Adaptive Feedback Control using Improved Variable Step-Size Affine Projection Algorithm for Hearing Aids

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***Abstract*—The affine projection algorithm (APA) is commonly used for adaptive filtering in acoustic echo cancellation (AEC) due to its higher convergence and tracking rate compared to the conventional normalized least mean squares (NLMS) algorithm, especially for spectrally colored incoming signals. However, its application to adaptive feedback control (AFC) in hearing aids (HAs) is still not common because of the inherent correlation between the loudspeaker and incoming signals as well as the increase in computational complexity. In this paper, we investigate a way to employ a low projection order APA in conjunction with an improved practical variable step-size (IPVSS) for the prediction error method (PEM) based adaptive feedback control in HAs. The proposed approach is evaluated for a speech incoming signal and for a sudden change of the acoustic feedback path. The experimental results show that the proposed approach yields much better performance than a system employing either the upper or the lower fixed step-size used in the IPVSS as well as the PEM using the IPVSS for the NLMS algorithm (PEM-IPVSS-NLMS). By choosing a small projection order for the APA there is only a slight increase in the computational complexity. Moreover, a small amount of frequency shifting (FS) is integrated to further improve the system's performance.**

I. Introduction

A coupling of a loudspeaker signal into a microphone in hearing aids produces an acoustic feedback problem which limits the achievable maximum stable gain as well as degrades the sound quality. In some cases, it can render the system unstable. Many acoustic feedback control (AFC) approaches were introduced in the literature to lower the detrimental impact of the acoustic feedback [1], [2], [3]. Those approaches estimate the impulse response (IR) of the acoustic feedback path by using an adaptive filter. Then this IR is used to compute the estimated feedback signal which is subtracted from the microphone signal. Unfortunately, the high correlation between the loudspeaker signal and microphone signal causes a bias in the estimate of the acoustic feedback path [1], [2], [4]. This correlation is present due to the closed-loop characteristic of hearing aids.

To address this problem, the prediction error method (PEM) seems to be a potential solution, especially for speech incoming signals [2], [5], [6]. In this method, it is assumed that the speech signal can be modeled by filtering a white Gaussian noise through a monic and inversely stable all-pole filter $G^{-1}(q)$. Then the PEM uses the pre-filter $\hat{G}(q)$ which is an estimate of $G(q)$ to whiten the input signals of the adaptive filter. It is proven that an unbiased solution may be achieved if the above assumption is fulfilled and there is at least one sample delay in the forward path [5].

The most common adaptive filtering algorithms are the least mean squares (LMS) and the normalized least mean squares (NLMS). In those algorithms, selecting a suitable step-size is important due to a compromise between a high steady-state error but fast convergence rate and low steady-state error but slow convergence rate [7], [8]. To improve the convergence rate while still providing a low steady-state error, some existing solutions have been developed based on powerful adaptive filtering algorithms such as affine projection algorithm (APA) [9], [10], [11], [12] and proportionate NLMS (PNLMS)/improved PNLMS [13], [14], [15], [16] or based on variable step-size control (VSS) [17], [18], [19], [20], [21]. The combinations of the APA and VSS were introduced for acoustic echo cancellation (AEC) [10] and for AFC [22], [23]. In addition, the AFC methods based on an affine combination of two adaptive filters using two different step sizes [24], [25], [26] are also potential solutions. Note that unlike the AEC systems, the AFC systems cope with possible high correlation between the loudspeaker and incoming signals.

In this paper, we investigate the improved practical variable step-size affine projection algorithm (IPVSS-APA) and implement it for the PEM-based AFC in HAs, forming a new AFC approach namely the PEM-IPVSS-APA. In the proposed approach, the PEM is utilized to reduce the bias in the estimation of the acoustic feedback path, while a small projection order APA is chosen to improve the convergence and tracking rate [12]. In addition, the IPVSS, which was successfully applied to the PEM using NLMS algorithm (PEM-IPVSS-NLMS)

[27], is developed for the APA in order to further control the convergence and tracking rate of the system. As a result, the proposed approach achieves a significant improvement with regards to convergence rate and tracking rate, while still maintaining a low steady-state misalignment. The simulation results show that the PEM-IPVSS-APA outperforms the system which only uses either of individual step-size used in the IPVSS for a speech incoming signal and for a suddenly change of the acoustic feedback path. It also outperforms the PEM-IPVSS-NLMS which is a special case of the PEM-IPVSS-APA when projection order $P = 1$. Furthermore, a small amount of frequency shifting (FS) is employed in the PEM-IPVSS-APA (called PEM-IPVSS-APA-FS) to significantly lower the misalignment as well as to further increase the added stable gain (ASG).

We also run simulations for the PEM using practical variable step-size affine projection algorithm (PEM-PVSS-APA) with $P = 2$ and a speech incoming signal to show that the PVSS-APA which was successfully employed in [10] for the AEC contexts does not work well for the AFC applications, even when the PEM is employed. The reason is the inherent correlation between the loudspeaker signal and the microphone signal in the AFC contexts.

This paper is organized as follows. Section II describes the proposed approach PEM-IPVSS-APA with/without frequency shifting. Section III presents simulation results. Section IV concludes the paper.

