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Robust Adaptive Feedback Canceller Based on Modified Pseudo Affine Projection Algorithm

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***Abstract*— This paper presents an adaptive feedback cancellation (AFC) algorithm with robust and stable performance. The proposed algorithm is based on the pseudo affine projection (PAP) algorithm which approximates the affine projection (AP) with a complexity comparable to the NLMS. Direct application of the PAP to AFC, however, often exhibits instability because of the delayed estimate of the linear prediction (LP) coefficients. This problem is solved in the proposed algorithm by utilizing an inverse gain filter (IGF) before the update of adaptive filter and by estimating the LP coefficients from the input signal without delay. Simulation results confirmed robustness and stability of the proposed algorithm**

I. Introduction

Howling due to the acoustic feedback is not only an annoying problem to the hearing aids users but also limits the maximum usable compensation gain. To efficiently reduce acoustic feedback, many adaptive feedback cancellation (AFC) techniques have been suggested [3,4,6]. Requirements for AFC include fast convergence speed, low steady-state level, small sound distortion and low computational complexity. Unfortunately, there are trade-offs between the requirements. The normalized least mean square (NLMS) algorithm has been widely used for AFC [1,2], mainly due to simplicity and efficiency. However, its main disadvantage is slow convergence behavior for colored inputs. The affine projection (AP) algorithm [7], on the other hand, provides faster convergence speed than the NLMS algorithm for colored inputs, but its computational complexity can be problematic because of the matrix inversion in the weight update equation. To solve this problem, many fast versions of AP algorithm have been proposed. Among them, the pseudo affine projection (PAP) algorithm [3] is known to closely approximate the AP algorithm with much smaller computational complexity.

Another problem associated with AFC is the bias in the estimate of feedback path due to correlation between the input and output signals of the hearing aids. Recently, several techniques have been proposed to reduce the bias, by adding probe signal to output [4], inserting the de-correlation filter [1] or time delays in the forward or filter path [5]. But these techniques often sacrifice tracking performance or sound quality at the output for bias reduction.

In general, the degree of hearing loss is different in each frequency band. Therefore, the gain for compensating the hearing loss should be applied as per hearing loss in frequency. Furthermore, hearing aids with wide dynamic range compression (WDRC), the compensation gains are highly time-varying. AFC algorithms are often evaluated by assuming that a constant gain was used for the compensation of hearing loss, which is, however, impractical in real-life situations. As will be shown in this paper, even though the adaptive algorithms demonstrate satisfying performance for the case of constant gain, we cannot expect similar performance when frequency-dependent compensation gains are used.

In this paper, we propose an AFC algorithm that can provide robust and stable feedback path estimates. To achieve robust and consistent performance under the condition of fast time-varying compensation gains, we use an inverse gain filter (IGF) before the update of adaptive feedback canceller. The proposed algorithm is based on the PAP algorithm [6]. Thus, it shows fast convergence but has low complexity. However, when the PAP algorithm is used for the feedback cancellation in hearing aids, it often exhibits instability which is mainly due to the delayed estimate of the linear prediction (LP) coefficients. This problem is solved in the proposed algorithm since, thanks to the IGF, the LP coefficients can be estimated from the input of the hearing aids without delay.

This paper is organized as follows: Section II describes the adaptive feedback canceller based on the PAP algorithm. In Section III, we proposed a robust feedback cancellation algorithm against compensation gains. Simulation results are presented in Section IV, and conclusions are drawn in Section V.

II. Pseudo Affine Projection (PAP) Based Adaptive Feedback Canceller

A. Pseudo Affine Projection (PAP) Algorithm

The AP algorithm [7] updates the weight vector based on a number of recent input vectors, as given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{X}(n)\left(\mathbf{X}^T(n)\mathbf{X}(n)\right)^{-1}\mathbf{e}(n), \quad (1)$$
$$\mathbf{e}(n) = \mathbf{y}(n) - \mathbf{X}^T(n)\mathbf{w}(n), \quad (2)$$

where $\mathbf{w}(n)$ is an weight vector for the estimation of the unknown path, μ is step-size, and $\mathbf{X}(n)$ denotes a $(N \times P)$ data matrix comprising P most recent data vectors, $\mathbf{e}(n)$ and $\mathbf{y}(n)$ represent $(P \times 1)$ error and primary input vectors,

