An Efficient Combined Active Noise Control and Noise Reduction Method for Hearing Aids

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Summary
Recently, a reduced complexity integrated noise reduction and active noise control approach has been proposed for improving speech intelligibility of digital hearing aids. The complexity reduction over the filtered-x multichannel Wiener filter MWF (FxMWF) has been obtained using the dichotomous coordinate descent approach, but a slight performance reduction has been reported as well. In this paper, a new method based on an approximation of the autocorrelation matrix is proposed. It is shown that the proposed method has a much-reduced numerical complexity, better performance/cost and memory requirements than the competing MWF based algorithms. The performance for various parameters is confirmed by different measurement metrics for a wide range of SNR values of the noisy speech.
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1. Introduction

Hearing aids (HA) are increasingly used by people of all ages. The typical behind the ear (BTE) hearing aid has a microphone, a signal processing unit and a loudspeaker [1]-[2]. The signal that reaches the microphone is amplified, but, unfortunately, the noise is amplified too. Several noise reduction (NR) schemes [3] have been proposed in order to improve the speech intelligibility in the presence of noise. An active noise control (ANC) algorithm can solve some problems associated with the open fitting hearing aid [4]. Numerous ANC algorithms have been proposed (e.g. [5]-[6]). One approach integrates the NR and active noise control (ANC) into the HA in order to alleviate the signal deterioration due to leakage through the vent issue and the secondary path effect [7], [8]. Recently, a version that does not degrade the speech intelligibility and uses the dichotomous coordinate descent (DCD) [9] has been proposed [4]. The DCD algorithm and the Gauss-Seidel algorithm have been found to reduce the numerical complexity of various algorithms [10]-[13]. It was shown that the numerical complexity in terms of multiplications involving the autocorrelation matrix inverse was reduced from an $O(N^3)$ to $O(N)$, where N is the weight vector length. Unfortunately, the number of additions increases a lot, depending on the parameters of the DCD method.

In this paper an even computationally simpler approach for the NR and ANC integrated scheme for the two-microphone ([4], [14]-[15]) behind the ear (BTE) hearing aid is proposed starting from an approximation of the autocorrelation matrix. It is shown that the results are very close to that of multichannel Wiener filter (MWF) approach without speech intelligibility degradation.

In Section 2 the proposed method is described, while simulation results are presented in Section 3. Finally, acknowledgement, conclusions and future work close the article.

2. Proposed method

The two-microphone BTE hearing aid from [4] that needs a near perfect voice activity detector (VAD) is considered. The input signals are the sum of the speech signal and the noise component:

$$x_i(n) = x_i^s(n) + x_i^n(n),\ i = 1,2 \qquad (1)$$

The signals from the two microphones in vector form are the following

$$\mathbf{x}_i(n) = \left[x_i(n),\ldots,x_i(n-N_i+1)\right]^T \qquad (2)$$

where N_i is the length of the ith microphone input vector. The output signal is

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \qquad (3)$$

where the above-mentioned vectors are $\mathbf{x}(n)=\left[\mathbf{x}_1^T(n)\ \mathbf{x}_2^T(n)\right]^T$, $\mathbf{w}^T(n)=\left[\mathbf{w}_1^T(n)\ \mathbf{w}_2^T(n)\right]$

$$\mathbf{w}_i(n)=\left[w_{i,0}(n),\dots,w_{i,N_i-1}(n)\right]^T \qquad (4)$$

The block diagram of the proposed method is shown in Figure 1. The recursive estimator from the diagram estimated only the cross-correlation vectors, and do not additionally estimates the autocorrelation matrix as in [4].

