_{i=1}^{L} \hat{c}_i(k)r(k-i+1)\,. \tag{33}$$

Remark 5: In Step 2, we should avoid the division by a small magnitude of a complex number. Therefore, in actual calculations, when the absolute value of $\hat{H}_2\left(e^{j2\pi i/L}, k\right)$ is too small, the calculating method should be modified by some manner such that numerical stabilization can be attained. For example, if it is less than a specified small value c, it will be replaced by c. Since the loudspeaker cannot give good response characteristics at very low frequencies, and usually the components of the canceling error in the high frequencies of the digital control system is rather small, the errors of the identified parameters relating to these frequency ranges may be large; therefore, the modifications will also be large in these frequency ranges.

Issue of persistent excitation property. In the identification of $H_1(z)$ and $H_2(z)$, when the signals $r(k)$ and $u(k)$ do not satisfy the persistence of excitation condition, we should introduce a dither signal $d(k)$ and add it to the input $u(k)$ as

$$u(k) = u(k) + d(k)\,, \tag{34a}$$

$$d(k) = f\,e(k-1)v(k) \tag{34b}$$

where $v(k)$ is a random sequence with a uniform distribution which is generated in the DSP, and added to the calculated control input $u(k)$ complying with (34), and f is a constant. By modulating $v(k)$ with the error $e(k-1)$, the effect of the dither signal on the canceling error can be mitigated.

It should be mentioned that in the noise control problems what we are interested in is the canceling error, not the parameter errors, while in some actual applications, even though the identified parameters do not converge to their true values, the satisfactory canceling performance may be attained by applying adaptive control.

Experimental Results

Fig. 2 shows an experimental air duct system of active noise attenuation, which is used to examine the proposed adaptive algorithms. The schematic diagram of the system is shown in Fig. 3. In this system, the primary source noise $s(k)$ is generated by a

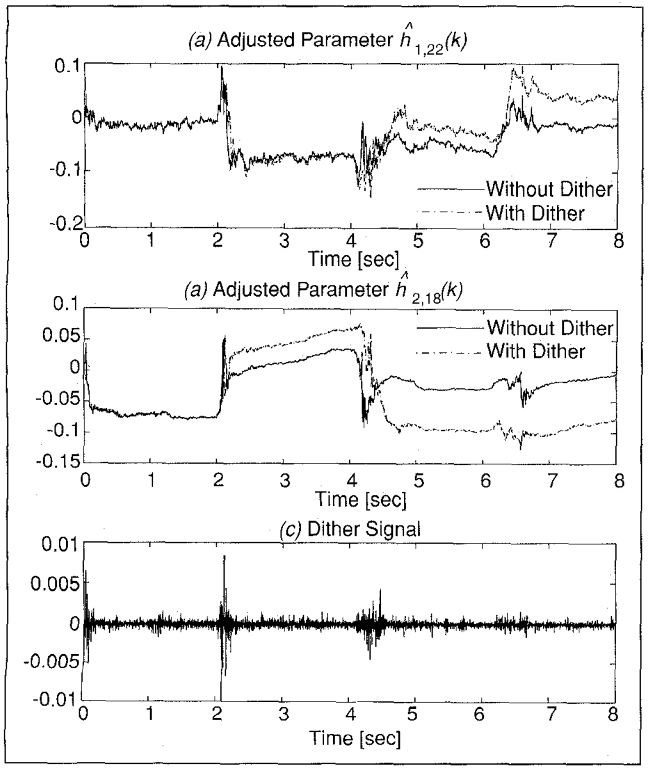

Fig. 7. Profiles of some identified parameters: (a) $\hat{H}_1(z, k)$ and (b) $\hat{H}_2(z, k)$, and dither signal (c).

loudspeaker whose control input is obtained by passing a white noise through a lowpass filter with a passband of 500 Hz. The noise sound is detected by the reference microphones placed at B, B′, and B″, respectively, upstream of the secondary loudspeaker C in the air duct, while the error microphones are placed at A, A′, and A″, respectively, downstream of the loudspeaker C. The three reference microphones are chosen and switched by using the switch #1, to simulate unknown changes of the path dynamics $G_2(z)$ and $G_3(z)$. Similarly the three error microphones are used and switched by the switch #2 to simulate changes in $G_1(z)$ and $G_4(z)$. Thus, by combinations of the two switches, we can realize arbitrary variations in all of the path dynamics and compare with canceling performances of various adaptive algorithms.

