論文 / 著書情報
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Citation	2017 Eighth International Workshop on Signal Design and Its Applications in Communications (IWSDA), pp. 59-63
Pub. date	2017, 11
DOI	http://dx.doi.org/10.1109/IWSDA.2017.8095736
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Lattice Adaptive Filtering-Based Method for Acoustic Feedback Cancellation in Hearing Aids With Robustness Against Sudden Changes in the Feedback Path

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Abstract This paper proposes a new method for continuous acoustic adaptive feedback cancelation (AFC) in digital hearing aids. The proposed method employs two adaptive filters working in tandem. The first adaptive filter is excited by the receiver (output) signal of the hearing aid, and uses microphone signal as its desired response. The lattice-predictor based adaptive algorithm is used to updated the coefficients of the first adaptive filter. The second adaptive filter is excited by a (random) probe signal. We propose coefficient monitoring strategy with two fold objectives: 1) both adaptive filters converge to a good estimate of the acoustic feedback path, and that 2) both adaptive filter are re-initialized when a sudden change in the acoustic feedback path is detected. Finally, the injected probe noise is controlled via time-varying gain in such a way that a low level noise is used when the system is operating in its steady state. Simulation results demonstrate that the proposed method achieves good modeling accuracy, preserves good speech quality, and provides robust performance for the sudden changes in acoustic feedback path.

key words: *Hearing aids, acoustic feedback, NLMS algorithm, probe noise, Lattice-predictor NLMS algorithm.*

1. Introduction

A simplified block diagram of a digital hearing aid comprising single input microphone, hearing aid signal processing block $G(z)$, and a single receiver (loudspeaker) is shown in Fig. 1. Here $s(n)$ denotes the input signal which is to be processed by $G(z)$ to compensate for hearing loss of hearing aid user. The processed signal, $y(n)$, received as output of $G(z)$ not only propagates to the user's ear, but is also fed back to input microphone via acoustic feedback (leakage) path (denoted as the transfer function $F(z)$ in Fig. 1). This acoustic coupling between the microphone and loudspeaker generates undesirable acoustic feedback and corrupts the microphone signal. If components shown in dashed box in Fig. 1. are not present, then $u(n) = x(n)$ and the closed loop transfer function between $y(n)$ and $s(n)$ can be expressed in z-domain as:

$$H(z) = \frac{G(z)}{1 - G(z)F(z)}, \tag{1}$$

which shows that due to the acoustic feedback the hearing aid will be unstable, if $G(z)$ is large enough so that $G(z)F(z) = 1$ at some frequency. The presence of the acoustic feedback degrades the speech quality. Furthermore, when operated at a high gain value, the acoustic feedback may cause the oscillations being perceived as whistling, screeching; the so called howling effect. In the worst case scenario, the hearing aid may become unstable. This limits the maximum gain available to the user; and hence it is very important to investigate methods to reduce (if not remove) the acoustic feedback.

In digital hearing aids, the most popular popular solution to mitigate acoustic feedback is adaptive feedback cancelation (AFC) [1] – [6]. As shown in Fig. 1, the adaptive filter $W(z)$ is employed to model the unknown acoustic feedback path $F(z)$. The coefficients of $W(z)$ are updated using the celebrated normalized least mean square (NLMS) algorithm [7] as:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{\boldsymbol{y}^T(n)\boldsymbol{y}(n) + \delta} e(n)\boldsymbol{y}(n), \tag{2}$$

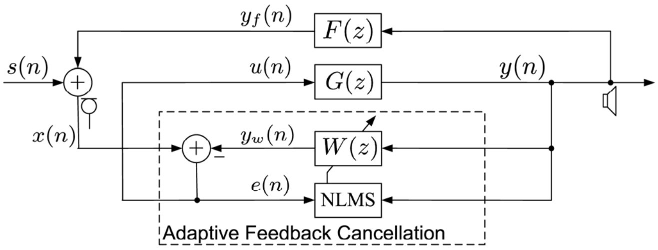

Fig. 1 A simplified block diagram of hearing aid employing NLMS algorithm-based conventional approach for AFC.

where μ is the step-size parameter, $\boldsymbol{w}(n)$ is the coefficient vector for $W(z)$, $e(n) = x(n) - y_w(n)$ is the error signal, $\boldsymbol{y}(n)$ is the vector for the received signal $y(n)$, and δ is a small positive constant to avoid division by zero. The objective of $W(z)$ is to provide an estimate of the acoustic feedback signal $y_f(n)$, such that $e(n) \approx s(n)$ can be used as an input to the hearing aid processing unit $G(z)$. However, the adaptive filter may convergence to a biased solution [8], due to strong correlation present between microphone signal $x(n)$ (used as a desired response for $W(z)$) and the receiver signal $y(n)$ (used as input to $W(z)$).

