BINAURAL NOISE REDUCTION FOR HEARING AIDS: PRESERVING INTERAURAL TIME DELAY CUES

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ABSTRACT

This paper presents a binaural extension of a monaural multi-channel noise reduction algorithm for hearing aids based on Wiener filtering. This algorithm provides the hearing aid user with a binaural output. In addition to significantly suppressing the noise interference, the algorithm preserves the interaural time delay (ITD) cues of the received speech, thus allowing the user to correctly localize the speech source. Unfortunately, binaural multi-channel Wiener filtering distorts the ITD cues of the noise source. By adding a parameter to the cost function the amount of noise reduction performed by the algorithm can be controlled, and traded off for the preservation of the noise ITD cues.

1. INTRODUCTION

Hearing impaired persons localize sounds better without their bilateral hearing aids than with them [1]. This is not surprising, since noise reduction algorithms currently used in hearing aids are not designed to preserve localization cues [2]. The inability to correctly localize sounds puts the hearing aid user at a disadvantage as well as at risk. The sooner the user can localize a speech signal, the sooner the user can begin to exploit visual cues. Generally, visual cues lead to large improvements in intelligibility for hearing impaired persons [3]. Moreover, in certain situations, such as traffic, incorrectly localizing sounds could endanger the user. This paper focuses specifically on interaural time delay (ITD) cues, which help the listener localize sounds horizontally [4]. ITD is the time delay in the arrival of the sound signal between the left and right ear. If the ITD cues of the processed signal are the same as the ITD cues of the unprocessed signal, we assume that a user will localize the processed signal and the unprocessed signal to the same source.

In [5], a binaural adaptive noise reduction algorithm is proposed, which we will refer to as algorithm-[5]. This algorithm takes a microphone signal from each ear as inputs. The inputs are filtered by a high-pass and a low-pass filter with the same cut-off frequency to create a high frequency and a low frequency portion. The high frequency portion is adaptively processed and added to the delayed low frequency portion. Since ITD cues are contained in the low-frequency regions, as the cut-off frequency increases more ITD information will arrive undistorted to the user [4]. The major drawback to this approach is that the low frequency portion containing speech energy also contains noise energy. Consequently, noise, as well as speech energy is passed from the input to the output unprocessed. Therefore, there is a trade-off between noise reduction and speech ITD cue preservation. As the cut-off frequency increases the preservation of the ITD cues improves at the cost of noise reduction.

This paper extends the monaural multi-channel Wiener filtering algorithm discussed in [6] to a binaural algorithm. This algorithm is well suited for binaural noise reduction because it makes no a priori assumptions (e.g. the location of the speech source), and is capable of estimating the speech components in all microphone channels.

In order to preserve the noise ITD cues, some of the noise signal must arrive at the output of the algorithm undistorted. Consequently, the binaural algorithm is modified so the emphasis on noise reduction can be controlled. As less emphasis is put on noise reduction, more noise arrives at the output of the algorithm unprocessed; accordingly more noise ITD cues will arrive undistorted to the user. Therefore, one can control the distortion of the ITD cues of the noise source.

2. SYSTEM MODEL

Figure 1 shows a binaural hearing aid user in a typical listening scenario. The speaker speaks intermittently in the continuous background noise. In this case, there is one microphone on each hearing aid. Nevertheless, we consider the case where there are M microphones on each hearing aid. We refer to the mth microphone of the left hearing aid and the mth microphone of the right hearing aid as the mth microphone pair. The received signals at time k, for k ranging from 1 to K, at the mth microphone pair are expressed in the equations below.

$$y_{L_m}[k] = x_{L_m}[k] + v_{L_m}[k] \quad (1)$$

$$y_{R_m}[k] = x_{R_m}[k] + v_{R_m}[k] \quad (2)$$

Where x_{L_m} and x_{R_m} are the speech components in the mth microphone pair, and v_{L_m} and v_{R_m} are the noise components in the mth microphone pair.

We make two standard assumptions that will be pertinent later. First, the speech signal is assumed to be statistically independent of the noise signal. Second, we assume that the noise is short-term stationary.

