Exploring an Efficient Approach for Active Noise Control Systems with Online Secondary Path Modeling

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***Abstract*—In this paper, we explore a new approach for controlled injection of probe noise for secondary path modeling (SPM) in the feedforward active noise control (ANC) systems. The existing approaches employ a single adaptive FIR filter for SPM in ANC systems. In the proposed approach, a separate filter temporarily holds a replica of the tap-weights of the SPM filter. Furthermore, a cost function - on the basis of difference of error powers from the two filters - is evaluated for keeping or suspending the injection of the probe noise. If the acoustic characteristics are changed in the secondary path after suspending the injection, outliers in the error signal from the SPM filter are detected for restarting the injection. Numerical simulations show that the noise-reduction performance is improved by introducing the proposed approach for the ANC systems.**

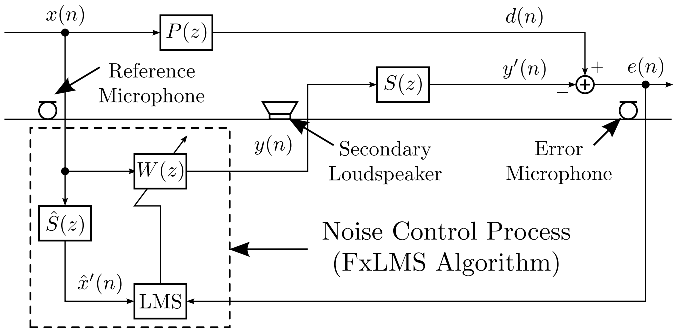


Fig. 1. Block diagram of feedforward ANC system

I. Introduction

Active noise control (ANC) [1] is based on the principle of destructive interference of acoustic waves between the sounds from a noise source and a loudspeaker used for sound deadening. Fig. 1 represents a single-channel feedforward ANC system. In Fig. 1, the sound from the noise source is obtained as a reference signal $x(n)$ by a reference microphone placed close to the noise source. An adaptive filter $W(z)$ (control filter) generates its output signal $y(n)$ by filtering $x(n)$, and $y(n)$ is emitted from a secondary loudspeaker to an acoustic field. For monitoring the result of the interference between the sound from the noise source passing through the primary path $P(z)$ and $y(n)$ passing through the secondary path $S(z)$, an error microphone is placed at the downstream and observes the result of the canceling as a residual error signal $e(n)$. Since the secondary path is connected after the control filter $W(z)$, the least mean square (LMS) algorithm for updating the tap-weights of the control filter is no longer adequate. In many applications, the filtered-x least means square (FxLMS) algorithm is used for correcting the effects by the presence of the secondary path. The FxLMS algorithm updates the control filter with the filtered reference signal $\hat{x}'(n)$ by the estimated secondary path $\hat{S}(z)$.

In some ANC systems, the secondary path is identified before the ANC operation, and the estimated secondary path is fixed and used for FxLMS algorithm in the ANC operation. However, the secondary path actually varies with time. An online secondary path modeling (SPM) method is therefore more desirable.

Eriksson et al. proposed a first version of the online SPM method by introducing an additional adaptive filter (SPM filter) [2]. The secondary path is modeled with injecting the probe noise from the secondary loudspeaker in the ANC operation. However, the overall performance of the ANC system is degraded because the injected probe noise always remains in the residual error signal. Several methods that improved the performance of Eriksson's method have been proposed [3], [4], [5], [6]. Akhtar et al. considerably improved the performance with two adaptive filters (a control filter and a SPM filter) similar to Eriksson' method whereas almost existing methods totally use three adaptive filters [5], [6].

Davari et al. recently proposed an On/Off scheduling of the probe noise injection by keeping or suspending [7]. Simulation results presented in [7] show an effectiveness of the controlled injection. However, empirically selected threshold parameters determine whether the injection should be suspended or resumed. It would probably be preferable in ANC systems to avoid the use of threshold parameters with latent ambiguity.

The proposed approach provides clear criteria for On/Off scheduling of the injection. In the proposed approach, a non-adaptive filter (replica filter) is introduced in the ANC system with the online SPM method, and the objective of the replica filter is to temporarily hold a replica of the tap-weights of the SPM filter at the proper time. The injection is suspended in the steady-state of the SPM filter using a cost function defined

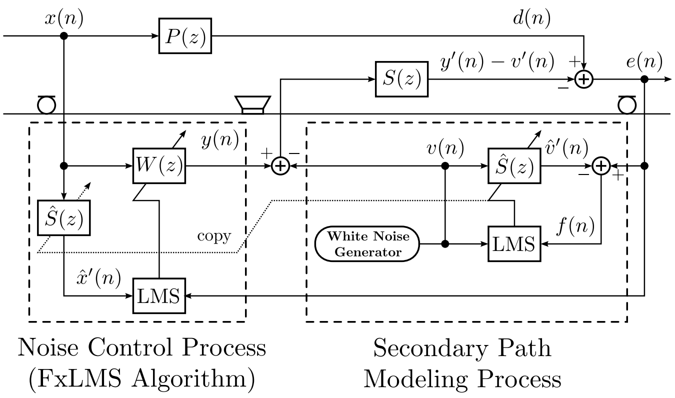


Fig. 2. Block diagram of Eriksson's online SPM method

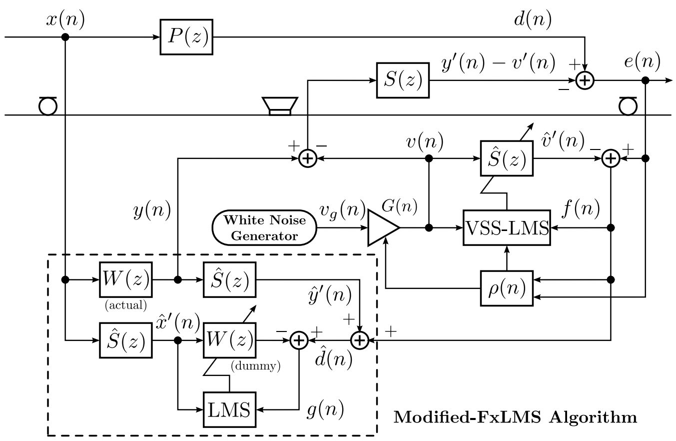


Fig. 3. Block diagram of Akhtar's online SPM method

by the accumulated difference of the error powers from these two filters. After suspending the injection, outliers in the error signal from the SPM filter indicates changes in the secondary path, thus the outliers are detected to resume the injection and remodel the secondary path. The results of numerical experiments show that the proposed method effectively works in the ANC system with reduced difficulties in tuning the parameters.

The rest of this paper is organized as follows. Section II provides a brief overview of the existing methods for online SPM. In Section III, the clear criteria for controlled injection driven by the On/Off scheduling are proposed. Section IV presents the results of numerical experiments. Discussion and concluding remarks are described in Section V.