The performance of the adaptive filter can be improved by performing decorrelation, for example by using an appropriate delay in the cancelation path [1], or in the forward path [9], or by employing Filtered-x least mean square (FxLMS) algorithm [11] In the FxLMS-based AFC, the error and/or input signal of $W(z)$ are filtered via the decorrelation filters, before being used in the update equation of the NLMS algorithm [10]. The frequency-domain techniques have also been proposed for AFC in hearing aids [12], however, these approaches result in an increased computational load and require a lot of battery power [2]. A very interesting approach has been proposed in [13, 14], where two microphones have been employed along with dual adaptive filtering to perform AFC. Yet another approach in the existing literature is to use an uncorrelated probe noise for AFC. A howling detector is employed to determine when howling occurs, and a probe noise is injected to achieve the AFC [15]. The probe noise is switched off, when the AFC achieves good performance which is indicated by removal of howling. However, the sudden bursts of probe noise (due to ON/OFF switching) produce annoying effects. In order to avoid these annoying effects, a continuous injection of probe noise has also been proposed [16, 17]. In our previous work [18], we have investigated a two-adaptive filter-based solution where the first adaptive filter is the same as in the conventional method, and a second adaptive filter is employed which is excited by the uncorrelated probe noise (see Fig. 2.). A delay is inserted in the path of probe signal, which allows implementing delay-based adaptive filtering [19] to track convergence-status of $W_2(z)$.

In this paper, we suggest many enhancements to our previous method in [18]. Essentially, the key features of the work presented in this paper are as follows. 1) we consider a two adaptive filter-based structure as in the previous method [18], 2) a delay-based adaptive filtering is used to adapt the second adaptive filter excited by the probe noise, 3) an efficient strategy is developed to transfer the weights between the two adaptive filters such that both adaptive filters give a good estimate of $F(z)$, and to identify whether $F(z)$ has been changed, 4) the problem of biased convergence is mitigated by freezing the adaptation once a good solution is obtained, and finally, 5) a time-varying gain is proposed to control the level of added probe noise: a large value is used at the start-up for a fast convergence, and gain is reduced to a small value as the system converges thus maintaining high SNR at the steady-state. Extensive computer simulations have been carried out to demonstrate the effectiveness of the proposed method. The rest of the paper is organized as follows. Section 2 briefly reviews the previous method [18] and gives details of the proposed method. Section 3 presents simulation results, followed by conclusions in Section 4.

Notation: For the sake of convenience, we have used mixed notation in the block diagram, where transfer function is expressed in z-domain, and input-output signals are in discrete-time domain. For example, $y_{w_1}(n) = W_1(z)y(n)$ would represent filtering of $y(n)$ via $W_1(z)$. In the algorithm description, on the other hand, filtering has been represented by inner product as $y_{w_1}(n) = \boldsymbol{w}_1^T(n)\boldsymbol{y}(n)$, where $\boldsymbol{w}_1(n)$ represents the coefficient vector of $W_1(z)$, and $\boldsymbol{y}(n)$ denotes the corresponding signal vector.

2. Details of Proposed Method

2.1 Previous Method

In [18], we have proposed a two adaptive filter-based solution for AFC in hearing aids (see Fig. 2). Here, the adaptive filter $W_1(z)$ is excited by $y(n)$ and is expected to provide a neutralization signal for the feedback component $y_f(n)$. The second adaptive filter $W_2(z)$ is excited by the probe signal $v(n)$, and is expected to provide cancellation signal for the feedback component $v_f(n)$ due to the added probe signal $v(n)$. It is assumed that $v(n)$ is a low-level white signal and it is uncorrelated with the input signal $s(n)$ and hence with the output signal $y(n)$. The signal picked up by the input microphone, $x(n)$, is now given as

$$x(n) = s(n) + y_f(n) + v_f(n), \qquad (3)$$

where $v_f(n) = f(n) * v(n - D)$ is the acoustic feedback component due to probe signal $v(n - D)$ where D is an appropriately selected delay. The error signal $e_1(n)$ (for adaptation of $W_1(z)$) is computed as

