MULTICHANNEL SPEECH DEREVERBERATION AND SEPARATION WITH OPTIMIZED COMBINATION OF LINEAR AND NON-LINEAR FILTERING

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ABSTRACT

In this paper, we propose a multichannel speech dereverberation and separation technique which is effective even when there are multiple speakers and each speaker's transfer function is time-varying due to fluctuation of the corresponding speaker's head. For robustness against fluctuation, the proposed method optimizes linear filtering with non-linear filtering simultaneously from probabilistic perspective based on a probabilistic reverberant transfer-function model, **PRTFM**. PRTFM is an extension of the conventional time-invariant transfer-function model under uncertain conditions, and PRTFM can be also regarded as an extension of recently proposed blind local Gaussian modeling. The linear filtering and the non-linear filtering are optimized in MMSE (Minimum Mean Square Error) sense during parameter optimization. The proposed method is evaluated in a reverberant meeting room, and the proposed method is shown to be effective.

Index Terms— Dereverberation, Local Gaussian modeling, Multichannel Wiener filter, Speech separation

1. INTRODUCTION

Dereverberation techniques are greatly required for communication systems such as TV conferencing systems in larger meeting rooms, because audio quality becomes severer in larger rooms due to reverberation. MINT theorem [1] is a major dereverberation technique with multiple microphones under the condition that the acoustic transfer functions between speech sources and microphones are known. However, the acoustic transfer functions cannot be obtained in advance. Therefore, many blind dereverberation techniques have been studied [2][3][4][5][6]. One way to reduce reverberation of microphone input signal is the MINT inverse filtering by using the estimated transfer function under time-invariant assumption of the transfer function. However, this way is not good in communication systems which use distant microphones such as TV conferencing systems because the transfer function between a speech source and a microphone easily fluctuates due to movement of human head, human body, and so on. To avoid performance-degradation in time-variant cases, dereverberation techniques which utilize non-linear filtering techniques such as spectral subtraction [2][3] have been proposed. These non-linear filtering techniques are robust against fluctuation of the transfer function at the expense of speech distortion. However, when fluctuation of the transfer function is small, the inverse filtering is better than the non-linear filtering. Therefore, case-bycase optimization for the non-linear filtering and the inverse-filtering separately is one of practical issues.

In this paper, we propose a simultaneous optimization technique of the non-linear filtering and the inverse-filtering from a probabilistic perspective. Instead of the conventional time-invariant model, we propose a novel probabilistic model for time-varying transfer function, namely probabilistic reverberant transfer function model (PRTFM). The optimization scheme under PRTFM is based on the semi-blind local Gaussian modeling proposed by one of authors [8]. In the proposed method, the inverse filtering and the non-linear filtering are optimized in MMSE (Minimum Mean Square Error) sense. In addition to dereverberation, separation of multiple speakers can be performed in the proposed method under the same framework. By evaluating the proposed method in a real meeting room, the proposed method is shown to be effective.

2. PROBLEM STATEMENT

2.1. Microphone Input Signal Model

In this paper, dereverberation is performed at time-frequency domain with multiple microphones. The number of microphones is M. The input signal is modeled in the time-frequency domain as follows:

$$\boldsymbol{x}_{f,\tau} = \sum_{n=1}^{N} \sum_{l=0}^{L-1} s_{n,f,\tau-l} \boldsymbol{a}_{n,f,\tau,l}, \qquad (1)$$

where f is frequency index, τ is frame index, L is the length of the acoustic transfer function, N is the number of speech sources, $s_{n,f,\tau}$ is the *n*-th source signal, and $a_{n,f,\tau,l}$ is the time-varying acoustic transfer function of the *l*-th tap between the *n*-th source and microphones. The input signal is divided into the dereverberated part and the late reverberation part as follows:

$$\boldsymbol{x}_{f,\tau} = \sum_{l=0}^{D-1} \boldsymbol{A}_{f,\tau,l} \boldsymbol{S}_{f,\tau-l} + \sum_{l=D}^{L-1} \boldsymbol{A}_{f,\tau,l} \boldsymbol{S}_{f,\tau-l}, \qquad (2)$$

