AUXILIARY NOISE POWER SCHEDULING FOR ON-LINE SECONDARY PATH MODELING IN SINGLE CHANNEL FEEDFORWARD ACTIVE NOISE CONTROL SYSTEMS

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ABSTRACT

Auxiliary noise, injected in active noise control (ANC) system for on-line secondary path modeling (SPM), contributes to the residual error (which we want to minimize). In this paper, two new schemes for controlling the auxiliary noise injection are proposed. The first method is ON/OFF control in which an additional fixed filter is used to temporarily hold the tap-weights of the adaptive on-line SPM filter. The decision (ON/OFF) is carried out on the basis of difference of power of errors from the two filters. After suspension of the auxiliary noise injection, the algorithm continuously checks for error outliers so that injection may be restarted in the case of path perturbation. In the second method a new auxiliary-noise-power scheduling strategy based on the error signal of the SPM filter is proposed. In both proposed schemes a fixed step-size is used for the SPM filter and the noise control filter, which reduces the computational complexity of the algorithms. In addition to this, in the second method, no off-line modeling (initial phase) of the secondary path is required.

***Index Terms*—** Noise scheduling, Normalized variable step-size (NVSS) LMS algorithm, Modified FxLMS algorithm.

1. INTRODUCTION

Active noise control (ANC) system is based on the principle of superposition in which the acoustic waves from the noise source and the controller interfere with each other destructively to reduce the effect of unwanted noise [1]. The block diagram of a single channel feedforward ANC system, with random noise based on-line secondary path modeling (SPM) [2] is shown in Fig. 1. It comprises one reference microphone to measure the reference signal, $x(n)$, one error microphone to sense the error signal, $e(n)$, $P(z)$ is the primary path transfer function from the reference sensor to the error sensor, $W(z)$ is the transfer function of the noise control filter, and $S(z)$ is the secondary path transfer function from the output of $W(z)$ to the error sensor. The characteristics of $S(z)$ are time varying, and LMS-based adaptive filter $\hat{S}(z)$ with white gaussian noise (WGN) input (auxiliary noise), $v(n)$, is used for tracking variations in $S(z)$.

The injection of WGN for on-line SPM contributes to the residual error which we want to minimize. One of the solution to this problem is auxiliary-noise-power scheduling. The detail of auxiliary-noise-power scheduling techniques can be found in [3]-[6]. Recently Carini and Malatini [5] proposed a new method for on-line SPM with auxiliary-noise-power schduling, where optimal step-size, based on delay-coefficient technique, is used for the on-line SPM filter. The problem with the Carini's method is that when ANC system converges the step-size for the secondary path modeling filter freezes to a minimum value, even when the acoustic paths are perturbed, which is undesirable for modeling time varying acoustic paths. In addition to this, the algorithm is computationally complex and requires two phases of operation of ANC system. In the first phase (duration of first phase is required to be tuned for stable operation) the $W(z)$ is not in operation and only the filter $\hat{S}(z)$ is active (updated). In the second phase both the noise control filter and the modeling filter are in operation.

In Davari's method [6], a novel ON/OFF controlling strategy is proposed, in which the auxiliary noise injection is stopped after ANC system converges. This removes contribution of the auxiliary noise from $e(n)$, however this method requires selection of too many empirical threshold parameters which must be tuned for correct decision about ON/OFF state of the auxiliary noise, and hence is not as much robust as Carini's method.

The first proposed method (ON/OFF control), hereafter called as the proposed method-1, improves the performance of Davari's method by giving a small steady-state residual error, and reducing the number of empirically selected threshold parameters for suspending/resuming the auxiliary noise injection. The proposed method-1 gives a clear criterion for ON/OFF decision of the auxiliary noise based on the evaluation of a cost function $\Psi(n)$. The second proposed method (continuous scheduling scheme), hereafter called as the proposed method-2, is to work out the problems with Carini's method by making ANC system sensitive to acoustic path perturbation, and reducing the computational complexity of the algorithm. The fixed step-size for the noise control filter and the SPM filter in proposed method-2 reduces the computational complexity of the algorithm compared to Carini's method, and the gain for the auxiliary noise is varied based on the error signal of $\hat{S}(z)$ to control its convergence. In addition to this no off-line modeling of the secondary path is required in the proposed method-2. Computer simulations demonstrate that both the proposed methods can effectively track the variations in the secondary path.