$$e_1(n) = s(n) + [y_f(n) - y_{w_1}(n)] + v_f(n), \qquad (4)$$

which is further used as the desired response for $W_2(z)$. The error signal $e_2(n)$ (for adaptation of $W_2(z)$) is given as

$$e_2(n) = s(n) + [y_f(n) - y_{w_1}(n)] + [v_f(n) - y_{w_2}(n)]. \qquad (5)$$

The convergence of $W_1(z)$ is very fast, as it is is excited by $y(n)$ (ideally an amplified version of $s(n)$). However, it may converge to a biased solution as discussed earlier. On the other hand, $W_2(z)$ would give a good steady-state estimate of the acoustic feedback path $F(z)$. However, convergence is slow as it is excited by a low-level probe signal $v(n)$. In order to make sure that both $W_1(z)$ and $W_2(z)$ give a good estimate of $F(z)$, the biased convergence of $W_1(z)$ must be avoided and the initial convergence of $W_2(z)$ must be improved. For this purpose, their weights are exchanged by a coefficient-transfer strategy as explained in [18]. The level of probe noise must be kept low, which affects the convergence speed. Furthermore, both adaptive filters are adapted continuously and there is no check on the biased convergence of the first adaptive filter. In this paper, we attempt to solve these issues.

2.2 Proposed Method

The block diagram of the proposed method is shown in Fig. 3, where AFC is achieved by two adaptive filters, $W_1(z)$ and $W_2(z)$, working in tandem as in the previous method. When compared with the previous method, the key differences are: 1) adaptation of the

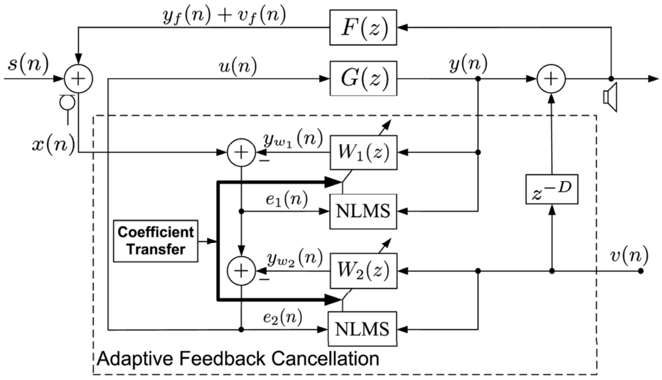

Fig. 2 Block diagram of hearing aid with previous method for AFC.

adaptive filter $W_1(z)$ is based on LMS-Newton-like algorithm employing lattice-predictor as a preprocessor (adopted from [20]), 2) coefficient transfer strategy to monitor convergence of two adaptive filters, and 3) computing a time-varying gain for the probe signal. The details are given in the following subsections.

2.2.1 Adaptive Algorithms

The output of the adaptive filter $W_1(z)$ is given as

$$y_{w_1}(n) = \boldsymbol{w}_1^T(n)\boldsymbol{y}(n - M), \qquad (6)$$

where $\boldsymbol{w}_1(n) = [w_{1,0}(n), w_{1,1}(n), \cdots, w_{1,L_1-1}(n)]^T$ is the tap-weight vector for $W_1(z)$, L_1 is the tap-weight length of $W_1(z)$, and $\boldsymbol{y}(n-M) = [y(n-M), y(n-M-1), \cdots, y(n-M-L_1+1)]^T$ is the signal vector comprising L_1 recent samples of $y(n - M)$. Here M denotes order of backward prediction-error filter $H_{b_M}(z)$, which is implemented in the lattice form [20]. The corresponding Levinson-Durbin algorithm to compute backward-prediction errors $b_M(n)$, and other lattice-predictor parameters is given below:

$$\boxed{\begin{array}{l}
f_0(n) = b_0(n) = y(n) \\
P_0(n) = \lambda P_0(n-1) + (1-\lambda)\dfrac{(f_0^2(n) + b_0^2(n-1))}{2} \\
\textbf{for } m = 1 : M \\
\quad f_m(n) = f_{m-1}(n) - k_m(n) b_{m-1}(n-1) \\
\quad b_m(n) = b_{m-1}(n-1) - k_m(n) f_{m-1}(n) \\
\quad k_m(n+1) = k_m(n) + \\
\qquad \frac{\mu_k}{P_{m-1}(n)+\delta}(f_{m-1}(n) b_m(n) + b_{m-1}(n-1) f_m(n)) \\
\quad P_m(n) = \lambda P_m(n-1) + (1-\lambda)\dfrac{(f_m^2(n) + b_m^2(n-1))}{2} \\
\quad \textbf{if } |k_m(n)| > \gamma, \quad k_m(n) = \gamma \cdot \mathrm{sgn}(k_m(n)), \quad \textbf{end if} \\
\textbf{end for}
\end{array}}, \qquad (7)$$