II. Over Viewing Existing Method

A. Eriksson's method

Eriksson's method [2] shown in Fig. 2 is composed of the control filter $W(z)$ and the SPM filter $\hat{S}(z)$. The probe noise $v(n)$ for identifying the secondary path $S(z)$ is injected from the secondary loudspeaker to the secondary path with the output signal $y(n)$ of $W(z)$. Then, the residual error signal $e(n)$ for the adaptation of $W(z)$ and the error signal $f(n)$ from $\hat{S}(z)$ are expressed as:

$$e(n) = d(n) - y'(n) + v'(n), \tag{1}$$

$$f(n) = d(n) - y'(n) + v'(n) - \hat{v}'(n), \tag{2}$$

where $d(n) = p(n) * x(n)$ is the primary disturbance signal, $y'(n) = s(n)*y(n)$ is the canceling signal, $v'(n) = s(n)*v(n)$ is the desired signal for $\hat{S}(z)$, $\hat{v}'(n) = \hat{s}(n) * v(n)$ is the estimated desired signal of $v'(n)$, and $p(n)$, $s(n)$ and $\hat{s}(n)$ are the impulse responses of the primary path $P(z)$, $S(z)$ and $\hat{S}(z)$ respectively. In Eriksson's method, $v'(n)$ always exist in $e(n)$ as long as injecting the probe noise is continued, and $v'(n)$ interrupts the adaptation of $W(z)$ as the disturbance signal.

B. Akhtar's method

Akhtar's method [5], [6] presented in Fig. 3 basically uses two adaptive filters as the same as Eriksson's method. The improvements from Eriksson's method are summarized below.

1) Using $f(n)$ as error signal for $W(z)$: In Eriksson's method, the residual error signal $e(n)$ is used to adapt the control filter $W(z)$. However, the disturbance signal $v'(n)$ always perturbs the adaptation of $W(z)$. Here, $f(n)$ has $v'(n) - \hat{v}'(n)$ as the ideal error signal for the SPM filter $\hat{S}(z)$. Then, $v'(n) - \hat{v}'(n)$ tends to zero in accordance with the convergence of $\hat{S}(z)$. This means decreasing the disturbance signal of $W(z)$ and suggests that $f(n)$ should be used to adapt $W(z)$.

2) Adaptation of $W(z)$ using MFxLMS algorithm: In the FxLMS algorithm, since the delay introduced by the secondary path appears after the output signal $y(n)$ of the control filter $W(z)$, the upper bound of the step size is reduced from $2/[LP_{\hat{x}'}]$ to $2/[(L+\Delta)P_{\hat{x}'}]$ [8], where L is the tap-length of $W(z)$, Δ is the delay introduced by the secondary path and $P_{\hat{x}'}$ is the power of the filtered reference signal $\hat{x}'(n)$. In the modified FxLMS (MFxLMS) algorithm [8], the SPM filter $\hat{S}(z)$ is used to generate a modified error signal for $W(z)$ without the delay of the secondary path, and the adaptation of $W(z)$ is performed using a simple LMS algorithm. This makes a larger step size than that of the FxLMS algorithm available for $W(z)$. As a result, a fast convergence can be achieved.

3) New variable step size algorithm for $\hat{S}(z)$: The SPM filter $\hat{S}(z)$ is adapted using a variable step size parameter $\mu_s(n)$ adjusted with the following rule:

$$\mu_s(n) = \rho(n)\mu_{s_{\min}} + (1 - \rho(n))\mu_{s_{\max}}, \tag{3}$$

where $\mu_{s_{\min}}$ and $\mu_{s_{\max}}$ are the lower and the upper bounds of $\mu_s(n)$ respectively, and $\rho(n) = P_f(n)/P_e(n)$ is a ratio between the powers of the error signal $f(n)$ from $\hat{S}(z)$ and the residual error signal $e(n)$. These powers are estimated as follows:

$$P_f(n) = \lambda P_f(n-1) + (1-\lambda) f^2(n), \tag{4}$$

$$P_e(n) = \lambda P_e(n-1) + (1-\lambda) e^2(n), \tag{5}$$

where λ is a forgetting factor for low-pass estimation. In the early stage of the adaptation of the control filter $W(z)$ and $\hat{S}(z)$, the canceling signal $y'(n)$ and the estimated desired

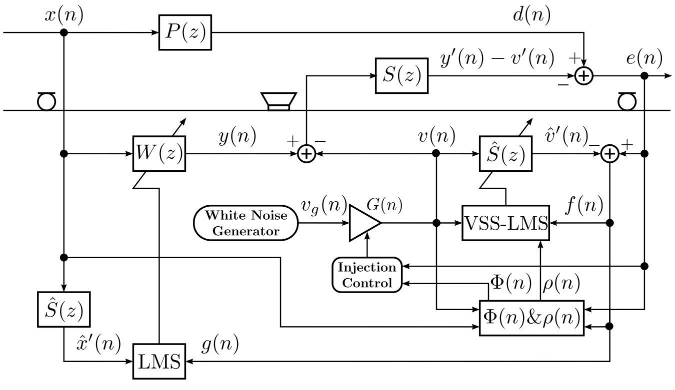


Fig. 4. Block diagram of Davari's online SPM method

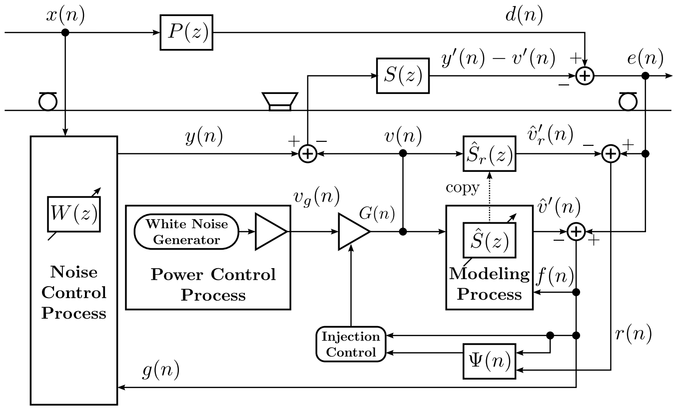


Fig. 5. Block diagram of the proposed online SPM method

signal $\hat{v}'(n)$ are almost zero and hence $\rho(n) \approx 1$. On the other hand, in the steady-state of $W(z)$ and $\hat{S}(z)$ as $n \to \infty$, $P_f(n)$ converge to zero and hence $\rho(n) \to 0$. Therefore $\mu_s(n)$ changes from $\mu_{s_{\min}}$ to $\mu_{s_{\max}}$ according to the convergence of both adaptive filters.

