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On Active Noise Control Systems With Online Acoustic Feedback Path Modeling

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***Abstract*—The presence of strong acoustic feedback degrades the convergence speed of the active noise control (ANC) filter, and in the worst case the ANC system may become unstable. A fixed feedback neutralization filter, obtained offline, can be used to neutralize the acoustic feedback. The feedback path, however, may be time varying, and we may need continual adjustments during online operation of the ANC system. This paper proposes a new method for online modeling of the acoustic feedback path in ANC systems. The proposed method uses three adaptive filters; a noise control filter, a feedback path modeling (FBPM) filter, and an adaptive noise cancelation (ADNC) filter. The objective of ADNC filter is to remove the disturbance from the desired response of FBPM filter. In comparison with the existing method, which works only for predicable noise sources, the proposed method can work, as well, with the broadband noise sources. The computer simulations are carried out for narrowband (predictable) (case I) and broadband (random) noise sources (case II). It is demonstrated that the proposed method performs better than the existing method in both cases.**

***Index Terms*—Acoustic feedback, active noise control (ANC), FxLMS algorithm, online feedback path modeling.**

I. Introduction

A SCHEMATIC diagram of a single channel feedforward active noise control (ANC) systems [1], [2] is shown in Fig. 1. Here $P(z)$ is the primary path between the noise source and the error microphone, $S(z)$ is the secondary path between canceling loudspeaker and error microphone, and $F(z)$ is the feedback path from canceling loudspeaker to the reference microphone. The ANC system uses the reference microphone to pick up the reference noise $x(n)$, processes this input with an adaptive filter to generate an antinoise $y(n)$ to cancel primary noise acoustically in the duct, and uses an error microphone to measure the error $e(n)$ and to update the adaptive filter coefficients. Unfortunately, a loudspeaker on a duct wall will generate the antinoise signal propagating both upstream and downstream. Therefore, the antinoise output to the loudspeaker not only cancels noise downstream, but also radiates upstream to the reference microphone, resulting in a corrupted reference signal $x(n)$. This coupling of acoustic waves from secondary loudspeaker to the reference microphone is called *acoustic feedback*.

Consider Fig. 2. which is a block diagram of the ANC system shown in Fig. 1. Here the filtered-x LMS (FxLMS) algorithm

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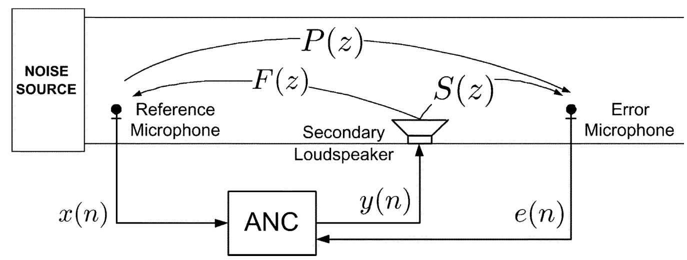

Fig. 1. Schematic diagram of a single-channel feedforward ANC system.

[3], [4] is used to adapt the ANC adaptive filter $W(z)$. Assuming that the feedback path modeling (FBPM) filter $\hat{F}(z)$ is not present, the error signal z-transform is expressed as

$$\begin{aligned} E(z) &= P(z)R(z) - S(z)Y(z) \\ &= P(z)R(z) - S(z)\frac{W(z)R(z)}{1 - W(z)F(z)}. \end{aligned} \tag{1}$$

The convergence of $W(z)$ means (ideally) $E(z) = 0$. This requires $W(z)$ to converge to the following solution:

$$W^{\circ}(z) = \frac{P(z)}{S(z) + P(z)F(z)}. \tag{2}$$

This simple analysis shows that due to acoustic feedback the ANC system will be unstable, if the coefficients of $W(z)$ are large enough so that $W(z)F(z) = 1$ at some frequency. Furthermore, the $W(z)$ may not converge to the optimal solution $P(z)/S(z)$.

A literature review shows that there are following ways to overcome the problem of acoustic feedback.

1) To use directional microphones and loudspeakers, and to place the components so that the acoustic feedback can be avoided [5]–[12]. These techniques are expensive, and often the performance is quite limited.
2) To use non-acoustic sensor to obtain the reference signal, so that the reference signal is free of any acoustic feedback component [13], [14]. This technique is applicable only to narrowband noise sources.
3) To use only error microphone, and employ the technique of feedback ANC. This approach is useful only in limited applications.
4) To process the reference signal, so that the feedback component is reduced if not removed. In this paper we restrict ourselves to signal processing methods for adaptive feedback neutralization.

