# SPEECH ENHANCEMENT IN DIGITAL HEARING AIDS: AN ACTIVE NOISE CONTROL APPROACH

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Digital hearing aid is one of the most widely used assistive listening device. A basic digital hearing aid consists of a microphone, a loudspeaker, a processing unit and a battery. In order to avoid occlusion effects in digital hearing aids, an open fitting scheme is usually followed. This leads to issues of acoustic feedback between the loudspeaker and the microphone. In addition, it reduces the effectiveness of noise reduction schemes which are implemented in digital hearing aids to improve speech quality. Open fitting also results in scenarios in which the ambient sound directly reaches the ear drum along with the sound produced by the hearing aid. The noise reduction capability in hearing aids is also affected by the secondary path, which is the path from the input of the loudspeaker to the ear drum. In order to overcome these limitations of noise reduction techniques, a reduced complexity integrated active noise cancellation approach has been introduced in this paper along with noise reduction schemes. The new scheme has been shown to effectively handle undesired leakage signals as well as the secondary path effects in comparison with traditional noise reduction schemes.

Keywords: Digital Hearing Aid, Active Noise Control, Noise Reduction

## 1. Introduction

Hearing aid is one of the most widely used assistive listening device. A basic behind the ear (BTE) hearing aid consists of a microphone, a signal processing unit and a loudspeaker [1, 2]. In addition to amplifying the sound signal sensed by the microphone, one of the objectives of the signal processing unit is to improve the speech intelligibility. A few noise reduction (NR) schemes have been reported in literature to improve the speech intelligibility in the presence of noise. In a multichannel Wiener filter (MWF) based NR scheme [3], an adaptive filter is updated with an objective to improve the speech quality. However, in an open fitting hearing aid, the performance of the above mentioned NR scheme is deteriorated due to the leakage through the vent. In addition, the presence of an acoustic path between the hearing aid loudspeaker and the eardrum (referred to as the secondary path) further degrades the speech quality. The above mentioned issues can be resolved by incorporating an active noise control (ANC) scheme into the hearing aid system. ANC works on the principle of destructive superposition of waves and an integrated NR-ANC scheme, which performs NR as well as overcomes the secondary path and leakage issues have been recently proposed [4, 5].

With an objective to reduce the computational load in estimating the weights of the adaptive filter in an integrated NR-ANC scenario, an attempt has been made in this paper to design a dichotomous coordinate descent (DCD) [6] based integrated NR-ANC scheme for digital hearing aids. The computations needed for obtaining the inverse of the autocorrelation matrix, which is necessary in a conventional integrated NR-ANC scheme, have been significantly reduced from an $O(N^3)$ to $O(N)$, where $N$ is the weight vector length. This reduction in complexity is achieved without degrading the speech intelligibility.

The rest of the paper is organized as follows. The proposed approach is developed in Section 2. A detailed simulation study is carried out in Section 3 to evaluate the performance of the proposed approach and the concluding remarks are drawn in Section 4.

## 2. Proposed Approach

A two-microphone BTE hearing aid has been considered in this study, with both the microphones placed behind the ear. For sake of simplicity, we have assumed all the signals to be of discrete time nature with $n$ as the sample index. The signals sensed by the two microphones are given by

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

where $x_i^s(n)$ represents the speech or desired component of the captured signal and $x_i^n(n)$ denotes the unwanted or noise component. One of the critical components needed for the successful implementation of the proposed approach is the availability of a near perfect voice activity detector (VAD), which can effectively detect presence or absence of speech in a given sound signal. The signals from the two microphones may be written in vector form as

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

with $N_i$ denoting the length of microphone signal input vector for the $i^{th}$ microphone and $T$ representing the transpose operation. The two microphone signal vectors may be combined together and may be written as

$$\mathbf{x}(n) = \left[\mathbf{x}_1^T(n) \;\; \mathbf{x}_2^T(n)\right]^T, \tag{3}$$

which is of length $N = N_1 + N_2$. The above mentioned input signal vector $\mathbf{x}(n)$ is filtered through an adaptive filter with a weight vector given by $\mathbf{w}(n) = \left[\mathbf{w}_1^T(n) \;\; \mathbf{w}_2^T(n)\right]^T$ with

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

to obtain the resultant output signal given by $y(n) = \mathbf{w}^T(n)\mathbf{x}(n)$.