4) Power scheduling of probe noise: The power of the probe noise $v(n)$ to identify the secondary path is also adjusted as follows:

$$v(n) = G(n)v_g(n), \tag{6}$$

$$G(n) = \sqrt{(1-\rho(n))\sigma^2_{v_{\min}} + \rho(n)\sigma^2_{v_{\max}}}, \tag{7}$$

where $v_g(n)$ is a white noise of unit variance, $\sigma^2_{v_{\min}}$ and $\sigma^2_{v_{\max}}$ are the lower and the upper bounds of the power of $v(n)$ respectively and $G(n)$ is the gain function of $v(n)$. Similar to varying $\mu_s(n)$, the power of $v(n)$ is modulated from $\sigma^2_{v_{\max}}$ to $\sigma^2_{v_{\min}}$.

C. Davari's method

Davari et al. recently proposed a novel scheme for online SPM by introducing On/Off scheduling of injecting the probe noise instead of the power scheduling of the probe noise [7]. The block diagram of Davari's method for online SPM is shown in Fig. 4. In Davari's method, the injection is controlled by a gain function $G(n)$ as follows:

$$v(n) = G(n)v_g(n), \tag{8}$$

$$G(n) = \begin{cases} 1 & (th_{\text{suspend}} \leq \Phi(n)) \\ 0 & (\Phi(n) < th_{\text{suspend}}) \end{cases}, \tag{9}$$

where $G(n) = 1$ and $G(n) = 0$ indicate the continuation and the suspension of the injection respectively, $\Phi(n)$ is a kind of the cost function and th_{suspend} is a threshold parameter for suspending the injection. $\Phi(n)$ is designed so that the value of $\Phi(n)$ decreases with time and is affected by the accumulated value of $\mu_{s_{\max}} - \mu_s(n)$. This suggests that the suspending timing of the injection hardly depends on the value of $\mu_{s_{\max}}$, $\mu_{s_{\min}}$ and th_{suspend} which are determined experimentally.

The injection should be resumed to remodel the secondary path if the path drastically changes after suspending the injection. In Davari's method, the changes of the secondary path are detected with the following rule:

$$th_{\text{resume}} < P_e(n), \tag{10}$$

where $P_e(n)$ is the power of the residual error signal $e(n)$ also estimated using (5) and th_{resume} is a threshold parameter for detecting the secondary path change. The injection and the calculation of $\Phi(n)$ are resumed when the above condition is satisfied. Simulation results in [7] show that good performances are achieved. However, there are excessive parameters needed to tuned carefully.

III. Proposed Method

We propose an alternative approach for On/Off scheduling of injecting the probe noise as shown in Fig. 5. The proposed approach for the On/Off scheduling is designed to perform without dependence on the algorithms or parameters of the control filter $W(z)$, the SPM filter $\hat{S}(z)$ and the power scheduling of the probe noise. For suspending the injection without the user-selected threshold parameter like th_{suspend} in Davari's method, the proposed approach aims to suspend the injection at steady-state of the SPM filter automatically. And a separate filter (replica filter) $\hat{S}_r(z)$ which temporarily holds a replica of the tap-weight of the SPM filter is introduced into the ANC system. Furthermore the outliers in the error signal $f(n)$ from $\hat{S}(z)$ are detected for resuming the injection with a simplified configuration of the parameter. These procedures are described in the following subsections.

A. Procedure for suspending the injection

Suspending the injection of the probe noise $v(n)$ is determined with the following rule as similar to Davari's method:

$$v(n) = G(n)v_g(n), \tag{11}$$

$$G(n) = \begin{cases} 1 & (th_{\text{suspend}}(n) \leq \Psi(n)) \\ 0 & (\Psi(n) < th_{\text{suspend}}(n)) \end{cases}, \tag{12}$$

where $\Psi(n)$ also denotes a cost function:

$$\Psi(n) = \Psi(n-1) + [P_r(n) - P_f(n)], \tag{13}$$

and $P_f(n)$ and $P_r(n)$ are the powers of the error signal $f(n)$ from the SPM filter $\hat{S}(z)$ and the error signal $r(n)$ from the replica filter $\hat{S}_r(z)$, respectively. These powers are estimated using a forgetting factor γ as follows:

$$P_f(n) = \gamma P_f(n-1) + (1-\gamma)f^2(n), \tag{14}$$

$$P_r(n) = \gamma P_r(n-1) + (1-\gamma)r^2(n). \tag{15}$$

The error signal $r(n)$ is calculated as:

$$r(n) = [d(n) - y'(n)] + [v'(n) - \hat{v}'_r(n)], \tag{16}$$

where $\hat{v}'_r(n) = \hat{s}_r(n) * v(n)$ is the estimated desired signal of $v'(n)$ by $\hat{S}_r(z)$ and $\hat{s}_r(n)$ is the impulse response of $\hat{S}_r(z)$. The threshold value $th_{\text{suspend}}(n)$ in (12) is determined as following variable value:

$$th_{\text{suspend}}(n) = -\alpha P_f(n), \tag{17}$$

where α is a positive constant parameter for promoting the suspension of the injection at steady-state of $\hat{S}(z)$ described later in this procedure.

The strategic methodology of replicating from $\hat{S}(z)$ to $\hat{S}_r(z)$ and suspending the injection is summarized below.

1) *Initialization*
The value of the cost function $\Psi(n)$ is initialized to zero. The tap-weights of the SPM filter $\hat{S}(z)$ and the replica filter $\hat{S}_r(z)$ are mutually initialized with the same coefficients. The initial values of the error powers $P_f(n)$ and $P_r(n)$ are also set to the same value as each other.
2) *Adaptation of the SPM filter $\hat{S}(z)$*
Only the SPM filter $\hat{S}(z)$ is adapted using a kind of adaptation algorithm at every step n.
3) *Estimation of the error powers $P_f(n)$ and $P_r(n)$*
The error signal $f(n)$ from the SPM filter $\hat{S}(z)$ and the error signal $r(n)$ from the replica filter $\hat{S}_r(z)$ are calculated by (2) and (16), respectively. The error powers $P_f(n)$ and $P_r(n)$ are also updated using (14) and (15) respectively.
4) *Calculation of the cost function $\Psi(n)$*
The cost function $\Psi(n)$ is calculated by (13). In general, an adaptive filter of FIR type has a unique (optimal) solution whereby the error power of the adaptive filter is minimized. The error power $P_f(n)$ of the SPM filter $\hat{S}(z)$ then becomes lower than the error power $P_r(n)$ of the replica filter $\hat{S}_r(z)$ when $\hat{S}(z)$ is converging yet. In this situation, $\Psi(n)$ increases because of $P_r(n) - P_f(n) > 0$. On the contrary, $P_f(n)$ becomes greater than $P_r(n)$ when the accuracy of $\hat{S}(z)$ is degraded by adaptation, and $\Psi(n)$ decreases because of $P_r(n) - P_f(n) \leq 0$.
5) *Decision of the replication*
If the value of $\Psi(n)$ has an increasing tendency, the accuracy of the SPM filter $\hat{S}(z)$ can be considered as greater than that of the replica filter $\hat{S}_r(z)$. For keeping the best estimated accuracy of $\hat{S}(z)$ into $\hat{S}_r(z)$, the following condition for the replication is set:

$$th_{\text{replicate}}(n) < \Psi(n), \tag{18}$$

where $th_{\text{replicate}}(n)$ is a threshold value for the replication determined as:

$$th_{\text{replicate}}(n) = P_f(n). \tag{19}$$

If (18) is satisfied, the replication and initialization are carried out as follows:

$$\hat{s}_r(n) = \hat{s}(n), \tag{20}$$
$$P_r(n) = P_f(n), \tag{21}$$
$$\Psi(n) = P_f(n), \tag{22}$$

where (20) indicates the copy of the impulse response from $\hat{S}(z)$ to $\hat{S}_r(z)$, initialization of $P_r(n)$ by $P_f(n)$ in (21) enables to compare the these powers accurately from the successive iterations, and also (22) is to replicate again when $\Psi(n)$ increases.
6) *Decision of suspending the injection*
Suspending the injection is controlled according to (12) independent of the decision of the replication. This procedure is repeated from the step 2) during $G(n) = 1$.