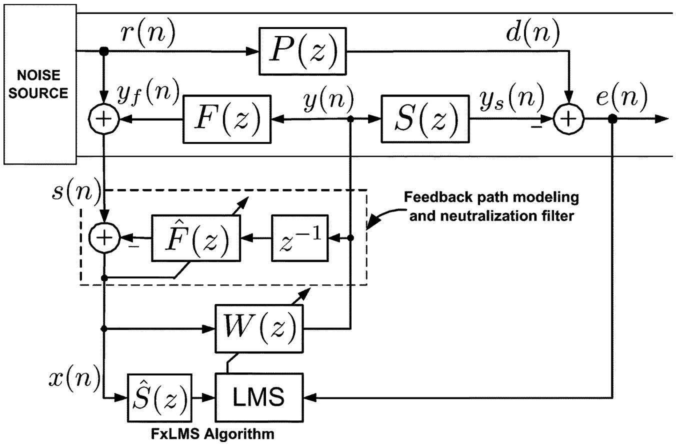

Fig. 2. ANC system of Fig. 1. with adaptive feedback neutralization.

Broadly speaking, there are two types of signal processing methods for adaptive feedback neutralization: 1) IIR-filter-based methods and 2) FIR-filter-based methods. The use of IIR filters for ANC systems, was first proposed by Eriksson [15], [16]. This approach considers the feedback as a part of the overall plant and the adaptive IIR filter deals with it directly as part of the problem. From (2) it is clear that the optimal solution is a pole-zero system. The IIR control system, being a pole-zero system, allows the system to dynamically track changes in the feedback and secondary paths during cancelation operation. There are a number of adaptive IIR algorithms: filtered-u recursive LMS (FuRLMS) [17], full-feedback IIR LMS [18], and filtered-v LMS (FvLMS) [19]. In these IIR-based structures, 1) the stability cannot be guaranteed, and 2) the adaptation may converge to a local minimum. To overcome these problems a few new algorithms have been proposed in [20]–[22]. It has been shown in [23], that the performance of these methods is degraded in the presence of strong acoustic feedback. Consequently, only the FIR-based methods are examined further in this paper.

The simplest FIR-filter-based approach to solving the feedback problem is to use a separate FBPM filter with in the controller, as shown in Fig. 2. This electrical model of the feedback path is driven by the antinoise signal, $y(n)$, and its output is subtracted from the reference sensor signal, $s(n)$. The FBPM filter, $\hat{F}(z)$, may be obtained offline and kept fixed during the operation of the ANC system (see Fig. 2 without adaptive link with $\hat{F}(z)$ in dashed box). In many practical cases, however, $F(z)$ may be time varying. For these cases, online modeling of $F(z)$ is needed to ensure the convergence and stability of the FxLMS algorithm for ANC systems. As proposed in [24], the FBPM filter $\hat{F}(z)$ can be made adaptive by using $x(n)$, the input to $W(z)$, as its error signal, as shown in Fig. 2. It is clear from Fig. 2, that the desired response for $\hat{F}(z)$, $s(n)$, is highly correlated with the antinoise signal $y(n)$, and hence $\hat{F}(z)$ will continue to adapt even when the feedback is perfectly canceled. Under this condition, $\hat{F}(z)$ attempts to incorrectly cancel the reference noise signal. Therefore, the adaptation of the feedback neutralization filter must be inhibited when the ANC system is in operation. This method [24], therefore, can not be used for online FBPM.

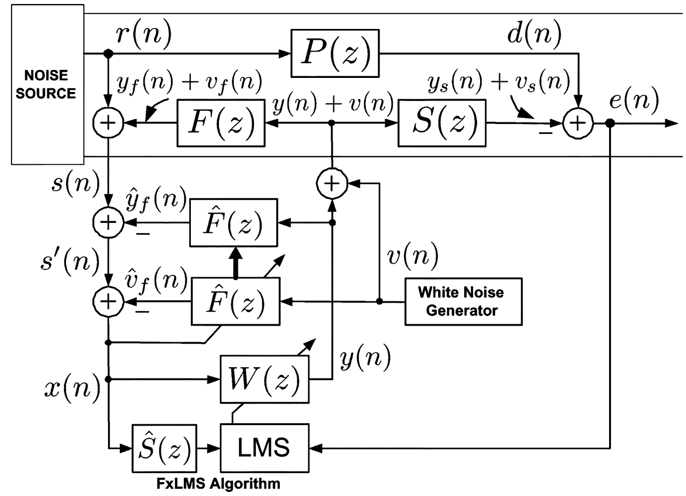

Fig. 3. Additive random noise-based method for online feedback path modeling.

Among the existing methods for online FBPM in ANC systems, the method proposed by Kuo [25] appears the best choice. The main problem with the method is that it can only work for noise signals that are predictable. In this paper we propose a new method for acoustic FBPM during online operation of ANC systems, which can work for both the predictable and unpredictable noise sources. The proposed method uses an adaptive noise cancelation (ADNC) filter to remove the disturbance in the desired response of FBPM filter. This improves the convergence of the FBPM filter, and hence the overall performance of the ANC system.

The organization of the paper is as follows. Section II presents an overview of the existing methods for online FBPM in ANC systems. Section III describes the proposed method, Section IV gives simulation results, and Section V concludes the paper.