where *D* is the step length, $A_{f,\tau,l} = \begin{bmatrix} a_{1,f,\tau,l} & \dots & a_{N,f,\tau,l} \end{bmatrix}$, and $S_{f,\tau} = \begin{bmatrix} s_{1,f,\tau} & \dots & s_{N,f,\tau} \end{bmatrix}^T (T$ is the operator for transpose of a matrix/vector). The first term includes the direct path and the early reverberation. The second term includes the late reverberation. The early reverberation does not have harmful effects for human audition. Therefore, the first term of Eq. 2 is defined as the dereverberated part, and goal is defined as extraction of each source signal in the first term from only the microphone input signal.

2.2. Dereverberation techniques based on time-invariant transferfunction model

In the conventional methods, dereverberation is performed based on the MINT theorem [1] under time-invariant assumption for the acoustic transfer function. When $a_{n,f,\tau,l}$ is time-invariant, the microphone input signal $x_{f,\tau}$ can be converted into the following equation [2][4]:

$$\boldsymbol{x}_{f,\tau} = \sum_{l=0}^{D-1} \boldsymbol{A}_{f,l} \boldsymbol{S}_{f,\tau-l} + \sum_{l=D}^{L_3-1} \boldsymbol{W}_{f,l} \boldsymbol{x}_{f,\tau-l}, \quad (3)$$

where $L_3 = L_2 + L - 1$, L_2 is the tap-length of the inverse filter of the acoustic transfer function, and $W_{f,l}$ is a prediction filter from $x_{f,\tau-l}$ to $x_{f,\tau}$. A reasonable way of parameter estimation is the maximum likelihood approach under the assumption that the probabilistic distribution of the microphone input signal is Gaussian distribution such as [4]. The log-likelihood function \mathcal{L} for each frequency bin is defined as follows:

$$\mathcal{L} = \frac{-1}{2} \{ \sum_{\tau=1}^{L_T} (\boldsymbol{x}_{f,\tau} - \boldsymbol{\mu}_{x,f,\tau})^H \boldsymbol{V}_{x,f,\tau}^{-1} (\boldsymbol{x}_{f,\tau} - \boldsymbol{\mu}_{x,f,\tau}) + \log |\boldsymbol{V}_{x,f,\tau}| \},$$
(4)

where L_T is the number of the frames, H is the operator for the Hermite transpose of a matrix/vector, $\mu_{x,f,\tau}$ is the mean value of $x_{f,\tau}$, and $V_{x,f,\tau}$ is the covariance matrix of $x_{f,\tau}$. $\mu_{x,f,\tau}$ and $V_{x,f,\tau}$ are modeled under time-invariant assumption of the acoustic transfer function as follows:

$$\mu_{x,f,\tau} = \sum_{l=D}^{L_3-1} W_{f,l} x_{f,\tau-l}, \qquad (5)$$

$$V_{x,f,\tau} = \sum_{n=1}^{N} |s_{n,f,\tau}|^2 a_{n,f} a_{n,f}^H.$$
 (6)

The model parameters are estimated based on an iterative method, and separation of each source can be performed simultaneously [4]. However, when the time-invariant assumption is not valid, reverberation cannot be reduced sufficiently by the conventional MINT based dereverberation techniques. We extend the conventional method under the assumption that the acoustic transfer function is time-varying.

3. PROBABILISTIC REVERBERANT TRANSFER-FUNCTION MODEL (PRTFM)

For dereverberation and separation under the condition that the acoustic transfer function is time-varying, we propose a probabilistic reverberant transfer-function model (PRTFM). In this section, the probabilistic density function of the microphone input signal in the proposed PRTFM is derived under the time-varying assumption of the acoustic transfer function.