The signals received at the microphones of the left and right hearing aids contain either noise, or speech and noise. We assume that we have access to a perfect VAD algorithm. In other words, we can identify without error when there is only noise present, and when there is speech and noise present. For simplicity, let us call the time instants when there is only noise present k^n and when there is speech and noise present k^{sn}.

As mentioned earlier, ITD cues, contained in the low-frequency regions, are essential for the listener to localize sounds horizontally [4]. We consider the ITD cues for the frequency region below 1500Hz. In order to calculate the ITD between two signals, we use cross-correlation.

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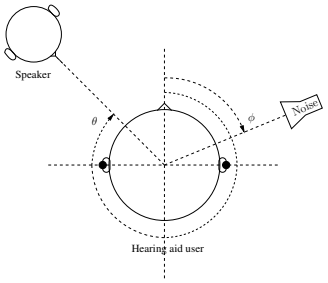


Figure 1: Typical listening scenario

3. BINAURAL MULTI-CHANNEL WIENER FILTERING

This algorithm is an extension of the multi-channel Wiener filtering technique discussed in [6]. The goal of this algorithm is to estimate the speech components of the mth microphone pair, $x_{L_m}[k]$ and $x_{R_m}[k]$, using all received microphone signals, $y_{L_{1:M}}[k]$ and $y_{R_{1:M}}[k]$. Therefore, we design two Wiener filters that estimate the noise components in the mth microphone pair, $\tilde{v}_{L_m}[k]$ and $\tilde{v}_{R_m}[k]$. To obtain the estimates of the speech components of the mth microphone pair, the estimates of the noise components are subtracted from the original signals received at the two microphones. The speech estimates are defined below.

$$z_{L_m}[k] = (x_{L_m}[k] + v_{L_m}[k]) - \tilde{v}_{L_m}[k] \tag{3}$$

$$z_{R_m}[k] = (x_{R_m}[k] + v_{R_m}[k]) - \tilde{v}_{R_m}[k] \tag{4}$$

The goal is to create a left and right multi-channel Wiener filter that minimizes the error signals, $e_{L_m}[k]$ and $e_{R_m}[k]$. See Figure 2 for a clear illustration.

Before going any further, a few definitions are necessary. We choose the filters $\mathbf{w}_{L_m}[k]$ and $\mathbf{w}_{R_m}[k]$ to be of length N. The filters are expressed in the following equations.

$$\mathbf{w}_{L_m}[k] = \left[w^0_{L_m}\ w^1_{L_m}\ \dots\ w^{N-1}_{L_m}\right]^T \tag{5}$$

$$\mathbf{w}_{R_m}[k] = \left[w^0_{R_m}\ w^1_{R_m}\ \dots\ w^{N-1}_{R_m}\right]^T \tag{6}$$

Next we create a stacked vector of the individual left and right microphone filters $\mathbf{w}_{L_m}[k]$ and $\mathbf{w}_{R_m}[k]$.

$$\mathbf{w}_L[k] = \begin{bmatrix} \mathbf{w}_{L_1}[k] \\ \mathbf{w}_{L_2}[k] \\ \vdots \\ \mathbf{w}_{L_M}[k] \end{bmatrix} \qquad \mathbf{w}_R[k] = \begin{bmatrix} \mathbf{w}_{R_1}[k] \\ \mathbf{w}_{R_2}[k] \\ \vdots \\ \mathbf{w}_{R_M}[k] \end{bmatrix} \tag{7}$$

Finally, using the above definitions we write

$$\mathbf{w}_{Left}[k] = \begin{bmatrix} \mathbf{w}_L[k] \\ \mathbf{w}_R[k] \end{bmatrix}. \tag{8}$$

The filter $\mathbf{w}_{Right}[k]$ is defined similarly. Both filters are vectors of length $2MN$. Correspondingly, we define the received microphone signals at mth microphone pair below.

$$\mathbf{y}_{L_m}[k] = [y_{L_m}[k]\ y_{L_m}[k-1]\ \dots\ y_{L_m}[k-N+1]]^T \tag{9}$$

$$\mathbf{y}_{R_m}[k] = [y_{R_m}[k]\ y_{R_m}[k-1]\ \dots\ y_{R_m}[k-N+1]]^T \tag{10}$$

We create a stacked vector of the microphone inputs.