The reference sound $r(k)$ and error sound $e(k)$ are processed according to the adopted adaptive algorithm, executed in the DSP chip loaded on the DSP board (DS1003). The connections between the analog devices and digital signals are completed by A/D and D/A converters. Here, the DSP chip (TMS320-C40 with 50 MFlops in performance) is supplied by the Texas Instrument Co., and the A/D and D/A converters with 12 bits (DS2001 and DS2101, respectively) are manufactured by the dSpace Co. In the experiments, the sampling period is chosen as 1 ms and the computational time for executing the adaptive algorithm (18) is about 2 ms. This computational time is added to the actual delay time of $G_4(z)$.

Direct Partially Adaptive Algorithm

When the control path dynamics $G_4(z)$ are known and not changing, we can apply the direct partially adaptive algorithm

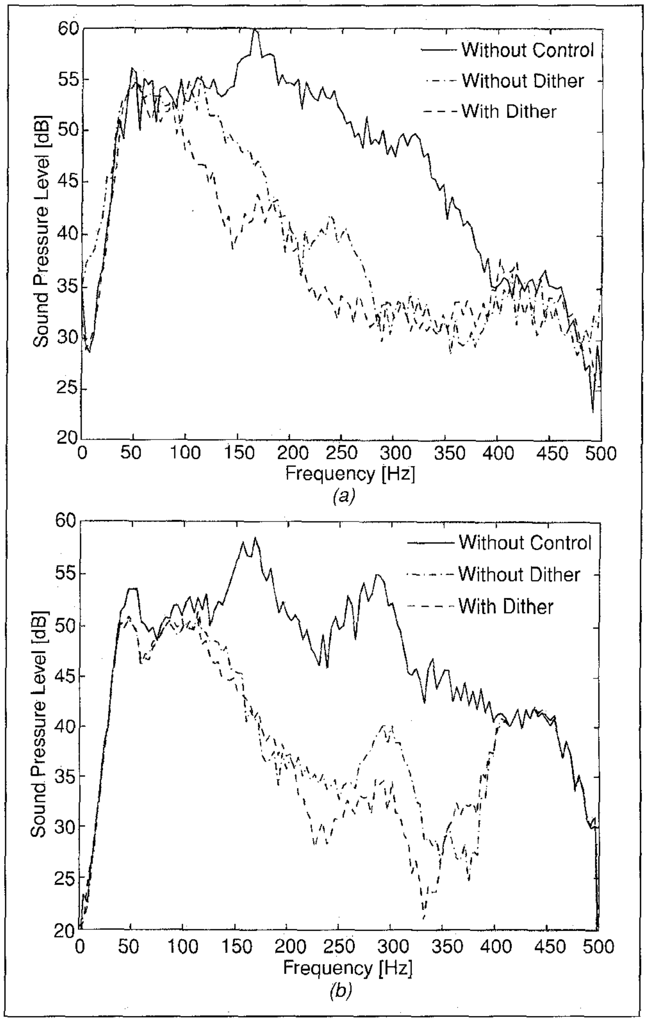

Fig. 8. Comparison of steady-state canceling performance in frequency domain between the proposed indirect algorithm with and without dither signal: (a) experiment results and (b) simulation results.

given by (18), which is stability-assured. Comparisons of the canceling performances between the proposed algorithm (18) and the filtered-x algorithm (20) are made as illustrated in Fig. 4. In the experiment, the error microphone was placed at point A and the reference microphone was placed at point B″ at first and then changed from B″ to B at 4 seconds after the adaptive control started. Fig. 4(a) gives the error $e(k)$ without control, Figs. 4(b) to (d) depict comparison of the canceled error $e(k)$ obtained by the filtered-x algorithm (20), the proposed algorithm (18) and the frequency domain algorithm [16], respectively. The frequency domain approach employs a frequency sampling filter (FSF) consisting of a comb filter $1 - z^{-L}$, followed by a second-order oscillator and a two-tapped delay line with two real weights, where $L = 65$. The two weights in each frequency bin can be adjusted by a stability-assured adaptive algorithm which is similar to (18). For both the filtered-x algorithm and the proposed algorithm, the controller $\hat{C}(z, k)$ was constructed by an FIR type of adaptive filter with the length $n = 60$. In the filtered-x algorithm, we carefully chose the step size $\gamma = 1.2$ which was near the stability limit. Therefore, after the start of control, it could result in a fast convergence like the proposed algorithm, but after the switching of the reference microphone the canceling error diverged in 300 ms after the change, as shown in Fig. 4(b). Comparatively, the proposed direct algorithm allows an arbitrary step size, so we chose a large one as $\gamma_0 = 10^8$. Figs. 4(c) and 4(d) show that stable convergence could be attained satisfactorily by applying the proposed algorithm in the time-domain and frequency-domain even if $G_2(z)$ and $G_3(z)$ were changed.