Let $d_{1,s}$ denote the delayed version of speech component of the first microphone, which is considered as the desired signal. The weights of the above mentioned adaptive filter are updated in such a way as to minimize the cost function given by

$$\xi(n) = \mathrm{E}\left[|d_{1,s}(n) - y(n)|^2\right] \tag{5}$$

where $\mathrm{E}[\cdot]$ is the expectation operator. Using an MWF approach, the optimal steady state weight vector for the adaptive filter can be obtained as

$$\mathbf{w}(n) = \mathbf{R}_{xx}^{-1}(n)\mathbf{r}_{xd_{1,s}}(n) \tag{6}$$

where $\mathbf{R}_{xx}(n) = \mathrm{E}\left[\mathbf{x}(n)\mathbf{x}^T(n)\right]$ is the autocorrelation matrix of $\mathbf{x}(n)$ and $\mathbf{r}_{xd_{1,s}}(n) = \mathrm{E}\left[\mathbf{x}(n)d_{1,s}(n)\right]$ is the cross-correlation vector between $\mathbf{x}(n)$ and $d_{1,s}(n)$. We can write

$$\mathbf{r}_{xd_{1,s}}(n) = \mathbf{r}_{xx_{1,\Delta}}(n) - \mathbf{r}_{x^n x^n_{1,\Delta}}(n) \tag{7}$$

under the assumption of uncorrelated desired and noise signals. In Eq. (7), $\mathbf{r}_{xx_{1,\Delta}}(n) = \mathrm{E}\left[\mathbf{x}(n)x_1(n-\Delta)\right]$ and $\mathbf{r}_{x^n x^n_{1,\Delta}}(n) = \mathrm{E}\left[\mathbf{x}^n(n)x_1^n(n-\Delta)\right]$, with $\Delta = N/2$. In a practical scenario, $\mathbf{R}_{xx}(n)$ and $\mathbf{r}_{xx_{1,\Delta}}(n)$

can be estimated during periods where both speech and noise are present (as detected by VAD) in a recursive manner as [7]

$$\widehat{\mathbf{R}}_{xx}(n) = \lambda\widehat{\mathbf{R}}_{xx}(n-1) + (1-\lambda)\mathbf{x}(n)\mathbf{x}^T(n) \tag{8}$$

and

$$\widehat{\mathbf{r}}_{xx_{1,\Delta}}(n) = \lambda\widehat{\mathbf{r}}_{xx_{1,\Delta}}(n-1) + (1-\lambda)\mathbf{x}(n)x_1(n-\Delta) \tag{9}$$

where $0 < \lambda < 1$ is the forgetting factor. In Eq. (8), $\widehat{\mathbf{R}}_{xx}(0) = \mathbf{0}_{N\times N}$ and in Eq. (9), $\widehat{\mathbf{r}}_{xx_{1,\Delta}}(0) = \mathbf{0}_{N\times 1}$. In a similar way, we can recursively estimate $\mathbf{r}_{x^n x^n_{1,\Delta}}(n)$ during periods where only noise is present (as detected by VAD) as

$$\widehat{\mathbf{r}}_{x^n x^n_{1,\Delta}}(n) = \lambda\widehat{\mathbf{r}}_{x^n x^n_{1,\Delta}}(n-1) + (1-\lambda)\mathbf{x}^n(n)x^n_1(n-\Delta) \tag{10}$$

with $\widehat{\mathbf{r}}_{x^n x^n_{1,\Delta}}(0) = \mathbf{0}_{N\times 1}$. The above mentioned adaptive filtering scheme indicates the NR method employed in a two-microphone BTE hearing aid [5].