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respectively. The error vector is equivalently expressed as [2]

$$\mathbf{e}(n) = \begin{bmatrix} e(n) \\ (1-\mu)\bar{\mathbf{e}}(n-1) \end{bmatrix}, \tag{3}$$

where $\bar{\mathbf{e}}(n-1)$ denotes a vector consisting of the uppermost $(P-1)$ elements of $\mathbf{e}(n-1)$. Consider a preprocessor that transform P input signal vectors $\mathbf{x}(n-i), 0 \le i < P$, into orthogonalized ones $\mathbf{u_i}(n), 0 \le i < P$. Let the transform be collectively represented by a $(P \times P)$ matrix $\mathbf{L}$ as $\mathbf{U}(n) = \mathbf{X}(n)\mathbf{L}$ where $\mathbf{U}(n) = [\mathbf{u}_0(n), \mathbf{u}_1(n), \cdots, \mathbf{u}_{P-1}(n)]$. Using the orthogonalized vectors, the AP algorithm can be re-expressed as [6]

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \sum_{i=0}^{P-1} \frac{\varepsilon_i(n)}{\|\mathbf{u}_i(n)\|_2 + \delta} \mathbf{u}_i(n), \tag{4}$$

where $\|\cdot\|$ represents Euclidean norm, δ is a regularization factor, and the $\varepsilon_i(n), 0 \le i < P$ are the elements of the transformed error vector in such a way that $\boldsymbol{\varepsilon}(n) = \mathbf{Le}(n)$. Considering the characteristic of the transformed input vectors, i.e. $\|\mathbf{u}_0(n)\|_2 \ge \|\mathbf{u}_1(n)\|_2 \ge \cdots \ge \|\mathbf{u}_{P-1}(n)\|_2$ the parts of (4) other than the major part concerning $\|\mathbf{u}_{P-1}(n)\|_2$ can be ignored. Then, the AP algorithm in Eq. (4) can be simplified as

$$\widehat{\mathbf{w}}(n+1) = \widehat{\mathbf{w}}(n) + \mu \frac{\varepsilon_{P-1}(n)}{\|\mathbf{u}_{P-1}(n)\|_2 + \delta} \mathbf{u}_{P-1}(n). \tag{5}$$

$$u_{P-1}(n) = x(n) - \boldsymbol{\alpha}^T \mathbf{x}(n-1), \tag{6}$$

$$\varepsilon_{P-1}(n) = e(n) - (1-\mu)\boldsymbol{\alpha}^T \bar{\mathbf{e}}_\mu(n-1), \tag{7}$$

where $\bar{\mathbf{e}}_\mu(n-1) = [e(n-1), (1-\mu)e(n-2), \dots, (1-\mu)^{N-2} e(n-N+1)]^T$ is the *a priori* error vector.

B. Adaptive Feedback Cancellation based on the PAP Algorithm

An AFC system based on the PAP algorithm is depicted in Fig. 1. The primary input signal $y(n)$ is composed of the input signal $s(n)$ and the feedback signal $f(n)$. The error signal $e(n)$ is obtained by subtracting the estimate feedback signal $\hat{f}(n)$ from $y(n)$. The processing block of the forward path $G(z)$ is to compensate for the hearing loss of the user's. The coefficient vector $\boldsymbol{\alpha}$ in Eqs. (6) and (7) is estimated from the linear prediction (LP) block $A(z)$ in Fig. 1. The LP block $A(z)$ eventually whitens the reference input, i.e., the hearing aid output $x(n)$. In general, whitening the reference input improves the convergence characteristics of the NLMS adaptive algorithm. The same principle applies to the PAP algorithm. However, main difference between the PAP and the NLMS combined with whitening filters can be found from the process of error prediction described in Eq. (7). The error prediction in the PAP is associated with the convergence parameter μ.

Under time-varying environment, $\boldsymbol{\alpha}$ can be recursively estimated using an adaptive LP such as lattice, Gram-Schmidt predictor [3] or Gauss-Seidel iteration [6]. The block $A_\mu(z)$ denotes the LP for the error vector given by Eq. (7).

