

Now the main purpose of this paper is to give a robustly stable adaptive algorithm for adjusting the parameters of the IIR or FIR adaptive filter in the above system with the feedforward and feedback compensations. On the assumptions that $v(k)$ is unknown but bounded as $|v(k)| < \beta$ and $H_3(z^{-1})$ is known a priori or can be identified, we will clarify that the error model depends on the both $H_3(z^{-1})$ and $F(z^{-1})$ and the proposed robust adaptive algorithm can assure the stability and boundedness of the error.

3. STABILITY-ASSURED ADAPTIVE FILTER

3.1 Description of error model

We shall clarify the conditions for that the sound pressure at A can be attenuated by the compensators $G(z^{-1})$ and $F(z^{-1})$. The transfer functions from $s(k)$ and $v(k)$ to $e(k)$ are given respectively by

$$e(k) = \left\{ \left(H_1(z^{-1}) - [H_1(z^{-1})H_4(z^{-1}) + H_2(z^{-1})H_3(z^{-1})]G(z^{-1}) \right) / \left(1 - H_4(z^{-1})G(z^{-1}) + H_3(z^{-1})F(z^{-1}) \right) \right\} s(k) + \frac{1 - H_4(z^{-1})G(z^{-1})}{1 - H_4(z^{-1})G(z^{-1}) + H_3(z^{-1})F(z^{-1})} v(k) \quad (1)$$

In the absence of the disturbances $v(k)$, the cancellation of $s(k)$ at the point A can be attained perfectly by selecting the feedforward compensator $G(z^{-1})$ as

$$G(z^{-1}) = \frac{H_1(z^{-1})}{H_1(z^{-1})H_4(z^{-1}) + H_2(z^{-1})H_3(z^{-1})} \equiv G^o(z^{-1}) \quad (2)$$

which does not depend on the feedback compensator $F(z^{-1})$. In the presence of disturbances, if $G(z^{-1})$ is chosen as $G^o(z^{-1})$ in (2), (1) becomes

$$e(k) = \frac{G^o(z^{-1})}{G^o(z^{-1}) + F(z^{-1})} v(k) \quad (3)$$

It should be noticed that the cancellation error $e(k)$ can be reduced by an appropriate choice of the feedback compensator $F(z^{-1})$.

3.2 Stability analysis of robust adaptive algorithm

When the location of the primary noise source is movable and the multipath effects appear, the transfer functions $H_1(z^{-1})$, $H_2(z^{-1})$ and $H_4(z^{-1})$ are changeable. Therefore we implement the feedforward compensator by the IIR adaptive filter to cope with the above uncertainties, as

$$G(z^{-1}, k) = \frac{\hat{b}_1(k)z^{-1} + \dots + \hat{b}_m(k)z^{-m}}{1 + \hat{a}_1(k) + \dots + \hat{a}_n(k)z^{-n}} \quad (4)$$

Let the output of the adaptive filter be denoted by $g(k)$, which is given by

$$g(k) = G(z^{-1}, k)r(k) = \hat{\theta}^T(k)\varphi(k) \quad (5)$$

where $\hat{\theta}(k) \equiv [\hat{a}_1(k), \dots, \hat{a}_n(k), \hat{b}_1(k), \dots, \hat{b}_m(k)]^T$, $\varphi(k) \equiv [-g(k-1), \dots, -g(k-n), r(k-1), \dots, r(k-m)]^T$. It follows from Fig.1 that

$$e(k) = H_1(z^{-1})s(k) - H_3(z^{-1})(g(k) + f(k)) + v(k) \\ f(k) = F(z^{-1})e(k)$$

Then, we have

$$e(k) = W_1(z^{-1})s(k) - W_2(z^{-1})g(k) + w(k) \quad (6)$$

where $W_1(z^{-1}) = H_1(z^{-1})/(1 + H_3(z^{-1})F(z^{-1}))$, $W_2(z^{-1}) = H_3(z^{-1})/(1 + H_3(z^{-1})F(z^{-1}))$ and $w(k) = W_3(z^{-1})v(k)$ where $W_3(z^{-1}) = 1/(1 + H_3(z^{-1})F(z^{-1}))$.