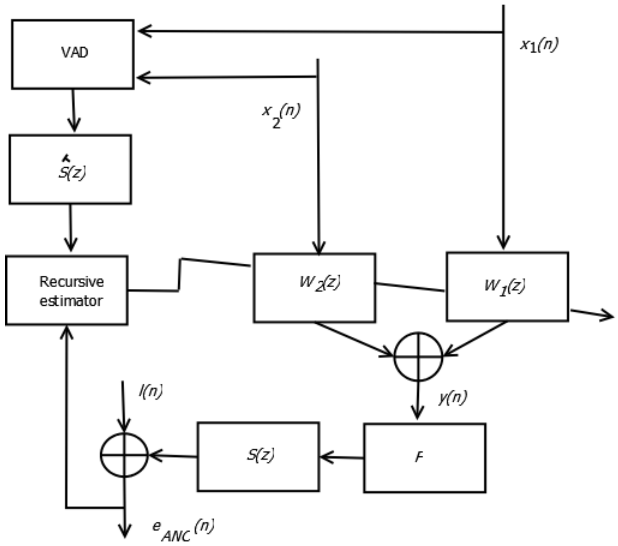

Figure 1. Block diagram.

Using an MWF approach, the optimal steady state weight vector for the adaptive filter can be obtained as follows [4]

$$\mathbf{w}(n)=\mathbf{R}_{xx}^{-1}(n)\mathbf{r}_{xd1,s}(n) \qquad (5)$$

where $\mathbf{R}_{xx}^{-1}(n)$ is the autocorrelation matrix of $\mathbf{x}(n)$ and $\mathbf{r}_{xd1,s}(n)=E\left[\mathbf{x}(n)d_{1,s}(n)\right]$ is the cross-correlation vector between $\mathbf{x}(n)$ and $d_{1,s}(n)$ is the delayed version of speech component of the first microphone.

In an open fitting scenario, there is a noise leaking that reaches the eardrum. The amplified version (a forward path gain, *F*) is also passed through the secondary path, having a transfer function denoted by *S*(z) and an impulse response given by $\mathbf{s}(n)$ [4]. A compensation for the secondary path effects has been obtained through using an ANC system. The leakage signal, *l*(n) is the sum of speech and noise components respectively. In this work, it has been assumed that an error microphone is near the eardrum and that the components of x(*n*) are uncorrelated. We define [4]

$$\mathbf{x}_f(n)=\mathbf{x}_f^s(n)+\mathbf{x}_f^n(n)=\left[\mathbf{x}_{f_1}^T(n)\ \mathbf{x}_{f_2}^T(n)\right]^T \qquad (6)$$

where $\mathbf{x}_{f_i}(n)$ is the filtered $\mathbf{x}_i(n)$ input signal vector through the secondary path, $\mathbf{x}_f^s(n)$ is the signal component of $\mathbf{x}_f(n)$ and $\mathbf{x}_f^n(n)$ is its noise component. The steady state adaptive filter weight vector can be obtained as follows [4]

$$\mathbf{w}(n)=\mathbf{R}_{x_f x_f}^{-1}(n)\mathbf{r}_{x_f d_{ANC}}(n) \qquad (7)$$

where $\mathbf{R}_{x_f x_f}(n)$ is the autocorrelation matrix of $\mathbf{x}_f(n)$ and $\mathbf{r}_{x_f d_{ANC}}(n)$ is the cross-correlation vector between $\mathbf{x}_f(n)$ and $d_{ANC}(n)$ is the desired signal at the eardrum. The following relation is obtained [4]

$$\mathbf{r}_{x_f}d_{ANC}(n)=\mathbf{r}_{x_f x_{1,\Delta}}(n)-F\cdot\mathbf{r}_{x_f^n x_{1,\Delta}^n}(n)-\mathbf{r}_{x_f^n l^n}(n) \qquad (8)$$

