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A New Delayless Sub-band Filtering Method for Cancelling the Effect of Feedback Path in Hearing Aid Systems

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***Abstract*— Various methods have been proposed to overcome the problem of compensating the acoustic feedback path that negatively impacts the performance of hearing aid devices. However, in most of them feedback path model is assumed to be fixed which is not quite realistic. In this paper, we consider fixed and variable feedback paths and analyze for each case the performance of one of the robust Adaptive Feedback Cancellation (AFC) schemes, i.e. the Prediction Error Method AFC which uses Partitioned Block Frequency-Domain Normalized Least Mean Square (PBFD- NLMS) algorithm. Based on the analysis results we propose varying the step size values for the same adaptive algorithm on the fly by monitoring the misalignment criteria. The experimental results using the proposed method show improvement made on the system performance.**

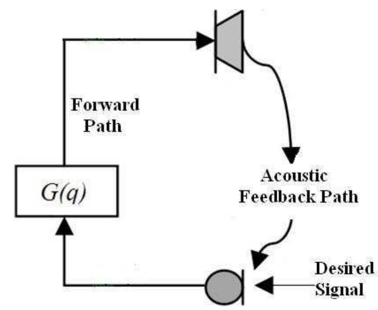

Fig. 1. Typical AFC algorithm

I. Introduction

In the current hearing aids, presence of acoustic feedback between loudspeaker and microphone causes some howling and whistling sound effects when the gain is increased in the forward path (Fig.1). Hence, Maximum Stable Gain (MSG) in the forward path is restricted by the acoustic feedback effect.

AFC is commonly used to reduce this negative effect. Fig. 1 shows the structure of a simple AFC. However, presence of the closed loop in this figure causes correlation between desired and feedback signals when the desired signal is a colored signal such as a speech signal. This correlation produces some amount of bias or error in the estimated coefficients of adaptive filter [1].

Different methods have been used to overcome this drawback and increase the precision of the AFC system. Perediction Error Method AFC (PEM-AFC) is a very successful method in this area in which whitening technique is performed to reduce the correlation between desired signal and feedback signal [1], [2]. This method consists of two adaptive procedures; one adaptively whitens the signal while the other one adaptively estimates the coefficients of the feedback path (Fig.2). Various methods can be used for mentioned adaptive filters [1], [3], and [4].

However, the majority of the proposed methods assume stationary feedback path while in practice the feedback path can change dynamically. In this paper, the method of PEM-AFC with PBFD-NLMS is analyzed assuming dynamic feedback path. The algorithm is briefly described and its performance for static and dynamic feedback paths is compared. Based on the analysis results we propose adjusting the step size values for the same adaptive algorithm by monitoring the misalignment criteria. The experimental results using the proposed method show improvement made on the system performance. The paper is organized as follows. Section II reviews PEM-AFC algorithm using Levinson-Durbin algorithm for whitening. Adaptive filter using PBFD-NLMS for estimating of feedback path coefficients is explained in section III. Experimental results are presented in section IV and section V is the conclusion.

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II. PEM-AFC

Common AFC algorithm suffers from bias in the estimated filter coefficients. Furthermore, correlation between desired signal and feedback signal causes some distortion in the processed signal.

PEM-AFC method (depicted in Fig. 2) reduces the correlation between these two signals and consequently lessens the amount of bias by means of whitening filters. This method, as it is shown in Fig.2, assumes that the desired signal $x[n]$ can be modeled by an AR process [1]:

$$x[n] = H(q,n)w[n] \tag{1}$$

Where $H(q,n)$ is an AR model and $w[n]$ is an impulse train or a zero-mean white noise sequence if the desired signal is voiced or unvoiced, respectively.

In Eq. 1, n and q^{-1} denote discrete-time index and discrete-time delay, respectively. $H(q,n)$ is a discrete-time FIR filter of length L which is a notation for:

$$H(q,n) = \mathbf{h}^T[n]\mathbf{q} \tag{2}$$

Where $\mathbf{h}[n] = [h_0[n]\ h_1[n]\ \ldots\ h_{L_F-1}[n]]^T$ is the vector of the filter coefficients and $\mathbf{q} = [1\ q^{-1}\ \ldots\ q^{-L_F+1}]^T$.