Here let consider the situation where $\Psi(n)$ decreases. At this time, the error power $P_f(n)$ of the SPM filter $\hat{S}(z)$ is greater than the error power $P_r(n)$ of the replica filter $\hat{S}_r(z)$, and this means that the accuracy of the $\hat{S}(z)$ is degraded than that of $\hat{S}_r(z)$ by the adaptation. There are two situations of the accuracy degradation as follows:

- *Steady-state error*
According to the convergence property of the adaptive filter, steady-state error whereby the filter randomly repeats ascent and descent of the accuracy near the optimal solution is appeared after the convergence of the filter. In the replicating procedure, the replica filter $\hat{S}_r(z)$ intends to hold the tap-weights of the best accuracy model of the SPM filter $\hat{S}(z)$. Therefore, $\Psi(n)$ decreases when $\hat{S}_r(z)$ obtains the best model of $\hat{S}(z)$ in its steady-state. This indicates that the proposed approach has a possibility for suspending the injection at steady-state of $\hat{S}(z)$.
- *False adaptation by disturbance signal*
In the early stage of the ANC systems, the control filter $W(z)$ is not converged and the canceling signal $y'(n)$ is almost zero. Then the disturbance signal $d(n) - y'(n)$ whereby the adaptation of the SPM filter $\hat{S}(z)$ is perturbed is large. As a result, decrements of $\Psi(n)$ are caused. For avoiding the suspension of the injection in this situation, (12) and (22) provide a range of $\Psi(n)$ as $-\alpha P_f(n) \leq \Psi(n) \leq P_f(n)$. In the early stage, the range widens with increase in $P_f(n)$ because of the large disturbance and error from the SPM filter $\hat{S}(z)$. After the convergence of $W(z)$ and $\hat{S}(z)$, $P_f(n)$ is reduced and the range narrows. The behavior of the range prompts suspending the injection in steady-state of $\hat{S}(z)$.

B. Procedure for resuming the injection

After suspending the injection of the probe noise, the automatic tracking for the secondary path change becomes unavailable. In the proposed approach for resuming the injection, the error signal $f(n)$ from the SPM filter $\hat{S}(z)$ is monitored and applied to detect the outliers excited by the secondary path change as follows:

$$th_{\text{resume}}(n) < f^2(n), \tag{23}$$

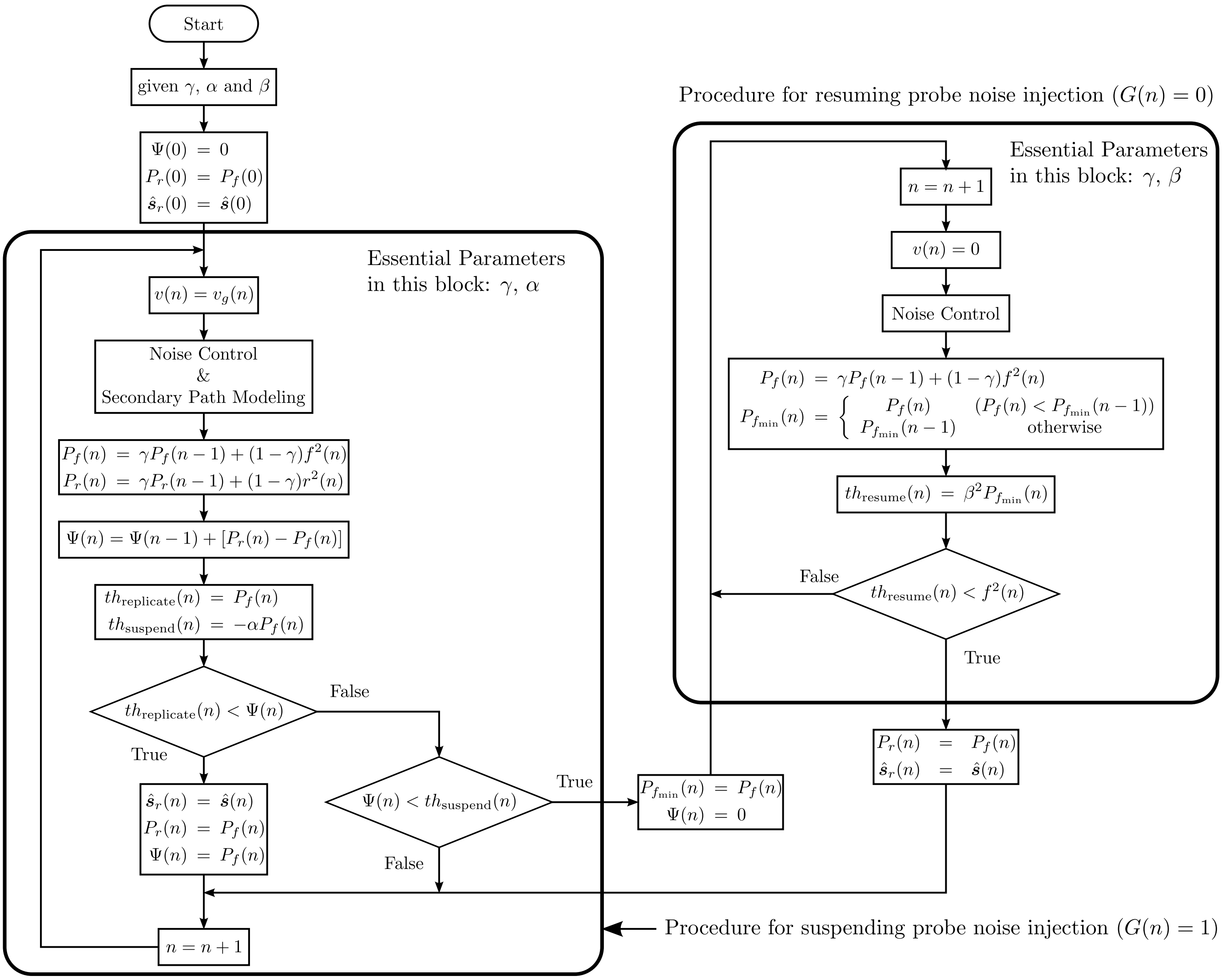


Fig. 6. Flowchart of the proposed On/Off scheduling of the probe noise injection

where $th_{\text{resume}}(n)$ is a threshold value for detecting the outliers determined as:

$$th_{\text{resume}}(n) = \beta^2 P_{f_{\min}}(n), \tag{24}$$

where β is a constant parameter and $P_{f_{\min}}(n)$ is the estimated minimum power of $f(n)$ updated as:

$$P_{f_{\min}}(n) = \begin{cases} P_f(n) & (P_f(n) < P_{f_{\min}}(n-1)) \\ P_{f_{\min}}(n-1) & \text{otherwise} \end{cases}, \tag{25}$$

where $P_f(n)$ is also estimated using (14). The injection is resumed when (23) is satisfied.