$$\mathbf{y}_L[k] = \begin{bmatrix} \mathbf{y}_{L_1}[k] \\ \mathbf{y}_{L_2}[k] \\ \vdots \\ \mathbf{y}_{L_M}[k] \end{bmatrix} \qquad \mathbf{y}_R[k] = \begin{bmatrix} \mathbf{y}_{R_1}[k] \\ \mathbf{y}_{R_2}[k] \\ \vdots \\ \mathbf{y}_{R_M}[k] \end{bmatrix} \tag{11}$$

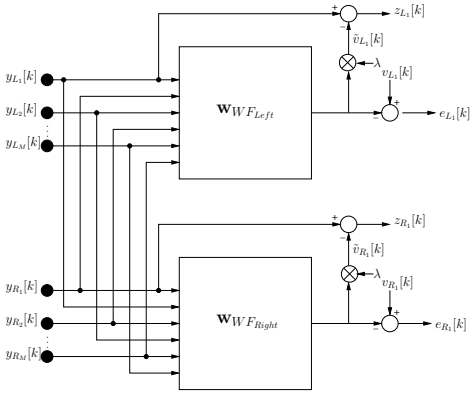


Figure 2: Binaural multi-channel Wiener filtering, $\lambda = 1$, and controlled binaural multi-channel Wiener filtering, $\lambda \in [0, 1]$

Finally, input vector $\mathbf{y}$, of length $2MN$, is defined below.

$$\mathbf{y}[k] = \begin{bmatrix} \mathbf{y}_L[k] \\ \mathbf{y}_R[k] \end{bmatrix} \tag{12}$$

First, we derive the left and right multi-channel Wiener filters in a statistical setting. Minimizing the following cost function,

$$E\left\{\left|\mathbf{y}^T[k]\,[\mathbf{w}_{Left}[k]\ \mathbf{w}_{Right}[k]] - [v_{L_m}[k]\ v_{R_m}[k]]\right|^2\right\}, \tag{13}$$

minimizes the errors of the noise estimates. In (13), $E\{\cdot\}$is the expectation operator. The filters achieving the minimum of the cost function are the well known Wiener filters expressed below.

$$\left[\mathbf{w}_{WF_{Left}}[k]\ \mathbf{w}_{WF_{Right}}[k]\right] =$$

$$E\left\{\mathbf{y}[k]\mathbf{y}^T[k]\right\}^{-1} E\left\{\mathbf{y}[k]\,[v_{L_m}[k]\ v_{R_m}[k]]\right\} \tag{14}$$

Owing to (1) and (2), we can define $\mathbf{x}[k]$ and $\mathbf{v}[k]$, where $\mathbf{y}[k] = \mathbf{x}[k] + \mathbf{v}[k]$. The first assumption, from our system model, asserts that the speech signal and the noise signal are statistically independent. More specifically $E\left\{\mathbf{x}[k]\mathbf{v}^T[k]\right\} = 0$. Using the first assumption we can rewrite (14) by making the following substitution.

$$E\left\{\mathbf{y}[k]\,[v_{L_m}[k]\ v_{R_m}[k]]\right\} = E\left\{\mathbf{v}[k]\,[v_{L_m}[k]\ v_{R_m}[k]]\right\} \tag{15}$$

Unfortunately, in real life these statistical quantities are not immediately available. Therefore we cannot calculate the left and right Wiener filters directly. Instead, we make a least squares approximation of the filters. This data based approach requires a few extra definitions. Using (12), we write the input matrix $\mathbf{Y}$, which is of size K by $2MN$.

$$\mathbf{Y}[k] = \begin{bmatrix} \mathbf{y}^T[k] \\ \mathbf{y}^T[k-1] \\ \vdots \\ \mathbf{y}^T[k-K+1] \end{bmatrix} \tag{16}$$

Analogously, the speech input matrix, $\mathbf{X}[k]$ and the noise input matrix, $\mathbf{V}[k]$, can be defined, where $\mathbf{Y}[k] = \mathbf{X}[k] + \mathbf{V}[k]$. Finally, we write the desired signals, $\mathbf{d}_L[k]$ and $\mathbf{d}_R[k]$, which are the unknown noise input vectors.