Then filtering of $w[n]$ by $H(q,n)$ can be represented by any of these two notations:

$$H(q,n)w[n] = \mathbf{h}^T\mathbf{w}[n] \tag{3}$$

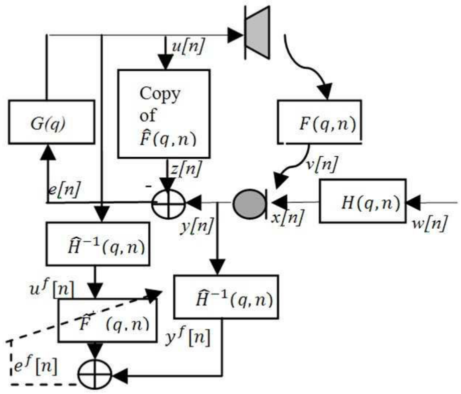

Fig. 2. PEM-AFC algorithm

where $w[n] = [w[n]\ w[n-1]\ \ldots\ w[n-L_F+1]]^T$.

In order to have whitened signal, Levinson-Durbin block computes the AR model corresponding to each frame of signal $e[n]$ and accordingly inverse of this AR model is used to whiten signals $y[n]$ and $u[n]$.

Optimum estimation of the feedback path is found by minimization of the following cost function [1].

$$\mathbf{J}(\hat{\mathbf{f}}[n]) = E\{|\hat{H}(q,n)^{-1}(y[n] - \hat{F}(q,n)u[n])|^2\}$$

$=\mathrm{E}\{\ |\ y^f[n] - \hat{\mathbf{f}}^T[n]\mathbf{u}^f[n]\ |^2\}(4)$

where $\mathbf{u}^f[n] = [u^f[n]\ u^f[n-1]\ \ldots\ u^f[n-L_{\hat{F}}+1]]^T$, and

$$y^f[n] = \hat{H}(q,n)^{-1}y[n] \quad (5)$$

$$u^f[n] = \hat{H}(q,n)^{-1}u[n] \quad (6)$$

Minimization of the cost function leads to [1]:

$$\hat{\mathbf{f}}[n] = E\{\hat{\mathbf{u}}^f[n]\hat{\mathbf{u}}^{f,T}[n]\}^{-1}E\{\hat{\mathbf{u}}^f[n]y^f[n]\} \quad (7)$$

And unbiased result can be found by assuming $\hat{H}(q,n) = H(q,n)$ and consequently replacing $y^f[n]$ by $w[n] + F(q,n)u^f[n]$.

III. PBFD-NLMS

PBFD-NLMS finds estimated coefficients of feedback path by implementing LMS algorithm in frequency domain and in blocked mode of operation.

To briefly explain this method, suppose an adaptive filter $\hat{F}$ of length N (where $N = P \times M$). Output of this filter can be found by the convolution of input signal and impulse response of the system. The idea in PBFD-NLMS is to partition this convolution into smaller convolutions which are individually calculated in frequency domain and stacked together to provide the output [5]. Fig. 3 represents the block diagram of this method using a set of adaptive filters with input data blocks of length L which have 50% overlap [5].

In the subsequent section, PBFD-NLMS is implemented using static (fixed) and dynamic (varying) feedback paths. Although the algorithm uses normalized step size (i.e. $\mu_0/power(\mathbf{U}^f)$, where $\mathbf{U}^f$ is the matrix of the input signal for adaptive filters [1]), our experimental results show that having larger μ_0 for dynamic path enables the algorithm to have better tracking ability. Moreover, we show that changing the values of μ_0 according to the variations of misalignment of the system can improve the performance of the system.

IV. Experimental Results

In this section, we use static (fixed) and dynamic (varying) feedback paths and simulate PBFD-NLMS as feedback canceller of hearing aid when the desired signal is a speech signal. In this experiment, forward path transfer function is considered to be [1]:

$$G(q) = Ge^{d_G} \quad (8)$$

where G and d_G are constants 5 and 10 (msec.), respectively.

Desired input signal is a speech file of length 15 sec. and sampling frequency of 16000 Hz. Levinson-Durbin block updates coefficients of the AR(20) model for each 10 ms frame of input signal.

Static feedback path model is an FIR filter of length 100 (depicted in Fig. 4) which has been measured and used in [1]. This model is also used as the initial condition for dynamic feedback model. We change the coefficients of this filter randomly every 4 seconds in such a way that the phase remains linear.

The adaptive filter we use has 64 coefficients; and input data block size of 32 is considered.

Algorithm is evaluated objectively using the following misalignment criterion:

$$Misalignment = 10log_(10)\frac{\int_0^{\pi}|F(e^{j\omega}) - \hat{F}(e^{j\omega})|^2\,d\omega}{\int_0^{\pi}|F(e^{j\omega})|^2\,d\omega} \quad (9)$$

Thus, lower Misalignment value indicates better system performance.