where $f_m(n)$, $b_m(n)$ and $k_m(n)$ $(m = 1, 2, \cdots, M)$ denote forward prediction errors, backward prediction errors and reflection coefficients, respectively, of the M-th order lattice predictor, μ_k is the step-size parameter for adaptation of the reflection coefficients $k_m(n)$, λ is the forgetting factor $(0.9 < \lambda < 1)$, and γ is a positive constant close to unity to avoid divergence of the reflection coefficients. Next, filtering of the backward prediction error signal $b_M(n)$ by $z^{-M}H_{b_M}(z)$ (which is forward equivalent of backward prediction error filter $H_{b_M}(z)$), and power normalization via $P_M^{-1}(n)$ produces samples of the signal $u_a(n)$ as follows:

$$\boxed{\begin{array}{l}
u_a(2 : L_1) = u_a(1 : L_1 - 1) \\
f'_0(n) = b'_0(n) = b_M(n) \\
P_0(n) = \lambda P_0(n-1) + (1-\lambda)\dfrac{(f_0^2(n) + b_0^2(n-1))}{2} \\
\textbf{for } m = 1 : M \\
\quad f'_m(n) = f'_{m-1}(n) - k_m(n) b'_{m-1}(n-1) \\
\quad b'_m(n) = b'_{m-1}(n-1) - k_m(n) f'_{m-1}(n) \\
\textbf{end for} \\
u_a(1) = f'_M(n)/(P_M(n) + \delta)
\end{array}}. \qquad (8)$$

Finally, coefficients of the adaptive filter $W_1(z)$ are updated using NLMS algorithm as:

$$\boldsymbol{w}_1(n+1) = \boldsymbol{w}_1(n) + \frac{\mu_1}{\boldsymbol{u}_a^T(n)\boldsymbol{u}_a(n)+\delta} e_1(n)\boldsymbol{u}_a(n), \quad (9)$$

where μ_1 is the step-size for $W_1(z)$, and $e_1(n)$ is the error signal being computed as:

$$e_1(n) = x(n-M) - y_{w_1}(n). \quad (10)$$

The adaptive filter $W_2(z)$ is an extended-length filter, and is adapted using a delay-based strategy. The delay-based technique has been largely applied in the field of acoustic echo cancelation [19]: An 'appropriate' delay D is inserted in the signal flow path and an 'extended filter' is used for system identification. The part of filter employed for modeling the delay has a known optimal solution (all zero-valued coefficients). Since the NLMS algorithm spreads the error among the filter coefficients, the norm of extension coefficients can be used as an estimate for filter convergence†. As shown in Fig. 3, a delay D is inserted in path for the probe signal $v(n)$, and hence $W_2(z)$ is considered with extended coefficient vector as

$$\boldsymbol{w}_2(n) = \begin{bmatrix} \boldsymbol{w}_z(n) \\ \boldsymbol{w}_F(n) \end{bmatrix}, \quad (11)$$

where $\boldsymbol{w}_z(n) = [w_{z,0}(n), w_{z,1}(n), \cdots, w_{z,D-1}(n)]^T$ represents the part used to model the delay (and would eventually converge to zero-valued coefficients), and $\boldsymbol{w}_F(n)$ models $F(z)$. The output $y_{w_2}(n)$ of the extended-length adaptive filter $W_2(z)$ is given as

$$y_{w_2}(n) = \boldsymbol{w}_2^T(n)\boldsymbol{v}(n), \quad (12)$$

where $\boldsymbol{w}_2(n) = [w_{2,0}(n), w_{2,1}(n), \cdots, w_{2,L_2-1}(n)]^T$ is the tap-weight vector for $W_2(z)$, $L_2 = D + L1$ is the tap-weight length of $W_2(z)$, and $\boldsymbol{v}(n) = [v(n), v(n-1), \cdots, v(n-L_2+1)]^T$ is a signal vector for the probe signal $v(n)$. The coefficient vector $\boldsymbol{w}_2(n)$ (for $W_2(z)$) is updated using the NLMS algorithm as