II. Proposed PEM-IPVSS-APA

A. PEM-IPVSS-APA

Fig. 1 depicts the proposed AFC system. In this system the microphone signal $x(k)$ is computed by adding a feedback signal $v(k) = F(q)\,y(k)$ to an incoming signal $u(k)$, i.e.,

$$x(k) = u(k) + v(k), \tag{1}$$

where k is the discrete-time index, $F(q)$ is the transfer function of the true acoustic feedback path and $y(k)$ is the loudspeaker signal for the case of no FS. The derivations in this subsection is for the system whithout FS. For the case of the system using FS, the notation $y(k)$ in all equations is replaced by $y_{FS}(k)$, where $y_{FS}(k)$ is a version of $y(k)$ after frequency shifting. We can represent the filter $F(q)$ as a polynomial transfer function in q, i.e., $F(q) = \mathbf{f}^T\mathbf{q}$ with $\mathbf{q} = [1, q-1, ..., q^{-L_f+1}]$, $\mathbf{f}$ is the L_f-dimensional impulse response of $F(q)$. The error signal $e(k)$ is calculated by subtracting the estimate of the feedback signal $\hat{v}(k) = \hat{F}(q)\,y(k)$ from the microphone signal, i.e.,

$$e(k) = x(k) - \hat{v}(k), \tag{2}$$

where $\hat{F}(q)$ is an estimate of $F(q)$. This error signal is delayed and amplified in the forward path, forming the loudspeaker signal as follows,

$$y(k) = K(q)\,e(k). \tag{3}$$

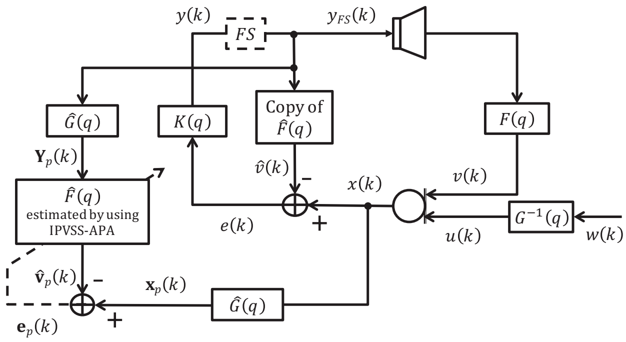


Fig. 1: The proposed AFC system

We assume the forward path comprises a delay d_k and an amplifier with broadband gain $|K|$, i.e., $K(q) = |K|\,q^{-d_k}$. The delay is chosen such that $d_k \geqslant 1$. The incoming signal is assumed to be modeled by filtering a white Gaussian noise sequence $w(k)$ via a monic and inversely stable all-pole filter $G^{-1}(q)$, i.e.,

$$u(k) = G^{-1}(q)\,w(k). \tag{4}$$

In the proposed AFC system, the pre-filters, which have been investigated in [2], [5], [28], are utilized to pre-whiten the input signals of the adaptive filter $\hat{F}(q)$, i.e.,

$$x_p(k) = \hat{G}(q)\,x(k), \tag{5}$$

$$y_p(k) = \hat{G}(q)\,y(k), \tag{6}$$

where $\hat{G}(q)$ is an estimate of $G(q)$. The pre-whitened error signal $e_p(k)$ is defined as

$$e_p(k) = x_p(k) - \hat{v}_p(k), \tag{7}$$

where $\hat{v}_p(k) = \hat{F}(q)\,y_p(k)$. From the error signal $e(k)$ we estimate the coefficients of $\hat{G}(q)$ using Levinson-Durbin algorithm [29].

By minimizing the mean-square prediction error, $J = E\left\{e_p^2(k)\right\}$, we obtain the Wiener solution for the acoustic feedback path estimate as

$$\hat{\mathbf{f}} = \mathbf{f} + \underbrace{\boldsymbol{R}_{\mathbf{y}_p}^{-1}\boldsymbol{r}_{\mathbf{y}_p u_p}}_{bias\,term}, \tag{8}$$

where $\boldsymbol{R}_{\mathbf{z}}$ is the auto-correlation matrix of vector $\mathbf{z}$, i.e, $\boldsymbol{R}_{\mathbf{z}} = E\left\{\mathbf{z}\mathbf{z}^{\mathbf{T}}\right\}$, and $\boldsymbol{r}_{\mathbf{z}\alpha} = E\{\mathbf{z}\alpha\}$ is the cross-correlation vector between vector $\mathbf{z}$ and the scalar α, $u_p(k)$ is the pre-whitened incoming signal, i.e., $u_p(k) = \hat{G}(q)\,u(k)$. By substituting (4) and (6) into (8) we may achieve an unbiased solution for the acoustic feedback path estimate if the assumption (4) is fulfilled and there is at least one sample delay in the forward path.

The NLMS is the most common algorithm for adaptive filtering, thus the estimated acoustic feedback path is recursively updated as follows,

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \frac{\mu}{(||\mathbf{y}_p(k)||_2^2 + \delta_{NLMS})}\mathbf{y}_p(k)\, e_p(k), \quad (9)$$

where μ is a fixed step-size, δ_{NLMS} is a small regularization parameter and $\mathbf{y}_p(k) = \left[y_p(k), y_p(k-1), \ldots, y\left(k - L_{\hat{f}} + 1\right)\right]^T$ with $L_{\hat{f}}$ is the length of $\hat{\mathbf{f}}$.

Moreover, if (4) is fulfilled, there is no correlation between $y_p(k)$ and $u_p(k)$. Thus,

$$E\left\{x_p^2(k)\right\} = E\left\{v_p^2(k)\right\} + E\left\{u_p^2(k)\right\}. \quad (10)$$

Supposing that the adaptive filter has converged close to the optimal value, we obtain

$$E\left\{\hat{v}_p^2(k)\right\} \approx E\left\{v_p^2(k)\right\}. \quad (11)$$

Hence, the power of the pre-whitened incoming signal can be approximated as

$$\hat{\sigma}_{u_p}^2(k) \approx \hat{\sigma}_{x_p}^2(k) - \hat{\sigma}_{\hat{v}_p}^2(k). \quad (12)$$

In practice, the power of microphone signal, the power of the estimated feedback signal and the power of error signal after pre-whitening process are recursively updated as follows

$$\hat{\sigma}_{x_p}^2(k) = \gamma\hat{\sigma}_{x_p}^2(k-1) + (1-\gamma)\, x_p^2(k), \quad (13)$$

$$\hat{\sigma}_{\hat{v}_p}^2(k) = \gamma\hat{\sigma}_{\hat{v}_p}^2(k-1) + (1-\gamma)\, \hat{v}_p^2(k), \quad (14)$$

$$\hat{\sigma}_{e_p}^2(k) = \gamma\hat{\sigma}_{e_p}^2(k-1) + (1-\gamma)\, e_p^2(k), \quad (15)$$

where γ is a positive value close to 1.