Fig. 5 illustrates misalignment of PBFD-NLMS algorithm versus time for static (fixed) feedback path using different $\mu_0$step size values. Misalignment of the same algorithm for dynamic (varying) model of feedback path using different μ_0 values is shown in Fig. 6. The misalignment curves in each figure correspond to μ_0 values for which the algorithm converges and the system gives acceptable performance. An evaluation of Fig. 5 shows that the adaptive filter with smallest μ_0 gives the best performance and misalignment. This is due to the fact that in a LMS-based adaptive algorithm, a large step size value may cause the algorithm to diverge, or if the algorithm converges then the final error may be unacceptably large resulting in large misalignment. The oscillatory behavior of the misalignment curves in Fig. 5 also indicates that the estimated models of the feedback path have not reached the optimum point and are oscillating around the optimum point because of the unsuitable choice of μ_0 values. As shown in Fig. 5 the smallest value of $\mu_0 = 0.0005$ gives the best performance and misalignment. We point out that the type of the feedback path, the length of the adaptive filter, and the characteristics of the input data play important roles in obtaining the best value of μ_0 for a particular application. The effect of the type of feedback path on μ_0 value , and thus the system performance, is seen in Fig. 6. Results shown in Fig.s

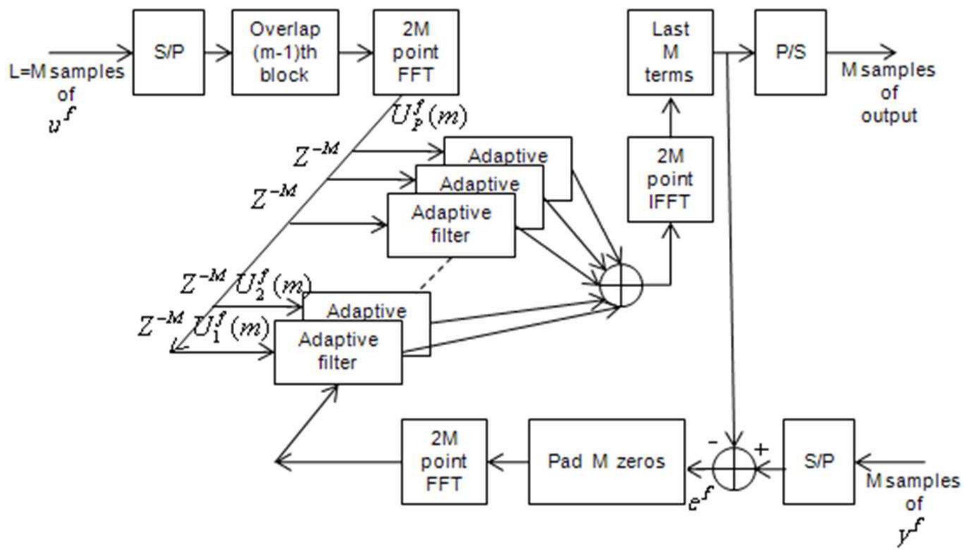

Fig. 3. PBFD-NLMS block diagram

5 and 6 are for two experiments differing only in the type of feedback path used. As seen in Fig. 6, for dynamic (varying) feedback path larger μ_0 values better. That is, for very small $\mu_0 = 0.0005$ the adaptive algorithm does not converge, or even if it does converge for some small value like $\mu_0 = 0.005$, still the system output shows howling and whistling effects. Conversely, large values (i.e. $\mu_0 = 0.1, 0.05$) make algorithm to track feedback changes better and faster. Focusing on Fig.s 5 and 6, we see that smaller μ_0 is more suitable for the first part of the curves in which the system is stationary, then larger μ_0 is more desirable when the feedback path starts to change. As a result, selecting a variable μ_0 value based on the behavior of the misalignment seems to be the best approach. Therefore in our approach, we let the adaptive algorithm starts with a small μ_0 value (e.g. $\mu = 0.0005$) while monitoring the misalignment. If the misalignment has a noticeable increase (e.g. above a prescribed threshold level), system will recognize it as a change of the feedback path and will increase the μ_0 value (e.g. to $\mu = 0.1$). On the other hand, if misalignment amount goes less than a threshold level (e.g. $-3dB$), it would indicate that the system has been successful in tracking the feedback path changes and thus, smaller μ_0 will be chosen to further decrease the error and improve the misalignment even further if possible. That is, μ_0 value is gradually decreased depending on the behavior of the misalignment. Fig. 7 shows the results of our approach.

Moreover,subjectively comparison of the results shows more than 14% improvement in Perceptual Evaluation of Speech Quality (PESQ) of the output signal when variable μ_0 is used. That is, by implementing our approach, the quality of processed signal increases for the listener, i.e for the Hearing Aid user.

V. CONCLUSION

PBFD-NLMS method based on the partitioned convolutions has been used as a feedback canceller in hearing aid. Static (fixed) and dynamic (varying) feedback models have been used to compare the performance of this algorithm. Our experimental results show that larger μ_0 is required to track dynamic changes of the feedback path. Thus, we have proposed replacing μ_0 in the PBFD-NLMS method by a misalignment-depended variable step size. Simulation results confirm obtaining significant improvement in fast cancellation of the varying feedback path and in the performance of Hearing Aid device using our proposed approach.

