Microphone array speech enhancement based on a generalized post-filter and a novel perceptual filter

Ning Cheng, Wen-Ju Liu, Peng Li, Bo Xu

National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences
Beijing 100080, P. R. China
E-mail: ncheng@nlpr.ia.ac.cn

Abstract: The theoretic foundation of traditional microphone array post-filters is the assumption that the noise between sensors is uncorrelated. However, this assumption is inaccurate in real environments since the correlated noise exists. In this paper, a generalized microphone array post-filter is proposed to deal with both the correlated and uncorrelated noise in environments and a novel perceptual filter is proposed to reduce the musical residual noise introduced by the post-filter. Experiments show that the proposed technique produces impressive results in terms of quality measures of the enhanced speech.

Key words: Microphone array, speech enhancement, post-filter, perceptual filter

I. INTRODUCTIONS

The problem of using microphone arrays for the task of speech enhancement has received much attention in recent years. So far, a variety of speech enhancement algorithms based on microphone arrays have been proposed [1]-[5]. A recently well studied technique is the post-filter algorithm due to its good noise reduction performance. The commonly used multichannel post-filter, which is based on the Wiener filter, was first introduced by Zelinski [1]. Based on the work of Zelinski, Marro et al. [2] suggested using the auto- and cross-power spectrums of the array inputs to estimate the post-filter transfer function. In this paper, this technique is referred to as the Zelinski post-filter. McCowan [3] provides a more general expression of the post-filter estimation based on a known noise field coherence function.

One problem of the traditional post-filter technique (the Zelinski post-filter) is that it is based on the signal model in which the noise on different channels is assumed to be uncorrelated. In another word, the Zelinski post-filter just considers the uncorrelated noise. However, in real environments, not only the uncorrelated noise exists but also the correlated noise exists.

In this paper, to deal with the problem of suppressing noise in arbitrary environments, we first propose a generalized post-filter based on a comprehensive signal model including both the correlated and uncorrelated noise. Then, a novel perceptual filter is proposed to reduce the musical residual noise introduced by the post-filter. The proposed method gives a superior performance as compared to the conventional post-filter algorithms.

II. THEORETICAL FRAMEWORK

In Figure 1, a linearly and equidistantly distributed microphone array in a noisy environment is considered. A generalized signal model is assumed in which the observed signals consist of three components. The first is the target speech signal coming from a direction. The second is the localized noise arriving from another direction and the third is the non-localized noise, propagating in all directions simultaneously. Obviously, the localized noise is correlated between sensors and the non-localized noise is assumed to be uncorrelated between sensors.

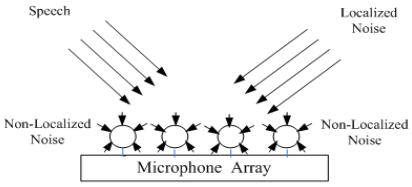


Fig.1 The signals imposing on the microphone array.

In Fig.1, the observed signal imposing on the microphone array can be given in the frequency domain as:

$$X = S \cdot d + N \tag{1}$$

$$N = M + V \tag{2}$$

where $X = [X_1, \cdots, X_L]^T$ is the noisy signal vector received by the microphone array, S is the target signal, $d = [d_1, \cdots, d_L]^T$ is the propagation vector of the signal source , $N = [N_1, \cdots, N_L]^T$ is the noise vector, $M = [M_1, \cdots, M_L]^T$ is the localized noise vector , $V = [V_1, \cdots, V_L]^T$ is the non-localized noise vector and L is the number of sensors.

Simmer et al. [4] give the demonstration of expressing the optimal broadband Minimum Mean Square Error (MMSE) filter solution as a classical Minimum Variance Distortionless Response (MVDR) beamformer followed by a single-channel Wiener filter, which is:

$$w_{opt} = \left[\frac{\phi_{SS}}{\phi_{SS} + \phi_{NN}} \right] \frac{\Phi_{NN}^{-1} d}{d^H \Phi_{NN}^{-1} d} \tag{3}$$

where w_{opt} is the optimal filter coefficients vector, ϕ_{SS} and ϕ_{NN} are respectively the (single-channel) target signal and noise auto-power spectrum vectors, and Φ_{NN} is the (multichannel) noise cross-spectral density matrix. The bracketed item in the expression (3) is the single-channel Wiener filter part and the remaining item is the well known solution for the MVDR beamformer [5].