In an open fitting scenario, noise leaked through the fitting reaches the eardrum in addition to the amplified sound which is produced by the hearing aid. In addition, the amplified version (passing through a forward path gain $F$) of the output signal of the NR unit (i.e. $y(n)$), is passed through an acoustic path before reaching the eardrum. This path is referred to as the secondary path, with a transfer function denoted by $S(z)$ (impulse response given by $\boldsymbol{s}(n)$). Thus the overall signal reaching the eardrum is given by

$$e(n) = \boldsymbol{s}(n) * [F \cdot y(n)] + l(n). \tag{11}$$

where $l(n)$ is the leakage signal. It may be noted that the secondary path attenuates the amplified sound before it reaches the eardrum. Thus a mechanism which will compensate for the secondary path effects as well as reduce the effects of leakage noise needs to be developed.

An ANC system has been recently incorporated into digital hearing aids to overcome the above mentioned limitations. In this scheme, the adaptive filter discussed above is designed to offer NR as well as ANC. The leakage signal in this setup may be written as $l(n) = l^s(n) + l^n(n)$, where $l^s(n)$ is the speech component of the leakage signal and $l^n(n)$ is the noise component. The overall cost function which needs to be updated in such a scheme is given by

$$\xi(n) = \mathrm{E}\left[|e_{ANC}|^2\right] = \mathrm{E}\left[|\boldsymbol{s}(n) * y(n) - d_{ANC}(n)|^2\right] \tag{12}$$

where

$$d_{ANC}(n) = F \cdot x^s_1(n-\Delta) - l^n(n) \tag{13}$$

is the desired signal at the eardrum and $e_{ANC}(n)$ is the error signal. In this work, it has be assumed that an error microphone, which measures $e_{ANC}(n)$ is available near the eardrum. Assuming that the speech and noise components of $\mathbf{x}(n)$ are uncorrelated, Eq. (12) may be written as

$$\xi(n) = \mathrm{E}\left[|\mathbf{w}^T(n)\mathbf{x}^s_f(n) - F \cdot x^s_1(n-\Delta)|^2\right] + \mathrm{E}\left[|\mathbf{w}^T(n)\mathbf{x}^n_f(n) + l^n(n)|^2\right] \tag{14}$$

where $\mathbf{x}_f(n) = \mathbf{x}^s_f(n) + \mathbf{x}^n_f(n) = \left[\mathbf{x}^T_{f_1}(n)\ \ \mathbf{x}^T_{f_2}(n)\right]^T$ is the filtered input signal vector with $\mathbf{x}_{f_i}(n)$ representing $\mathbf{x}_i(n)$ filtered through the secondary path, $\mathbf{x}^s_f(n)$ is the signal component of $\mathbf{x}_f(n)$ and $\mathbf{x}^n_f(n)$ is its noise component. It can be observed from the objective function that this objective function can handle both secondary path compensation as well as NR. The secondary path compensation is handled by the term $\mathrm{E}\left[|\mathbf{w}^T(n)\mathbf{x}^s_f(n) - F \cdot x^s_1(n-\Delta)|^2\right]$ and NR incorporating ANC is achieved using $\mathrm{E}\left[|\mathbf{w}^T(n)\mathbf{x}^n_f(n) + l^n(n)|^2\right]$. The steady state adaptive filter weight vector can be obtained as

$$\mathbf{w}(n) = \mathbf{R}^{-1}_{x_f x_f}(n)\mathbf{r}_{x_f d_{ANC}} \tag{15}$$