A short version of this paper was presented at a conference [26].

II. Existing Methods for Online Feedback Path Modeling

In order to overcome problems with the method of [24] and to achieve online FBPM, Kuo and Luan [27] have proposed an additive random noise-based method as shown in Fig. 3. Here the adaptive FBPM filter is excited by a low level random (white) signal, $v(n)$, which is injected at the secondary loudspeaker for the identification of feedback path.[1] After adaptation the weights are copied to the fixed FBPM filter taking $y(n)$ as its input. The reference signal picked up by the reference microphone, $s(n)$, is now given as

$$s(n) = r(n) + y_f(n) + v_f(n) \quad (3)$$

where $r(n)$ is the reference noise signal generated by the noise source, $y_f(n) = f(n) * y(n)$ is the feedback component due to the antinoise signal $y(n)$, $v_f(n) = f(n) * v(n)$ is the feedback

[1]The same white signal can also be used for simultaneous online modeling of secondary path $S(z)$ [1]. In this paper, however, we assume that secondary path is exactly identified and $\hat{S}(z) = S(z)$.

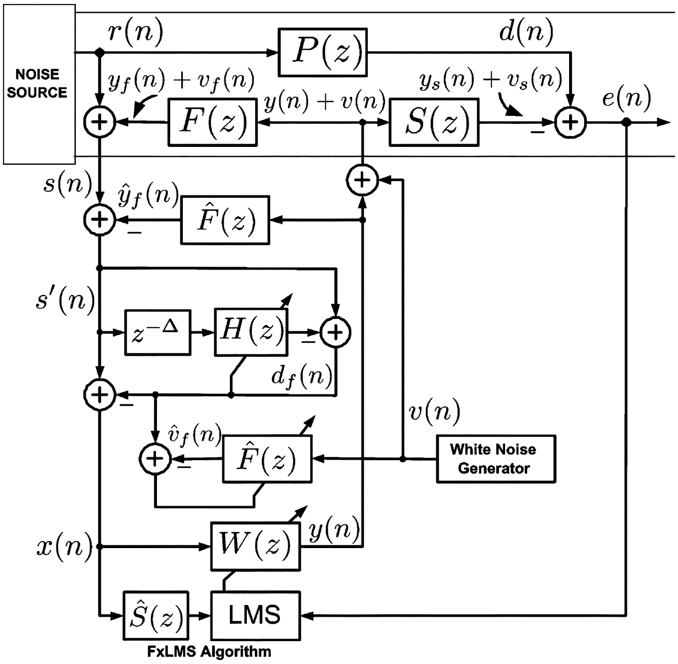

Fig. 4. Additive random noise-based method with signal discrimination filter for improved online feedback path modeling.

component due to the modeling signal $v(n)$, and $*$ denotes the linear convolution. The desired response for the adaptive FBPM filter is given as

$$s'(n) = r(n) + [y_f(n) - \hat{y}_f(n)] + v_f(n). \qquad (4)$$

where $\hat{y}_f(n)$ is an estimate of $y_f(n)$ obtained through FBPM filter $\hat{F}(z)$

$$\hat{y}_f(n) = \hat{\boldsymbol{f}}^T(n)\boldsymbol{y}_{L_f}(n) \qquad (5)$$

where $\hat{\boldsymbol{f}}(n) = [\hat{f}_0(n), \hat{f}_1(n), \cdots, \hat{f}_{L_f-1}(n)]^T$ is the impulse response of $\hat{F}(z)$, L_f is the tap-weight length of $\hat{F}(z)$, and $\boldsymbol{y}_{L_f}(n) = [y(n-1), y(n-2), \cdots, y(n-L_f)]^T$ is the L_f-sample output signal vector. It is important to note that there is one sample delay in appearance of acoustic feedback at the reference microphone [1], as shown in Fig. 2. (This delay is not shown in Figs. 3–5, just for the sake of simplicity.)

In (4), only $v_f(n)$ is required for identification and rest of components act as a disturbance signal. Due to this large disturbance signal [note that $r(n)$ will be present all the times] the convergence of the FBPM filter may be very slow.

In order to improve the convergence of $\hat{F}(z)$ in above method, Kuo proposed using a predictor as a signal discrimination filter (see Fig. 4.) [25]. This method assumes that the reference noise signal is predicable. The signal discrimination filter can predict $r(n) + [y_f(n) - \hat{y}_f(n)]$ in (4), and hence, can cancel it. Thus desired response for the adaptive FBPM filter is free of any disturbance signal, i.e. $d_f(n) \approx v_f(n)$. The input signal for $W(z)$ is computed by subtracting $d_f(n)$ from $s'(n)$