In the PEM-IPVSS-NLMS [27] the acoustic feedback path is estimated using a variable step-size $\mu_{IPVSS-NLMS}(k)$, i.e.,

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \frac{\mu_{IPVSS-NLMS}(k)}{(||\mathbf{y}_p(k)||_2^2 + \delta_{NLMS})}\mathbf{y}_p(k)\, e_p(k), \quad (16)$$

where

$$\mu_{IPVSS-NLMS}(k) = \begin{cases} \mu_U & if\ \ \mu_c(k) > \mu_U \\ \mu_L & if\ \ \mu_c(k) < \mu_L \\ \mu_c(k) & otherwise \end{cases}, \quad (17)$$

with

$$\mu_c(k) = \mu_U \left| 1 - \frac{\sqrt{\left|\hat{\sigma}_{x_p}^2(k) - \hat{\sigma}_{\hat{v}_p}^2(k)\right|}}{\hat{\sigma}_{e_p}(k) + \zeta} \right|, \quad (18)$$

where ζ is a small positive value, μ_U and μ_L are the upper and lower limits of the step-size, respectively. Those step-size limits are used to control the step-size range [27].

However, the convergence and tracking rates of the system using the NLMS algorithm degrade for the case of spectrally colored incoming signals. Therefore, the APA which can provide a superior convergence and tracking rate compared to the NLMS algorithm is a potential solution.

In this paper, we investigate the IPVSS for the APA, then integrate the IPVSS-APA into the PEM to further improve the convergence and tracking rate of the AFC system. In the PEM-IPVSS-APA, we use P most recent input vectors to estimate the IR of an adaptive filter, where P is the projection order. Therefore, the input matrix of the adaptive filter $\hat{F}(q)$ can be expressed as

$$\mathbf{Y}_p(k) = \left[\mathbf{y}_p(k), \mathbf{y}_p(k-1), \ldots, \mathbf{y}_p(k-P+1)\right]. \quad (19)$$

The pre-whitened microphone vector and the estimated feedback vector are denoted as $\mathbf{x}_p(k) = \left[x_p(k), x_p(k-1), \ldots, x_p(k-P+1)\right]^T$ and $\hat{\mathbf{v}}_p(k) = \mathbf{Y}_p^T(k)\,\hat{\mathbf{f}}(k)$, respectively. Hence, the pre-whitened error vector $\mathbf{e}_p(k)$ is computed as

$$\mathbf{e}_p(k) = \mathbf{x}_p(k) - \hat{\mathbf{v}}_p(k). \quad (20)$$

In the IPVSS-APA the IR of the acoustic feedback path is estimated as follows

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \mathbf{Y}_p(k)\left[\mathbf{Y}_p^T(k)\,\mathbf{Y}_p(k) + \delta_{APA}\mathbf{I}_P\right]^{-1}. \\ \boldsymbol{\mu}_{IPVSS-APA}(k)\,\mathbf{e}_p(k), \quad (21)$$

where $\boldsymbol{\mu}_{IPVSS-APA}(k) = \mathrm{diag}\left\{\mu_0(k), \ldots, \mu_{P-1}(k)\right\}$ is the variable step-size for the PEM-IPVSS-APA; δ_{APA} is a regularization parameter; $\mathbf{I}_P$ is an $(P\times P)$ identity matrix. The regularization parameter is selected such that the lager δ_{APA} for the lager value of the projection order and vice versa. The reason is that the condition number of the matrix $\mathbf{Y}_p^T(k)\,\mathbf{Y}_p(k)$ increases when the projection order increases. Table I provides the relationship between the projection order and the regularization parameter [10], where $\hat{\sigma}_{y_p}^2$ denotes the power of the pre-whitened loudspeaker signal. The value of $\hat{\sigma}_{y_p}^2$ is recursively updated, i.e.,

$$\hat{\sigma}_{y_p}^2(k) = \gamma\hat{\sigma}_{y_p}^2(k-1) + (1-\gamma)\, y_p^2(k). \quad (22)$$

We compute the variable step-size for each projection order as

$$\mu_i(k) = \begin{cases} \mu_U & if\ \ \mu_{c,i}(k) > \mu_U \\ \mu_L & if\ \ \mu_{c,i}(k) < \mu_L \\ \mu_{c,i}(k) & otherwise \end{cases}, \quad (23)$$

TABLE I: REGULARIZATION PARAMETERS FOR APA

Projection order	Regularization parameter
$P=1$	$\delta_{APA} = 20\hat{\sigma}_{y_p}^2$
$P=2$	$\delta_{APA} = 50\hat{\sigma}_{y_p}^2$
$P=4$	$\delta_{APA} = 100\hat{\sigma}_{y_p}^2$
$P=8$	$\delta_{APA} = 200\hat{\sigma}_{y_p}^2$

TABLE II: PEM-IPVSS-APA

Initial parameters: $\hat{\mathbf{f}}(0) = \mathbf{0}_{L_{\hat{f}} \times 1}$; $\hat{\sigma}^2_{x_p}(0) = 0$; $\hat{\sigma}^2_{\hat{v}_p}(0) = 0$;

for $i = 0$ to $P-1$

$\quad \hat{\sigma}^2_{e_{p,i+1}}(0) = 0$

end

for $k = 1, 2, ...$

$\quad \hat{\mathbf{v}}_p(k) = \mathbf{Y}_p^T(k)\hat{\mathbf{f}}(k)$

$\quad \mathbf{e}_p(k) = \mathbf{x}_p(k) - \hat{\mathbf{v}}_p(k)$

$\quad \hat{\sigma}^2_{x_p}(k) = \gamma\hat{\sigma}^2_{x_p}(k-1) + (1-\gamma)x_p^2(k)$

$\quad \hat{\sigma}^2_{\hat{v}_p}(k) = \gamma\hat{\sigma}^2_{\hat{v}_p}(k-1) + (1-\gamma)\hat{v}_p^2(k)$