$$\boldsymbol{w}_2(n+1) = \boldsymbol{w}_2(n) + \frac{\mu_2(n)}{\boldsymbol{v}^T(n)\boldsymbol{v}(n)+\delta} e(n)\boldsymbol{v}(n), \quad (13)$$

where $\mu_2(n)$ is a time varying step-size parameters being computed as in [19]

$$\mu_2(n) = \begin{cases} \frac{\hat{N}_D(n)}{P_e(n)}; & \frac{\hat{N}_D(n)}{P_e(n)} > \mu_{2_{\min}} \\ \mu_{2_{\min}}; & \text{otherwise} \end{cases} \quad (14)$$

where $\mu_{2_{\min}}$ is the minimum value of the step-size parameter $\mu_2(n)$, and $\hat{N}_D(n)$ is being computed as in [19]

$$\hat{N}_D(n) = \lambda \hat{N}_D(n-1) + (1-\lambda)\left(\boldsymbol{w}_z^T(n)\boldsymbol{w}_z(n)\boldsymbol{v}^T(n)\boldsymbol{v}(n)\right)/D. \quad (15)$$

2.2.2 Strategy for Convergence Monitoring

The (Euclidian) norm of extension coefficients $\boldsymbol{w}_z(n)$ being computed as:

$$\rho(n) = \|\boldsymbol{w}_z(n)\|^2, \quad (16)$$

can be used to monitor convergence of $W_2(z)$. Furthermore, by comparing $P_{e_1}(n)$ and $P_{e_2}(n)$, (where $P_{e_1}(n)$ and P_{e_2} denote power of $e_1(n)$ and $e_2(n)$, respectively), following strategy is employed to check when/whether $W_1(z)$ gives a good estimate of $F(z)$:

if	$P_{e_1}(n) \le P_{e_2}(n)$,	$\boldsymbol{w}_F(n) \leftarrow \boldsymbol{w}_1(n)$
elseif	$\rho(n) < T_1$,	$\widetilde{\boldsymbol{f}}(n) = \boldsymbol{w}_1(n)$

(17)

where, T_1 is an appropriately chosen threshold (as discussed later),

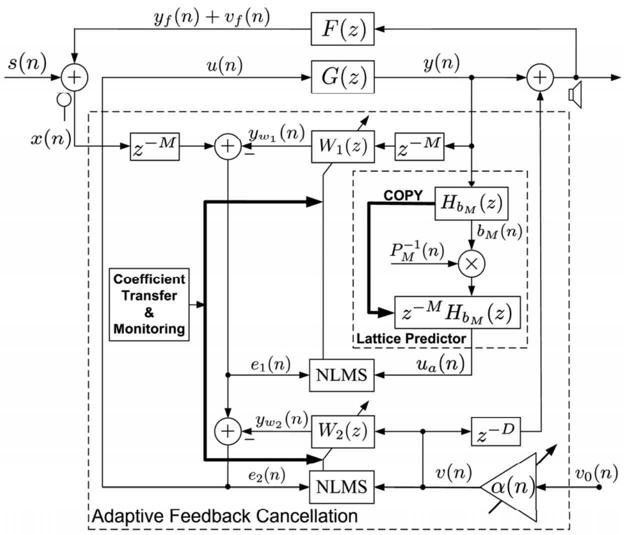

Fig. 3 Block diagram of the proposed method for continuous AFC.

$\widetilde{\boldsymbol{f}}(n)$ is an estimate of impulse response for $F(z)$, and $P_{e_1}(n)$ and $P_{e_2}(n)$ can be obtained by lowpass estimator of type

$$P_q(n) = \lambda P_q(n-1) + (1-\lambda)q^2(n), \quad (18)$$

where $q(n)$ is the signal of interest. At the startup ($n = 0$), $P_{e_1}(n) \approx P_{e_2}(n)$; as discussed $W_1(z)$ converges faster as compared with $W_2(z)$, it will cause $P_{e_1}(n) < P_{e_2}(n)$ for $n > 0$. Finally, as $n \to \infty$, $W_2(z)$ converges too and hence $P_{e_2}(n) < P_{e_1}(n)$. At this point, we can say that both adaptive filters have converged to a good estimate of the unknown feedback path $F(z)$. Once estimate for $F(z)$ is available, the adaptation of $W_1(z)$ is stopped (due to its tendency to converge to a biased solution), where as $W_2(z)$ is continuously adapted. Now the normalized squared deviation (NSD) for $W_2(z)$, $\widetilde{\Delta W}_2(n)$, is defined as:

$$\widetilde{\Delta W}_2(n) = 10\log\left\{\frac{\|\widetilde{\boldsymbol{f}}(n) - \boldsymbol{w}_F(n)\|^2}{\|\widetilde{\boldsymbol{f}}(n)\|^2}\right\}. \quad (19)$$