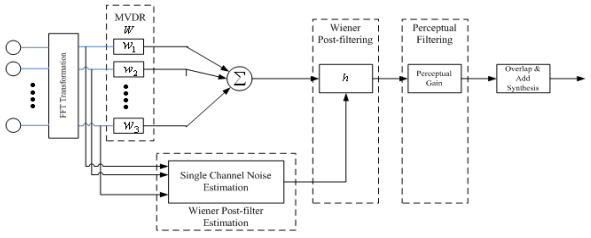


Fig.2 Diagram of the multichannel system.

978-1-4244-2179-4/08/$25.00 ©2008 IEEE

According to (3), a multichannel speech enhancement system is constructed as shown in Fig.2, which mainly consists of three parts: the MVDR beamformer to maximize the directivity of the array response, the Wiener post-filter estimator to estimate the post-filter transfer function and the post-filtering part to further enhance the beamformer output. In addition, to reduce the musical residual noise made by the post-filter, we add a perceptual filter part in the system.

III. A GENERALIZED POST-FILTER

In this section, we focus on solving the problem of estimating the post-filter term in the expression (3) which is:

$$h = \left[\frac{\phi_{SS}}{\phi_{SS} + \phi_{NN}} \right]. \tag{4}$$

Under the noise field assumptions that:

1) The target signal and noise are uncorrelated.
2) The noise power spectrum is the same on all sensors.
3) The noise is uncorrelated between sensors.

The Zelinski post-filter is given as follows:

$$\hat{h} = \frac{\frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} \Re\{\phi_{X_i X_j}\}}{\frac{1}{L} \sum_{i=1}^{L} \phi_{X_i X_i}} \tag{5}$$

where $\Re\{\bullet\}$ is the real operator and L is the number of the microphone array sensors.

However, above assumptions are inaccurate in real environments since the localized noise is correlated between sensors.

Considering the practical situations, following assumptions are adopted for our comprehensive signal model:

1) The target speech signal, the localized noise and the non-localized noise are uncorrelated with each other ($\phi_{S_i M_j} = 0$, $\phi_{S_i V_j} = 0$, $\phi_{M_i V_j} = 0$, $\forall i, j$).
2) The noise power spectrum is the same on all sensors ($\phi_{M_i M_i} = \phi_{MM}, \phi_{V_i V_i} = \phi_{VV}, \forall i$).
3) The localized noise is correlated between sensors $(\phi_{M_i M_j} = \phi_{MM}, \forall i, j)$ and the non-localized noise is uncorrelated between sensors $(\phi_{V_i V_j} = 0, \forall i \neq j)$.

Under these assumptions, the post-filter term (4) can be rewritten as:

$$h = \frac{\phi_{SS}}{\phi_{SS} + \phi_{MM} + \phi_{VV}}. \tag{6}$$

Calculating the auto- and cross-power spectrums of the aligned signals on channels i and j, leads to:

$$\begin{aligned} \phi_{X_i X_i} &= \phi_{S_i S_i} + \phi_{M_i M_i} + \phi_{V_i V_i} + 2\Re\{\phi_{S_i M_i} + \phi_{S_i V_i} + \phi_{M_i V_i}\} \\ &= \phi_{SS} + \phi_{MM} + \phi_{VV} \end{aligned} \tag{7}$$

$$\begin{aligned} \phi_{X_i X_j} &= \phi_{S_i S_j} + \phi_{M_i M_j} + \phi_{V_i V_j} \\ &\quad + \phi_{S_i M_j} + \phi_{S_i V_j} + \phi_{M_i S_j} + \phi_{M_i V_j} + \phi_{V_i S_j} + \phi_{V_i M_j} \\ &= \phi_{SS} + \phi_{MM}. \end{aligned} \tag{8}$$