$$\mathbf{d}_L[k] = \begin{bmatrix} v_{L_m}[k] \\ v_{L_m}[k-1] \\ \vdots \\ v_{L_m}[k-K+1] \end{bmatrix} \tag{17}$$

The vector $\mathbf{d}_R[k]$ is defined similarly. We define the desired matrix $\mathbf{D}[k]$ as $[\mathbf{d}_L[k]\ \mathbf{d}_R[k]]$. We can now estimate $E\left\{\mathbf{y}[k]\mathbf{y}^T[k]\right\}$ by the matrix $\mathbf{Y}^T[k]\mathbf{Y}[k]$ (up to a scaling). In order to estimate $E\left\{\mathbf{v}[k]\left[v_{L_m}[k]\ v_{R_m}[k]\right]\right\}$ (up to the same scaling), we must use the second assumption we made in our system model; since the input noise matrix $\mathbf{V}[k]$, and therefore the desired matrix $\mathbf{D}[k]$ are not known explicitly. We assume that the noise signal is short-term stationary. Therefore, $E\left\{\mathbf{v}[k]\left[v_{L_m}[k]\ v_{R_m}[k]\right]\right\}$ is the same whether it is calculated during noise only periods, k^n, or at all time instants, k. Invoking assumption two, allows us to estimate $E\left\{\mathbf{v}[k]\left[v_{L_m}[k]\ v_{R_m}[k]\right]\right\}$ by $\mathbf{V}^T[k^n]\mathbf{D}[k^n]\}$ at time instants where only noise is present. Therefore we can write the least squares approximation of the Wiener filter as,

$$\left[\mathbf{w}_{LS_{Left}}\ \mathbf{w}_{LS_{Right}}\right] = \left(\mathbf{Y}^T[k]\mathbf{Y}[k]\right)^{-1}\mathbf{V}^T[k^n]\mathbf{D}[k^n]. \tag{18}$$

This least squares approximation of the Wiener filter is what we use in practice.

4. CONTROLLED BINAURAL MULTI-CHANNEL WIENER FILTERING

This section modifies the binaural multi-channel Wiener filtering algorithm, discussed above, by adding a parameter that controls the emphasis placed on noise reduction. As less emphasis is placed on noise reduction, some of the noise signal arrives at the output of the algorithm unprocessed; accordingly more noise ITD cues will arrive undistorted to the user.

The controlled binaural multi-channel Wiener filtering algorithm attempts to estimate the speech component and the desired amount of residual noise of the mth microphone pair. Accordingly, the Wiener filters are designed to estimate only a portion, λ, of the noise components of the mth microphone pair. Therefore, a portion of the noise signal will arrive undistorted at the output of the algorithm. The estimates of the noise signals at the mth microphone pair are $\tilde{v}_{L_m}[k]$ and $\tilde{v}_{R_m}[k]$, which estimate $\lambda v_{L_m}[k]$ and $\lambda v_{R_m}[k]$ respectively. The errors of the left and right estimates are e_{L_m} and e_{R_m}. Correspondingly the speech and residual noise estimates are be expressed below.

$$z_{L_m} = x_{L_m}[k] + (1-\lambda)v_{L_m}[k] + e_{L_m} \tag{19}$$

$$z_{R_m} = x_{R_m}[k] + (1-\lambda)v_{R_m}[k] + e_{R_m} \tag{20}$$

Figure 2 depicts the approach of this algorithm.

Using the new noise estimates, $\tilde{v}_{L_m}$ and $\tilde{v}_{R_m}$, the new cost function is defined as,

$$E\left\{\left|\mathbf{y}^T[k]\left[\mathbf{w}_{Left}[k]\ \mathbf{w}_{Right}[k]\right] - \lambda\left[v_{L_m}[k]\ v_{R_m}[k]\right]\right|^2\right\}. \tag{21}$$

Similarly, the Wiener filter that minimizes the above cost function is defined below.

$$\left[\mathbf{w}_{WF_{Left}}[k]\ \mathbf{w}_{WF_{Right}}[k]\right] =$$

$$E\left\{\mathbf{y}[k]\mathbf{y}^T[k]\right\}^{-1} E\left\{\mathbf{y}[k]\left(\lambda\left[v_{L_m}[k]\ v_{R_m}[k]\right]\right)\right\} \tag{22}$$

Again, we assume that the speech signal is statistically independent of the noise signal, and that the noise is short-term stationary. Since λ is a scalar, the least squares estimate of the Wiener filter can be written as,

$$\left[\mathbf{w}_{LS_{Left}}\ \mathbf{w}_{LS_{Right}}\right] = \lambda\left(\mathbf{Y}^T[k]\mathbf{Y}[k]\right)^{-1}\mathbf{V}^T[k^n]\mathbf{D}[k^n], \tag{23}$$

which is a scaled version of (18).