$$x(n) = r(n) + [y_f(n) - \hat{y}_f(n)] + [v_f(n) - d_f(n)]. \qquad (6)$$

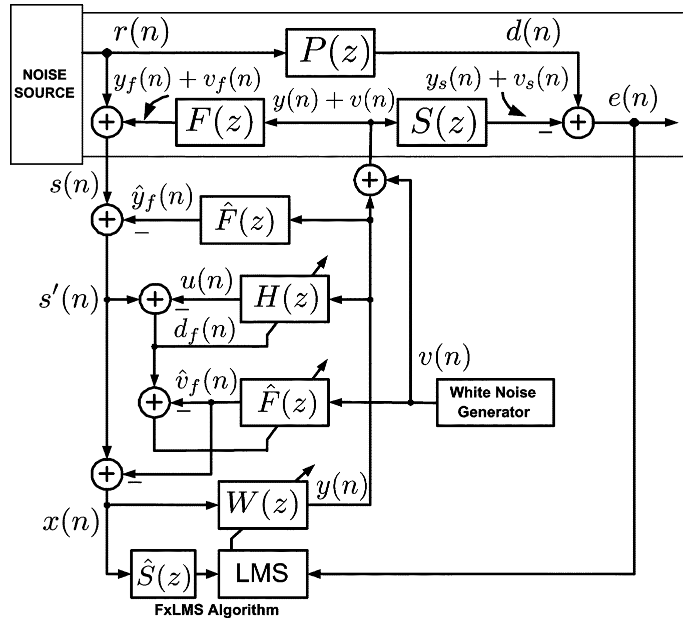

Fig. 5. Proposed method for online feedback path modeling in ANC systems.

When the adaptive filters $H(z)$, and $\hat{F}(z)$ are converged; $d_f(n) \approx v_f(n)$, $\hat{y}_f(n) \approx y_f(n)$ and $\hat{v}_f(n) \approx v_f(n)$. Thus input to $W(z)$ is $x(n) \approx r(n)$, and is free of any noise. This method [25] improves convergence performance of the FBPM filter, and generates an appropriate reference signal $x(n)$ for FxLMS-based ANC adaptive filter $W(z)$. There are, however, a few problems as shown in the following.

1) It can work only if the reference signal is predictable.
2) The performance of this method depends on the proper choice the decorrelation delay Δ.
3) In the case of a broadband noise source, the signal discrimination filter will not be able to predict it, and hence convergence of FBPM filter will be same as in previous method by Kuo *et al.* [27]. Furthermore, the reference signal $x(n)$ will be highly corrupted, and it will degrade the convergence of $W(z)$.

III. Proposed Method for Online Feedback Path Modeling

The proposed method for online FBPM in ANC systems is shown in Fig. 5. This method uses ADNC filter to improve the desired response for online FBPM filter. As in Kuo's methods, a random noise signal, $v(n)$, uncorrelated with the reference noise, is added with the output $y(n)$ of $W(z)$. The sum $y(n) + v(n)$ is propagated through the secondary loudspeaker. The residual error signal $e(n)$ is thus given as

$$e(n) = [d(n) - y_s(n)] - v_s(n) \qquad (7)$$

where $d(n) = p(n) * r(n)$ is the primary noise signal, $y_s(n) = s(n) * y(n)$ is the antinoise signal, $v_s(n)$ is a component due to the modeling signal $v(n)$, and $p(n)$ and $s(n)$ are impulse responses of the primary path $P(z)$ and secondary path $S(z)$,