III. ROBUST PSEUDO AFFINE PROJECTION ALGORITHM BASED AFC

Assume that the input signal $s(n)$ is modeled as an AR process, in such a way that $S(z) = H(z)V(z)$, where $V(z)$ and $H(z)$ denote white noise and transfer function of the AR system in z-domain, respectively. Then, the error signal in Fig 1 can be expressed as

$$e(n) = s(n) + f(n) - \hat{f}(n), \tag{8}$$

or

$$E(z) = H(z)V(z) + \big(F(z) - W(z)\big)X(z), \tag{9}$$

where $F(z)$ is the transfer function of feedback path. The hearing aids output is then given by

$$X(z) = G(z)E(z). \tag{10}$$

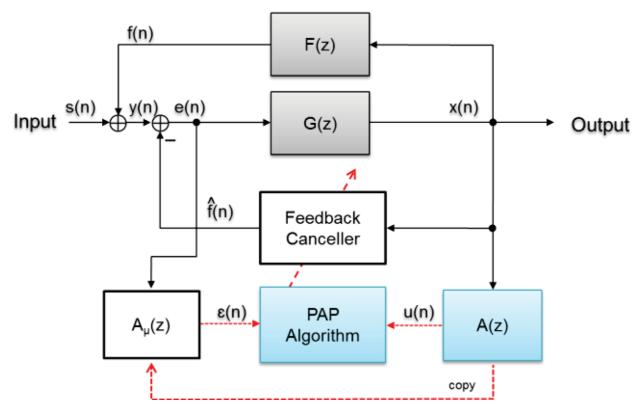

Figure 1. Pseudo affine projection (PAP) based adaptive feedback canceller

From Eqs. (9) and (10), the transfer function between the source signal (white noise) $V(z)$ and the output $X(z)$ can be found:

$$K(z) = \frac{G(z)H(z)}{1 - G(z)(F(z) - W(z))}. \tag{11}$$

Assuming that the adaptive feedback canceller closely copies the feedback path, i.e., $W(z) \approx F(z)$, $K(z)$ can be

$$K(z) \approx G(z)H(z). \tag{12}$$

If we further assume that the compensation system $G(z)$ is modeled as a constant gain with pure delay, the output $x(n)$ becomes a delayed and scaled version of input as $x(n) = gs(n-\Delta)$. It should be remembered that the goal of the block $A(z)$ in Fig. 1 is to whiten the output $X(z)$ using an LP process. In this case, the LP process can reasonably identify the input model in an inversed and scaled form as $A(z) = (1/g)H^{-1}(z)$, as long as the input model is inversely stable. Then, $x(n)$ is perfectly whitened.

However, most hearing aids have muti-band structure, and different gains are used to signals in different frequency bands. In this case, $A(z)$ is expected to inversely model $K(z)$ rather than $H(z)$, in a way that $A(z) \approx (G(z)H(z))^{-1}$. In practice, signal model $H(z)$ is unknown and time-varying. The compensation gain $G(z)$ is also time-varying but it is known *a priori* since it is prefixed or determined from the measured input level through WDRC.

Since both $H(z)$ and $G(z)$ are highly time-varying, mismatch between $A(z)$ and inverse of $G(z)H(z)$ is likely to occur, and which may result in creating a bias in the estimate of feedback path and hindering the system instability. However, since the compensations gains are determined before synthesizing the output, we can easily remove the effect of $G(z)$ from the output $x(n)$.

We can model the compensation system as $G(z) = G_m(z)z^{-\Delta}$ where $G_m(z)$ denotes a minimum-phase system whose magnitude response is the same as $G(z)$. Using this model, we can remove the effect of the time-varying compensation gains on the system adaptation. By applying an inverse-gain filter (IGF) given by $|G_m(z)|^{-1}$ to the output $x(n)$, we have $\hat{X}(z) = |G_m(z)|^{-1}X(z)$. Then, the transfer function between the source signal $V(z)$ and the gain-inverted output $\hat{X}(z)$ is obtained as

$$\hat{K}(z) = \frac{H(z)z^{-\Delta}}{1-G(z)(F(z)-W(z))}. \tag{13}$$

Now, the LP block $A(z)$ applied on the signal $\hat{x}(n)$ tends to inversely model the input signal model as $A(z) \approx H^{-1}(z)$ under the condition that the adaptive feedback canceller closely copies the feedback path, i.e., $F(z) \approx W(z)$. In this case, almost perfect whitening of $\hat{x}(n)$ is possible. In the perspective of the convergence of adaptive algorithm, once the reference input of the adaptive filter is whitened using an LP, the error signal also should be converted to the same whitened domain [7]. To meet this requirement, we apply the same IGF to the error signal before coefficient update.

