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Acoustic feedback cancellation in digital hearing aids: A sparse adaptive filtering approach

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A B S T R A C T

Cancelling the effect of acoustic feedback is a challenging task in the design of a behind the ear digital hearing aid. In traditional behind the ear digital hearing aids, feedback cancellation is usually achieved using an adaptive finite impulse response filter, the weights of which are updated using a suitable learning rule. However, the impulse response of the acoustic feedback path in a hearing aid is sparse in nature and traditional feedback cancellation systems are not designed to utilize this sparseness. An adaptive feedback canceller, which is trained using a set of sparse adaptive algorithms is designed in this paper to take advantage of the sparseness. Further, an attempt has been made to enhance the convergence of the feedback cancellation mechanism by introducing an adaptive de-correlation filter as well as using the concept of probe noise injection. The proposed feedback cancellation schemes are shown to provide improved and accurate feedback cancellation over traditional feedback cancellation mechanisms.

1. Introduction

Hearing loss is a very common form of sensory impairment in people. On an estimate, more than 10% of the total population and more than 50% of the people above the age of 65 suffer from one or the other form of hearing loss. A hearing aid is an assistive listening device, which helps in improving the hearing by providing an amplified sound to the user. A basic electronic hearing aid consists of a microphone, a signal conditioning unit, a loudspeaker and a battery. In the more recent digital hearing aids, the signal conditioning job has been undertaken by a digital signal processor [1,2]. Digital hearing aids are mainly of three types: Behind the ear (BTE), in the ear (ITE) and in the canal (ITC). The most common and cheaper form among the three versions is the BTE hearing aid. In a BTE hearing aid, the microphone, the necessary circuitry as well a battery unit are housed behind the ear and the amplified sound is fed to the ear through a small duct [3,4].

Acoustic feedback occurs when the amplified sound produced by the loudspeaker at the output of the hearing aid is sensed by the input microphone. This limits the amount of gain that can be achieved by a hearing aid [5]. This problem can be eliminated if the loudspeaker sound is completely shielded from the input microphone by using a suitable ear muff. But this in turn produces the occlusion effect, whereby an echo-like sensation is produced when the hearing aid user hears their voice. This arises out of the trapping of bone conducted sound when the outer portion of the ear is occluded. A solution to this problem is to have open vents in hearing aids. This creates a conflicting situation whereby closing the vent produces occlusion effect and opening the vent leads to the problems of acoustic feedback. One of the schemes for reducing acoustic feedback is to reduce the gain of the frequency zone in which the feedback occurs. The gain reduction mechanism will be actuated only if a feedback is detected. The disadvantage of this scheme is that the gain of the desired acoustic signal may also get reduced [6].

Adaptive feedback cancellation schemes, which employ an adaptive filter to cancel out the feedback, have become popular in the recent past [7–9]. Fig. 1 shows the basic schematic of a digital hearing aid with a feedback cancellation scheme. In the figure, $x(t)$ is the microphone input, $x(n)$ is the discrete version of $x(t)$, $y(n)$ is the adaptive filter output, $e(n) = x(n) - y(n)$ is the error signal used for the filter update, $v(n)$ is the amplifier output mixed with some probe signal and $v(t)$ is the input to the loudspeaker. The main objective of the adaptive filter it to minimize a suitable norm of the error signal. In a conventional digital hearing aid, a least mean square (LMS) algorithm or a normalized LMS (NLMS) algorithm is utilized as the adaptive algorithm for updating the filter weights.

Impulse responses of acoustic paths are generally sparse in nature [10–13]. A significant number of the coefficients in the impulse response are zeros or near zeros and conventional LMS algorithm based adaptive filtering algorithms are not effective in accurately modeling these impulse responses [14]. A set of sparse LMS

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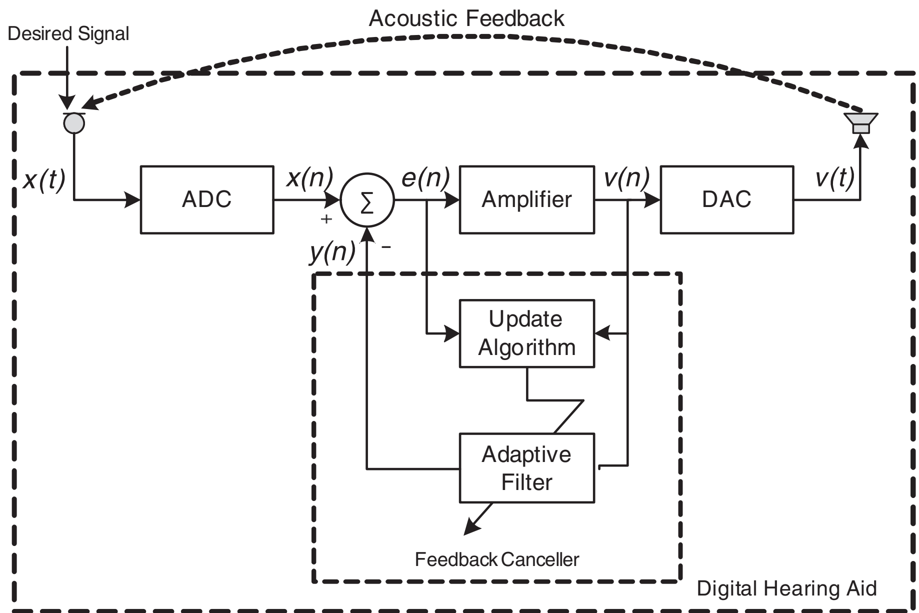