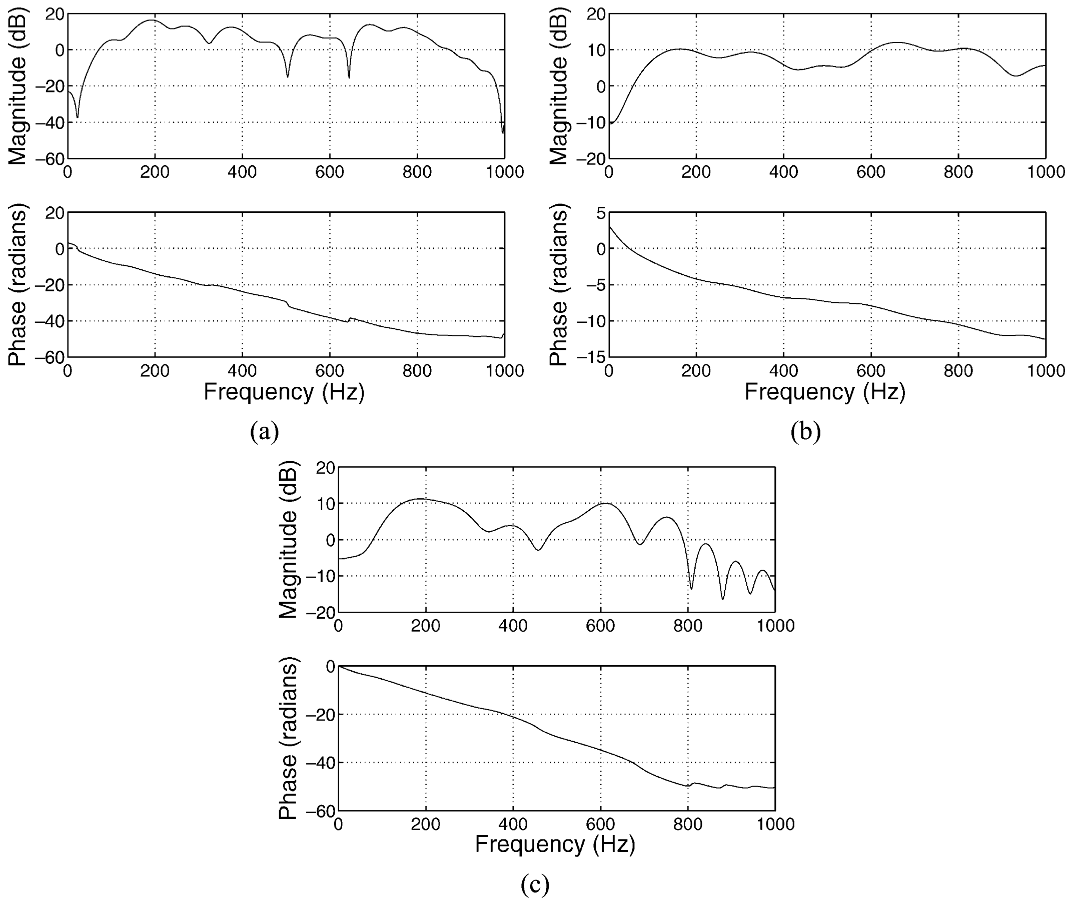

Fig. 6. Frequency response of the acoustic paths. (a) Primary path $P(z)$, (b) secondary path $S(z)$, and (c) feedback path $F(z)$.

respectively. The ANC filter $W(z)$ is adapted on the basis of this error signal by FxLMS algorithm

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu_w e(n)\boldsymbol{x}'(n) \tag{8}$$

where μ_w is the step size for $W(z)$, $\boldsymbol{x}'(n) = [x'(n), x'(n-1), \cdots, x'(n-L_w+1)]^T$, and $x'(n)$ is the reference signal $x(n)$ filtered through the secondary path modeling filter $\hat{S}(z)$. Assuming that $\hat{S}(z)$ is represented by an FIR filter of tap-weight length L_s, the filtered-reference signal $x'(n)$ is obtained as

$$x'(n) = \hat{\boldsymbol{s}}^T(n)\boldsymbol{x}_{L_s}(n) \tag{9}$$

where $\hat{\boldsymbol{s}}(n) = [\hat{s}_0(n), \hat{s}_1(n), \cdots, \hat{s}_{L_s-1}(n)]^T$ is the impulse response of the $\hat{S}(z)$ and $\boldsymbol{x}_{L_s}(n) = [x(n), x(n-1), \cdots, x(n-L_s+1)]^T$ is the L_s-sample reference signal vector.

The ADNC filter $H(z)$ takes $y(n)$ as its input, and $s'(n)$ as its desired response. The error signal of $H(z)$ is given as

$$d_f(n) = r(n) + [y_f(n) - \hat{y}_f(n)] - u(n) + v_f(n) \tag{10}$$

where $u(n)$ is the output of ADNC filter $H(z)$, give as

$$u(n) = \boldsymbol{h}^T(n)\boldsymbol{y}_{L_h}(n) \tag{11}$$

where $\boldsymbol{h}(n) = [h_0(n), h_1(n), \cdots, h_{L_h-1}(n)]^T$ is the impulse response of $H(z)$, L_h is the tap-weight length of $H(z)$, and $\boldsymbol{y}_{L_h}(n) = [y(n-1), y(n-2), \cdots, y(n-L_h)]^T$ is the L_h-sample output signal vector. The coefficients of $H(z)$ are updated by LMS algorithm

$$\boldsymbol{h}(n+1) = \boldsymbol{h}(n) + \mu_h d_f(n)\boldsymbol{y}_{L_h}(n) \tag{12}$$

where μ_h is step size parameter for $H(z)$.

The adaptive FBPM filter $\hat{F}(z)$ is excited by random (white) noise $v(n)$, and its output is an estimate of feedback component $v_f(n)$

$$\hat{v}_f(n) = \hat{\boldsymbol{f}}^T(n)\boldsymbol{v}(n) \tag{13}$$

where $\boldsymbol{v}(n) = [v(n), v(n-1), \cdots, v(n-L_f+1)]^T$ is the L_f-sample modeling noise vector. The error signal of $H(z)$, $d_f(n)$, is used as a desired response for the adaptive FBPM filter $\hat{F}(z)$ and its coefficients are updated by LMS algorithm

$$\hat{\boldsymbol{f}}(n+1) = \hat{\boldsymbol{f}}(n) + \mu_f [d_f(n) - \hat{v}_f(n)]\, \boldsymbol{v}(n) \tag{14}$$

where μ_f is step size parameter for $\hat{F}(z)$. After updating the tap-weights are copied to the fixed FBPM filter $\hat{F}(z)$, taking $y(n)$ as its input.