The problem is formulated as follows: Find the robust adaptive algorithm for adjusting the parameters so as to attenuate $e(k)$, by using the linear combination form $W_2(z^{-1})[\hat{\theta}^T(k)\varphi(k)]$. Thus from (5) and (6) the error model is described by

$$e(k) = W_2(z^{-1})[\hat{\theta}^T(k)\varphi(k)] - W_2(z^{-1})[\hat{\theta}^T(k)\varphi(k)] + w(k) \quad (7)$$

Now we give a new robust algorithm assuring the stability based on the strictly positive real property of the error model. For the purpose we introduce the auxiliary variable $e_a(k)$ and the extended error $\varepsilon(k)$ as

$$e_a(k) = \hat{\theta}^T(k)W_2(z^{-1})\varphi(k-1) - W_2(z^{-1})\hat{\theta}^T(k-1)\varphi(k-1) \quad (8a)$$

$$\varepsilon(k) = e(k-1) - e_a(k) \quad (8b)$$

respectively. Thus we have the new error model form (7) and (8) as

$$\varepsilon(k) = (\bar{\theta} - \hat{\theta}(k))^T \psi(k-1) + w(k-1) \quad (9)$$

where $\psi(k-1) = W_2(z^{-1})\varphi(k-1)$. From (9) we obtain the gradient type of basic adaptive algorithm as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \Gamma \psi(k-1)\varepsilon(k) \quad (10)$$

Because $\varepsilon(k)$ includes $\hat{\theta}(k)$, (10) cannot be directly carried out. Therefore, substituting (10) into (8), and rewriting $\varepsilon(k)$ in (8) gives

$$(1 + \psi^T(k-1)\Gamma\psi(k-1))\varepsilon(k) = e(k-1) + W_3(z^{-1})g(k-1) - \hat{\theta}^T(k-1)\psi(k-1)$$

Thus we can give the RLS type of robust adaptive filter algorithm as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \alpha(k-1)\Gamma(k-1)\psi(k-1)\varepsilon(k) \quad (11)$$

$$\varepsilon(k) = \frac{\eta(k)}{1 + \psi^T(k-1)\Gamma(k-1)\psi(k-1)} \\ \eta(k) = e(k-1) + W_2(z^{-1})g(k-1) - \hat{\theta}^T(k-1)\psi(k-1) \\ \bar{\Gamma}(k) = \Gamma(k-1) \left[I - \frac{\alpha(k-1)\psi(k-1)\psi^T(k-1)\Gamma(k-1)}{1 + \psi^T(k-1)\Gamma(k-1)\psi(k-1)} \right]$$

$$\Gamma(k) = \lambda^{-1}(k)\bar{\Gamma}(k), \\ \lambda(k) = \frac{\text{trace}[\bar{\Gamma}(k)]}{\text{trace}[\Gamma(0)]}, \quad \Gamma(0) = \Gamma^T(0) > 0$$

$$\delta(k-1) = \beta^2 [1 + \psi^T(k-1)\Gamma(k-1)\psi(k-1)]^{1/2}$$

$$\alpha(k-1) = \begin{cases} 0: & \eta^2(k-1) \leq \delta^2(k-1) \\ 1: & \eta^2(k-1) > \delta^2(k-1) \end{cases}$$

where, if $\Gamma(k) \equiv \Gamma = \alpha I$, we have a robust LMS algorithm, which is easily implemented.

Theorem: The above algorithm satisfies that

$$(a) \limsup_{k \rightarrow \infty} (\eta^2(k) - \delta^2(k)) \leq 0 \quad (12a)$$

$$(b) \lim_{k \rightarrow \infty} \|\hat{\theta}(k) - \hat{\theta}(k-1)\| = 0 \quad (12b)$$

Let the parameter error be $\tilde{\theta}(k) \equiv \theta - \hat{\theta}(k)$ and let the Lyapunov function be $V(k) = \tilde{\theta}^T(k) \Gamma^{-1}(k) \tilde{\theta}(k)$. Then we can prove the robust stability which assures that the output error $e(k)$ is bounded for any time, by showing that $\Delta V(k) = V(k) - V(k-1) \leq 0$ and then the error signal and parameter error are both bounded.

4. STABLE ADAPTIVE ALGORITHM IN FREQUENCY DOMAIN

Adaptive algorithms in the frequency domain are very useful not only in the fields of adaptive digital signal processing [7] but also adaptive control [9]. The frequency domain approach is normally based on FFT, however, which requires batch processing of L time samples of the signal at a time. Therefore use of a frequency sampling filter (FSF) is adequate for real-time processing which is required to adaptive control as we reported in [9]. Let the feedforward controller $G(z^{-1})$ be implemented by an FIR type of filter as

$$\begin{aligned} G(z^{-1}) &= \sum_{k=0}^{L-1} c_k z^{-k} = \sum_{k=0}^{L-1} \frac{1}{L} \sum_{i=0}^{L-1} \tilde{C}_i e^{j\omega_i k T} z^{-k} \\ &= \frac{1-z^{-L}}{L} \sum_{i=0}^{L-1} \frac{\tilde{C}_i}{1-W_L^i z^{-1}} \end{aligned} \quad (13)$$