Figs. 5(b) and 5(c) illustrate the steady-state canceling performance in the frequency domain at different points in the air duct, obtained by the proposed algorithm (18). Fig. 5(b) gives the power spectra of $e(k)$ at three points $r = 0$ cm, $r = 5$ cm, and $r = 15$ cm on the cross-section at $\ell = 0$ cm (see Fig. 5(a)). At the objective point indicated by $r = 0$ cm and $\ell = 0$ cm, we could attenuate 20 dB to 25 dB over the entire frequency range of interest. At other points, the noise attenuation could not be done in the frequency range over 300 Hz. Fig. 5(c) plots the power spectra of $e(k)$ at different points at the duct end ($\ell \cong 70$ cm). We could obtain cancellation of 15 dB to 20 dB over the range 0 to 350 Hz, which is independent of the points of the duct end.

Indirect Fully Adaptive Algorithm

When all of the path dynamics are uncertain and changing, the indirect fully adaptive algorithm is efficient to deal with these uncertain factors. In the filtered-x and direct partially adaptive algorithm, the control path dynamics $G_4(z)$ should be known, which motivates us to investigate how the algorithms are affected when $G_4(z)$ is changing. Fig. 6 shows comparison of canceling errors obtained by the filtered-x algorithm (20) employing an FIR adaptive filter with $n = 32$ (see (d)), the direct partially adaptive algorithm (18) adopting an FIR adaptive filter with the same order (see (e)), and the indirect fully adaptive algorithm without the dither signal (see (b)) and with the dither signal (see (c)), under the conditions that all the path dynamics were unknown and the control path dynamics $G_4(z)$ was changing (for the filtered-x and direct partially adaptive algorithm, the initial dynamics of $G_4(z)$ could be available).

The variations of the $G_4(z)$ was realized by changing the switch #2. At the start of control, the reference microphone and error microphone were placed at B and A″, respectively. With the known $G_4(z)$, the filtered-x algorithm (19) could also keep its convergence by carefully choosing a step size as $\gamma = 10$. The direct adaptive approach (18) can also attain convergence for an arbitrary large step size, where $\gamma_0 = 10^3$ was used. At 2.1, 4.2, and 6.3 seconds, the error microphone was switched from the initial location A″ to A, A″ and A′, respectively, which caused the large changes in the path dynamics $G_4(z)$ (and $G_1(z)$); therefore, the filtered-x algorithm (20) and the direct adaptive algorithm (18) failed to adapt to this change and canceling errors diverged soon after the change took place.

On the other hand, the indirect fully adaptive algorithm could attain stabilized convergence for all of the changes. In the on-line identification, we set the orders of FIR models for both $\hat{H}_1(z,k)$ and $\hat{H}_2(z,k)$ as $\bar{m} = \bar{n} = 32$. The step size in (31) was set at $\gamma_0 = 10^3$. The on-line calculation of the controller parameters could be given by executing FFT and IFFT algorithms, where $L = 32$ was chosen.

To investigate the effect of the dither signal to the identification as well as canceling performance, the experiment results of using the dither signal are also given. The dither signal $v(k)$ used is given in Fig. 7(c), which is a uniformly distributed random sequence with the zero mean and variance of one. To make the introduced dither signal take effect in identification but affect the canceling error less, the maximum magnitude of $v(k)$ was selected as about 4% of the absolute mean of control signal $u(k)$ in its steady state. When the path dynamics changes the proportion is about 20%.