The rest of the paper is organized as follows. Section 2 gives a brief overview of the existing methods. Section 3 describes the proposed methods. The simulation results are discussed in Section 4. For comparison, only the simulation results for Davari's method are included in this paper, and finally Section 5 gives the concluding remarks.

2. EXISTING METHODS

2.1. Akhtar's Method

Fig. 1 (without components in dashed box, with $D = 0$, and $\hat{S}(z) = \hat{S}_1(z)$) shows the block diagram of Akhtar's method [3]. From Fig. 1, the residual error signal, $e(n)$, and the error signal, $f(n)$, of $\hat{S}(z)$ are given, respectively, as

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

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

where $d(n) = p(n) * x(n)$ is output of $P(z)$, $y(n) = w(n) * x(n)$ is output of $W(z)$, $\hat{v}'(n) = \hat{s}(n) * v(n)$ is output of $\hat{S}(z)$, $y'(n) - v'(n) = s(n)*(y(n)-v(n))$ is output of $S(z)$, $*$ represents the convolution operation, and $p(n)$, $w(n)$, $s(n)$ and $\hat{s}(n)$ are the impulse responses of $P(z)$, $W(z)$, $S(z)$ and $\hat{S}(z)$, respectively. Variable step-size (VSS) LMS algorithm is employed for $\hat{S}(z)$, and modified FxLMS (MFxLMS) algorithm is used for $W(z)$. In Akhtar's method a noise scheduling scheme is used in order to get fast initial convergence of $\hat{S}(z)$, and to minimize the contribution of auxiliary noise in residual error at steady-state. In Akhtar's method gain, $G(n)$, to vary input auxiliary-noise-power, is computed as

$$G(n) = \sqrt{\rho(n)\sigma^2_{\max} + (1-\rho(n))\sigma^2_{\min}}, \quad (3)$$

where $\sigma^2_{\min}$ and $\sigma^2_{\max}$ are experimentally determined parameters and $\rho(n) = P_f(n)/P_e(n)$, ($\rho(0) = 1,\ \rho(n) \to 0 \text{ as } n \to \infty$), where $P_f(n)$ and $P_e(n)$ are powers of the signals $f(n)$ and $e(n)$, respectively, that are estimated on-line using low pass estimator as

$$P_q(n) = \lambda P_q(n-1) + (1-\lambda)q^2(n), \quad (4)$$

where $q(n)$ is the signal of interest, and $0.9 < \lambda < 1$ is a forgetting factor. The output of $G(n)$ is given by $v(n) = G(n)v_g(n)$, where $v_g(n)$ is an internally generated WGN. The weight update equation for $W(z)$ is given by

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu_w g(n)\hat{\boldsymbol{x}}'(n), \quad (5)$$

where $g(n)$ is the error signal, μ_w is the step-size parameter for $W(z)$, and $\hat{\boldsymbol{x}}'(n) = [\hat{x}'(n), \hat{x}'(n-1), ...\hat{x}'(n-L_w+1)]^T$ is the filtered-reference signal vector, where L_w is the tap-weight length of $W(z)$. Assuming $\hat{S}(z)$ is an FIR filter of tap-weight length L_s, the filtered-reference signal, $\hat{x}'(n)$, is computed as $\hat{x}'(n) = \hat{\boldsymbol{s}}^T(n)\boldsymbol{x}(n)$, where $\boldsymbol{x}(n) = [x(n), x(n-1), ...x(n-L_s+1)]^T$ is an L_s-sample input vector for $\hat{S}(z)$. Finally, the weight update equation for $\hat{S}(z)$ is given as

$$\hat{\boldsymbol{s}}(n+1) = \hat{\boldsymbol{s}}(n) + \mu_s(n)f(n)\boldsymbol{v}_{L_s}(n), \quad (6)$$

where $\boldsymbol{v}_{L_s}(n) = [v(n), v(n-1), ...v(n-L_s+1)]^T$ is the input signal vector, and $\mu_s(n)$ is VSS parameter for $\hat{S}(z)$, and is given as:

$$\mu_s(n) = \rho(n)\mu_{s_{\min}} + (1-\rho(n))\mu_{s_{\max}}, \quad (7)$$

where $\mu_{s_{\min}}$ and $\mu_{s_{\max}}$ are minimum and maximum values of $\mu_s(n)$, respectively, that are selected by trial and error method for fast and stable convergence of ANC system.