This metric can be used to monitor convergence of the $W_2(z)$. If $\widetilde{\Delta W}_1(n) > T_2$ (where T_2 is appropriately chosen threshold), then $W_2(z)$ have diverged indicating that the unknown feedback path have changed. Thus, a new estimate for the feedback path must be obtained which is achieved by re-initializing the adaptive filters $W_1(z)$ and $W_2(z)$, and resuming adaptation of $W_1(z)$.

Remarks on Choosing Thresholding Parameters: 1) $\boldsymbol{w}_z(n) \to \mathbf{0}$ (null vector) and hence $T_1 > 0$ in (17) can be selected as a small number close to zero. 2) NSD as defined in (19) is 0 dB initially, and a large negative value indicates good modeling accuracy. If the unknown feedback path $F(z)$ changes, then $W_1(z)$ (being frozen at the previously found optimal solution) is not able to remove the acoustic feedback component $y_f(n)$. Therefor, $e_1(n)$ diverges and so does $W_2(z)$. This divergence in $W_2(z)$ is captured by positive values of $\widetilde{\Delta W}_1(n)$, and hence $T_2 > 0$ can be selected accordingly.

2.2.3 Time-Varying Gain for Probe Signal

In the proposed method (see Fig. 3), $\alpha(n)$ is a time-varying gain for the probe signal $v(n)$. Intuitively, we would like to use a high-level probe noise at the start-up (or when there is a change in the acoustic feedback path) so that convergence of $W_2(z)$ is fast. After $W_2(z)$ has converged, the gain for the probe signal $v(n)$ must be reduced to have good output SNR at the steady-state. In (16), we have defined a parameter $\rho(n)$ which can be used to monitor the convergence status of $W_2(z)$: from a large value at the start-up it convergence to a small value $\boldsymbol{w}_{2z}(n) \to \mathbf{0}$ (null vector) as $n \to \infty$.

† Setting D too low would yield a poor estimator; however, the extension of the adaptive filter implies increased memory and complexity requirements: thus there is a tradeoff situation.

Based on this observation, we propose to compute the time-varying gain $\alpha(n)$ as:

$$\alpha(n) = 0.99\alpha(n-1) + 1 \times 10^{-4} \frac{\rho(n)}{\rho(n) + C} \quad (20)$$

where C is a positive constant, and a lowpass estimator has been employed to get a smoothed value. Finally, the probe signal is computed as:

$$v(n) = \alpha(n) v_0(n). \quad (21)$$

When $\rho(n)$ is large (far from optimal solution), then $v(n)$ tends to $v_0(n)$. On the other hand, when $\rho(n)$ is small (close to optimal solution), the gain $\alpha(n)$ and hence the probe signal $v(n)$ is small.

3. Simulation Results and Discussion

Fig. 4 shows the characteristics of the feedback path, $F(z)$ which is adopted from [21]. All adaptive filters are assumed to be FIR filters of tap-weight length 64. The sampling frequency is $F_s = 16$ kHz. The forward path representing the hearing-aid processing unit, is assumed to be given as $G(z) = Kz^{-\Delta}$, where K and Δ, respectively, represent the gain and delay of the system. The following methods† are considered in this simulation study (where the simulation parameters are determined experimentally for fast and stable convergence). NLMS-algorithm based conventional method: $\mu = 1 \times 10^{-3}$, $\delta = 0.02$. Previous method [18]: $\mu_1 = 1 \times 10^{-3}$, $\mu_2 = 1 \times 10^{-4}$, $\delta = 0.02$, $\lambda = 0.97$, $\text{SNR}_{\text{probe}} = \sigma_v^2/\sigma_s^2 = -15$ dB, $D = 64$, $\mu_{2_{\min}} = 1 \times 10^{-6}$, $T_1 = 1 \times 10^{-3}$, $T_2 = -20$ dB. Proposed method: $\mu_k = 1 \times 10^{-6}$, $\mu_1 = 1 \times 10^{-4}$, $\mu_2 = 1 \times 10^{-3}$, $\gamma = 0.9$, $C = 1.5$, $T_2 = 10$ dB, $v_0(n)$ is zero-mean unit-variance white Gaussian noise, and the rest of the parameters are set to the same value as in the previous method. The following performance measures have been employed for the performance comparison:

