The Modified Filtered-X Multichannel Wiener Filter

Felix Albu
Dept. of Electronics, Valahia University of Targoviste, Targoviste, Romania
Email: felix.albu@valahia.ro

***Abstract*— In this paper, a new numerical efficient multichannel Wiener filter method for two-microphone behind the ear digital hearing aids, based on an approximation of the autocorrelation matrix is proposed. It is shown that, due to the use of noise reduction and active noise control, similar intelligibility improvements are obtained at greatly reduced overall numerical complexity.**

Keywords—active noise control; filtered-x multichannel Wiener filter; dichotomous coordinate descent

I. Introduction

Hearing aids (HA) are used by numerous people to overcome their hearing loss. The typical behind the ear (BTE) hearing aid has a microphone, a signal processing unit and a loudspeaker [1]. Unfortunately, not only the useful signal is amplified, but also the noise. There are several noise reduction (NR) schemes [2] proposed to improve the speech intelligibility in the presence of noise. It is known that active noise control (ANC) algorithm can solve some problems associated with the open fitting hearing aid [1]. Numerous ANC algorithms have been proposed (e.g. [3]-[5]). It was shown in [6] and [7] how to integrate NR and ANC into the HA in order to alleviate the signal deterioration due to leakage through the vent issue and the secondary path effect. The algorithm was called filtered-x multichannel Wiener filter (FxMWF). The complexity of FxMWF in terms of multiplication has been reduced by using dichotomous coordinate descent (DCD) iterations [8]. The algorithm was called DCD filtered-x multichannel Wiener filter (DCD-FxMWF) [9]. The numerical complexity in terms of multiplications involving the autocorrelation matrix inverse was reduced from $O(N^3)$ to $O(N)$, where N is the weight vector length [9]. Unfortunately, the number of additions required by the DCD increases a lot [8] and depends of its parameters, N_u, the number of updates and M_b, the number of bits [9]. This aspect was not considered in [9] when taking into account the DCD-FxMWF numerical complexity. The solution of [9] involved the two-microphone behind the ear (BTE) hearing aid. Such two-microphone solutions were also proposed in [10] and [11].

In this paper an even computationally simpler approach for the NR and ANC integrated scheme for the two-microphone 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 together with its numerical complexity is described, while simulation results are presented in Section 3. Finally, conclusions and future work close the article.

II. The Proposed Method

The two-microphone BTE hearing aid from [9] that needs a near perfect voice activity detector (VAD) is considered. The block diagram of the proposed method is shown in Fig. 1.

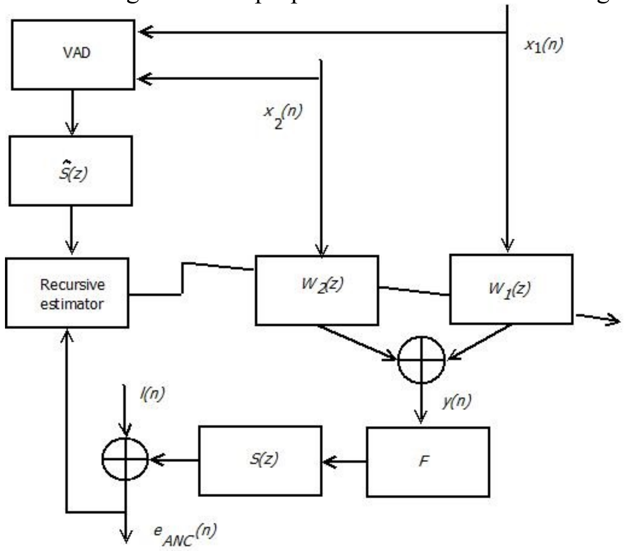

Fig. 1. Block diagram.

The input signals are the sum of the speech signal and the noise component:

$$x_i(n) = x_i^s(n) + x_i^n(n),\ i = 1,2 \tag{1}$$

The signals from the two microphones in vector form are as follows

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

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

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

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

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

The recursive estimator from the diagram estimates only the cross-correlation vectors, and do not additionally estimates the autocorrelation matrix as in [9]. Using an MWF approach, the optimal steady state weight vector for the adaptive filter can be obtained as follows [9]

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

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 the delayed version of speech component of the first microphone $d_{1,s}(n)$.