In Akhtar's method, the value of the parameter $\rho(n)$ is never zero in steady-state and $\sigma^2_{\max}$ in (3) affects the steady-state value of auxiliary-noise-power. In Carini's method two improvements are suggested to Akhtar's method: 1) optimal step-size parameters are used for $\hat{S}(z)$ and $W(z)$, and 2) a new self-tuning noise scheduling strategy is proposed.

2.2. Carini's Method

The block diagram of Carini's method is shown in Fig. 1 (without components in dashed box), where delay-coefficient technique [7], based on delay D, is used to estimate optimal value for step-size $\mu_s(n)$. The weight update equations for Carini's method are the same as in Akhtar's method except the step-size parameters are replaced by optimal normalized variable step-size (NVSS) parameters. The optimal NVSS for on-line SPM filter is computed as

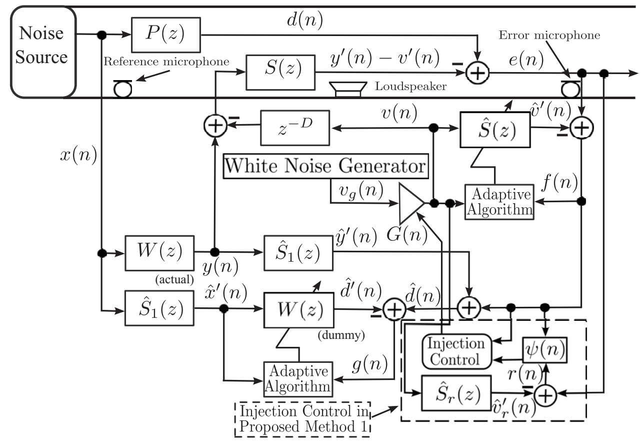

Fig. 1: Block diagram for Akhtar's, Carini's and Proposed methods ($D = 0$, $\hat{S}_1(z) = \hat{S}(z)$ for Akhtar's and Proposed methods).

$$\mu_s(n) = \begin{cases} \dfrac{\hat{N}_s(n)}{P_f(n)(\boldsymbol{v}^T_{L_s+D}(n)\boldsymbol{v}_{L_s+D}(n))}; & \dfrac{\hat{N}_s(n)}{P_f(n)} > \mu_{s_{\min}} \\ \dfrac{\mu_{s_{\min}}}{(\boldsymbol{v}^T_{L_s+D}(n)\boldsymbol{v}_{L_s+D}(n))}; & \text{Otherwise,} \end{cases} \quad (8)$$

$$\hat{N}_s(n) = \lambda\hat{N}_s(n-1) + \frac{1-\lambda}{D}(\hat{\boldsymbol{s}}^T_0(n)\hat{\boldsymbol{s}}_0(n)\boldsymbol{v}^T_{L_s+D}(n)\boldsymbol{v}_{L_s+D}(n)), \quad (9)$$

where $\hat{\mathbf{s}}(n) = [\hat{\mathbf{s}}_0(n) \quad \hat{\mathbf{s}}_1(n)]$ is a vector of length $D + L_s$, D is the length of $\hat{\mathbf{s}}_0(n)$, L_s is the tap-weight length of $\hat{\mathbf{s}}_1(n)$, $\hat{\mathbf{s}}(n)$ is the impulse response of $\hat{S}(z)$, and $\boldsymbol{v}_{L_s+D}(n) = [v(n), v(n-1), ...v(n-L_s-D+1)]^T$. The optimal NVSS for $W(z)$ is computed as

$$\mu_w(n) = \frac{\hat{N}_w(n)}{P_g(n)(\hat{\boldsymbol{x}}'^T(n)\hat{\boldsymbol{x}}'(n))}, \quad (10)$$