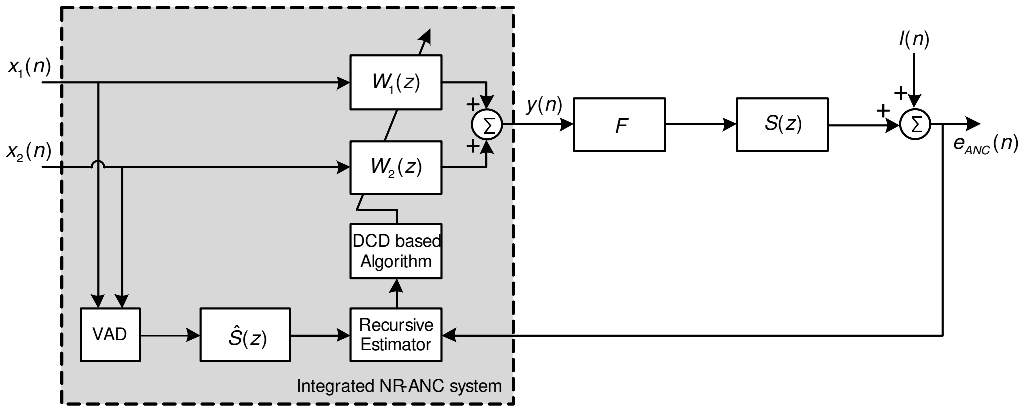


Figure 1: Block diagram of the proposed approach. The Recursive Estimator in the diagram recursively estimates the autocorrelation matrix and cross-correlation vectors.

where $\mathbf{R}_{x_f x_f}(n) = \mathrm{E}\left[\mathbf{x}_f(n)\mathbf{x}_f^T(n)\right]$ is the autocorrelation matrix of the filtered input signal vector $\mathbf{x}_f(n)$ and $\mathbf{r}_{x_f d_{ANC}}(n) = \mathrm{E}\left[\mathbf{x}_f(n) d_{ANC}(n)\right]$ is the cross-correlation vector between $\mathbf{x}_f(n)$ and $d_{ANC}(n)$. Assuming that the desired speech and the undesired noise components are uncorrelated, we can write

$$\mathbf{r}_{x_f d_{ANC}}(n) = \mathbf{r}_{x_f^s d_{NR}}(n) - \mathbf{r}_{x_f^n l^n}(n) = \mathbf{r}_{x_f x_{1,\Delta}}(n) - F \cdot \mathbf{r}_{x_f^n x_{1,\Delta}^n}(n) - \mathbf{r}_{x_f^n(n) l^n}(n) \tag{16}$$

where $\mathbf{r}_{x_f x_{1,\Delta}}(n) = \mathrm{E}\left[\mathbf{x}_f(n) x_1(n-\Delta)\right]$, $\mathbf{r}_{x_f^n x_{1,\Delta}^n}(n) = \mathrm{E}\left[\mathbf{x}_f^n(n) x_1^n(n-\Delta)\right]$ and $\mathbf{r}_{x_f^n l^n}(n) = \mathrm{E}\left[\mathbf{x}_f^n(n) l^n(n)\right]$ In a practical scenario, similar to the NR case, we can estimate $\mathbf{R}_{x_f x_f}(n)$ and $\mathbf{r}_{x_f x_{1,\Delta}}(n)$ recursively during periods when speech and noise occurs together (as estimated by the VAD) as

$$\widehat{\mathbf{R}}_{x_f x_f}(n) = \lambda \widehat{\mathbf{R}}_{x_f x_f}(n-1) + (1-\lambda)\mathbf{x}_f(n)\mathbf{x}_f^T(n) \tag{17}$$

and

$$\widehat{\mathbf{r}}_{x_f x_{1,\Delta}}(n) = \lambda \widehat{\mathbf{r}}_{x_f x_{1,\Delta}}(n-1) + (1-\lambda)\mathbf{x}_f(n) x_1(n-\Delta). \tag{18}$$