Figs. 7(a) and (b) plot the profiles of some identified parameters of $\hat{H}_1(z,k-1)$ and $\hat{H}_2(z,k-1)$ in cases without and with using the dither signal. All the path dynamics were the same during the time intervals from 0 to 2.1 seconds and from 4.2 to 6.3 seconds; therefore the identified parameters of $\hat{H}_1(z,k-1)$ and $\hat{H}_2(z,k-1)$ should also be the same in the corresponding interval. It can be seen that this consistency can be better attained when the dither signal was used. The estimated parameters obtained without using the dither signal could not go back to their estimate in the first interval, while those with the dither signal could return their estimate in the first interval between 4.2 to 6.3 seconds, even though the path dynamics changed large, as shown in Figs. 7(a) and 7(b).

The effect of introducing the dither signal on the canceling performance can be summarized according to Figs. 6(b) and 6(c) as well as in Fig. 8. Figs. 6(b) and 6(c) give the canceling errors in the dynamic state in time domain from which we can see that there are no obvious differences between the two. Fig. 8(a) gives the experiment results of the canceling errors in the steady state in the frequency domain, which shows that the canceling performance was improved to a certain degree when the dither signal was introduced. The results indicate that even if the persistent excitation condition of identification is not satisfied, the proposed algorithm can attain satisfactory canceling performance without using the dither signal, and that the canceling performance can be improved to a certain extent when the dither signal is used. To examine the correctness of the experiment result, a simulation run under the same condition is also given in Fig. 8(b), which shows that the two results coincided.

Conclusion

When the path dynamics are uncertain and changing, the adaptive feedforward control is an efficient strategy for the online adjustment of the controller parameters. In this article, we have categorized four typical cases in which the noise and control path dynamics are partially or totally unknown, and correspondingly two types of adaptive algorithms have been proposed and investigated. One is a direct adaptive approach which is stability-guaranteed when the control path dynamics are known and the upper bound of disturbances is also given *a priori*. The other is an identification-based indirect adaptive approach which is fully adaptive to the uncertain and changes of all the path dynamics. We have examined the adaptive performance of these algorithms through experimental studies on the active noise cancellation of an air duct system.

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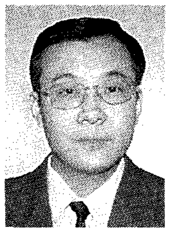
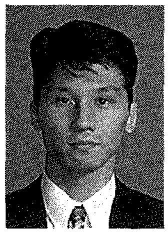
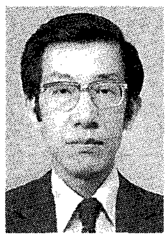


Fan Jiang received the B.E degree from Xi'an Jiaotong University, China, in 1982. From 1982 to 1993 he worked at the Department of Information and Control Engineering of Xi'an Jiaotong University, during which he received the M.E. degree in 1989. He received the Science and Technology Achievements Award from the National Education Ministry of China in 1992. He is currently a candidate for the Ph.D. degree in the Department of Electrical Engineering, Keio University, Japan. His research interests are in instrumentation, engineering control applications, robot force control, and adaptive control.



Hiroyuki Tsuji received the B.S., M.S., and Ph.D. degrees from Keio University, Japan, in 1987, 1989, and 1992, respectively. Since 1992, he has been working at Communication Research Laboratory of Ministry of Posts and Telecommunications. His research interests are in digital and adaptive signal processing, particularly as applied to communications. He received the Institute of Electronics, Information and Communication Engineers' 1996 Young Engineer Award.

Hiromitsu Ohmori received the B.E., M.E., and Ph.D. degrees in electrical engineering from Keio University, Japan, in 1983, 1985, and 1988, respectively. Since 1988 he has been at Keio University. He is currently an associate professor of the Department of Electrical Engineering. From 1993 to 1994 he was a visiting researcher at Newcastle University in Australia. His research interests are in adaptive control theory and robust control theory, and their applications.



Akira Sano received the M.S. and Ph.D. degrees in mathematical engineering and information physics from The University of Tokyo in 1968 and 1971, respectively. Since 1971 he has been at Keio University. He is currently a professor of the Department of Electrical Engineering. His main research interests are in adaptive control and system identification, including applications to control of sounds and vibrations, industrial motors, and mobile communication systems. He was awarded the Kelvin Premium by the Institute of Electrical Engineers in 1986. He is a coauthor of the textbook *State Variable Methods in Automatic Control*.