$\quad$ *for* $i = 0$ to $P-1$

$\quad\quad \hat{\sigma}^2_{e_{p,i+1}}(k) = \gamma\hat{\sigma}^2_{e_{p,i+1}}(k-1) + (1-\gamma)e^2_{p,i+1}(k)$

$$\mu_{c,i}(k) = \mu_U \left| 1 - \frac{\sqrt{\left|\hat{\sigma}^2_{x_p}(k-i) - \hat{\sigma}^2_{\hat{v}_p}(k-i)\right|}}{\hat{\sigma}_{e_{p,i+1}}(k) + \zeta} \right|$$

$$\mu_i(k) = \begin{cases} \mu_U & if \;\; \mu_{c,i}(k) > \mu_U \\ \mu_L & if \;\; \mu_{c,i}(k) < \mu_L \\ \mu_{c,i}(k) & otherwise \end{cases}$$

$\quad$ *end*

$\quad \boldsymbol{\mu}_{IPVSS-APA}(k) = \mathrm{diag}\{\mu_0(k), \ldots, \mu_{P-1}(k)\}$

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \mathbf{Y}_p(k)\left[\mathbf{Y}_p^T(k)\mathbf{Y}_p(k) + \delta_{APA}\mathbf{I}_P\right]^{-1}\boldsymbol{\mu}_{IPVSS-APA}(k)\,\mathbf{e}_p(k)$$

end

where

$$\mu_{c,i}(k) = \mu_U \left| 1 - \frac{\sqrt{\left|\hat{\sigma}^2_{x_p}(k-i) - \hat{\sigma}^2_{\hat{v}_p}(k-i)\right|}}{\hat{\sigma}_{e_{p,i+1}}(k) + \zeta} \right|. \quad (24)$$

The pre-whitened error signal corresponding to each projection order is recursively updated as

$$\hat{\sigma}^2_{e_{p,i+1}}(k) = \gamma\hat{\sigma}^2_{e_{p,i+1}}(k-1) + (1-\gamma)e^2_{p,i+1}(k), \quad (25)$$

with $i = 0, \ldots, P-1$.

It can be seen that the PEM-IPVSS-NLMS is only a special case of the PEM-IPVSS-APA when $P = 1$.

To avoid a significant increase in computational complexity due to the high projection order of the APA, we chose the smallest projection order, i.e., $P = 2$ for our proposed approach. The proposed approach PEM-IPVSS-APA is summarized in Table II.

B. Frequency Shifting

The frequency shifting (FS) technique [3], [30], [31], [32], [33] is known as a non-linear operation which contributes to the decorrelation between the loudspeaker signal and the incoming signal. As a result, a lower bias in the estimation of the acoustic feedback path can be obtained. We integrate the FS into the PEM-APA, PEM-IPVSS-NLMS and PEM-IPVSS-APA. In this paper, we use the FS which is similar as proposed in [32], except the FS now is used for broadband signal, c.f. Fig. 1. The frequency shifting is applied to the signal $y(k)$ representing the output of the hearing aid processing. The analytical representation of the signal $y(k)$ is denoted as

$$y_{\mathrm{a}}(k) = y(k) + jy_{\mathrm{H}}(k), \quad (26)$$

where $y_{\mathrm{H}}(k)$ is the Hilbert transform of $y(k)$. We model the frequency shifting as a periodically time-varying filter, i.e.,

$$h(k) = \exp\left(j2\pi\frac{f_0}{f_s}k\right), \quad (27)$$

where f_s is the sampling frequency and f_0 is the amount of frequency shifting. Now the loudspeaker signal $y_{FS}(k)$, i.e., the output of the FS, can be computed as follows

$$y_{FS}(k) = \mathrm{Re}\{y_{\mathrm{a}}(k)h(k)\}. \quad (28)$$

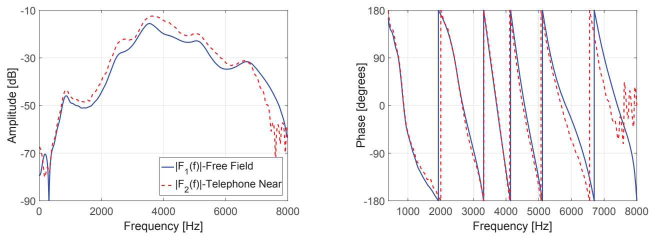
By substituting (26) and (27) into (28) we obtain

$$y_{FS}(k) = y(k)\cos(2\pi f_0 k) - y_{\mathrm{H}}(k)\sin(2\pi f_0 k). \quad (29)$$

The FS can significantly reduce the bias in the adaptive process but it also produces roughness for the signals. Therefore, a small amount of the FS is recommended [32].

III. Simulation Results

In all simulations, we use the acoustic feedback paths measured by a two-microphone behind-the-ear hearing aid [34]. Fig. 2 depicts the amplitude responses and phase responses of the measured acoustic feedback paths, where the first acoustic feedback path ($F_1(f)$) denotes the measure in free-field and the second acoustic feedback path ($F_2(f)$) denotes the measure with a telephone receiver placed close to the ear. The acoustic feedback path changes from the first feedback path to the second feedback path after 40 s. The incoming signal is speech which is generated by concatenating male and female speech segments extracted from Noizeus database [35]. We set the following parameters for all simulations. The lengths of the measured acoustic feedback path and the estimated acoustic



(a) (b)

Fig. 2: Measured acoustic feedback paths: a) Amplitude responses, b) Phase responses

feedback path are $L_f = 100$ and $L_{\hat{f}} = 64$, respectively. The sampling frequency $f_s = 16\text{kHz}$, the forward path gain $|K| = 30\,dB$, the delay in the forward path $d_k = 96$ samples, the delay in the feedback canceller path $d_{fb} = 1$ sample are chosen. The upper and lower bounds of the step-sizes are $\mu_U = 0.005$, $\mu_L = 0.0005$, respectively. The weighting factor $\gamma = 0.9999$ and the parameter $\zeta = 10^{-6}$ are also selected. The regularization parameters δ_{APA} are chosen following Table I. We select the smallest projection order, i.e., $P = 2$ to avoid a large increase in computational complexity. The order of 20 is assigned for the prediction-error filter $\hat{G}(q)$ which is estimated by using the Levinson-Durbin algorithm every 10 ms. For evaluating the performance of mentioned AFC approaches, the normalized misalignment (MIS) and the added stable gain (ASG) are calculated as follows [2], [36]

$$\text{MIS} = 10\log_{10}\left(\frac{\int_0^\pi \left|F\left(e^{j\omega}\right) - e^{-j\omega d_{fb}}\hat{F}\left(e^{j\omega}\right)\right|^2 \mathrm{d}\omega}{\int_0^\pi \left|F\left(e^{j\omega}\right)\right|^2 \mathrm{d}\omega}\right), \tag{30}$$