In terms of the outliers detected by the proposed approach, there may be some causalities such as sudden changes of the reference signal, impulsive disturbance sound at the error microphone and so on. However, the proposed approach for suspending the injection is designed to work with a steady-state of $\hat{S}(z)$. Hence, even though the injection is resumed with a false detection of the outlier, the injection is suspended immediately when the secondary path is not changed.

The flowchart of the proposed On/Off scheduling is shown in Fig. 6. The effectiveness of the proposed approach is confirmed in the following section.

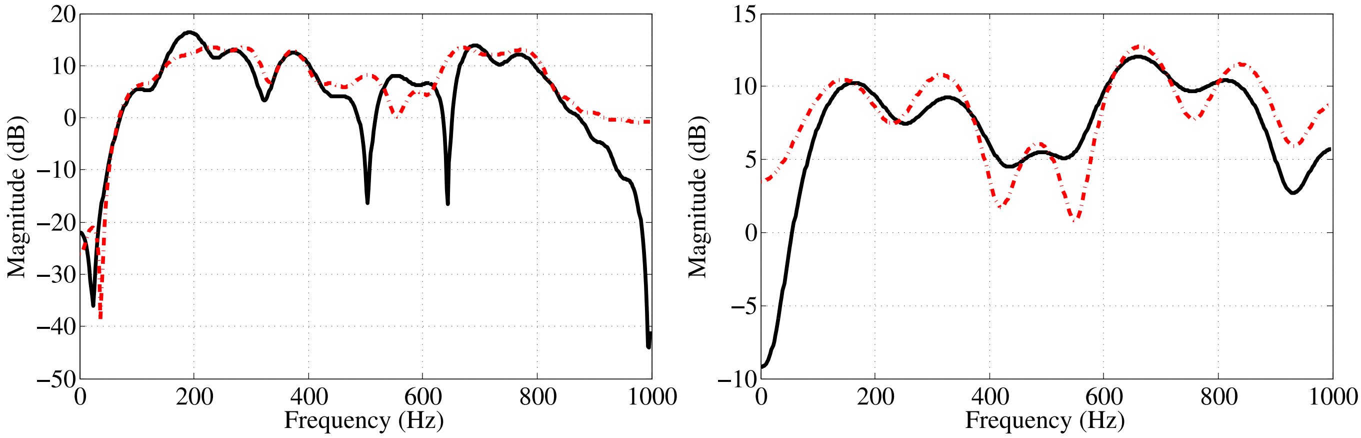
IV. Simulation Results

The numerical simulations are performed to verify the effectiveness of the proposed approach in comparison with Davari's ANC system and Akhtar's ANC system. The performance comparisons are carried out with the following performance measurements:

- The estimation error of the SPM filter $\hat{S}(z)$ defined as:

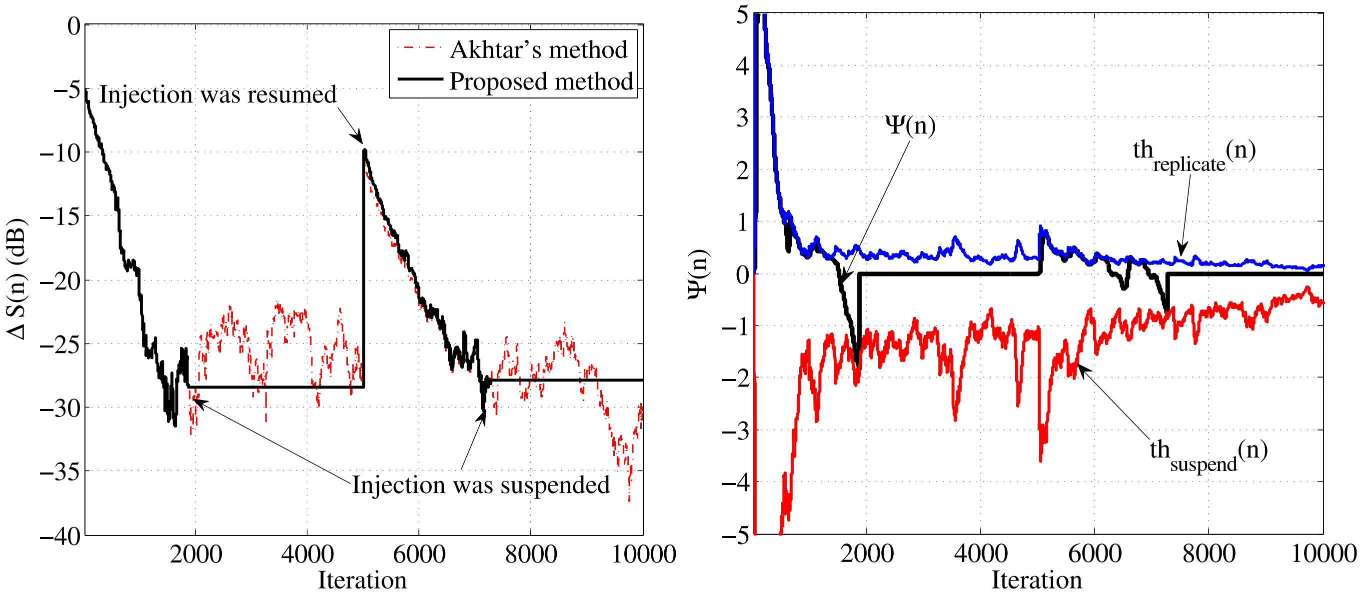
$$\Delta S(n) = \frac{||\boldsymbol{s} - \hat{\boldsymbol{s}}(n)||^2}{||\boldsymbol{s}||^2}, \tag{26}$$

  where $\boldsymbol{s}$ and $\hat{\boldsymbol{s}}(n)$ are the impulse responses of $S(z)$ and $\hat{S}(z)$ respectively, and $||\cdot||$ denotes the Euclidean norm.
- Mean-squared-error (MSE) at the error microphone defined as $E\{e^2(n)\}$.