In addition, from Eqs. (10) and (13), it is straightforward to see that $\hat{X}(z) = z^{-\Delta}E(z)$ or $\hat{x}(n) = e(n-\Delta)$. Therefore, the LP on the gain-inverted signal $\hat{x}(n)$ is equivalent to the LP on the delayed error signal $e(n-\Delta)$. When an adaptive AFC algorithm is associated with the signal whitening through LP, the delay in estimation of LP coefficient has a possibility of causing degradation and even instability of the adaptive feedback canceller. Thus, fast and early adaptation of the LP coefficients is desirable. In fact, due to this reason, simulation results for the PAP-based AFC exhibited instability when the feedback path was fast changing. Thus, we further modified the PAP algorithm by applying the adaptive LP to the error signal $e(n)$ by removing the delays in the gain-inverted output signal given by $\hat{x}(n) = e(n-\Delta)$, which will enhance the stability of the PAP-based feedback canceller.

Finally, we have a new adaptive feedback canceller which is depicted in Fig. 2.

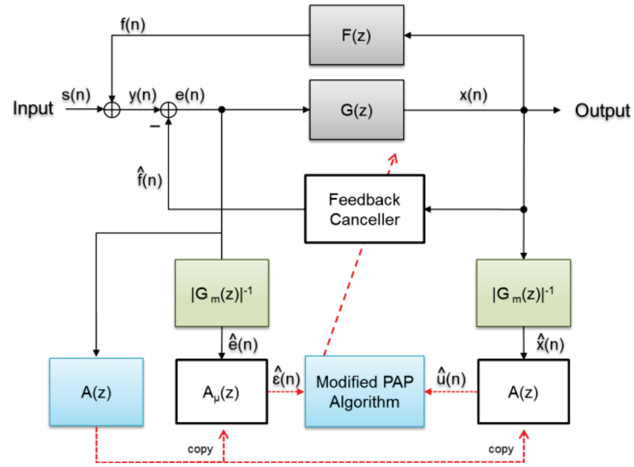

Figure 2. Modified pseudo affine projection (MPAP) based robust adaptive feedback canceller

In the proposed algorithm, the adaptive LP block $A(z)$ is applied to the error signal $e(n)$ so as to inversely estimate the signal model as $A(z) = H^{-1}(z)$ using the least square (LS) problem:

$$min_{\boldsymbol{\alpha}} \|e(n) - \boldsymbol{\alpha}^T \bar{\mathbf{e}}(n-1)\|_2 \tag{14}$$

For adaptive estimation of the LP coefficients, we utilized the Burg lattice algorithm which guarantees stability [7]. The estimated LP coefficients are copied to the LP blocks in both $x(n)$ and $e(n)$ branches. Then, the modified PAP (MPAP) algorithm for the adaptive feedback canceller is summarized as

$$\hat{\mathbf{w}}_R(n+1) = \hat{\mathbf{w}}_R(n) + \mu \frac{\hat{\varepsilon}(n)}{\|\hat{\mathbf{u}}(n)\|_2 + \delta} \hat{\mathbf{u}}(n), \tag{17}$$

$$\hat{u}(n) = \hat{x}(n) - \hat{\boldsymbol{\alpha}}^T(n)\hat{\mathbf{x}}(n-1), \tag{18}$$

$$\hat{\varepsilon}(n) = \hat{e}(n) - (1-\mu)\hat{\boldsymbol{\alpha}}^T(n)\bar{\hat{e}}_\mu(n-1), \tag{19}$$

where $\hat{\boldsymbol{\alpha}}(n)$ is the estimated LP coefficient vector and $\bar{\hat{\mathbf{e}}}_\mu(n-1)$ is the *a priori* error vector filtered using the IGF.

The IGF is to invert the compensation gains prior to the adaptation of feedback canceller. One possible implementation is using a filter with frequency response $|G_m(z)|^{-1}$, which is, however, not trivial because we have to design new filters whenever any band gain changes. In this paper, we used a FFT filterbank for the frequency band partitioning. Thus, the IGF can be conveniently implemented by applying the inverse of gain values $1/\hat{G}_m(k,l)$ to each frequency bin, and synthesizing the signals $\hat{x}(n)$ and $\hat{e}(n)$ via IFFTs.

IV. Simulation Results

The performance of the proposed AFC was evaluated and compared with the conventional algorithms including NLMS, AP, and PAP-based AFCs. In the simulation, the cases of constant 30dB gain and frequency-dependent gains were tested. For the frequency-dependent gains, we set 10dB gain at frequencies below 1kHz, linearly rising gains to 30dB at between 1 and 2kHz, 30dB gains at between 2 and 7kHz and linearly falling gain to 20dB at between 7 and 8kHz. We used a feedback path being modeled as a 64-tap FIR filter. Order of adaptive filter was set to 64-tap. A speech-shaped AR noise input was used as the input. The AR noise was generated by passing white noise through a 20th order all-pole filter $(P = 20)$ with background white noise of 30dB SNR. A smoothing factor for Burg lattice algorithm was $(1 - 1/64)$. Projection order of the AP was 20 and the same order LP was used for PAP and MPAP. Step-sizes used in simulations are summarized in Table 1. For performance evaluation, we measured misalignment as $20(\log_{10}\|w_0 - w(n)\|_2/\|w_0\|_2)$ and signal-to-feedback ratio (SFR) as $20(\log_{10}\|s(n)\|_2/\|s(n) - e(n)\|_2)$. All the curves were obtained by averaging 100 independent trials.