The estimated vectors and matrices of the filtered-x MWF (FxMWF) algorithm are [4]:

$$\hat{\mathbf{r}}_{x_f^n x_{1,\Delta}^n}(n)=\lambda\hat{\mathbf{r}}_{x_f^n x_{1,\Delta}^n}(n)+(1-\lambda)\mathbf{x}_f^n(n)x_1^n(n-\Delta) \qquad (9)$$

$$\hat{\mathbf{r}}_{x_f x_{1,\Delta}}(n)=\lambda\hat{\mathbf{r}}_{x_f x_{1,\Delta}}(n)+(1-\lambda)\mathbf{x}_f(n)x_1(n-\Delta) \qquad (10)$$

$$\mathbf{r}_{x_f^n l^n}(n)=\lambda\mathbf{r}_{x_f^n l^n}(n)+(1-\lambda)x_f^n(n)l^n(n) \qquad (11)$$

$$\hat{\mathbf{R}}_{x_f x_f}(n)=\lambda\hat{\mathbf{R}}_{x_f x_f}(n)+(1-\lambda)\mathbf{x}_f(n)\mathbf{x}_f^T(n) \qquad (12)$$

where λ is a forgetting factor, usually very close to one.

The approximation used in the proposed method is that the elements outside the main diagonal are close to zero, i.e. only the diagonal elements $\mathbf{r}_{x_f x_f}(n)$ are computed as follows:

$$\mathbf{r}_{x_f x_f}(n)=\lambda\mathbf{r}_{x_f x_f}(n)+(1-\lambda)\mathbf{x}_f^2(n) \qquad (13)$$

Therefore, each *i*th element of the weight vector $\mathbf{w}(n)$, i.e. $w^i(n)$, can be obtained as

$$w^i(n)=r_{xd1,s}^i(n)/r_{x_f x_f}^i(n) \quad 1\le i\le N \qquad (14)$$

where $r_{xd1,s}^i(n)$ and $r_{x_f x_f}^i(n)$ are the *i*th element of $\mathbf{r}_{xd1,s}(n)$ and $\mathbf{r}_{x_f x_f}(n)$ respectively. The resulting algorithm, called filtered-x simplified MWF (FxSMWF) algorithm, has a much lower computational complexity than FxMWF algorithm. When VAD = 0 the number of additions and multiplications per sample of each algorithm is:

$$M_{FxMWF}=N^3/6+4N^2+19N/3 \qquad (15)$$

$$A_{FxMWF}=N^3/6+3N^2+23N/3-5 \qquad (16)$$

$$M_{DCD-FxMWF} = 3N^2/2 + 15N/2 \qquad (17)$$

$$A_{DCD-FxMWF} = 2N^2 + N\left(15/2 + 2*N_u + M_b\right) + N_u - 5 \qquad (18)$$

$$M_{FxSMWF} = 23N/2 \qquad (19)$$

$$A_{FxMWF} = 21N/2 - 5 \qquad (20)$$

When VAD = 1 the number of additions and multiplications per sample of each algorithm is:

$$M_{FxMWF} = N^3/6 + N^2 + 25N/3 \qquad (21)$$

$$A_{FxMWF} = N^3/6 + N^2 + 25N/3 - 5 \qquad (22)$$

$$M_{DCD-FxMWF} = 21N/2 \qquad (23)$$

$$A_{DCD-FxMWF} = N\left(15/2 + 2*N_u + M_b\right) + N_u - 5 \qquad (24)$$

$$M_{FxSMWF} = 29N/2 \qquad (25)$$

$$A_{FxMWF} = 23N/2 - 5 \qquad (26)$$

A comparison of the computational complexity in terms of multiplications of FxMWF algorithm, the Dichotomous Coordinate Descent FxMWF (DCD-FxMWF) algorithm, and FxSMWF algorithm is shown in Fig. 2.

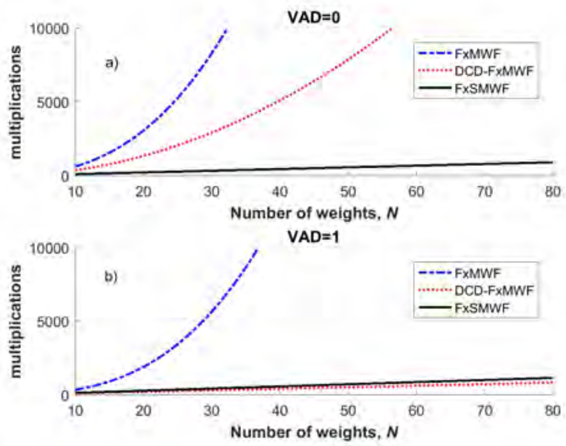

Figure 2. The number of multiplications of the investigated algorithms.