Obviously, the expression (5) is not the accurate estimation of the expression (6) because under the adopted assumptions, $\frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} \Re\{\phi_{X_i X_j}\}$ is not the estimate of ϕ_{SS}, but the estimate of $\phi_{SS} + \phi_{MM}$. An accurate expression of ϕ_{SS} is needed to estimate the expression (6). According to (7) and (8), two estimates are given as follows:

$$\phi_{SS} + \phi_{MM} = \frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} \Re\{\phi_{X_i X_j}\} \tag{9}$$

$$\phi_{SS} + \phi_{MM} + \phi_{VV} = \frac{1}{L} \sum_{i=1}^{L} \phi_{X_i X_i}. \tag{10}$$

ϕ_{SS} can be obtained if the noise power spectrum $\phi_{MM} + \phi_{VV}$ is available. We estimate the noise in each single channel. The computation of the auto- and cross-power spectrums of the noise on channels i and j, results to:

$$\begin{aligned} \phi_{N_i N_i} &= \phi_{M_i M_i} + \phi_{V_i V_i} + 2\Re\{\phi_{M_i V_i}\} \\ &= \phi_{MM} + \phi_{VV} \end{aligned} \tag{11}$$

$$\begin{aligned} \phi_{N_i N_j} &= \phi_{M_i M_j} + \phi_{M_i V_j} + \phi_{V_i M_j} + \phi_{V_i V_j} \\ &= \phi_{MM}. \end{aligned} \tag{12}$$

According to (11), $\phi_{MM} + \phi_{VV}$ can be estimated as follows:

$$\phi_{MM} + \phi_{VV} = \frac{1}{L} \sum_{i=1}^{L} \phi_{N_i N_i}. \tag{13}$$

Combining (10) and (13), we have:

$$\phi_{SS} = \frac{1}{L} \left(\sum_{i=1}^{L} \phi_{X_i X_i} - \sum_{i=1}^{L} \phi_{N_i N_i} \right). \tag{14}$$

According to (10) and (14), an estimate of the expression (6) is obtained as follows:

$$\begin{aligned} \hat{h} &= \frac{\phi_{SS}}{\phi_{SS} + \phi_{MM} + \phi_{VV}} \\ &= \frac{\frac{1}{L} \left(\sum_{i=1}^{L} \phi_{X_i X_i} - \sum_{i=1}^{L} \phi_{N_i N_i} \right)}{\frac{1}{L} \sum_{i=1}^{L} \phi_{X_i X_i}}. \end{aligned} \tag{15}$$

IV. A NOVEL PERCEPTUAL FILTER

While reducing the background noise, the post-filter inevitably introduces some musical residual noise which makes the signal perceptual quality bad. In this section, a novel perceptual filter is proposed to reduce the residual noise. This perceptual filter is based on the human auditory masking phenomenon which can be explained by the so called critical bands. Within one critical band, one sound (the maskee) becomes inaudible in the presence of another sound (the masker) with a higher intensity. The human auditory frequency range spreads from 0 to 15500 Hz and covers approximately 24 critical bands [6].

First, we need to compute the subband energy $E(k)$:

$$E(k) = \sum_{b(k)} \left| \tilde{S}(e^{j\omega}) \right|^2 \tag{16}$$

where $\tilde{S}(e^{j\omega})$ is the post-filter output, $b(k)$ is the frequency index depending on the lower and upper frequency boundary of the critical band k, $k = 1, \cdots, K$ and K is the critical band number which is decided by the actual frequency range of the data.

An excitation pattern $C(k)$ can be regarded as an energy

distribution along the basilar membrane. It can be calculated by convolving the subband energy $E(k)$ with a spreading function $SF(k)$:

$$C(k) = SF(k) * E(k). \quad (17)$$

An analytical expression for the spreading function is given by [7]:

$$SF(k) = 15.81 + 7.5(k + 0.474) - 17.5\sqrt{1 + (k + 0.474)^2}. \quad (18)$$

The noise masking threshold (NMT) $T(k)$ is obtained as follows:

$$T(k) = 10^{\log_{10}|C(k)| - |O(k)/10|} \quad (19)$$

where $O(k)$ is a relative threshold offset indicating whether a frame is tone-like or noise-like [8].

The estimate of the target signal $\hat{S}(e^{j\omega})$ is expressed as:

$$\hat{S}(e^{j\omega}) = G(e^{j\omega})\widetilde{S}(e^{j\omega}) \quad (20)$$

where $G(e^{j\omega})$ is the perceptual gain function and $\widetilde{S}(e^{j\omega})$ is the post-filter output.