$$\hat{N}_w(n) = \lambda\hat{N}_w(n-1) + (1-\lambda)g(n)\hat{\boldsymbol{m}}^T(n)\hat{\boldsymbol{x}}'(n), \quad (11)$$

$$\hat{\boldsymbol{m}}(n) = \hat{\lambda}\hat{\boldsymbol{m}}(n-1) + (1-\hat{\lambda})g(n)\hat{\boldsymbol{x}}'(n)/(\hat{\boldsymbol{x}}'^T(n)\hat{\boldsymbol{x}}'(n)), \quad (12)$$

where $g(n)$ is the error signal of $W(z)$, $P_g(n)$ can be estimated using (4), $\hat{\lambda}$ is in range [0.6, 0.9], and $\hat{x}'(n) = \hat{\boldsymbol{s}}^T_1(n)\boldsymbol{x}(n)$.

In Carini's method [5], the ratio between the residual primary noise power and the auxiliary-noise-power at the error microphone is constant in all operating conditions. The gain for the auxiliary-noise-power variation is calculated by

$$G(n) = \sqrt{\frac{P_e(n)}{(R+1)P_{s_1}(n)}}, \quad (13)$$

where $R = E\left[(d(n) - y'(n))^2\right]/E\left[(v'(n))^2\right]$, $P_e(n)$ can be estimated using (4), and $P_{s_1}(n)$ is computed as

$$P_{s_1}(n) = \lambda P_{s_1}(n-1) + (1-\lambda)\hat{\boldsymbol{s}}^T_1(n)\hat{\boldsymbol{s}}_1(n). \quad (14)$$

The delay-coefficient technique to compute optimal NVSS $\mu_s(n)$ (as given in (8) and (9)) for $\hat{S}(z)$, does not work well for time-varying secondary path $S(z)$. Furthermore, overall computational complexity of Carini's method is very high as compared with Akhtar's method.

3. PROPOSED METHODS

3.1. Proposed Method-1 (ON/OFF control)

In Davari's method [6], instead of continuous noise schedualing, a novel ON/OFF controlling strategy of auxiliary noise is proposed. In Davari's method the suspension of the auxiliary noise strongly depends on many user-selected thresholding parameters. In many practical situations, it is a laborious job to find suitable values for such thresholding parameters.

The proposed method-1 as shown in Fig. 1 (with $D = 0$, and $\hat{S}(z) = \hat{S}_1(z)$) employs a *non-adaptive filter* $\hat{S}_r(z)$ (fixed filter), which temporarily holds the copy of the tap-weights of $\hat{S}(z)$, for the decision to suspend the injection. Here $\hat{S}(z)$ and $W(z)$ are updated with conventional LMS algorithm and MFxLMS algorithm, respectively. The injection is aimed to be suspended at the steady-state of $\hat{S}(z)$. The steady-state of $\hat{S}(z)$ is evaluated on the basis of a cost function, which is defined by the accumulated difference between powers of the error signals for $\hat{S}_r(z)$ and $\hat{S}(z)$ as

$$\Psi(n) = \Psi(n-1) + [P_r(n) - P_f(n)], \tag{15}$$

where error powers $P_r(n)$ and $P_f(n)$ of $\hat{S}_r(z)$ and $\hat{S}(z)$, respectively, are estimated by (4), $\Psi(0)$ is initialized with zero, and both $\hat{S}(z)$ and $\hat{S}_r(z)$ are initialized with same tap-weights, and thus $P_f(0) = P_r(0)$ is satisfied. The gain, $G(n)$, in proposed method-1 is computed as

$$G(n) = \begin{cases} \sqrt{\sigma_v^2}; & \Psi(n) \geq -\epsilon P_f(n) \\ 0; & \text{Otherwise,} \end{cases} \tag{16}$$

where ϵ is a positive constant determined empirically, and σ_v^2 is a parameter for gain, $G(n)$.