(a) (b)

Fig. 7. Magnitude response of acoustic paths. (a) Primary path $P(z)$, (b) Secondary path $S(z)$ (solid line: original path, dot-dashed line: changed path)



(a) (b)

Fig. 8. The results of *simulation 1*. (a) The estimation error $\Delta S(n)$, (b) The cost function $\Psi(n)$, $th_{\mathrm{replicate}}(n)$ and $th_{\mathrm{suspend}}(n)$

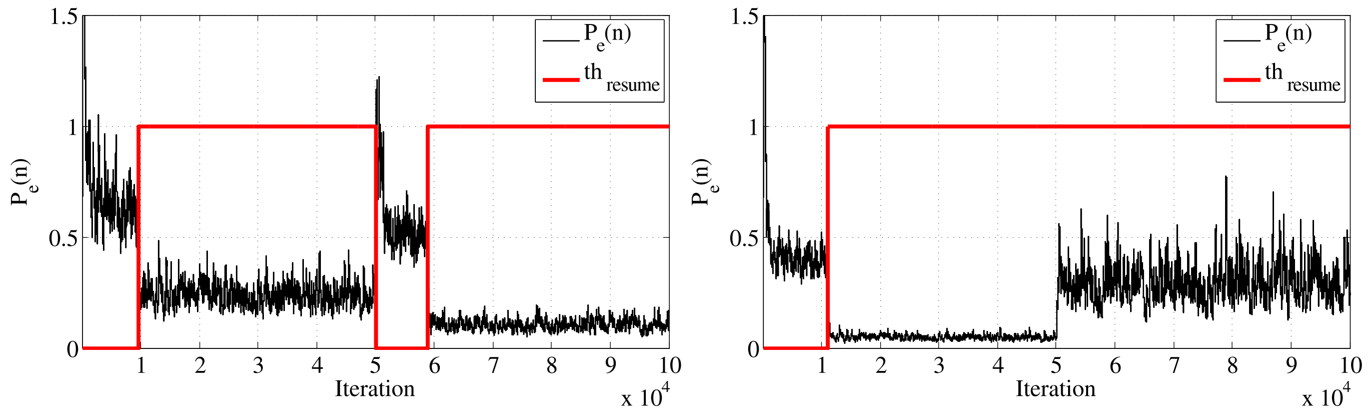
A sampling frequency of 2kHz is used. The acoustic characteristics of the primary path and the secondary path are shown in Fig. 7. These data used in the simulations are provided as IIR filters by Kuo et al. [1], and modeled as FIR filters of the tap-length 48 and 16 for the primary path and the secondary path, respectively. The control filter $W(z)$ and the SPM filter $\hat{S}(z)$ are FIR type, and the tap-length are 32 and 16 respectively. $\hat{S}(z)$ is initialized so that the estimation error $\Delta S(n)$ becomes -5dB for the stable operation of the ANC system.

Three cases of the reference signal $x(n)$ are used as follows:

- *Case 1:* A tonal signal with 300Hz frequency and variance 2.0 corrupted with a zero-mean white noise at 30dB SNR.
- *Case 2:* A narrowband signal with 100, 200, 300 and 400Hz frequencies and variance 2.0 corrupted with a zero-mean white noise at 30dB SNR.
- *Case 3:* A broadband zero-mean white noise with passband 100-400Hz and variance 1.0.

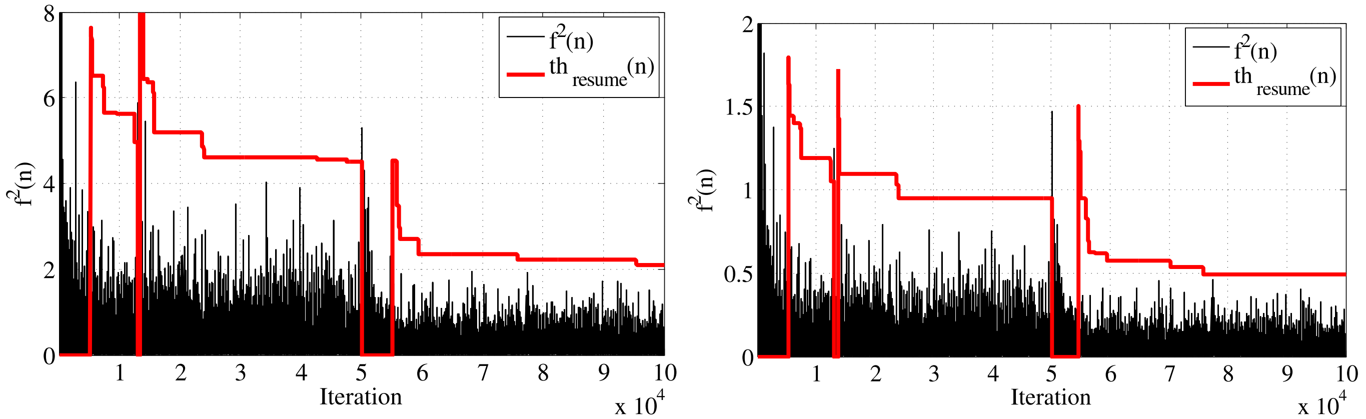
The following parameters are used in all simulations:

- *Davari's ANC system:*
$\mu_w = 1\times10^{-3}$, $\mu_{s_{\max}} = 5\times10^{-2}$, $\mu_{s_{\min}} = 9\times10^{-3}$, $\lambda = 0.99$, $\gamma = 0.999$, $th_{\mathrm{suspend}} = 3.28 \times 10^{-5}$, $th_{\mathrm{resume}} = 1.0$, the power of $v(n) = 0.05$.
- *Akhtar's ANC system:*
$\mu_w = 5 \times 10^{-4}$, $\mu_{s_{\max}} = 1 \times 10^{-2}$, $\mu_{s_{\min}} = 1 \times 10^{-3}$, $\sigma^2_{v_{\max}} = 1.0$, $\sigma^2_{v_{\min}} = 0.0$, $\lambda = 0.99$.
- *Proposed On/Off scheduling:*
$\gamma = 0.99$, α in (17) $= 4.0$, β in (24) $= 6.0$.



(a) (b)

Fig. 9. The results of Davari's On/Off scheduling in *simulation 2*. (a) In case of the reference signal with variance 1.0. (b) In case of the reference signal with variance 0.2.



(a) (b)

Fig. 10. The results of proposed On/Off scheduling in *simulation 2*. (a) In case of the reference signal with variance 1.0. (b) In case of the reference signal with variance 0.2.

A. *Simulation 1*

This simulation is conducted to confirm the behavior of the cost function $\Psi(n)$. The proposed On/Off scheduling for injecting the probe noise is implemented with Akhtar's ANC system. The reference signal of *Case 3* is used and both the primary path and the secondary path are altered at $n = 5000$. The results of the simulation with one realization are shown in Fig. 8.