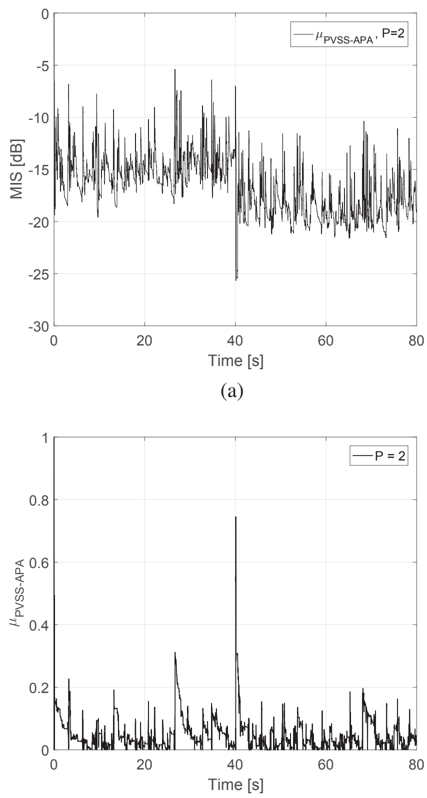
$$\begin{aligned}\text{ASG} \; = \; & 20\log_{10}\left(\min_\omega \frac{1}{\left|F\left(e^{j\omega}\right) - e^{-j\omega d_{fb}}\hat{F}\left(e^{j\omega}\right)\right|}\right) \\ & -20\log_{10}\left(\min_\omega \frac{1}{\left|F\left(e^{j\omega}\right)\right|}\right),\end{aligned} \tag{31}$$

where $\hat{F}(e^{j\omega})$ and $F(e^{j\omega})$ are the frequency responses of estimated and measured acoustic feedback paths at the normalized angular frequency, respectively. We also use the perceptual evaluation of speech quality (PESQ) recommended by Loizou [35] to evaluate the speech quality. In the PESQ measures the incoming signal $u(k)$ and the error signal $e(k)$ are chosen for the reference signal and the test signal, respectively. In this paper the PESQ is measured when the system has converged (during the period of 75 s-79 s).

A. PEM-IPVSS-APA Evaluation

In this subsection, the FS is not considered. We first run simulation for the PEM-PVSS-APA with $P = 2$ and a speech incoming signal to prove that the PVSS-APA which was introduced in [10] for the AEC contexts seems not to work well for the AFC applications, even when the PEM is employed. The reason is the inherent correlation between the loudspeaker signal and the microphone signal in the AFC contexts. Fig. 3a shows that the misalignment behavior of the PEM-PVSS-APA is poor due to the frequent fluctuation of the variable step-size $\mu_{PVSS-APA}$ over a large range (see Fig. 3b). We second evaluate the performance of the proposed PEM-IPVSS-APA with $P = 2$ using a speech incoming signal.

Fig. 4 compares the MIS and ASG of the proposed PEM-IPVSS-APA for the speech incoming signal and a sudden change of the acoustic feedback path after 40s to the PEM-IPVSS-NLMS and the PEM-APA using only the upper or



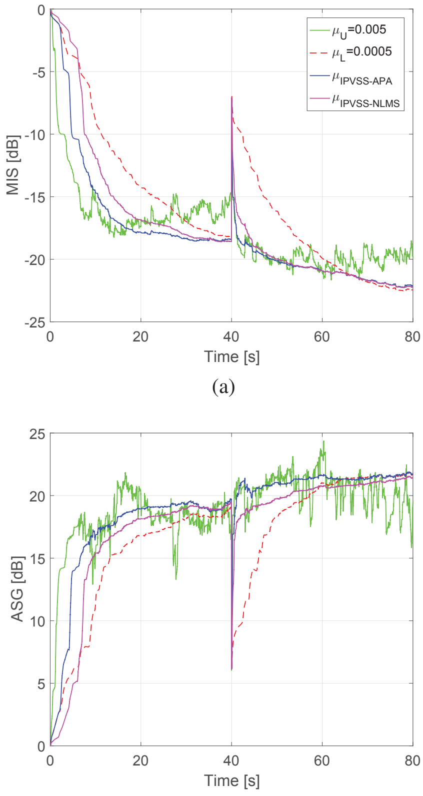
(a) (b)

Fig. 3: (a) MIS and (b) practical variable step-size results for PEM-PVSS-APA (P=2) with a speech incoming signal, a sudden change of acoustic feedback path and no FS.

the lower step-sizes which is utilized as the boundaries in the IPVSS-APA. It can be seen that the proposed approach outperforms the PEM-APA. In fact, it provides much higher convergence and tracking rate but still maintains a similar steady-state error and a similar ASG level compared to the PEM-APA using μ_L. Moreover, the proposed approach yields a significant improvement in steady-state error while a similar tracking rate compared to the PEM-APA using μ_U is achieved. Furthermore, the PEM-IPVSS-APA converges quicker and can track the abrupt change of the acoustic feedback path faster than the PEM-IPVSS-NLMS, while providing a similar steady-state error as well as a similar ASG level when the system converges.

Fig. 5 depict the variable step-size $\mu_{IPVSS-APA}$ for the PEM-IPVSS-APA with the speech incoming signal. We can see that this step-size tends to pick up larger values when the system is unstable, e.g., when the acoustic feedback path changes or at the beginning of simulation, and to get small values when the system has converged. Thus the system will obtain high convergence rate as well as tracking rate while still maintaining a low steady-state error.