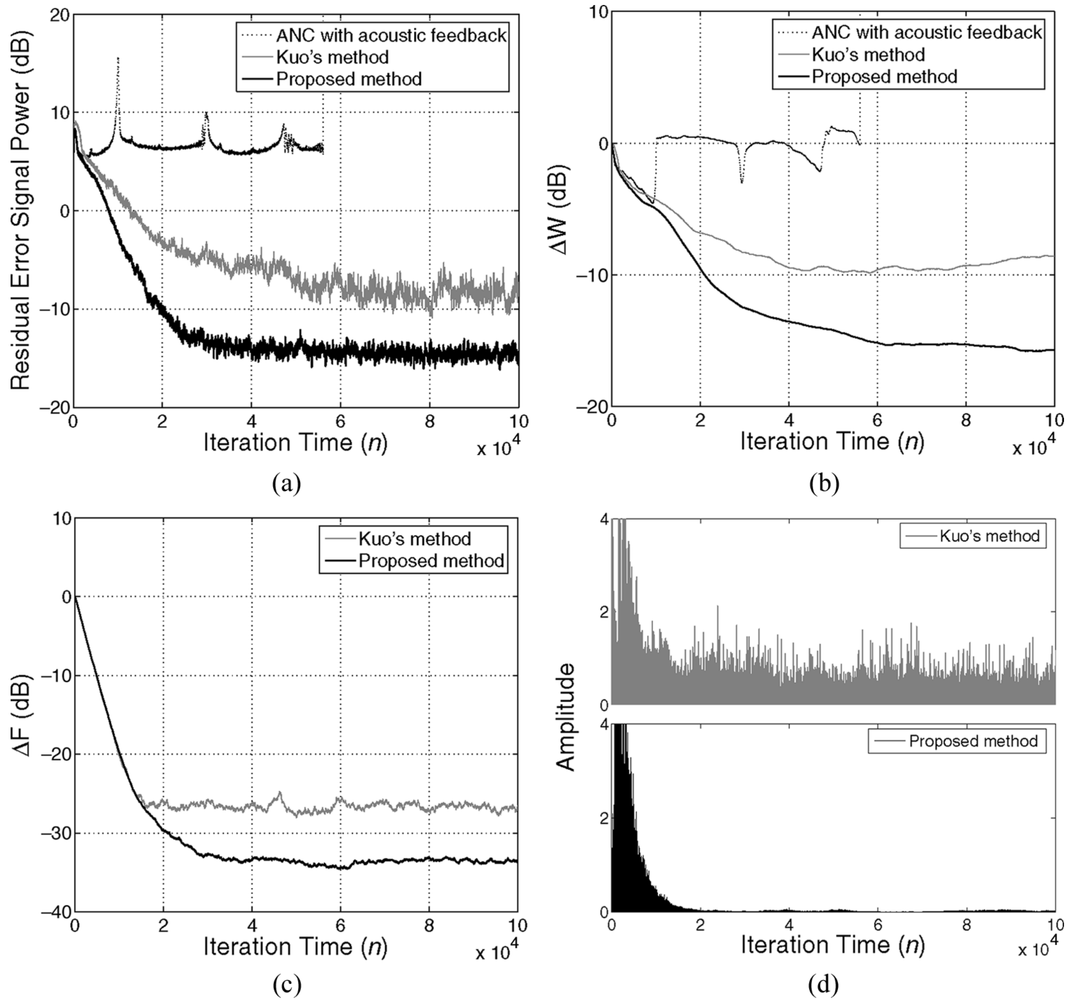

Fig. 7. Simulation results for a narrowband reference signal comprising frequencies of $150 + 300 + 450$ Hz. (a) The power of residual error signal $e(n)$. (b) The estimation error in $W(z)$, ΔW(dB). (c) The relative modeling error ΔF(dB). (d) The error in the reference signal $x(n) : \Delta X(n) = [x(n) - r(n)]^2$.

The reference signal $x(n)$ for $W(z)$ is computed by subtracting $\hat{v}_f(n)$ from $s'(n)$, and is given as

$$x(n) = r(n) + [y_f(n) - \hat{y}_f(n)] + [v_f(n) - \hat{v}_f(n)]. \quad (15)$$

When $H(z)$ converges, $u(n) \rightarrow r(n) + [y_f(n) - \hat{y}_f(n)] \Rightarrow d_f(n) \approx v_f(n)$. Thus, adaptive FBPM filter $\hat{F}(z)$ receives a desired response $d_f(n)$ free of any disturbance. When $\hat{F}(z)$ converges, i.e. $\hat{F}(z) \approx F(z)$, then (ideally), $\hat{y}_f(n) \approx y_f(n)$ and $\hat{v}_f(n) \approx v_f(n)$. Thus the reference signal for the ANC filter $W(z)$ is given as $x(n) \approx r(n)$, and is free of any acoustic feedback component of the canceling signal.