In Fig. 8, the part (a) shows the estimation error $\Delta S(n)$, and the part (b) shows the cost function $\Psi(n)$ and the threshold values $th_{\text{replicate}}(n)$ and $th_{\text{suspend}}(n)$, respectively. In both the parts, the constant value in $\Delta S(n)$ and $\Psi(n) = 0$ indicate the time periods of suspending the injection. We can see that $\Psi(n)$ increases when the SPM filter $\hat{S}(z)$ is converging in the initial stage of modeling, and can verify decreasing $\Psi(n)$ and suspending the injection in steady-state of $\hat{S}(z)$.

B. *Simulation 2*

Here, the proposed and Davari's approaches for the On/Off scheduling are compared with each other to validate the effectiveness of resuming the injection. In this simulation, the proposed approach for On/Off scheduling is equipped with Davari's ANC system. The reference signal of *Case 3* and that which the variance is reduced to 0.2 are used. Both the primary path and the secondary path are altered at $n = 50000$. The all results of this simulation are illustrated in Fig. 9 and Fig. 10 with one realization.

Fig. 9 represents the power $P_e(n)$ of the residual error signal $e(n)$ as a monitored signal and the threshold parameter th_{resume} in Davari's On/Off scheduling. Fig. 10 represents $f^2(n)$ as a monitored signal and the threshold value $th_{\text{suspend}}(n)$ in the proposed On/Off scheduling. The part (a) and (b) of these figures show the results when the variance of the reference signal is 1.0 and 0.2 respectively. In these results, th_{suspend} and $th_{\text{suspend}}(n)$ are set to 0 during the time periods of keeping the injection. From these figures, in case of the reference signal with variance 1.0, both methods can detect the secondary path change and resume the injection. However, Davari's On/Off scheduling can not detect the path change when the variance of the reference signal is reduced to 0.2 because of the rather small variance, whereas the proposed approach can track the path change without altering the value of β. In the proposed approach in Fig. 10, there are some false

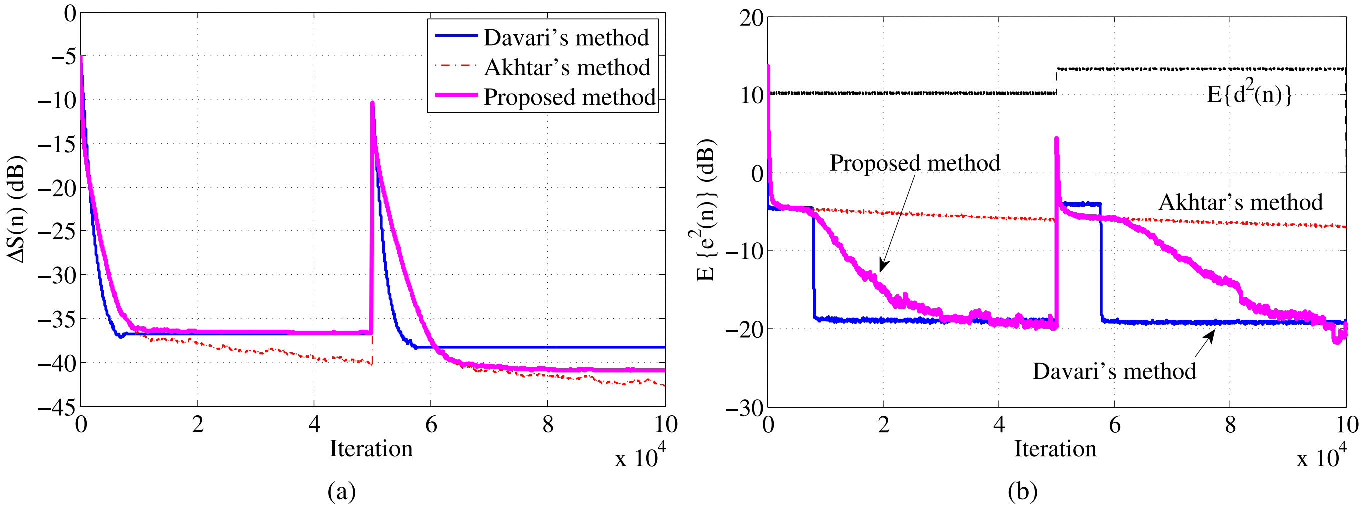


Fig. 11. The results of *simulation 3*. The reference signal of *Case 1* is used. (a) The estimation error $\Delta S(n)$, (b) Mean-squared-error at the error microphone $E\{e^2(n)\}$ and $E\{d^2(n)\}$ for a reference.

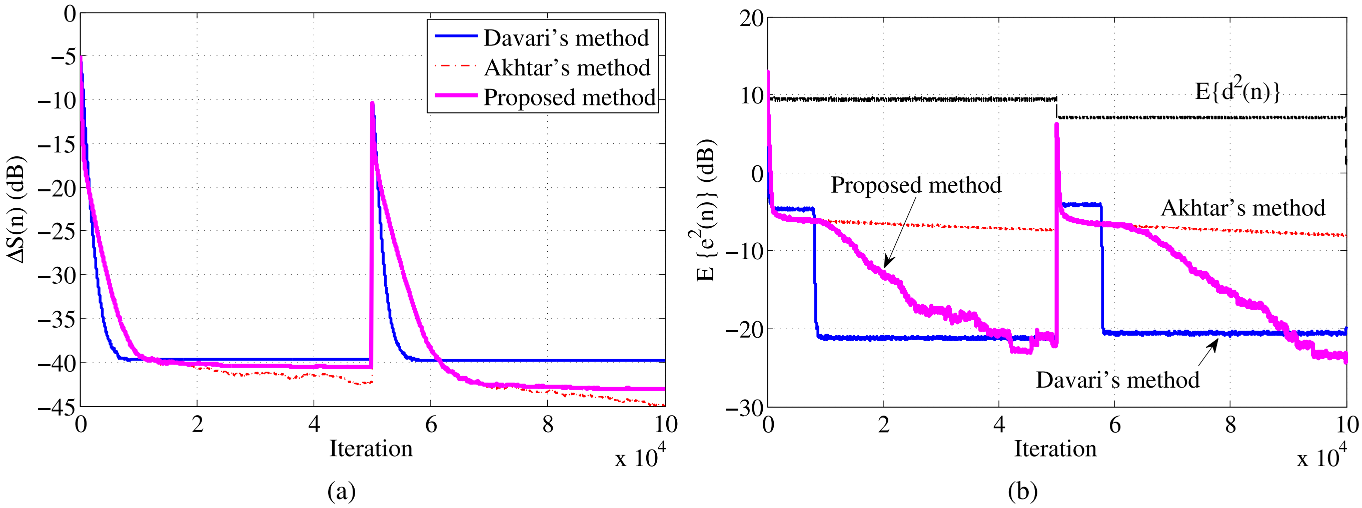


Fig. 12. The results of *simulation 3*. The reference signal of *Case 2* is used. (a) The estimation error $\Delta S(n)$, (b) Mean-squared-error at the error microphone $E\{e^2(n)\}$ and $E\{d^2(n)\}$ for a reference.

detections of the path change. However, we can see that the injection is promptly suspended.