Clearly, λ controls the emphasis placed on noise reduction. If $\lambda = 1$, then the algorithm is the same is as the binaural multi-channel Wiener filtering algorithm discussed in the previous section, and the maximum amount of noise reduction is performed. On the other hand when $\lambda = 0$ no noise reduction is performed; the output signals are exactly the same as the input signals. Therefore, a value for $\lambda \in [0, 1]$ must be chosen that suits the current acoustical situation and the current user.

5. PERFORMANCE

5.1. Experimental setup

The recordings used in the following simulations were made in an anechoic room. Two CANTA behind the ear (BTE) hearing aids each with two omni-directional microphones were placed on a CORTEX MK2 artificial head. The speech and noise sources were placed one meter from the center of the artificial head. The sound level measured at the center of the artificial head was 70dB SPL. Speech and noise sources were recorded separately at a sampling frequency of 32kHz. HINT sentences and ICRA noise[1] were used for the speech and noise signals [8].

In the simulations only the front microphone signal from each hearing aid was used. The signals were 10 seconds in length. The first half of the signal consisted of noise only. A short one and a half second sentence was spoken in the second half amidst the continuous background noise.

For the simulations the speech source varied from $\theta = 0$ to 345 degrees in increments of 15 degrees. The noise source remained fixed throughout the simulations at $\phi = 90$ degrees. Figure 1 depicts this situation. For the binaural multi-channel Wiener filtering algorithm the filter length, N, was fixed at 100. The same filter length was used for the controlled binaural multi-channel Wiener filter, and the parameter λ was set at 0.7 and 0.6. The filter length of algorithm-[5] was 201. Algorithm-[5] was adapted during periods of noise only by a normalized LMS algorithm. Cut-off frequencies of $500Hz$ and $1200Hz$ were simulated.

5.2. Performance measures

The ITD of the processed and unprocessed signals are calculated. If the ITD cues of the processed and unprocessed signals match, then ITD is preserved.

The intelligibility weighted signal-to-noise-ratio (SNR_{INT}), defined in [9], is used to quantify the noise reduction performance.

$$SNR_{INT} = \sum_{j=1}^{J} w_j SNR_j \tag{24}$$

The weight, w_j, emphasizes the importance of the jth frequency band's overall contribution to intelligibility, and SNR_j is the signal-to-noise-ratio of the jth frequency band. The band definitions and the individual weights of the J frequency bands are given in [7].

5.3. Results

Using the approximate values for λ and the cut-off frequency necessary to preserve speech and noise ITD cues, simulations were run to explore the performance of the algorithms when the speech source varied from 0 to 345 degrees and the noise source remained fixed at 90 degrees. Figure 3 shows the absolute difference between the input ITD and the output ITD of the speech component and the noise component. The noise reduction performance of the algorithms can be seen in Figure 4.

Looking closely at Figure 3 we see that there is no speech ITD error (except for a few slight errors that probably arise from the ITD calculation) for the binaural multi-channel Wiener filtering

[1] ICRA 1: Unmodulated random Gaussian noise, male weighted (HP 100Hz 12dB/oct.) idealized speech spectrum [7]

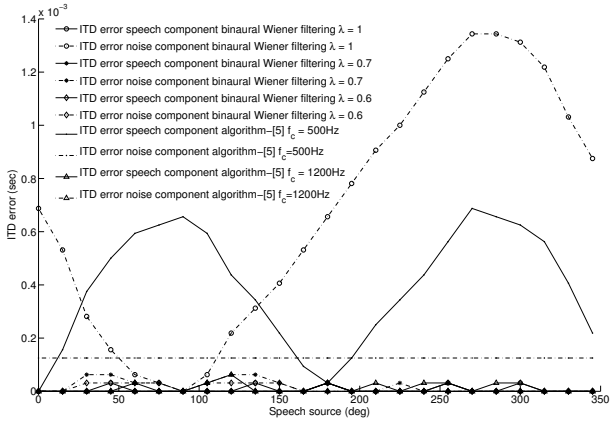


Figure 3: ITD error: the absolute difference between the input ITD and output ITD