where $0 < \lambda < 1$ is the forgetting factor. In Eq. (17), $\widehat{\mathbf{R}}_{x_f x_f}(0) = \mathbf{0}_{N\times N}$ and in Eq. (18), $\widehat{\mathbf{r}}_{x_f x_{1,\Delta}}(0) = \mathbf{0}_{N\times 1}$. Similarly, $\mathbf{r}_{x_f^n x_{1,\Delta}^n}(n)$ and $\mathbf{r}_{x_f^n l^n}(n)$ when only noise is present (as estimated using VAD) as

$$\widehat{\mathbf{r}}_{x_f^n x_{1,\Delta}^n}(n) = \lambda \widehat{\mathbf{r}}_{x_f^n x_{1,\Delta}^n}(n-1) + (1-\lambda)\mathbf{x}_f^n(n) x_1^n(n-\Delta) \tag{19}$$

$$\widehat{\mathbf{r}}_{x_f^n l^n}(n) = \lambda \widehat{\mathbf{r}}_{x_f^n l^n}(n-1) + (1-\lambda)\mathbf{x}_f^n(n) l^n(n) \tag{20}$$

with $l^n(n) \approx e_{ANC}^n(n) - \mathbf{w}^T(n)\mathbf{x}_f^n(n)$, in Eq. (19), $\widehat{\mathbf{r}}_{x_f^n x_{1,\Delta}^n}(0) = \mathbf{0}_{N\times 1}$, and in Eq. (20), $\widehat{\mathbf{r}}_{x_f^n l^n}(n) = \mathbf{0}_{N\times 1}$ The above mentioned scheme of estimating the weights of the adaptive filter is referred to as the filtered-x MWF (FxMWF) algorithm [7, 5]. The filtered versions of the signals are obtained by filtering the signals through a perfect model of the secondary path, which is estimated offline.

In order to find the optimum weight vector for the controller we have to solve Eq. (15), but from hardware implementation point of view, these require $O(N^3)$ computations. With the aim of lowering down the complexity to $O(N)$ without degrading the performance, an attempt has been made in this paper to employ a DCD based approach [6], [8]. In the proposed scheme, the weight vector of Eq. (15) is estimated as follows:

Step 1: Initialize $\mathbf{w(n)} = \mathbf{0}_{N\times 1}$ and bit count $m = 1$.
Step 2: Compute $\boldsymbol{r} = [r_1, r_2, \ldots, r_k, \ldots, r_N] = \mathbf{r}_{x_f d_{ANC}}$ and $\mathbf{R} = \mathbf{R}_{x_f x_f}(n)$.
Step 3: Let $\alpha = H/2$ where $H$ is the range of the weight vector.
Step 4: Let iteration index $i = 1$.

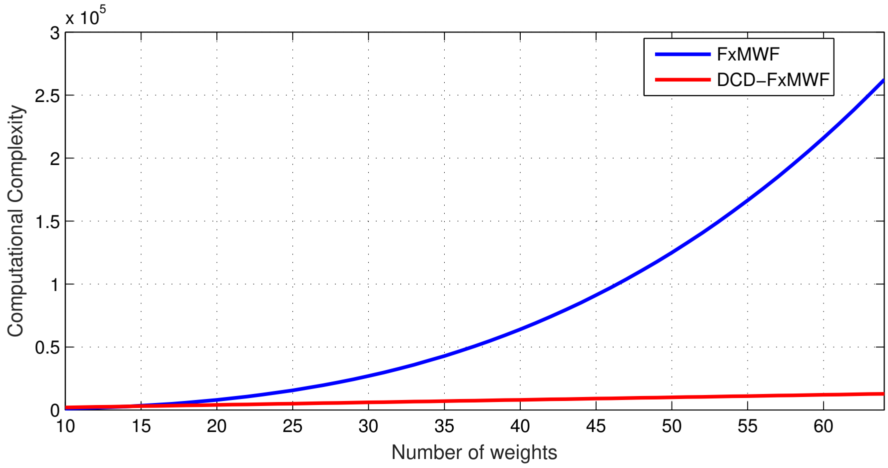


Figure 2: Comparison of computational complexity of FxMWF and DCD-FxMWF algorithms for $M_b = 24$, $N_u = 100$.