1. *Normalized Squared Deviation (NSD)* for filter $W_1(z)$, $\Delta W_1(n)$, being computed as:

$$\Delta W_1(n) = 10 \log \left\{ \frac{\|\boldsymbol{f}(n) - \boldsymbol{w}_1(n)\|^2}{\|\boldsymbol{f}(n)\|^2} \right\}. \quad (22)$$

2. *Maximum Stable Gain (MSG)* being computed as:

$$\text{MSG} = 20 \log \left\{ \max_{\omega} \|F(\omega) - W_1(\omega)\|^2 \right\}, \quad (23)$$

which is determined by the frequency where the mismatch between the actual and the estimated path is greatest. However, the system will only be unstable when the phase at that frequency equals a multiple of 2π [14].

3. *Perceptual Evaluation of Speech Quality (PESQ)* is an ITU-T standard to evaluate quality of speech signals [23]. The maximum score of 4.5 is for clean signal with no degradation.

3.1 Case 1: Stationary Acoustic Path

Fig. 5 shows speech signals, and Fig. 6 presents the corresponding simulation results for hearing aid model with $K = 10$ (low gain scenario) and $K = 30$ (high gain scenario). Figs. 6(a) and (c) show NSD curves averaged over all speech signals, and Figs. 6(b) and (d) show MSG curves averaged over all speech signals. The initial convergence is highlighted by a small window in each subfigure. We observe that the proposed method do no update $W_1(z)$ once a good solution is obtained. This avoids any fluctuations (due to the non-stationarity of speech signal for example), which we do observe in the previous and conventional methods. In fact, we 'hear' some musical noise in the case of the conventional and previous methods, whereas, the proposed method produces no such musical noise. Furthermore, the proposed method gives largest MSG as compared with the other methods considered in this paper. It is also very interesting to see that the proposed method gives stable performance for a high amplification scenario of $K = 30$, whereas the rest of methods become unstable. Table 1 summarizes the corresponding results for MSG and PESQ averaged over all speech signals (from mid sample to the last value). We observe that the proposed method gives the best performance as compared with the rest of methods considered in this paper.

†In [22], Authors have recently proposed employing delay in the forward path of hearing aid. However, delay in the forward path would limit the maximum delay available for signal processing tasks (for example, noise reduction, subband equalization, etc.). Therefore, method in [22] is not considered in the performance comparison in this paper.

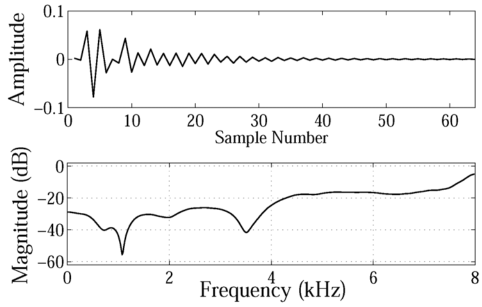

Fig. 4 The impulse response (top) and magnitude response (bottom) characteristics of electro-acoustic feedback path used in computer simulations.

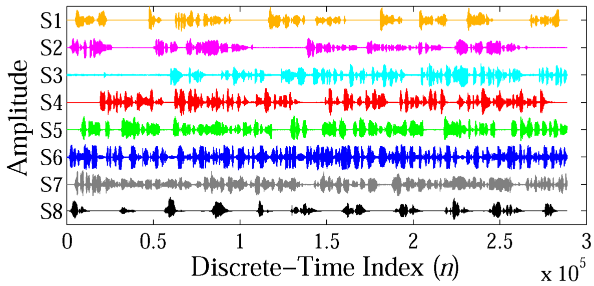

Fig. 5 Plots for speech signals used in the computer simulations.