Initially, the cost function $\Psi(n)$ has an increasing behaviour, because only $\hat{S}(z)$ converges to the secondary path $S(z)$, and hence $P_f(n)$ becomes lower than $P_r(n)$. In contrast, the decreasing behaviour of $\Psi(n)$ appears in steady-state, when $P_r(n)$ is lower than $P_f(n)$, and this indicates that compared to $\hat{S}(z)$, $\hat{S}_r(z)$ is more close to $S(z)$. The tap-weights of $\hat{S}(z)$, whose accuracy is higher than that of $\hat{S}_r(z)$, are replicated to $\hat{S}_r(z)$ with the condition of $\Psi(n) > P_f(n)$. The replication is followed by the re-initializations of the error powers and $\Psi(n)$, as $P_r(n) = P_f(n)$ and $\Psi(n) = P_f(n)$, respectively. By employing the replication procedure, $\hat{S}_r(z)$ has the best model of $S(z)$. The replication will be carried out as long as $\Psi(n)$ has increasing behaviour, and $\hat{S}(z)$ converges to $S(z)$. After the convergence of $\hat{S}(z)$, the error power $P_f(n)$ fluctuates and sometimes becomes larger than $P_r(n)$ due to the steady-state error of $\hat{S}(z)$. At this situation, $\Psi(n)$ decreases and the injection is suspended by (16). However, the injection may be sometimes suspended at the initial stage of the on-line SPM, because initially a large disturbance, $d(n) - y'(n)$, exists in the error signal, $f(n)$, as given in (2). To avoid this, the positive constant, ϵ and the gain parameter, σ_v^2, are tuned to be large values. The large value of ϵ will improve the robustness of the decision for ON/OFF state of auxiliary noise, and the large value of σ_v^2 will improve the convergence of $\hat{S}(z)$.

After the suspension of the auxiliary noise injection, the secondary path should be re-identified when the path is changed. The proposed method-1 monitors the error signal $f(n)$, which increase when the acoustic paths in the ANC systems are changed, and resumes the injection with the condition of $f^2(n) > \xi^2 P_{f_{\min}}(n)$, where ξ is an empirically determined constant, $P_{f_{\min}}(n)$ is the minimum power of $f(n)$ which is updated as follows

$$P_{f_{\min}}(n) = \begin{cases} P_f(n); & P_{f_{\min}}(n-1) > P_f(n) \\ P_{f_{\min}}(n-1); & \text{Otherwise,} \end{cases} \tag{17}$$

where $P_f(n)$ is given by (4). The minimum error power $P_{f_{\min}}(n)$ is initialized with $P_f(n)$ when the injection is suspended. After resuming the injection, the calculation of $\Psi(n)$, and the replication procedure are also resumed for suspending the injection again.

Table 1: Simulation parameters for various methods discussed in this paper.

	Parameters
Akhtar's method	$\mu_w = 0.00005$, $\mu_{s_{\min}} = 0.001$, $\mu_{s_{\max}} = 0.01$, $\sigma^2_{\min} = 0.001$, $\sigma^2_{\max} = 4$, $P_f(0) = P_e(0) = 1$
Carini's method	$\mu_{s_{\min}} = 0.004$, $D = 8$, $\hat{\lambda} = 0.6$, $R = 1$, $\hat{N}_s(0) = \hat{N}_w(0) = 0$ $P_f(0) = P_e(0) = P_g(0) = P_{s_1}(0) = 1$
Davari's method	$\mu_w = 0.001$, $\mu_{s_{\min}} = 0.009$, $\mu_{s_{\max}} = 0.05$, $th_{suspend} = 3.28 \times 10^{-5}$, $th_{resume} = 1$,$\gamma = 0.999$, $\sigma_v^2 = 0.05$
Proposed method-1	$\mu_w = 0.0005$, $\mu_s = 0.003$, $\varepsilon = 5$, $\xi = 7$, $\sigma_v^2 = 0.5$
Proposed method-2	$\mu_w = 0.00005$, $\mu_s = 0.007$, $\beta(0) = 0$, $\alpha = 0.9985$, $\gamma = 0.004$, $G(0) = 1$

3.2. Proposed Method-2 (Continuous scheduling scheme)

In order to solve problems with Carini's method [5], i.e., to track time-varying secondary path, and to reduce the computational complexity, a new scheduling strategy based on the error signal, $f(n)$, of the $\hat{S}(z)$ is proposed. The block diagram of proposed method-2 is shown in Fig. 1 (without components in dashed box, with $D = 0$, and $\hat{S}(z) = \hat{S}_1(z)$).