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 $\mathbf{s}$ [9]. 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. 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 [9]

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

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 [9]

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

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 the desired signal at the eardrum $d_{ANC}(n)$. The following relation is obtained [8]

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

The estimated vectors and matrices of the filtered-x MWF (FxMWF) algorithm are [9]:

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

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

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

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

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

The approximation that is used in the proposed method is that the elements outside the main diagonal are close to zero and the elements of the main diagonal are equal, i.e.

$$\hat{\mathbf{R}}_{x_f x_f}(n)\approx r_{x_f x_f}(n)\mathbf{I}_N \tag{13}$$

where $\mathbf{I}_N$ is the identify matrix with size $N\times N$, and $r_{x_f x_f}(n)$ is estimated as follows

$$r_{x_f x_f}(n)=\lambda r_{x_f x_f}(n)+(1-\lambda)x_f^2(n) \tag{14}$$

The weight vector for the adaptive filter can be obtained as

$$\mathbf{w}(n)=\mathbf{r}_{xd1,s}(n)/r_{x_f x_f}(n) \tag{15}$$

Therefore, the weight vector depends only on the $\mathbf{r}_{xd1,s}(n)$ cross-correlation vector and $r_{x_f x_f}(n)$. The resulting algorithm is called the modified filtered-x simplified MWF (MFxMWF) algorithm.

A. Numerical complexity

The numerical complexity per sample of each algorithm in terms of multiplications and additions for both VAD outputs is presented in Table I and Table II.

TABLE I. THE NUMBER OF MULTIPLICATIONS

VAD	**Algorithms**		
	DCD-FxMWF	***FxMWF***	***MFxMWF***
0	$17N/2$	$N^3/6+N^2+22N/3$	$19N/2$
1	$3N^2+13N/2$	$N^3/6+4N^2+16N/3$	$15N/2$

TABLE II. THE NUMBER OF ADDITIONS

VAD	**Algorithms**		
	DCD-FxMWF	***FxMWF***	***MFxMWF***
0	$N_u(19/2+2N)+M_b$	$N^3/6+N^2+25N/3$	$19N/2$
1	$N(15/2+2N_u)$ $+N^2+M_b$	$N^3/6+2N^2+19N/3$	$17N/2$

where $N_1=N_2=N/2$. A plot of the computational complexity in terms of multiplications of FxMWF algorithm, the Dichotomous Coordinate Descent FxMWF (DCD-FxMWF, $N_u=16$, and $M_b=16$) algorithm, and MFxMWF algorithm is shown in Fig. 2.

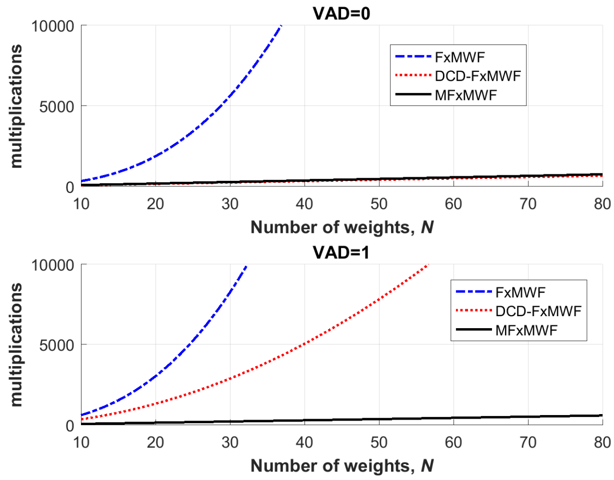

Fig. 2. The number of multiplications of the investigated algorithms, $N_u=16$, $M_b=16$.

It can be seen that the FxMWF is the most complex algorithm. The proposed algorithm has almost the same number of multiplication as the DCD-FxMWF for VAD=0, but lower number of multiplications for VAD=1. The computational complexity comparison in terms of additions is shown in Fig. 3. It can be easily noticed that the MFxMWF algorithm is the least complex. The computational savings of MFxMWF over DCD-FxMWF is even higher for higher N, M_b and N_u values. It is obvious from Figs. 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 also smaller for the proposed algorithm because there is no need to store autocorrelation matrix elements.

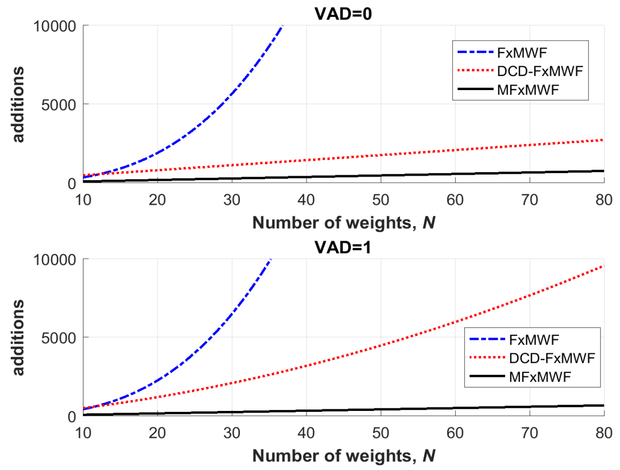

Fig. 3. The number of additions of the investigated algorithms, $N_u = 16$, and $M_b = 16$.