It can be seen that the FxMWF is the most complex algorithm. The proposed algorithm has much fewer multiplication than DCD-FxMWF for VAD = 0 and almost the same number of multiplications for VAD = 1. Therefore, for a typical speech signal, where the noise can be detected up to 50% of the time, the proposed algorithm has the least number of multiplications among the investigated algorithms. The computational complexity comparison in terms of additions is shown in Figure 3. For the DCD-FxMWF algorithms are $N_u = 32$, and $M_b = 24$. It can be easily noticed that the FxSMWF algorithm is the least complex.

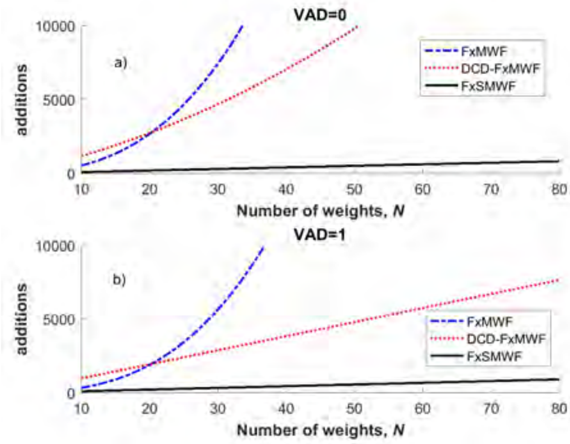

Figure 3. The number of additions of the investigated algorithms, $N_u = 32$, $M_b = 24$.

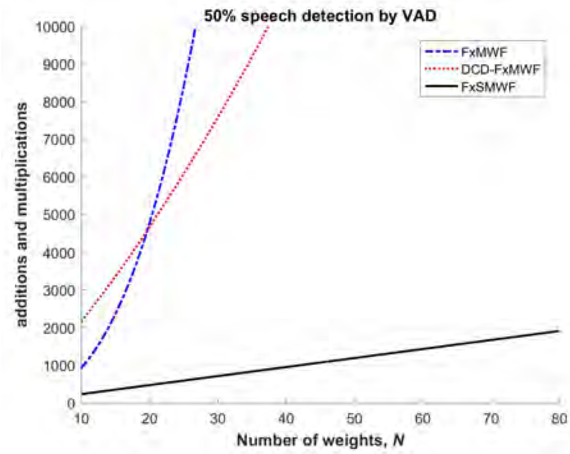

Figure 4. The number of additions and multiplications of the investigated algorithms for 50% speech detection by VAD.

Also, for the chosen parameters, there is a minimum number of weights needed for the DCD-FxMWF algorithm to become less complex than FxMWF algorithm. For the specific DCD parameters considered in these simulations, the overall complexity of DCD-FxMWF starts being smaller than that of FxMWF when $N > 20$. It is obvious from figures 2 and 3 that, for typical speech signals, the numerical complexity of the proposed algorithm is by far the smallest among the competing algorithms. This fact is exemplified in Figure 4 for a 50% VAD speech detection case. The memory requirements are smaller for the proposed algorithm because there is no need to store autocorrelation matrix elements.

3. Simulation results

The investigated algorithms were tested on speech signals mixed with babble noise, the noisy speech having an SNR of 10 dB. The noisy speech segments were collected from NOIZEUS database [16]. All the signals were sampled at 8 kHz and the leakage signal SNR is set at 0 dB as in [4].

The performance measurement metrics used in this study are the normalized-covariance measure (NCM) [17] and coherence speech intelligibility index (CSII) [18]. The parameters were N =64, $M_b = 24$, $N_u = 32$, and H =4.