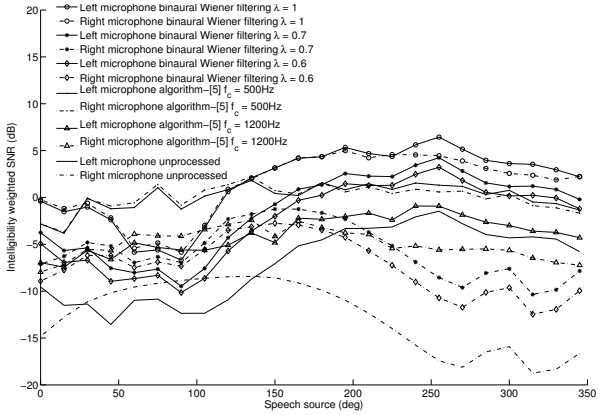


Figure 4: Intelligibility weighted SNR

algorithm. In other words, the speech ITD cues are consistently preserved. In addition, the speech ITD cues are preserved for the controlled binaural multi-channel Wiener filtering algorithm for $\lambda = 0.6$ and 0.7.

On the other hand, algorithm-[5] sacrifices noise reduction performance in order to preserve the speech ITD cues. With a cut-off frequency equal to $500Hz$, there are still large ITD errors for the speech component. In order to preserve the speech ITD cues the cut-off frequency must be increased to $1200Hz$. Such a high cut-off frequency causes poor noise reduction performance.

Despite preserving the speech ITD cues, the processing carried out by the binaural multi-channel Wiener filtering algorithm does affect the ITD cues of the noise component. The controlled binaural multi-channel Wiener filtering algorithm is designed to combat that. Clearly as λ decreases from 1 to 0.7 and again to 0.6, the error of the noise ITD also decreases. Unfortunately, this comes at a price. Looking at Figure 4, it is clear that the noise reduction performance of the algorithm also degrades as λ decreases. Similarly, as the cut-off frequency of algorithm-[5] increases, more ITD information arrives to the user undistorted. Correspondingly, the noise reduction performance of the algorithm also drops as the cut-off frequency increases.

6. CONCLUSION

In conclusion, the binaural multi-channel Wiener filtering algorithm and the controlled binaural multi-channel Wiener filtering algorithm preserve the speech ITD cues without sacrificing noise reduction performance. As discussed above, the ITD cues of the speech component are exactly the same in the processed and unprocessed signal. Therefore, the user can always localize the speech source. Conversely, algorithm-[5] sacrifices noise reduction performance in order to preserve the speech ITD cues.

Nevertheless, in order to preserve noise ITD cues some noise must arrive at the output of the algorithm unprocessed. Therefore, noise reduction performance must be sacrificed. In the controlled binaural multi-channel Wiener filtering algorithm, the parameter λ controls the amount of noise reduction performed by the algorithm; accordingly the parameter λ also controls the distortion of the noise ITD cues. Similarly, as the cut-off frequency of algorithm-[5] increases, more speech and noise ITD cues arrive undistorted to the user. Therefore, noise reduction performance decreases as the cut-off frequency increases.

If the acoustical situation and the user require a small amount of improvement in SNR_{INT}, then the parameter λ can be decreased. If λ can be sufficiently decreased, noise ITD cues will be preserved. However, if the user and acoustical situation call for a large improvement in SNR_{INT}, λ can be increased to provide the necessary improvement in noise reduction. If λ is too large, noise ITD cues may not be preserved, but speech ITD cues will always be preserved. On the other hand for algorithm-[5], the acoustical situation and the user may require an improvement in SNR_{INT} that causes both speech and noise ITD cues to be distorted. Therefore, the binaural multi-channel Wiener filtering and controlled multi-channel Wiener filtering have a clear advantage over algorithm-[5].

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