Eq. (2) shows error signal, $f(n)$, used for adaptation of $\hat{S}(z)$ and $W(z)$. In (2), $d(n) - y'(n)$ is a desired component for $W(z)$ and acts as disturbance for $\hat{S}(z)$, and $v'(n) - \hat{v}'(n)$ plays exactly a reverse role, i.e., desired component for $\hat{S}(z)$ and a disturbance for $W(z)$. At startup, the interference terms are very large, therefore a small fixed step-size is selected for $W(z)$ and $\hat{S}(z)$. The fixed step-size value for $W(z)$ (MFxLMS algorithm) and $\hat{S}(z)$ (LMS algorithm) reduces the computational complexity. Furthermore, a fixed and small value of step-size for $\hat{S}(z)$ eliminates the need for off-line modeling of $\hat{S}(z)$, while still keeping the ANC system stable. In order to improve the convergence speed of on-line SPM filter, we propose following strategy to vary gain, $G(n)$, of auxiliary noise, $v(n)$

$$\beta(n) = \alpha\beta(n-1) + \gamma f^2(n), \tag{18}$$

$$G(n) = \begin{cases} P_x/P_{v_g}; & \beta(n) > P_x \\ \beta(n)/P_{v_g}; & \text{Otherwise,} \end{cases} \tag{19}$$

where $0 < \alpha < 1$ and $\gamma > 0$ are controlling parameters, P_x and P_{v_g} are the powers of the reference signal, $x(n)$, and auxiliary noise $v_g(n)$, respectively, and can be estimated using (4).

At the startup, the error signal $f(n)$ is large, therefore setting the gain $G(n)$ to a higher value, upper bounded by the P_x/P_{v_g}. This will increase the convergence speed of $\hat{S}(z)$. The error signal $f(n)$ is decreasing in nature, therefore as the ANC system converges, the signal $f(n)$ and hence the gain $G(n)$ decreases, thereby reducing the contribution of the auxiliary noise in residual error signal $e(n)$. In the case of variation in acoustic paths the error signal $f(n)$ will increase, setting the gain, $G(n)$, again to a larger value, and hence to efficiently track the perturbation in the acoustic paths.

4. SIMULATION RESULTS

In this section, simulation results are presented, to compare the performance of the proposed methods with Akhtar's , Carini's and Davari's methods. The performance comparison is carried out on the basis of mean-squared error (MSE), $E[e^2(n)]$, and relative modeling error of secondary path being defined as, $\Delta S(n)(\text{dB}) = 10\log_{10} ||\boldsymbol{s}(n) - \hat{\boldsymbol{s}}(n)||^2/||\boldsymbol{s}(n)||^2$.

For simulation results $P(z)$, $W(z)$ and $S(z)$ are selected as FIR filters of tap-weight length 48, 32 and 16, respectively. The data for simulation is obtained from a disk provided with [1]. The filter $\hat{S}(z)$

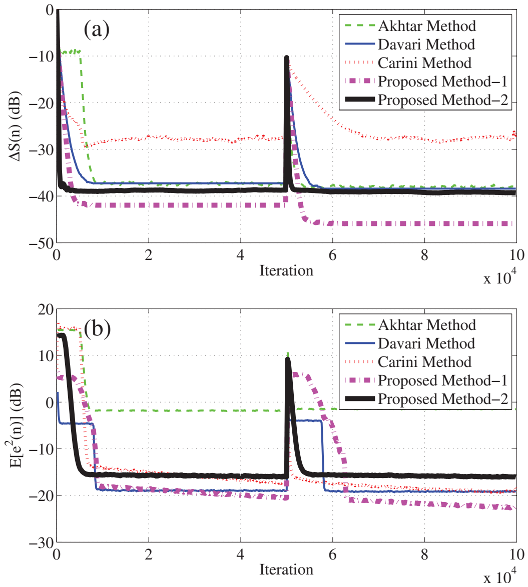

Fig. 2: Simulation results for tonal signal in Case 1. (a) Modeling error $\Delta S(n)$ in dB (b) Residual error power in dB.