The error item is defined as the difference between the clean signal and the estimated (enhanced) signal, which is:

$$\begin{aligned} E(e^{j\omega}) &= \hat{S}(e^{j\omega}) - S(e^{j\omega}) \\ &= G(e^{j\omega})\widetilde{S}(e^{j\omega}) - S(e^{j\omega}) \\ &= [G(e^{j\omega}) - 1]S(e^{j\omega}) + G(e^{j\omega})\widetilde{N}(e^{j\omega}) \end{aligned} \quad (21)$$

where $S(e^{j\omega})$ is the clean signal, $\hat{S}(e^{j\omega})$ is the estimated signal and $\widetilde{N}(e^{j\omega})$ is the musical residual noise.

The first term in equation (21) describes the speech distortion which can be minimized if the perceptual gain function $G(e^{j\omega}) = 1$. The second term describes the noise distortion which can be minimized by $G(e^{j\omega}) = 0$. A perceptual function $G(e^{j\omega})$ can be computed to make the noise or speech distortions fall below the masking threshold. This paper chooses the perceptual gain function to minimize the noise distortion and a variable speech distortion is allowed. Therefore, the perceptual gain function G is chosen to satisfy the following criterion:

$$|G(e^{j\omega})|^2 |\widetilde{N}(e^{j\omega})|^2 \leq |T| \quad (22)$$

where T is the NMT estimated in the expression (19).
An analytical expression of the psychoacoustically motivated gain function is proposed in the following form:

$$G(e^{j\omega}) = \sqrt{|T| / |\widetilde{N}(e^{j\omega})|^2}. \quad (23)$$

V. EXPERIMENTS AND RESULTS

The CMU microphone array database [9] is used for the experiments. The recordings were collected in a computer lab by a linear microphone array with eight sensors spaced 7 cm apart, at a sampling rate of 16 kHz. The array was placed on a desk and the speaker was seated directly in front of it at a distance of 1 m from its center. The room had multiple noise sources, including several computer fans and overhead air blowers. The corpus consists of 130 utterances, 10 speakers of 13 utterances each. The time aligned noisy inputs of the array are divided in time into frames of 25ms with overlap of 15ms between adjacent frames. At each frame a Hamming window is applied and a STFT analysis takes place. The critical band number is $K = 21$. The single channel noise is estimated as in [8].

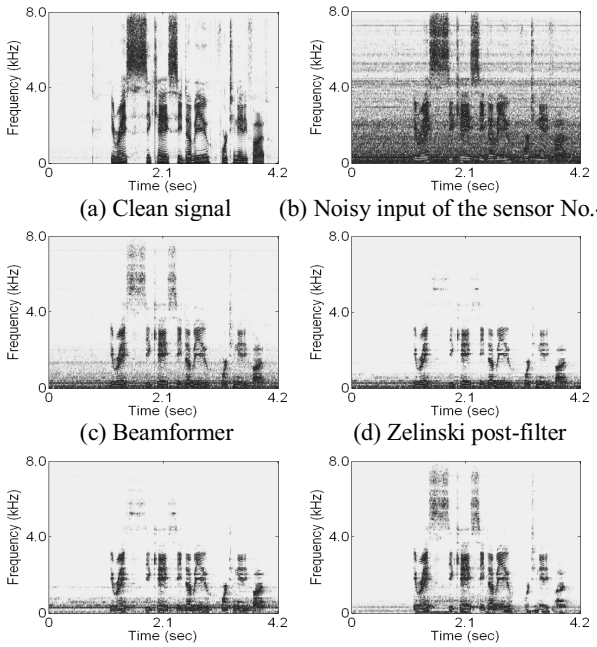
The adopted evaluation criteria are the segmental signal-to-noise ratio enhancement (SSNRE), the Log-spectral distance (LSD), and the Log-area ratio (LAR) [3][10]. High values of the SSNRE and low values of the LSD and LAR denote high speech quality.