Table III computes the PESQ measures for the above approaches. It shows that all mentioned approaches yield good PESQ scores, but the proposed approach achieves a



(a) (b)

Fig. 4: (a) MIS and (b) ASG results for PEM-APA and PEM-IPVSS-APA with a speech incoming signal, a sudden change of acoustic feedback path and without FS.

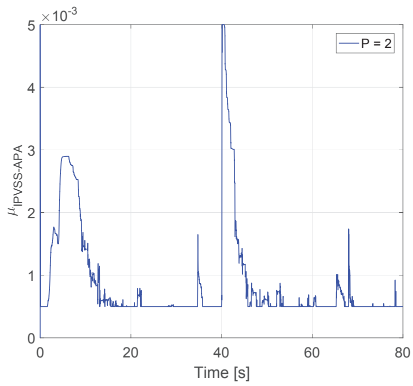


Fig. 5: Variable step-sizes $\mu_{IPVSS-APA}$ for PEM-IPVSS-APA with a speech incoming signal and a sudden change of acoustic feedback path.

better PESQ score compared to the PEM-APA with μ_U while providing a similar PESQ score (approximately 4.4) compared to the remained approaches.

B. PEM-IPVSS-APA-FS Evaluation

In this subsection, we evaluate the proposed approach with FS in comparison with the PEM-APA-FS using either μ_U or μ_L and the PEM-IPVSS-NLMS-FS. We choose a small

TABLE III: PESQ FOR A SPEECH INCOMING SIGNAL WITH A SUDDEN CHANGE OF ACOUSTIC FEEDBACK PATH AND NO FREQUENCY SHIFTING

AFC methods	$PESQ$
PEM-APA, $\mu_U = 0.005$	3.99
PEM-APA, $\mu_L = 0.0005$	4.39
PEM-IPVSS-APA	4.37
PEM-IPVSS-NLMS	4.36

TABLE IV: PESQ FOR A SPEECH INCOMING SIGNAL WITH FREQUENCY SHIFTING 5 HZ

AFC methods	Acoustic feedback path	$PESQ$
PEM-APA, $\mu_U = 0.005$	not changes	3.64
PEM-APA, $\mu_L = 0.0005$		4.34
PEM-IPVSS-APA		4.35
PEM-IPVSS-NLMS		4.40
PEM-APA, $\mu_U = 0.005$	changes	3.64
PEM-APA, $\mu_L = 0.0005$		4.35
PEM-IPVSS-APA		4.36
PEM-IPVSS-NLMS		4.39

amount of frequency shifting, i.e., $f_0 = 5$ Hz, and apply the FS for the broadband signal. By choosing such small frequency shifting almost no degradation in the signal quality is noticed.

Fig. 6 evaluates the convergence rate of the PEM-IPVSS-APA-FS in comparison with the PEM-APA-FS and the PEM-IPVSS-NLMS-FS for the case of a speech incoming signal and the first acoustic feedback path. It can be observed that the proposed method yields quicker convergence rate compared to both the PEM-IPVSS-NLMS-FS and the PEM-APA-FS with μ_L. For instance, a significant improvement in the MIS of approximately 4 dB and 9 dB during convergence is achieved for the proposed method compared to the PEM-IPVSS-NLMS-FS and the PEM-APA-FS with μ_L, respectively. Moreover, three methods including the PEM-APA-FS with μ_L, the PEM-IPVSS-NLMS-FS and the PEM-IPVSS-APA-FS converge to a similar steady-state error (approximately -31 dB) which is much lower than that of the PEM-APA-FS with μ_U.

Fig. 7 evaluates the tracking rate of the proposed method for the speech incoming signal and a sudden change of acoustic feedback path after 40 s. It shows that the PEM-IPVSS-APA-FS can track the change of the acoustic feedback path quicker than the PEM-IPVSS-NLMS-FS as well as the PEM-APA-FS with μ_L. By comparing the steady-state level of the PEM-IPVSS-APA-FS to that of the PEM-IPVSS-APA when the system converges we can see that the frequency shifting can provide approximately 9 dB improvement for the MIS as well as for the ASG.

Table IV shows that there is a reduction of approximately 0.25 score of the PESQ for the PEM-APA-FS using μ_L compared to the case without FS. For all remained methods, similar PESQ scores are obtained compared to those corresponding methods with no FS for both cases with/without a change of the acoustic feedback path.

Fig. 8 depicts the $\mu_{IPVSS-APA}$ for the PEM-IPVSS-APA-FS for the speech incoming signal and with/without a change of the acoustic feedback path. The behavior of the

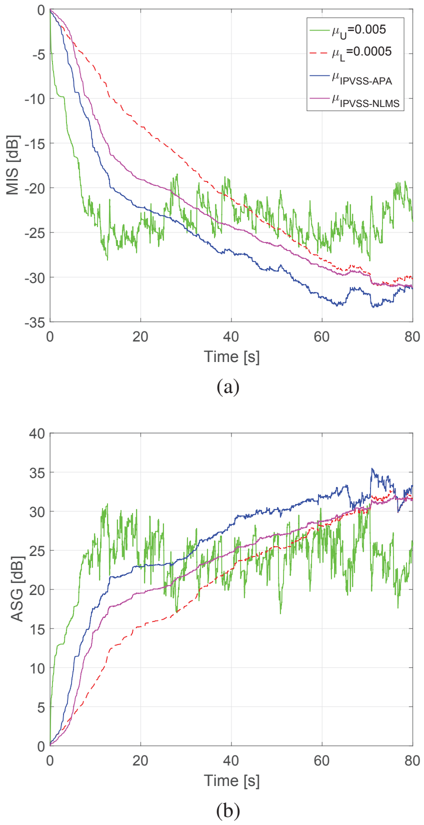


Fig. 6: (a) MIS and (b) ASG results for PEM-APA-FS and PEM-IPVSS-APA-FS with $f_0 = 5Hz$, the first acoustic feedback path and a speech incoming signal.