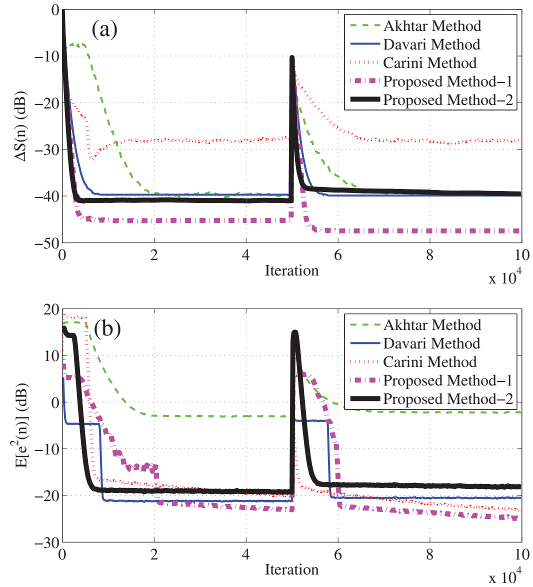

Fig. 3: Simulation results for multi-tonal signal in Case 2. (a) Modeling error $\Delta S(n)$ in dB (b) Residual error power in dB.

is selected as FIR filter of tap-weight 16 in all methods except for Carini's method. In Carini's method filters $\hat{S}(z)$ and $\hat{S}_1(z)$ are selected as FIR filter of tap-weight length $16 + D$ and 16 respectively. The value of D and other simulation parameters are given in Table. I. The reference signal $x(n)$, is generated as follows:

Case 1: Tonal input with frequency 300 Hz.

Case 2: Multi-tonal input with frequencies 100,200,300,400Hz.

The variance of $x(n)$ is adjusted to 2 and a zero mean WGN with SNR of 30dB is added to it. The variance of the auxiliary noise $v_g(n)$ is set to unity for all methods. For Davari's method and the proposed method-1, -5dB initialization is used for $\hat{S}(z)$. For Akhtar's method and Carini's method two phase operation is used. In the first phase (the duration of initial phase is tuned for stable operation) the filter $W(z)$ is inactive and in the second phase both $W(z)$ and $\hat{S}(z)$ are active. For the simulation results, the first phase is upto $n = 5000$. In the proposed method-2 no off-line modeling is required and the weights for the modeling filter are initialized by null vectors. The value of forgetting factor λ is chosen as 0.99. All the simulation results presented below are averaged over 100 independent realizations of the process.

Simulation results for tonal signal in Case 1 are shown in Fig. 2. Fig. 2(a) shows modeling error $\Delta S(n)$, where we observe that the proposed methods can provide fast convergence of the modeling filter before and after the perturbation. Akhtar's and Davari's methods also give good performance in terms of modeling the secondary path before and after the perturbation. Carini's method has low tracking capability because of freezing of the step-size to lower value and is not suitable for time varying secondary path ANC systems. Fig. 2(b) shows MSE curves for different methods discussed in this paper. As proposed method-2 does not need any initial phase operation, so residual error quickly settle down to the steady-state value. The steady-state performance is not as good as given by Carini's method but still a significant improvement is achieved in terms of modeling accuracy of SPM filter. As stated earlier the value of $\rho(n)$ in Akhtar's method is never zero. This will result in large value of the gain at steady-state, and thus degrades the noise reduction performance. The proposed method-1 reduces the number of tuning parameters and gives the best steady-state residual error performance before and after the perturbation. Simulation results for multi-tonal signal in Case 2 are shown in Fig. 3. We observe similar performance comparison as for Case 1.

5. CONCLUSION

Two methods for auxiliary-noise-power scheduling are proposed. proposed method-1 gives a clear criterion for noise suspending/resuming, and reducing the number of empirically determined parameters for ON/OFF decision. Proposed method-2 is a noise scheduling technique based on the error signal of the $\hat{S}(z)$. In both proposed methods, fixed step-size used for $W(z)$ and $\hat{S}(z)$ reduces the computational complexity. Simulation results show that both methods can provide satisfactory performance.

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