TABLE I
STEP-SIZES USED IN SIMULATIONS.

Gain	NLMS	AP	PAP	RPAP
Constant	0.1	0.005	0.09	0.1
Frequency-dependent	0.02	0.001	0.02	0.1

Fig. 3 shows misalignments according to varying delay in forward path from zero to 100. For the case of constant gain ((a) in Fig. 3) the performance of MPAP is similar to both PAP and AP. Even for small delays, low biases are observed for all algorithms except NLMS. However, for the case of frequency-dependent gains, MPAP shows the lower bias than the others. Again, the NLMS shows the highest bias.

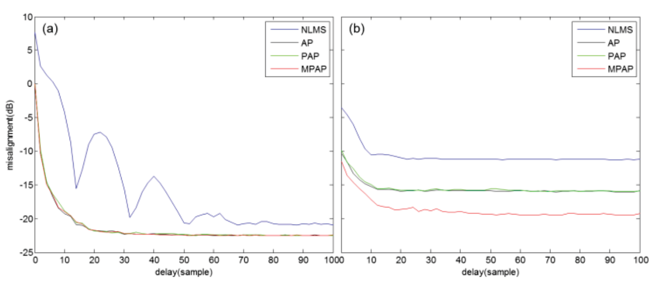

Fig. 3. Steady-state misalignment according to the forward path delay for the cases of (a) constant gain, and (b) frequency-dependent gains.

Next, we tested the algorithms under a time-varying feedback path situation. The delay in the forward path was set to 60 samples and the feedback path was changed at 5second. The change was simulated by inserting zeros to the beginning of impulse response of the feedback path. Figs. 4 and 5, respectively, show results for the cases of constant gain and frequency-dependent gain. For the constant gain case, convergence behaviors of all algorithms except NLMS are similar. But SFR results show that MPAP has the best performance. The PAP-based AFC, on the other hand, diverged right after the feedback path was changed. For the case of frequency-dependent gain, MPAP showed much smaller bias and higher SFR's than the other algorithms. PAP, on the other hand, also diverged right after the feedback path change. All these results confirm robustness and stability of the proposed algorithm.

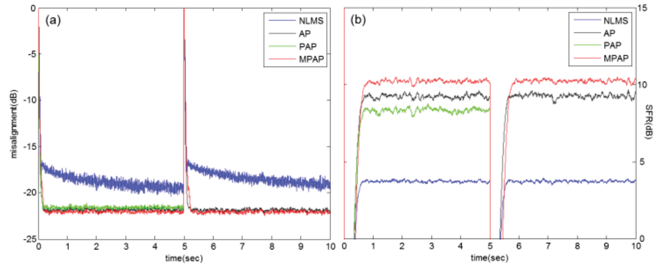

Figure 4. Misalignment curve (a) and signal-to-feedback ration (b) for a constant gain of 30dB

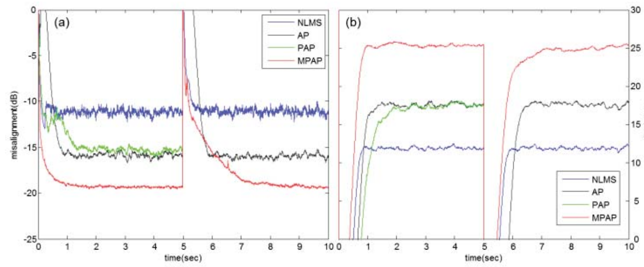

Figure 5. Misalignment curve (a) and signal-to-feedback ratio (b) for the compensation gains

V. CONCLUSION

In this paper, we propose a robust and stable AFC algorithm for digital hearing aids. The proposed algorithm performs LP on error signal without delay and inverse-gain filter is utilized before the adaptation of AFC. Simulation results showed that the proposed algorithm has the stable and robust convergence characteristics and provides small bias in feedback path estimates in all the simulated cases.

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