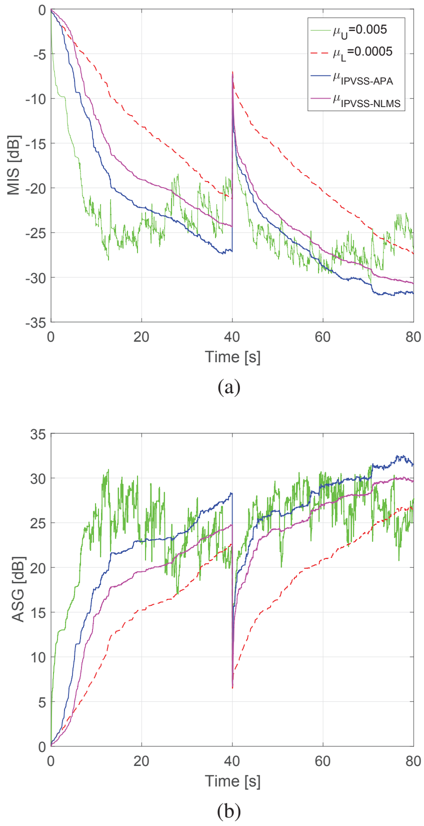


Fig. 7: (a) MIS and (b) ASG results for PEM-APA-FS and PEM-IPVSS-APA-FS with $f_0 = 5Hz$, a sudden change of acoustic feedback path, and a speech incoming signal.

$\mu_{IPVSS-APA}$ for the system with FS is similar to that for the system without FS, i.e., it also picks up high values when the system is unstable and low values when the system has converged.

For all above simulations, the proposed approach seems to have a slower initial convergence rate and a slower tracking rate than the PEM-APA using μ_U since (10) and (11) are biased in these situations [10].

IV. Conclusions

In this paper, we investigate the IPVSS-APA and apply it to the PEM for acoustic feedback control in hearing aids. A small projection order for the APA, e.g., $P = 2$, is chosen to ensure that only a slightly increase in computational complexity compared to the NLMS algorithm [12]. Simulation results show that the proposed method PEM-IPVSS-APA outperforms the PEM-APA using either lower or upper step-sizes which are used as boundaries in the IPVSS-APA. Moreover, it also obtains significant improvements on the convergence rate and tracking rate while maintaining a similar level of MIS and ASG when the system converges compared to the PEM-IPVSS-NLMS. Furthermore, a small frequency shifting, e.g., $f_0 = 5$ Hz, is used for broadband signal in order to further improve the MIS and ASG of the proposed approach.

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References

[1] M. G. Siqueira and A. Alwan, “Steady-state analysis of continuous adaptation in acoustic feedback reduction systems for hearing-aids,” *IEEE Trans. Speech, Audio Process.*, vol. 8, no. 4, pp. 443–453, 2000.

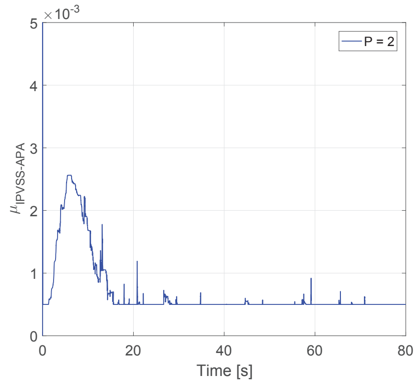
[2] A. Spriet, S. Doclo, M. Moonen, and J. Wouters, “Feedback control in hearing aids,” in *Springer Handbook Speech Process.* Springer, 2008, pp. 979–1000.

[3] T. van Waterschoot and M. Moonen, “Fifty Years of Acoustic Feedback Control: State of the Art and Future Challenges,” *Proc. IEEE*, vol. 99, no. 2, pp. 288–327, 2011.

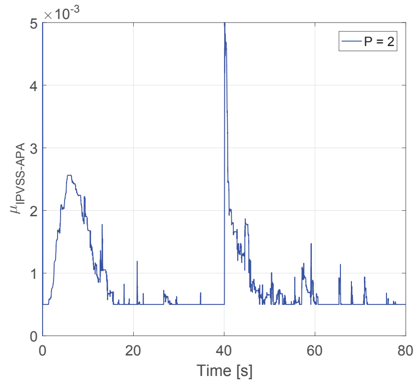
[4] J. Hellgren and U. Forssell, “Bias of feedback cancellation algorithms in hearing aids based on direct closed loop identification,” *IEEE Trans. Speech and Audio Process.*, vol. 9, no. 8, pp. 906–913, 2001.

[5] A. Spriet, I. Proudler, M. Moonen, and J. Wouters, “Adaptive feedback cancellation in hearing aids with linear prediction of the desired signal,” *IEEE Trans. Signal Process.*, vol. 53, no. 10, pp. 3749–3763, 2005.

[6] G. Rombouts, T. Van Waterschoot, and M. Moonen, “Robust and Efficient Implementation of the PEM-AFROW Algorithm for Acousic Feedback Cancellation,” *J. Audio Eng. Soc.*, vol. 55, no. 11, pp. 955–966, 2007.



(a)



(b)

Fig. 8: Variable step-sizes $\mu_{IPVSS-APA}$ for PEM-IPVSS-APA-FS with speech incoming signal (a) without a change of acoustic feedback path, (b) with a sudden change of acoustic feedback path.

[7] A. H. Sayed, *Fundamental adaptive filtering*. John Wiley & Sons, 2003.

[8] S. Haykin, *Adaptive Filter Theory*. Prentice-Hall, 2002.

[9] S. Lee, I.-Y. Kim, and Y.-C. Park, "Approximated affine projection algorithm for feedback cancellation in hearing aids," *Comp. methods and programs in biomedicine*, vol. 87, no. 3, pp. 254–261, 2007.

[10] C. Paleologu, J. Benesty, and S. Ciochina, "A variable step-size affine projection algorithm designed for acoustic echo cancellation," *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 16, no. 8, pp. 1466–1478, 2008.