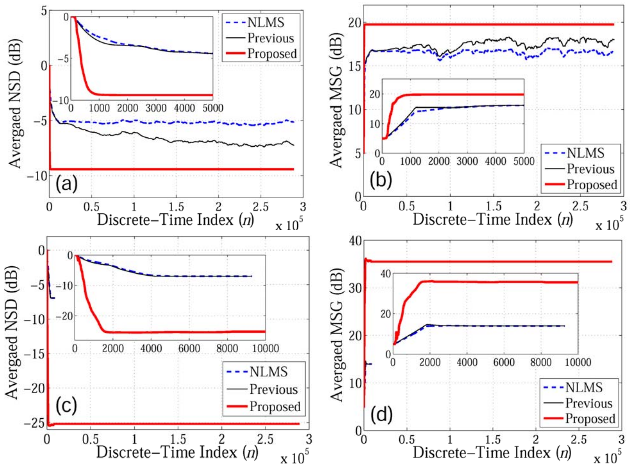

Fig. 6 Simulation results for stationary acoustic feedback path (Case 1). (a) and (b) Averaged NSD and MSG, respectively, for hearing aid gain $K = 10$. (c) and (d) Averaged NSD and MSG, respectively, for hearing aid gain $K = 30$.

3.2 Case 2: Sudden Change in Acoustic Path

In this case study, we consider sudden change in the acoustic feedback path $F(z)$. This situation may arise in practical scenarios, when the hearing aid user brings, for example, mobile phone near to his/her ear. At the startup, the acoustic path is same as considered in the previous case. At the middle of the simulation, the acoustic

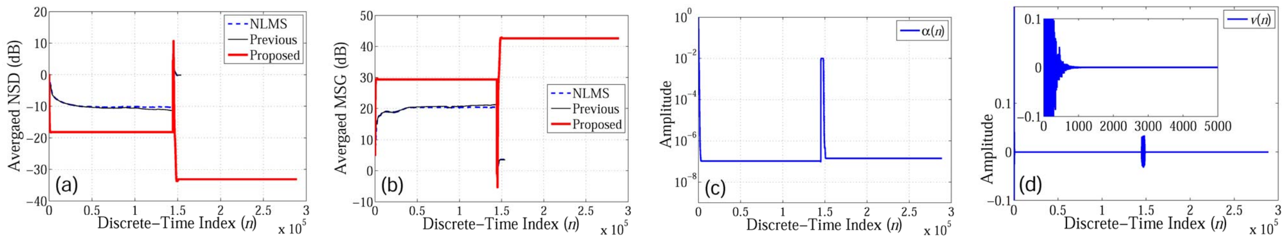

Fig. 7 Simulation results for sudden change in acoustic feedback path and hearing aid gain $K = 20$ (Case 2). (a) and (b) Averaged NSD and MSG, respectively. (c) Variation of gain $\alpha(n)$ for probe noise in the proposed method. (d) Plot of probe noise $v(n)$ in the proposed method.

Table 1 Quantitative assessment of various methods.

		$K = 10$			$K = 30$		
		NLMS	Previous	Proposed	NLMS	Previous	Proposed
MSG	Mean	16.530	17.7708	**19.7561**	–	–	**35.4968**
	SD	1.0126	1.4458	1.1585	–	–	1.5874
	Median	16.6630	17.8566	19.3212	–	–	35.2541
PESQ	Mean	3.8623	3.8445	**4.4180**	–	–	**4.3227**
	SD	0.5098	0.4302	0.0600	–	–	0.1247
	Median	4.1028	3.9491	4.4221	–	–	4.3601

feedback is suddenly changed to a new one. The changed acoustic path has been obtained by giving 5 sample right circular shift to the impulse response vector of $F(z)$ considered in Case 1. The simulation parameters are adjusted to the same values as found in Case 1, and the hearing aid gain is adjusted to $K = 20$. The simulation results for speech signals S1-S8 are presented in Fig. 9. We make following observations: 1) As compared with the other methods, the proposed method methods shows best convergence speed before and after the change, 2) the existing methods become unstable after the acoustic path changes. Fig. 9(c) shows variation of the time varying gain $\alpha(n)$, and Fig. 9(d) shows the corresponding probe noise signal $v(n)$ for speech signal signal S15. It is evident that initially (and when acoustic path changes), high level probe noise is injected resulting is fast convergence of AFC. The probe noise reduces to very small level as soon as the AFC system converges. In fact, we have observed that probe noise is not at all audible at the steady state.

4. Concluding Remarks and Future Work

The simulation results show excellent performance of the proposed method, and it appears as a promising choice for practical hearing aids. It is worth mentioning that the proposed method, being comprising two adaptive filters, has an increased computational complexity as compared with the conventional method. This increased computational complexity is the price paid for an improved performance. A detailed computational complexity analysis is omitted for the sake of space. A theoretical analysis of the proposed method is a task for the future work.

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