C. *Simulation 3*

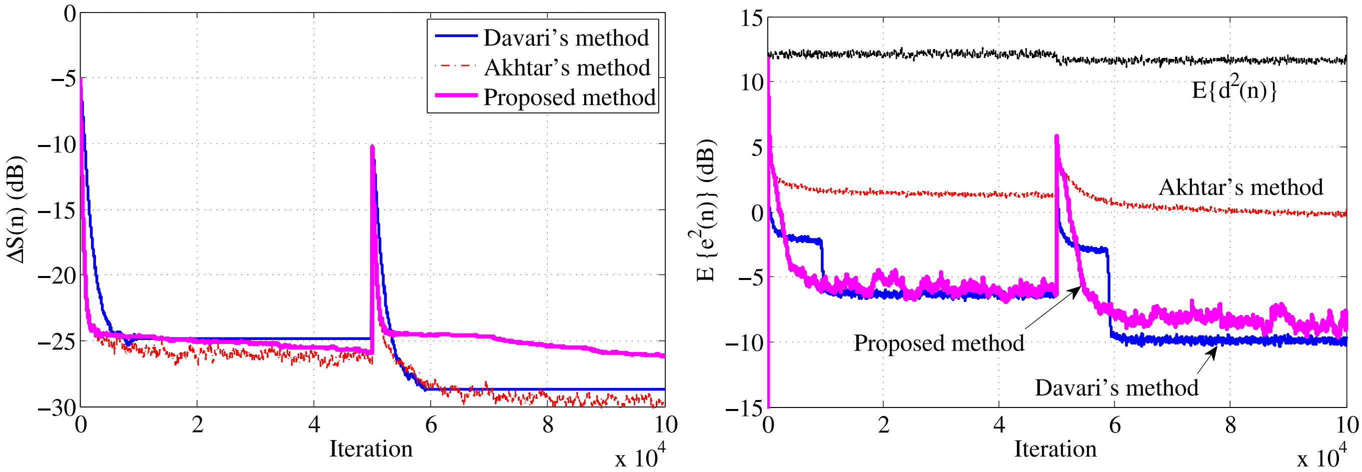
In this simulation, the overall performance among Davari's ANC system, Akhtar's ANC system and Akhtar's ANC systems with proposed approach are compared with each other. The reference signals of *Case 1, 2* and *3* are used, and both the primary path and the secondary path are also altered at $n = 50000$. Fig. 11, 12 and 13 represent the simulation results of *Case1, 2* and *3* respectively with averaging of 100 realizations.

The part (a) of these figures show the estimation error of the SPM filter $\hat{S}(z)$. Akhtar's ANC system with the proposed approach achieves sufficient accuracy of $\hat{S}(z)$ compared with Davari's ANC system and Akhtar's original ANC system. The part (b) of these figures show MSE at the error microphone. Davari's ANC system and the proposed approach considerably reduce the residual error signal by suspending the injection. As described in Section III, the proposed approach provides more clear criteria for On/Off scheduling of the injection than that of Davari's ANC system. The proposed approach would be considered effective as the online SPM method from various perspectives.

V. Discussion and Concluding Remarks

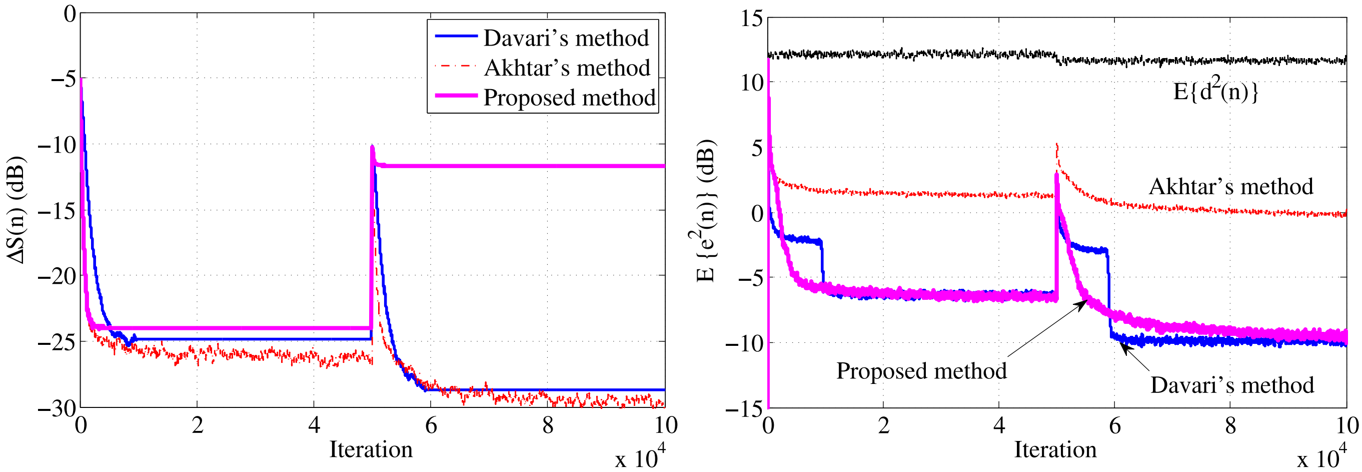
In this paper, we proposed an On/Off scheduling of injecting the probe noise to identify the secondary path. In the proposed approach, the replica filter having its replicating strategy is introduced into the ANC system equipped with the online SPM method to suspend the injection in the steady-state of the SPM filter. After suspending the injection, the outliers in the error signal from the SPM filter are detected for resuming the injection and modeling the secondary path again.

From numerical simulations, we found that selecting a large value for β results in a low false detection of the secondary path change and the performance of detecting the true path change is degraded. The results in *Simulation 3* using the



(a) (b)

Fig. 13. The results of *simulation 3*. The reference signal of *Case 3* is used. (a) The estimation error $\Delta S(n)$, (b) Mean-squared-error at the error microphone $E\{e^2(n)\}$ and $E\{d^2(n)\}$ for a reference.



(a) (b)

Fig. 14. The results of *simulation 3* with $\beta = 10$. The reference signal of *Case 3* is used. (a) The estimation error $\Delta S(n)$, (b) Mean-squared-error at the error microphone $E\{e^2(n)\}$ and $E\{d^2(n)\}$ for a reference.

reference signal of *Case 3* with $\beta = 10.0$ is shown in Fig. 14. The results plotted in Fig. 14 (a) show that the performance of modeling the secondary path in the proposed approach is poor after the path change because the true path changes were detected correctly only 29 times in 100 realizations. However, the ANC system is still stable and MSE in Fig. 14 (b) is lower than that in Fig. 13 (b) with $\beta = 6.0$. This means that the high accuracy of the SPM filter is not so important for the convergence of the control filter.

We therefore conclude that detecting the secondary path change which destabilizes the ANC system is important in the On/Off scheduling and the proposed approach is effective for online SPM from the point of view of the noise-reduction performance in the ANC systems.

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