In comparison with Kuo's method (Fig. 4) [25], the main advantage of the proposed method is that it can work for any type of noise sources; whether predictable or unpredictable. The reason is that it does not use prediction error filter and one does not need to consider correlation between $s'(n)$ and $s'(n - \Delta)$. Even in case of predictable noise sources Kuo's method may fall behind the proposed method, as its performance depends on the proper choice of the decorrelation delay Δ.

It is important to note that the computational complexity, in terms of number of computations required per iteration, of the proposed method is same as that of the Kuo's method.

IV. Simulations

This section presents the simulation experiments performed to verify the effectiveness of the proposed method. Here we compare the performance of the proposed method with Kuo's method [25], which is the best existing method for online FBPM in ANC systems. The performance comparison is done on the basis of following performance measures:

- the power of the residual error signal $e(n)$;
- the estimation error for $W(z)$:

$$\Delta W(\mathrm{dB}) = 10 \log_{10} \left\{ \frac{\sum_{i=0}^{M-1} [w_i^{\circ}(n) - w_i(n)]^2}{\sum_{i=0}^{M-1} [w_i^{\circ}(n)]^2} \right\} \quad (16)$$

  where $\boldsymbol{w}^{\circ}(n)$ is the optimal value of the weight vector of the ANC controller. (This is obtained by using FxLMS algorithm under no-acoustic-feedback condition.);

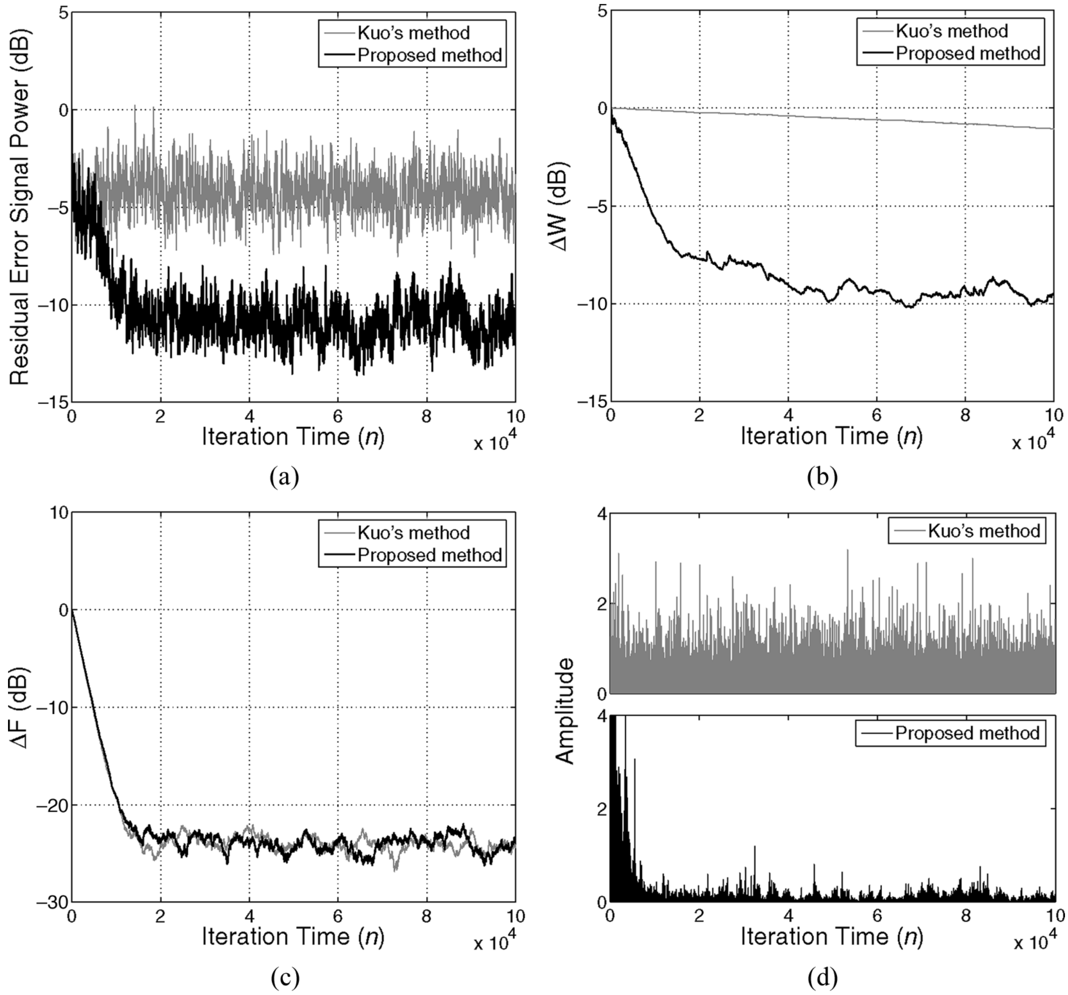

Fig. 8. Simulation results for a broadband reference signal. (a) The power of residual error signal $e(n)$. (b) The estimation error in $W(z)$, ΔW(dB). (c) The relative modeling error ΔF(dB). (d) The error in the reference signal $x(n) : \Delta X(n) = [x(n) - r(n)]^2$.