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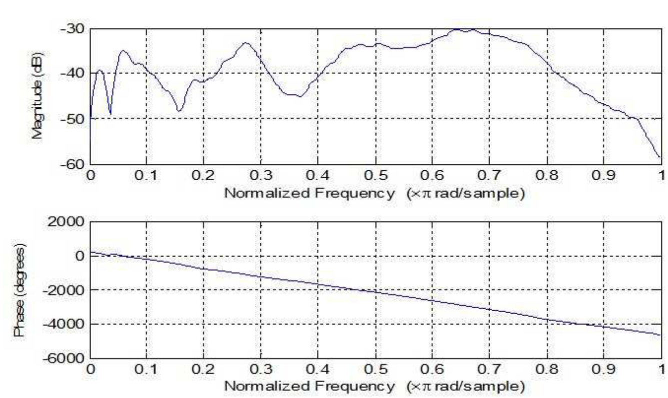

Fig. 4. Feedback Path Transfer Function

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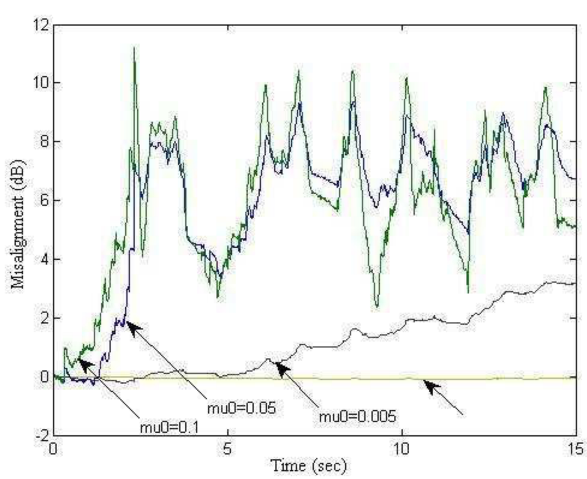

Fig. 5. Misalignment of PBFD-NLMS with static (fixed) feedback path using different step size values

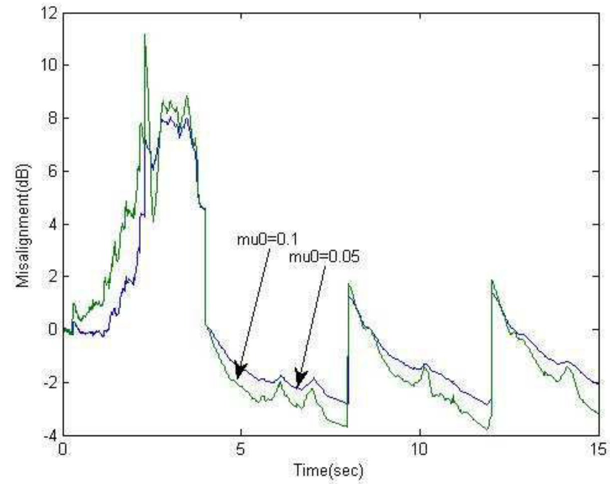

Fig. 6. Misalignment of PBFD-NLMS with dynamic (varying) feedback path using different step size values. The results are the average of 40 executions in each of which the initial feedback path is the one depicted in Fig. 4 and the other feedback models are randomly generated.

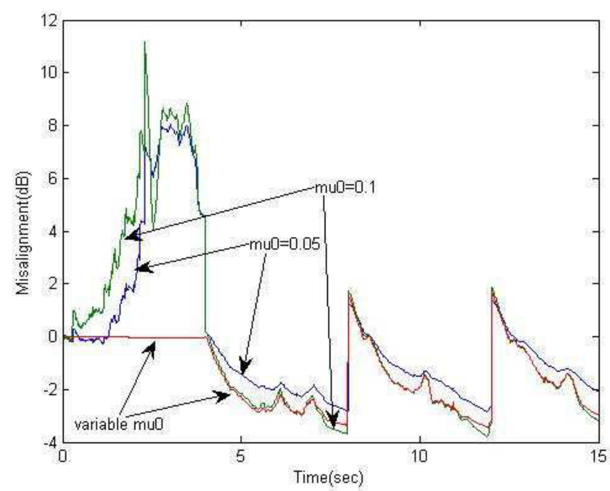

Fig. 7. Misalignment of PBFD-NLMS with dynamic (varying) feedback path (a) with constant step size (b) with variable step size. The results are the average of 40 executions in each of which the initial feedback path is the one depicted in Fig. 4 and the other feedback models are randomly generated.