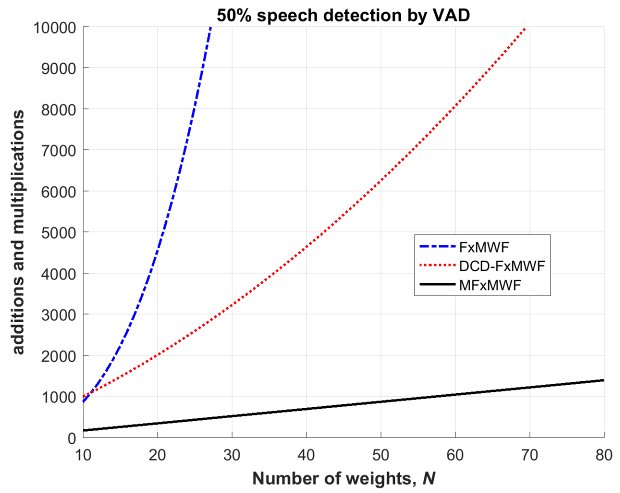

Fig. 4. The number of additions and multiplications of the investigated algorithms for 50% speech detection by VAD, $N_u = 16$ and $M_b = 16$.

III. 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 [12]. All the signals were sampled at 8 kHz and the leakage signal SNR is set at 0 dB as in [9]. The same forward and secondary path from [9] were used. The performance measurement metrics used in this study are the normalized-covariance measure (NCM) [13] and coherence speech intelligibility index (CSII) [14]. The parameters were N = 64, $\lambda = 0.9975$, $M_b = 16$, $N_u = 16$, and H = 4.

In Fig. 5, the absolute amplitude difference between the weights of FxMWF and the MFxMWF and DCD-FxMWF respectively is plotted. The amplifier gain was 5 dB. The absolute amplitude difference between FxMWF and MFxMWF is about 600 times smaller than the amplitude difference between FxMWF and DCD-FxMWF. Therefore, the weights of MFxMWF are much closer to those of FxMWF than DCD-FxMWF. In Fig. 6, the absolute amplitude difference between the weights of FxMWF and the MFxMWF and DCD-FxMWF respectively is plotted, but the amplifier gain was changed from 5 dB to 15 dB.

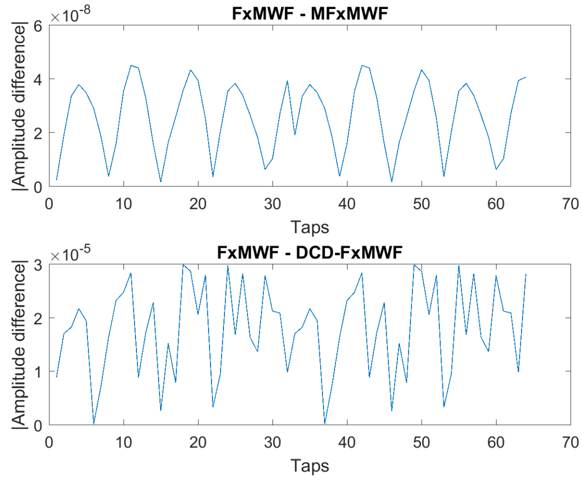

Fig. 5 The absolute amplitude difference between the weights for a SNR = 5 dB a) FxMWF and MFxMWF; b) FxMWF and DCD-FxMWF.

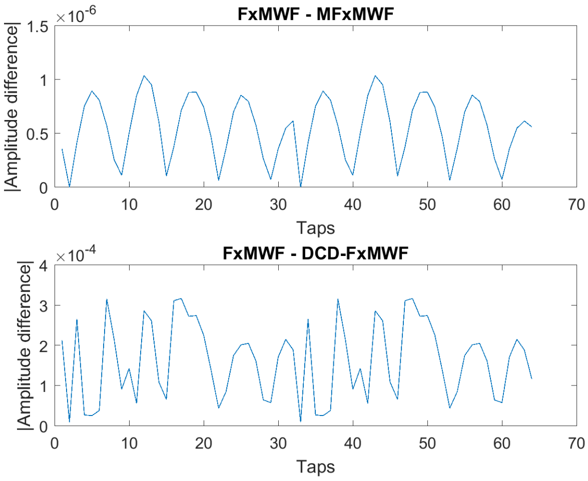

Fig. 6. The absolute amplitude difference between the weights for a SNR = 15 dB a) FxMWF and MFxMWF; b) FxMWF and DCD-FxMWF.

It is confirmed for the 15 dB gain case, that the weights of MFxMWF are much closer to those of FxMWF than

DCD-FxMWF. Also, it can be noticed from Figs. 5 and 6 that the amplitude differences are higher in case of 15 dB gain than those for a 5 dB gain.