- the estimation error for $F(z)$

$$\Delta F(\mathrm{dB}) = 10\log_{10}\left\{\frac{\sum_{i=0}^{M-1}\left[f_i(n) - \hat{f}_i(n)\right]^2}{\sum_{i=0}^{M-1}\left[f_i(n)\right]^2}\right\} \quad (17)$$

- the error in the reference signal $x(n)$

$$\Delta X(n) = [x(n) - r(n)]^2 \quad (18)$$

where $r(n)$ is the noise source signal and $x(n)$ is the reference signal used in adaptation of $W(z)$.

For acoustic paths, the experimental data provided by [1] is used. Using this data, $P(z)$, $S(z)$ and $F(z)$ are selected as FIR filters of tap-weight lengths 48, 16, and 32, respectively. The frequency response of these paths is shown in Fig. 6. The control filter $W(z)$, FBPM filter $\hat{F}(z)$, and the third filter $H(z)$ are FIR filters of tap-weight length $L_w = 32$, $L_f = 32$, and $L_h = 16$, respectively. All the adaptive filters are initialized by null vectors of an appropriate order. A sampling frequency of 2 kHz is used. All the curves shown below are averaged over 10 experiments.

A. Case I: Narrowband Noise Signal

In the first case, the reference signal $x(n)$ comprises sinusoids of 150, 300, and 450 Hz, and a zero-mean white noise is added with SNR of 30 dB. The modeling excitation signal $v(n)$ is a zero-mean white Gaussian noise of variance 0.05. The step size parameters are adjusted for fast and stable convergence, and, by trial-and-error, are found to be $\mu_w = 1 \times 10^{-5}$, $\mu_f = 5 \times 10^{-3}$, $\mu_h = 5 \times 10^{-4}$. The decorrelation delay Δ in Kuo's method [25] is 48. The simulation results are presented in Fig. 7. The curves for the residual error signal $e(n)$ are shown in Fig. 7(a). From this figure, we see the following.

1) If acoustic feedback is not compensated, then the ANC system becomes unstable.
2) Kuo's method and proposed method can reduce the effect of the acoustic feedback and, hence, can achieve stable performance.
3) The proposed method can reduce the residual error to a lower level as compared with the Kuo's method.

The curves for ΔW (dB) are shown in Fig. 7(b). Again, the proposed method gives better results than the Kuo's method. Fig. 7(c) shows the curves for relative modeling error ΔF (dB) for proposed method in comparison with the Kuo's method. We see that the proposed method can reduce ΔF (dB) to somewhat lower level. The curves for the error is the reference signal,

$\Delta X(n)$, are given in Fig. 7(d) for single realization. In comparison with Kuo's method, the proposed method is better in removing the feedback components from the reference signal.

B. Case II: Broadband Noise Signal

Here we consider a broadband reference noise signal. A 64 order FIR filter with a passband of [150 350] Hz is designed using Matlab function `fir1`. A zero-mean white Gaussian noise of unit variance is filtered through this bandpass filter to generate the reference signal $x(n)$. As in the previous case, a zero-mean white Gaussian noise of variance 0.05 is used in the modeling process. The step size parameters are found experimentally for fast and stable convergence, and are adjusted to $\mu_w = 1 \times 10^{-4}$, $\mu_f = 5 \times 10^{-3}$, $\mu_h = 5 \times 10^{-4}$. The decorrelation delay Δ in Kuo's method [25] is 60. The simulation results are shown in Fig. 8. We see that the the overall performance of the proposed method is much better than the Kuo's method. With the broadband reference signal, the noise reduction performance of Kuo's method is highly degraded. This is due to the fact that, that $H(z)$ in Kuo's method cannot predict-and-remove the effect of the broadband noise source from the reference signal $x(n)$.

V. Concluding Remarks

We have proposed a new method for online FBPM in ANC systems. The proposed method uses an ADNC filter to remove disturbance in the desired response of FBPM filter. This improves the convergence of the FBPM filter, and hence the overall performance of the ANC system. In contrast to the existing method, which can work only for predictable noise sources, the proposed method can work as well for broadband noise sources. The computer simulations are carried out which demonstrate the effectiveness of the proposed method.

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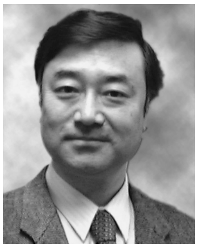

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