Step 5: Compute $j = \text{argmax}_{k=1,2,\ldots,N} |r_k|$.
Step 6: If $|r_j| \leq (\alpha/2)\mathbf{R}_{j,j}$ and $m \leq M_b$ go to Step 7 else go to Step 9.
Step 7: $m = m + 1$ and $\alpha = \alpha/2$.
Step 8: $w_j(n) = w_j(n) + \text{sign}(r_j)\alpha$ and $\boldsymbol{r} = \boldsymbol{r} - \text{sign}(r_j)\alpha\mathbf{R}^{(j)}(n)$.
Step 9: If $i < N_u$, $i = i + 1$ and go to Step 5 else go to Step 10.
Step 10: The estimated weights are available in $\mathbf{w}(n)$.

In the above mentioned scheme, $r_j$ and $w_j(n)$ are the $j^{th}$ element of corresponding vectors. FxMWF algorithm, which employs the above mentioned DCD approach is hereafter referred to as the DCD-FxMWF algorithm. The complete block diagram of the proposed reduced complexity integrated NR-ANC scheme is shown in Fig. 1. A comparison of computational complexity associated with weight update of FxMWF and DCD-FxMWF for different number of weights is shown in Fig. 2. The reduced complexity offered by the proposed scheme is evident from the figure.

## 3. Simulation Study

The effectiveness of the proposed approach has been tested using a simulation study in this section. We have considered two types of noisy speech signals, and each with two different signal to noise ratio (SNR) levels. In the first, we have used a speech segment mixed with babble noise with a resultant SNR of 5 dB, whereas in the second case, the same noisy speech with an SNR of 10 dB is considered. For the third and fourth experiments, we have taken a speech segment mixed with a car noise with a resultant SNR of 5 dB and 10 dBs respectively. All the noisy speech segments were collected from NOIZEUS database [9]. All the signals were sampled at $8$ kHz and the leakage signal SNR is set at $0$ dB.

The performance measurement metrics used in this study are the normalized-covariance measure (NCM) [10] and coherence speech intelligibility index (CSII) [11, 9] of the signal reaching at the eardrum. The NCM takes values between $0$ and $1$ and so does CSII. The higher the values of NCM and CSII, the more intelligible the processed speech is. The overall CSII of a speech signal is usually calculated as

$$\text{CSII} = \frac{1}{1 + \exp(-c)} \tag{21}$$

where

$$c = -3.47 + 1.84c_{low} + 9.99c_{mid} + 0.0c_{high}, \tag{22}$$

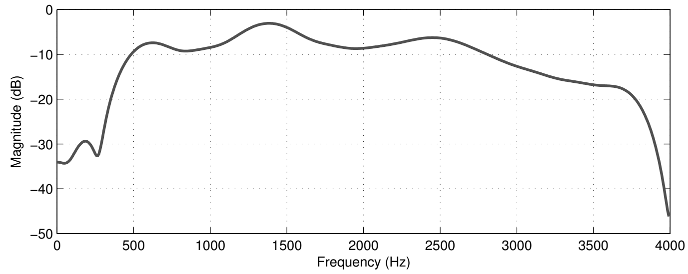


Figure 3: Magnitude of the frequency characteristics of the secondary path.

with $c_{low}$, $c_{mid}$ and $c_{high}$ are the CSII values of the low, mid and high level regions of the signal reaching the eardrum. The other simulation parameters used in all the cases are: $\lambda = 0.9975$, $H = 4$, $M_b = 24$ and $N_u = 100$.