[11] K. Lee, Y.-h. Baik, Y. Park, D. Kim, and J. Sohn, "Robust adaptive feedback canceller based on modified pseudo affine projection algorithm," in *Annual Int. Conf. of the IEEE Engin. in Medicine and Biology Soc.*, 2011, pp. 3760–3763.

[12] L. T. T. Tran, H. H. Dam, and S. Nordholm, "Affine projection algorithm for acoustic feedback cancellation using prediction error method in hearing aids," *Proc. IEEE Int. Workshop Acoust. Signal Enhan. (IWAENC)*, 2016.

[13] D. L. Duttweiler, "Proportionate normalized least-mean-squares adaptation in echo cancelers," *IEEE Trans. Speech and Audio Process.*, vol. 8, no. 5, pp. 508–518, 2000.

[14] J. Benesty and S. L. Gay, "An improved PNLMS algorithm," in *Proc. Int. Conf. Acoust., Speech, and Signal Process. (ICASSP)*, vol. 2. IEEE, 2002, pp. II–1881.

[15] F. Albu, R. Nakagawa, and S. Nordholm, "Proportionate algorithms for two-microphone active feedback cancellation," in *Proc. 23rd Eur. Signal Process. Conf. (EUSIPCO)*. IEEE, 2015, pp. 290–294.

[16] L. T. T. Tran, H. Schepker, S. Doclo, H. H. Dam, and S. Nordholm, "Proportionate NLMS for adaptive feedback control in hearing aids," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, 2017.

[17] R. H. Kwong and E. W. Johnston, "A variable step size LMS algorithm," *IEEE Trans. Signal Process.*, vol. 40, no. 7, pp. 1633–1642, 1992.

[18] J. Benesty, H. Rey, L. Rey Vega, and S. Tressens, "A nonparametric VSS NLMS algorithm," *IEEE Signal Process. Lett.*, vol. 13, no. 10, pp. 581–584, 2006.

[19] S. Thipphayathetthana and C. Chinrungrueng, "Variable step-size of the least-mean-square algorithm for reducing acoustic feedback in hearing aids," in *Proc. IEEE Asia-Pacific Conf. Circuits and Syst. (APCCAS)*, 2000, pp. 407–410.

[20] M. Rotaru, F. Albu, and H. Coanda, "A variable step size modified decorrelated NLMS algorithm for adaptive feedback cancellation in hearing aids," *Proc. ISETC. Timisoara*, pp. 263–266, 2012.

[21] C. Paleologu, S. Ciochină, and J. Benesty, "Variable step-size NLMS algorithm for under-modeling acoustic echo cancellation," *IEEE Signal Process. Lett.*, vol. 15, pp. 5–8, 2008.

[22] Y.-S. Kim, J.-h. Song, S.-K. Kim, and S. Lee, "Variable step-size affine projection algorithm based on global speech absence probability for adaptive feedback cancellation," *J. Central South University*, vol. 21, no. 2, pp. 646–650, 2014.

[23] L. T. T. Tran, S. Nordholm, H. Dam, W. Yan, and C. Nakagawa, "Acoustic feedback cancellation in hearing aids using two microphones employing variable step size affine projection algorithms," in *Proc. IEEE Int. Conf. Digit. Signal Process. (DSP)*, 2015, pp. 1191–1195.

[24] J. Arenas-García, A. R. Figueiras-Vidal, and A. H. Sayed, "Mean-square performance of a convex combination of two adaptive filters," *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 1078–1090, 2006.

[25] R. Candido, M. T. Silva, and V. H. Nascimento, "Transient and steady-state analysis of the affine combination of two adaptive filters," *IEEE Trans. Signal Process.*, vol. 58, no. 8, pp. 4064–4078, 2010.

[26] H. Schepker, L. T. T. Tran, S. Nordholm, and S. Doclo, "Improving adaptive feedback cancellation in hearing aids using an affine combination of filters," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, 2016.

[27] L. T. T. Tran, H. Schepker, S. Doclo, H. H. Dam, and S. Nordholm, "Improved practical variable step-size algorithm for adaptive feedback control in hearing aids," in *Proc. IEEE Int. Conf. Signal Process. and Commun. Syst. (ICSPCS)*, 2016.

[28] A. Spriet, G. Rombouts, M. Moonen, and J. Wouters, "Adaptive feedback cancellation in hearing aids," *Elsevier J. Franklin Inst.*, vol. 343, no. 6, pp. 545–573, 2006.

[29] J. R. Deller Jr, J. G. Proakis, and J. H. Hansen, *Discrete time Process. of speech signals*. Prentice Hall PTR, 1993.

[30] H. A. L. Joson, F. Asano, Y. Suzuki, and T. Sone, "Adaptive feedback cancellation with frequency compression for hearing aids," *J. Acoust. Soc. Am.*, vol. 94, no. 6, pp. 3248–3254, 1993.

[31] M. Guo, S. H. Jensen, J. Jensen, and S. L. Grant, "On the use of a phase modulation method for decorrelation in acoustic feedback cancellation," in *Proc. Eur. Signal Process. Conf. (EUSIPCO)*, 2012, pp. 2000–2004.

[32] F. Strasser and H. Puder, "Adaptive feedback cancellation for realistic hearing aid applications," *IEEE/ACM Trans. Audio, Speech, Lang. Process.*, vol. 23, no. 12, pp. 2322–2333, 2015.

[33] M. Guo and B. Kuenzle, "On the periodically time-varying bias in adaptive feedback cancellation systems with frequency shifting," in *Proc. Int. Conf. Acoust., Speech and Signal Process. (ICASSP)*. IEEE, 2016, pp. 539–543.

[34] T. Sankowsky-Rothe, M. Blau, H. Schepker, and S. Doclo, "Reciprocal measurement of acoustic feedback paths in hearing aids," *J. Acoust. Soc. Am.*, vol. 138, no. 4, pp. EL399–EL404, 2015.

[35] P. C. Loizou, *Speech enhancement: theory and practice*. CRC press, 2013.

[36] J. M. Kates, "Room reverberation effects in hearing aid feedback cancellation," *J. Acoust. Soc. Am.*, vol. 109, no. 1, pp. 367–378, 2001.