Table 1: Experiment results on the CMU database

	Input	Beamformer	Zelinski	McCowan	Prop1	Prop2
SSNRE(dB):	-	0.33	1.08	5.07	6.90	9.41
LSD:	7.07	6.63	6.78	5.78	5.45	5.21
LAR:	8.70	11.24	15.03	11.31	10.08	8.87

Table 1 displays the average experiment results. The "Input" corresponds to the average value of the array inputs. The "Prop1" and "Prop2" correspond to the outputs of the proposed post-filter (15) and perceptual filter (23), respectively. Namely the relative % average improvements achieved compared to the best of the reference approaches were 85.6% in SSNRE, 9.9% in LSD and 21.1% in LAR.

Figure 3 shows the spectrograms of the clean speech, the noisy input and the enhanced speech of all the test algorithms for an utterance corresponding to the string of "erisckcw1485" for comparison.



(a) Clean signal (b) Noisy input of the sensor No.4

(c) Beamformer (d) Zelinski post-filter

(e) McCowan post-filter (g) Proposed algorithm

Fig.3 Spectrograms for the utterance of "erisckcw1485".

From Fig.3, we note that the competing algorithms are incapable of removing the noise. For the MVDR beamformer, this inadequacy is attributed to the fact that the beamformer has a low directivity factor in the low frequency region where the noise between sensors is significantly correlated. The poor performance of the Zelinski post-filter is due to the reason that this method is based on the assumption of a spatially uncorrelated field. For the McCowan post-filter, the differences between the assumed and actual coherence functions result in its performance significant degradation. Compared with these algorithms, the proposed technique reduces more noise and gets better enhanced speech since it considers the correlated noise in

the post-filter estimation process and the perceptual filter indeed helps the residual noise shaping.

VI. CONCLUSIONS

This paper has presented an effective microphone array speech enhancement approach. First, a generalized post-filter is formulated to handle a comprehensive noise field including both the correlated and uncorrelated noise. Then, a novel perceptual filter is proposed to reduce the musical residual noise made by the post-filter. Experiment results show that the proposed technique gives significant improvement over the existing array algorithms in terms of objective speech quality measures.

ACKNOWLEDGEMENT

This work was supported in part by the China National Nature Science Foundation (No. 60675026, No. 60121302), 863 China National High Technology Development Project (No.20060101Z4073, No.2006AA01Z194) and the National Grand Fundamental Research 973 Program of China (No. 2004CB318105).

REFERENCES

[1] R. Zelinski, "A microphone array with adaptive post-filtering for noise reduction in reverberant rooms," in Proc. of ICASSP-88, Vol. 5, pp. 2578–2581, 1988.

[2] C.Claude Marro, Y.Yannick Mahieux, and K. U.K. Uwe Simmer, "Analysis of noise reduction and dereverberation techniques based on microphone arrays with postfiltering," IEEE Trans. Speech Audio Process., Vol. 6, pp. 240–259, May 1998.

[3] Iain A. McCowan, Hervé Bourlard, "Microphone array post-filter based on noise field coherence", IEEE Trans. Speech Audio Process., Vol.11, pp.709-715, Nov. 2003.

[4] K. Uwe Simmer, et al, "Post-filtering techniques," in Microphone Arrays, M. Brandstein and D.Ward, Eds. New York: Springer, ch. 3, pp. 36–60, 2001.

[5] H. Cox, R. Zeskind, and M. Owen, "Robust adaptive beamforming," IEEE Trans. Acoust., Speech, Signal Process., Vol. 35, pp. 1365–1376, Oct. 1987.

[6] E.Zwicker and E.Terhardt, "Analytical expressions for critical-band rate and critical bandwidth as a function of frequency," JASA, Vol.68, no.5, pp.1523-1525, 1980.

[7] M. R. Schroeder, B. S. Atal and J. L. Hall, "Optimizing digital speech coders by exploiting masking properties of the human ear," Journal of the Acoustical society of America, Vol 66, no. 6, pp. 1647 – 1652, 1979.

[8] Virag, N., 1999. Single channel speech enhancement based on masking properties of the human auditory system. IEEE Trans. Speech Audio Process. 7 (2), 126 – 137.

[9] Sullivan, T., 1996. CMU microphone array database. http://www.speech.cs.cmu.edu/databases/micarray

[10] Hansen, J.H.L., Pellom, B.L., "An effective quality evaluation protocol for speech enhancement algorithms." ICSLP, pp. 2819 – 2822, 1998.