### 3.1 Case I

In the first case, we have considered a scenario with an adaptive filter is of length $N = 64$ and the magnitude of the frequency response of the secondary path used in this study is shown in Fig. 3. The speech intelligibility measures computed for all the three algorithms for a forward gain of 5 dB are shown in Table 1 and 2. FxMWF algorithm has been shown to offer improved speech intelligibility over the conventional MWF approach. The proposed DCD-FxMWF scheme provides a speech intelligibility similar to that of FxMWF, but with a reduced computational load. Fig. 4 (a) shows the comparison of the controller weights for the FxMWF and the DCD-FxMWF schemes studied. The similar steady state controller weights obtained by both the algorithms are clear from the figure. In order to understand the effect of forward path gain on speech intelligibility, we have conducted another experiment by changing the forward path gain to 20 dB. From the comparison of speech intelligibility indices shown in Table 1 and 2, we can observe that there is no significant deviation in the speech intelligibility with respect to the gain of the forward path.

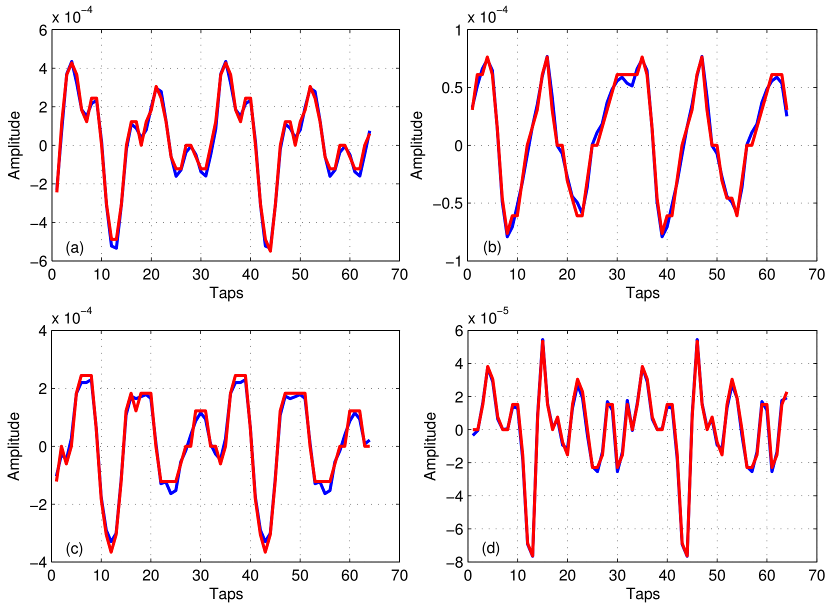


Figure 4: Comparison of steady state weights of FxMWF (blue) and DCD-FxMWF (red) with an amplifier gain of 5 dB. (a) Input: Noisy speech (mixed with babble noise) with SNR=5 dB, (b) Input: Noisy speech (mixed with babble noise) with SNR=10 dB, (c) Input: Noisy speech (mixed with car noise) with SNR=5 dB, (d) Input: Noisy speech (mixed with car noise) with SNR=10 dB.

### 3.2 Case II

In this case, we have used a noisy speech signal similar to that of the previous case, but with an SNR of 10 dB. The forward path gains as well as the secondary path used are also same as that of Case I. The comparison of speech intelligibility for MWF, FxMWF and DCD-FxMWF are shown in Table 1 and Table 2 for forward path gain of 5 dB and 20 dB. Similar to Case I, an improvement in speech intelligibility has been observed for the FxMWF approach and a comparable speech intelligibility measure has been recorded for the DCD-FxMWF scheme. The steady sate weight values of the controllers based on DCD-FxMWF methods are compared with FxMWF method in Fig. 4 (b). We can observe that similar steady state weights have been achieved with a reduced computation load.

### 3.3 Case III and IV

The input signal used in case III is a car noise, resulting in an overall SNR of 5 dB and in case IV the overall SNR is set to 10 dB. The forward and secondary paths used in Case III and IV are similar to that of the previous cases.