Tables III and IV shows the CSII and NCM measures, respectively. Two gains values were considered: -5 dB and 10 dB. For both investigated measures, higher values mean more intelligible speech signal. It can be noticed from both tables that CSII and NCM measures of MFxMWF are much closer to those of FxMWF than those of DCD-FxMWF for both forward path gains.

TABLE III. CSII MEASURES

Gain (dB)	**Algorithms**		
	DCD-FxMWF	***FxMWF***	***MFxMWF***
-5	0.6543	0.6543	0.6543
10	0.6543	0.6542	0.6542

TABLE IV. NCM MEASURES

Gain (dB)	**Algorithms**		
	DCD-FxMWF	***FxMWF***	***MFxMWF***
-5	0.6261	0.6262	0.6262
10	0.6251	0.6233	0.6225

Therefore, it can be concluded that the improved speech intelligibility of FxMWF and MFxMWF is the same. It can be noticed from tables III and IV that the variability of the computed measures is higher for 10 dB gain than for -5 dB gain. Similar results were obtained for various noise types and strengths. It should be noted 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 [15]-[16].

IV. CONCLUSIONS

An integrated NR-ANC scheme for a two microphone BTE hearing aid with reduced numerical complexity is proposed in this paper. The computational complexity advantage over the previous MWF approaches is demonstrated. The simulations also proved the similar improved speech intelligibility of the competing methods.

ACKNOWLEDGMENT

This work was supported by a grant of the Romanian National Authority for Scientific research and Innovation, CNCS/CCCDI-UEFISCDI project number PN-III-P4-ID-PCE-2016-0339.

REFERENCES

[1] J. M. Kates, Digital hearing aids. Plural publishing, 2008.

[2] S. Doclo, A. Spriet, J. Wouters, and M. Moonen, “Frequency-domain criterion for the speech distortion weighted multichannel wiener filter for robust noise reduction,” Speech Communication, vol. 49, pp. 636–656, 2007.

[3] M. Bouchard, F. Albu, “The Multichannel Gauss-Seidel Fast Affine Projection Algorithm for Active Noise Control”, IEEE ISSPA 2003, pp. 579-582, July 2003.

[4] A. Gonzalez, M. Ferrer, F. Albu and M. de Diego, “Affine projection algorithms: evolution to smart and fast multichannel algorithms and applications,” in Proc. of Eusipco 2012, pp. 1965-1969.

[5] A. Gonzalez, F. Albu, M. Ferrer and M. Diego, “Evolutionary and variable step size affine projection algorithms for active noise control”, IET Signal Processing, 7(6), pp. 471-476, 2013.

[6] R. Serizel, M. Moonen, J. Wouters, and S. Jensen, “Combined active noise control and noise reduction in hearing aids,” in Proc. of IWAENC 2008.

[7] R. Serizel, M. Moonen, J. Wouters and S. Jensen, “Integrated active noise control and noise reduction in hearing aids,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 18, pp. 1137–1146, 2010.

[8] Y. Zakharov, “Low-complexity implementation of the affine projection algorithm,” IEEE Signal Processing Letters, 15, pp. 557–560, 2008.

[9] S. Pradhan, S. S. Bhattacharjee, V. Patel and N. V. George, “Speech enhancement in digital hearing aids: an active noise control approach,” in Proc. of ICSV 2017, pp. 1-8, 2017.

[10] C. R. C. Nakagawa, S. Nordholm, F. Albu and W.-Y. Yan, “Closed-loop feedback cancellation utilizing two microphones and transform domain processing,” in Proc. IEEE ICASSP 2014, pp. 3645–3649, 2013.

[11] F. Albu, R. Nakagawa, and S. Nordholm, “Proportionate algorithms for two-microphone active feedback cancellation,” in Proc. of EUSIPCO 2015, 290–294.

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

[13] I. Holube and B. Kollmeier, “Speech intelligibility prediction in hearing-impaired listeners based on a psychoacoustically motivated perception model,” The Journal of the Acoustical Society of America, vol. 100, pp. 1703–1716, 1996.

[14] J.M. Kates and K.H. Arehart, “Coherence and the speech intelligibility index,” The Journal of the Acoustical Society of America, vol. 117, pp. 2224–2237, 2005.

[15] S. Pradhan, V. Patel, K. Patel, J. Maheshwari and N.V. George, “Acoustic feedback cancellation in digital hearing aids: A sparse adaptive filtering approach”, Applied Acoustics, vol. 122, pp. 138-145, 2017.

[16] Y. Li, Y. Wang and F. Albu, “Sparse channel estimation based on a reweighted least-mean mixed-norm adaptive filter algorithm,” in Proc. of EUSIPCO 2016, pp. 2380-2384, 2016.