where $\{c_i\}$ are the FIR parameters, T is the sampling interval and $W_L \equiv e^{j2\pi/L}$. (13) implies that $G(z^{-1})$ can be constructed by interpolating the L -point frequency response \tilde{C}_i for $i = 0, 1, \dots, L-1$. If the frequency response is expressed by the M pairs of absolute values and phases on the unit circle as $|\tilde{C}_i|, \phi_i; i = 0, 1, \dots, M; M \equiv (L-1)/2$, $G(z^{-1})$ can be determined by the interpolation using the frequency sampling filter as

$$G(z^{-1}) = \sum_{i=0}^M \Lambda_i(z^{-1}) \Phi_i(z^{-1}) \quad (14)$$

where

$$\Phi_0(z^{-1}) = \frac{1-z^{-L}}{L} \cdot \frac{1}{1-z^{-1}} \quad (15a)$$

$$\Phi_i(z^{-1}) = \frac{1-z^{-L}}{L} \cdot \frac{1}{1-2(\cos \omega_i)z^{-1}+z^{-2}} \quad (15b)$$

$$\Lambda_0(z^{-1}) = \lambda_0^A + \lambda_0^B z^{-1}, \quad \lambda_0^B = 0 \quad (16a)$$

$$\Lambda_i(z^{-1}) = \lambda_i^A + \lambda_i^B z^{-1} \quad \text{for } i = 1, \dots, M \quad (16b)$$

It is noticed from (14) to (16) that the feedforward controller $G(z^{-1})$ can be constructed by a comb filter $1-z^{-L}$ followed by a second-order oscillator followed by a two-tapped delay line with two real weights λ_i^A and λ_i^B .

Now, the adaptive feedforward control $u(k)$ is given by

$$\begin{aligned} g(k) &= \sum_{i=0}^M (\hat{\lambda}_i^A(k) + \hat{\lambda}_i^B(k)z^{-1}) \Phi_i(z^{-1}) r(k-1) \\ &= \sum_{i=0}^M (\hat{\lambda}_i^A(k) \bar{r}_i(k-1) + \hat{\lambda}_i^B(k) \bar{r}_i(k-2)) \\ &= \hat{\theta}^T(k) \varphi(k) \end{aligned} \quad (17)$$

where $\bar{r}_i(k) = \Phi_i(z^{-1}) r(k)$, $\hat{\theta}^T(k) = (\hat{\lambda}_1^A(k), \hat{\lambda}_1^B(k), \dots, \hat{\lambda}_M^A(k), \hat{\lambda}_M^B(k))$, $\varphi(k) = (\bar{r}_1(k-1), \bar{r}_1(k-2), \dots, \bar{r}_M(k-1), \bar{r}_M(k-2))^T$.

Thus the error model is represented from (7) as

$$\begin{aligned} e(k) &= W_1(z^{-1}) s(k) - W_2(z^{-1}) u(k) + n(k) \\ &= W_2(z^{-1}) ((\theta - \hat{\theta}(k))^T \varphi(k-1)) + \bar{w}(k) \end{aligned} \quad (18)$$

where $\bar{w}(k)$ is an uncertain term caused by the unstructured controller error due to the use of an FIR model and disturbances. For assuring stability of the adaptive system, $\bar{w}(k)$ is assumed to be bounded by β . On the robustness of the adaptive system we will not argue in this paper. Like the time-domain approach, we introduce an auxiliary variable and augmented error to derive a similar RLS algorithm as (11). An LMS algorithm reduces to a more simple form, as given by

$$\begin{aligned} \hat{\theta}_i(k) &= \hat{\theta}_i(k-1) + \gamma_i \psi_i(k-1) \varepsilon(k) \\ \varepsilon(k) &= \frac{e(k-1) + W_2(z^{-1}) u(k-1) - \sum_{i=1}^M \hat{\theta}_i^T(k-1) \psi_i(k-1)}{1 + \sum_{i=1}^M \gamma_i \psi_i^T(k-1) \psi_i(k-1)} \end{aligned} \quad (19)$$

where $i = 0, 1, \dots, M$, $\gamma_i > 0$, $\hat{\theta}_i^T(k) = (\hat{\lambda}_i^A(k), \hat{\lambda}_i^B(k))$, $\varphi_i(k) = (\bar{r}_i(k-1), \bar{r}_i(k-2))^T$, $\psi_i(k-1) = W_2(z^{-1}) \varphi_i(k-1)$.