Table 1: Comparison for NCM

| Case I | | | | Case II | | |
|---|---|---|---|---|---|---|
| Gain (dB) | MWF | FxMWF | DCD-FxMWF | MWF | FxMWF | DCD-FxMWF |
| 5 | 0.5556 | 0.6506 | 0.6474 | 0.5524 | 0.6376 | 0.6500 |
| 20 | 0.5664 | 0.6476 | 0.6462 | 0.5217 | 0.6350 | 0.6427 |
| Case III | | | | Case IV | | |
| Gain (dB) | MWF | FxMWF | DCD-FxMWF | MWF | FxMWF | DCD-FxMWF |
| 5 | 0.6058 | 0.6887 | 0.6847 | 0.5712 | 0.6489 | 0.6417 |
| 20 | 0.5409 | 0.6649 | 0.6862 | 0.5228 | 0.6535 | 0.6733 |

Table 2: Comparison for CSII

| | | Case I | | | | Case II | | | |
|---|---|---|---|---|---|---|---|---|---|
| Gain | Algorithm | $c_{low}$ | $c_{mid}$ | $c_{high}$ | CSII | $c_{low}$ | $c_{mid}$ | $c_{high}$ | CSII |
| 5 | MWF | 0.0088 | 0.3653 | 0.6205 | 0.5487 | 0.0446 | 0.3545 | 0.5972 | 0.5200 |
| | FxMWF | 0.0269 | 0.4348 | 0.6671 | 0.7158 | 0.0182 | 0.4178 | 0.6789 | 0.6764 |
| | DCD-FxMWF | 0.0239 | 0.4363 | 0.6763 | 0.7177 | 0.0178 | 0.4308 | 0.6587 | 0.7041 |
| 20 | MWF | 0.0022 | 0.3806 | 0.5799 | 0.5834 | 0.0018 | 0.3679 | 0.5574 | 0.5519 |
| | FxMWF | 0.0176 | 0.4299 | 0.6654 | 0.7021 | 0.0094 | 0.4219 | 0.6491 | 0.6818 |
| | DCD-FxMWF | 0.0245 | 0.4183 | 0.6825 | 0.6801 | 0.0211 | 0.4258 | 0.6571 | 0.6948 |
| | | Case III | | | | Case IV | | | |
| Gain | Algorithm | $c_{low}$ | $c_{mid}$ | $c_{high}$ | CSII | $c_{low}$ | $c_{mid}$ | $c_{high}$ | CSII |
| 5 | MWF | 0.0023 | 0.3631 | 0.5958 | 0.5402 | 0.0022 | 0.3581 | 0.5954 | 0.5279 |
| | FxMWF | 0.0101 | 0.4113 | 0.6510 | 0.6588 | 0.0153 | 0.3986 | 0.6577 | 0.6319 |
| | DCD-FxMWF | 0.0145 | 0.4191 | 0.6630 | 0.6779 | 0.0064 | 0.4265 | 0.6769 | 0.6906 |
| 20 | MWF | 0.0041 | 0.3563 | 0.5195 | 0.5242 | 0.0283 | 0.4105 | 0.4632 | 0.6644 |
| | FxMWF | 0.0110 | 0.4105 | 0.6344 | 0.6572 | 0.0081 | 0.4301 | 0.6619 | 0.6988 |
| | DCD-FxMWF | 0.0139 | 0.4074 | 0.6441 | 0.6515 | 0.0230 | 0.4337 | 0.6796 | 0.7120 |

Table 1 and Table 2 show the comparison of speech intelligibility for the algorithms compared for forward path gains of 5 and 20 dBs. The improved speech intelligibility offered by FxMWF and DCD-FxMWF approaches are evident from the results. The similarity of the steady state weights obtained for FxMWF and DCD-FxMWF algorithms can be seen from Fig. 4 (c) and (d).

## 4. Conclusions

A reduced complexity integrated NR-ANC scheme, which offers enhanced speech intelligibility in a digital hearing aid has been developed in this paper. The computational complexity of the proposed scheme has been reduced by using a DCD approach. The improvement in speech quality is evident from the simulation results.

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