Fig. 1. Schematic diagram of a digital hearing aid in the presence of acoustic feedback.

algorithms have been recently proposed to overcome this limitation of LMS algorithms [15–18]. One of them is a zero attracting LMS (ZALMS) algorithm, which forces the near zero coefficients to zero thereby aiding the convergence process. A re-weighted ZALMS (RZALMS) algorithm has been proposed in [19] to further improve the convergence when applied for modeling sparse systems.

Similar to other acoustic paths, the acoustic feedback path in a BTE hearing aid may also be considered as a sparse system and the acoustic feedback cancellation task may be improved by considering the sparse nature of the feedback path. However, the task is not straightforward because of the significant correlation between the desired input to the microphone and output of the hearing aid processing unit, which in turn leads to correlated input and error signals for the adaptive feedback canceller. This will lead to biased estimation of the acoustic feedback path and in worst case scenario leading to deterioration of cancellation performance [20,11]. The correlation effects have been reduced by implementing a de-correlation filter [21,22] and by injecting an appropriate probe noise [23]. Considering the above mentioned scenarios, in this paper, an attempt has been made to develop a sparse feedback cancellation mechanism, with a de-correlation filter and probe noise injection to improve convergence. Several attempts have been made in literature in order to improve the convergence speed of adaptive filters using methods including proportionate affine projection [24–26] and affine projection like algorithms [27]. In an endeavor to further improve the convergence of the proposed scheme for speech type signals, the fixed de-correlation filter has been replaced by an adaptive de-correlation filter [9,21,22].

The rest of the paper is organized as follows. The proposed scheme is introduced in Section 2. An introduction to feedback cancellation in digital hearing aids is also made in the section. A brief analysis of the proposed algorithm is carried out in Section 3. The effectiveness of the proposed schemes are tested for three hearing aid scenarios in Section 4 and the concluding remarks are made in Section 5.

2. Proposed scheme

In a traditional adaptive feedback cancellation scheme employed in BTE digital hearing aids, the adaptive filter used is a finite impulse response (FIR) filter, the weights of which are updated using an LMS algorithm based update rule. Fig. 2 shows the block diagram of a digital hearing aid in the presence of acoustic feedback, with a de-correlation filter and probe noise injection. In the figure, $s(n)$ represents the primary desired signal which the user wishes to hear, $f(n)$ is the feedback signal, $H(z)$ is the transfer function of the feedback path, $x(n)$ is a mixture of the desired as well as the feedback signals, $F(z)$ is the transfer function of the forward path, $L(z)$ is the transfer function of the pre-whitening (de-correlation) filter and $W(z)$ represents the transfer function of the adaptive filter which acts as the feedback canceller.

The weights $\boldsymbol{w}(n)$ of the adaptive filter are updated with an objective to minimize the cost function

$$\xi(n) = \mathrm{E}\left[\widehat{e}^2(n)\right] \tag{1}$$

where $\mathrm{E}[\cdot]$ is the expectation operator and $\widehat{e}(n)$ is the signal

$$e(n) = x(n) - y(n) = x(n) - \boldsymbol{v}^T(n)\boldsymbol{w}(n) \tag{2}$$

filtered through the pre-whitening filter with impulse response $l(n)$, with $\boldsymbol{v}(n)$ denoting the tap delayed output signal. Considering $\xi(n) \approx \widehat{e}^2(n)$, the weights are updated as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) - \mu \frac{\partial \xi(n)}{\partial \boldsymbol{w}(n)}. \tag{3}$$

with μ as the step size parameter used to control the learning rate. In (3),

$$\frac{\partial \xi(n)}{\partial \boldsymbol{w}(n)} = -2\widehat{e}(n)\widehat{\boldsymbol{v}}(n) \tag{4}$$

where $\widehat{\boldsymbol{v}}(n)$ is $\boldsymbol{v}(n)$ filtered through the pre-whitening filter. substituting (4) in (3), we get

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + 2\mu\widehat{e}(n)\widehat{\boldsymbol{v}}(n), \tag{5}$$

which is the de-correlated LMS (DLMS) algorithm employed for achieving feedback cancellation when an FIR filter is used as the adaptive filter. The normalized version of the DLMS is given by

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + 2\frac{\mu}{\left[\widehat{\boldsymbol{v}}^T(n)\widehat{\boldsymbol{v}}(n) + \eta\right]}\widehat{e}(n)\widehat{\boldsymbol{v}}(n), \tag{6}$$

where η is a small positive constant and (6) is referred to as the de-correlated normalized LMS (DNLMS) algorithm.