In Figure 5, the amplitude difference between the weights of FxMWF and the FxSMW and DCD-FxMWF respectively is plotted. The amplifier gain was 5 dB. It can be easily noticed that the amplitude difference between FxMWF and FxSMWF is two orders of amplitude smaller than the amplitude difference between FxMWF and DCD-FxMWF. Therefore, the weights of FxSMWF are much closer to those of FxMWF than DCD-FxMWF.

In Figure 6, the amplitude difference between the weights of FxMWF and the FxSMW and DCD-FxMWF respectively is plotted, but the amplifier gain was changed from 5 dB to 15 dB.

It is confirmed for the 15 dB gain case, that the weights of FxSMWF are much closer to those of FxMWF than DCD-FxMWF. Also, the amplitude differences are higher in case of 15 dB gain than those for a 5 dB gain.

Tables I and II shows the NCM and CSII measures, respectively.

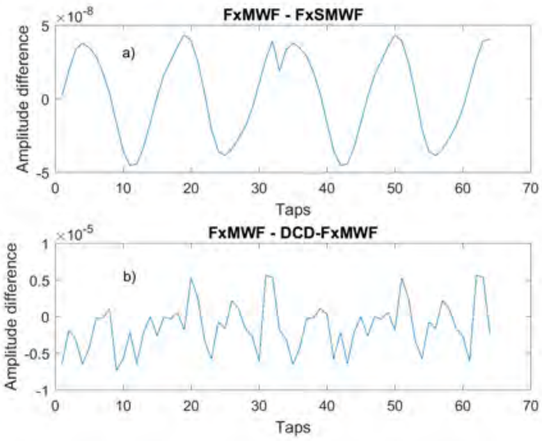

Figure 5. The amplitude difference between the weights for a SNR = 5 dB a) FxMWF and FxSMWF; b) FxMWF and DCD-FxMWF.

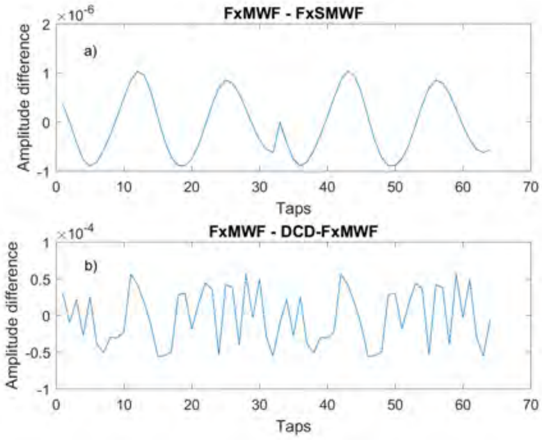

Figure 6. The amplitude difference between the weights for a SNR = 15 dB a) FxMWF and FxSMWF; b) FxMWF and DCD-FxMWF.

Two gains values were considered: 0dB and 25 dB. For both investigated measures, higher values mean more intelligible speech signal. It can be noticed from both tables that the improved speech intelligibility of FxMWF and FxSMWF is the same. The DCD-FxMWF measures are slightly lower than those of FxMWF and FxSMWF for a 25 dB forward path gain. It should be noted the the performance of the MWF based versions depends on the accuracy of the VAD scheme. Future work will be focused on exploiting the sparsity of feedback path by using techniques from [19]-[21].

Table I. NCM measures for the investigated algorithms.

Gain	*FxMWF*	*DCD-FxMWF*	*FxSMWF*
0	0.625	0.625	0.626
25	0.619	0.612	0.619

Table II. CSII measures for the investigated algorithms.

Gain	*FxMWF*	*DCD-FxMWF*	*FxSMWF*
0	0.654	0.654	0.654
25	0.654	0.653	0.654

4. Conclusions

A simplified integrated NR-ANC scheme for a two microphone BTE hearing aid is proposed in this paper. The computational complexity advantage over the previous MWF approaches is demonstrated, while the simulations proved the improved speech intelligibility.

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