For comparison, an ordinary filtered-x LMS algorithm for updating $\hat{\theta}_i(k)$ is described by

$$\hat{\theta}_i(k) = \hat{\theta}_i(k-1) + \gamma_i \psi_i(k-1) e(k) \quad (20)$$

where $i = 0, 1, \dots, M$, and it is noticed that (20) can be calculated in parallel at each frequency point, however, its stability cannot be assured, while the computation of $\hat{\theta}_i(k)$ in the proposed algorithm (19) needs other weights $\{\hat{\theta}_j(k)\}$ at different frequency points. Further, the extended error $\varepsilon(k)$ is also used in place of the error signal $e(k)$. These modifications enables stabilization of the adaptive algorithm (19).

5. ADAPTIVE ACTIVE NOISE CONTROL

The setup of experiment is given in Fig.2, in which the location of noise source can be changed by switching the two loudspeakers. Fig.3 shows the comparison of convergence of errors between the ordinary filtered-x algorithm (b) and the proposed robust adaptive algorithms (c) and (d). The result for the filtered-x is a limit of stability obtained by choosing the step size γ very carefully. The order of the IIR type of filter was chosen as $n = 31$ and $m = 16$ in

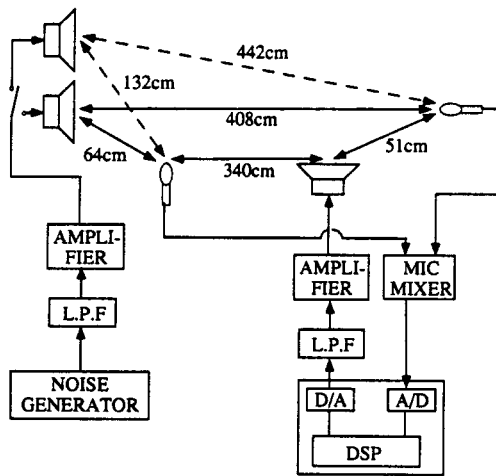


Fig.2 Experimental system for adaptive active noise control.

case (c), which is not sufficient. Therefore the proposed robust adaptive algorithm worked efficiently. Fig.4 gives the power spectrum of the error signal controlled by the proposed adaptive algorithm for the IIR filter, in which noise attenuation could be attained.

6. CONCLUSIONS

The stability-assured adaptive algorithms have been proposed and discussed in time domain and frequency domain for adaptive feedforward control. The adaptive algorithms depends on the controller structure involving the feedback compensator. The validity of the algorithms has been examined by making comparison of the ordinary filtered-x algorithms.

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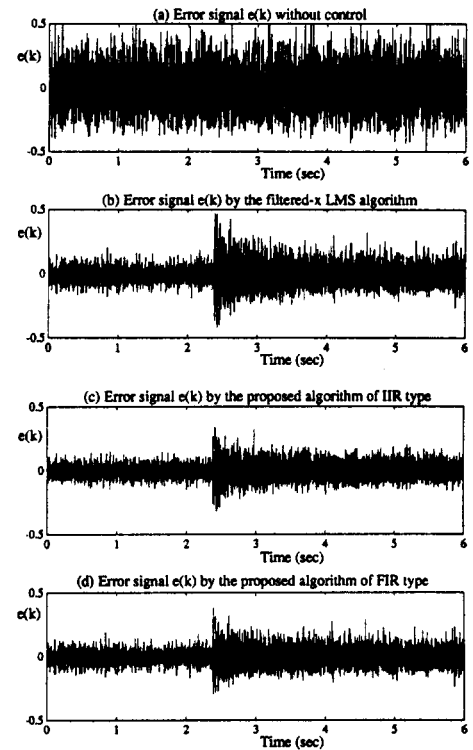


Fig.3 Comparison of controlled results: (a) no control, (b) the filtered-x algorithm for IIR, (c) proposed adaptive algorithm for IIR, and (d) proposed adaptive algorithm for FIR.

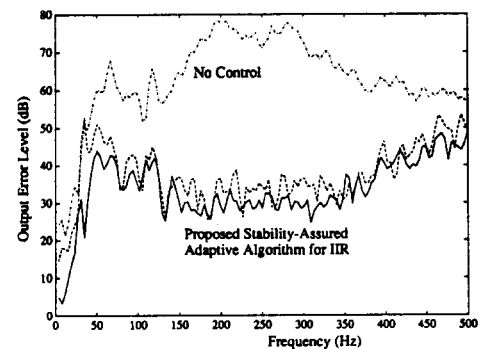


Fig.4 Power spectrum of controlled error signal obtained by the proposed algorithm.