At first, a new autoregressive model with the time-varying acoustic transfer function is derived. The time-varying acoustic transfer function $A_{f,\tau,l}$ is modeled as $A_{f,\tau,l} = \hat{A}_{f,l} + \Delta_{A_{f,\tau,l}}$, where $\hat{A}_{f,l}$ is the time-invariant part and the second term is the fluctuation part. When there is no common zero in $\hat{A}_{f,l}$, the MINT inverse filter for $\hat{A}_{f,l}$ exists. The MINT inverse filter for $\hat{A}_{f,l}$ exists. The MINT inverse filter for $\hat{A}_{f,l}$ is set to be $\hat{B}_{f,k}$. By multiplying the microphone input signal by the MINT inverse filter, we can obtain the following equation:

$$S_{f,\tau} = \sum_{k=0}^{L_2 - 1} B_{f,k} x_{f,\tau-k} - \sum_{k=0}^{L_2 - 1} B_{f,k} \sum_{l=0}^{L-1} \Delta_{A_{f,\tau-k,l}} S_{f,\tau-k-l}.$$
(7)

By substituting $S_{f,\tau}$ in the second term of Eq. 2, a new autoregressive model for the microphone input signal can be obtained as follows:

$$\boldsymbol{x}_{f,\tau} = \sum_{l=0}^{D-1} \boldsymbol{A}_{f,\tau,l} \boldsymbol{S}_{f,\tau-l} + \sum_{l=D}^{2L_3-2} \boldsymbol{W}_{f,\tau,l} \boldsymbol{x}_{f,\tau-l} + \boldsymbol{\epsilon}_{f,\tau}, \quad (8)$$

where $\epsilon_{f,\tau}$ is the residual-error term, and this term can be neglected when fluctuation $\Delta_{A_{f,\tau,l}}$ is sufficiently small. We regard $W_{f,\tau,l}$ as a probabilistic prediction matrix for the late reverberation. Eq. 8 is a natural extension of the conventional autoregressive model (Eq. 3) under the time-varying assumption.

Secondly, the probabilistic density function of the microphone input signal is derived. When the expected value of the fluctuation $\Delta_{A_{f,\tau,l}}$ is **0**, the expected value of $W_{f,\tau,l}$, $E[W_{f,\tau,l}]$ (*E* is the operator for the mathematical expectation), is equivalent to the time-invariant prediction filter $W_{f,l}$ in Eq. 3. Mean value :

$$\boldsymbol{\mu}_{x,f,\tau} = \sum_{l=D}^{2L_3-2} \boldsymbol{W}_{f,l} \boldsymbol{x}_{f,\tau-l}.$$
(9)

For the covariance matrix modeling, we assume that fluctuation of the probabilistic prediction matrix $W_{f,\tau,l}$ is stationary and mutually independent for l, and each column vector of $W_{f,\tau,l}$, $W_{f,\tau,l,m}$, is mutually independent for m. In consideration of non-stationary nature of speech sources, the covariance matrix of each speech source can be modeled by the local Gaussian modeling [7] as follows:

$$\boldsymbol{E}[\sum_{l=0}^{D-1} |s_{n,f,\tau-l}|^2 \boldsymbol{a}_{n,f,\tau,l} \boldsymbol{a}_{n,f,\tau,l}^H] = v_{n,f,\tau} \boldsymbol{R}_{n,f}, \quad (10)$$

where $v_{n,f,\tau} = E[\sum_{l=0}^{D-1} |s_{n,f,\tau-l}|^2]$ and $\mathbf{R}_{n,f}$ is the full-rank covariance matrix of each source and defined as $\sum_{l=0}^{D-1} E[\mathbf{a}_{n,f,\tau,l}\mathbf{a}_{n,f,\tau,l}^H]$. The covariance matrix of the microphone input signal is modeled as follows:

Covariance matrix :

$$V_{x,f,\tau} = \sum_{n=1}^{N} v_{n,f,\tau} \mathbf{R}_{n,f} + \sum_{l=D}^{2L_3-2} \sum_{m=1}^{M} |x_{f,\tau-l,m}|^2 \mathbf{G}_{l,m}, \quad (11)$$

where $G_{l,m}$ is the stationary covariance matrix of $W_{f,\tau,l,m}$.

Under the PRTFM, the mean value of the microphone input signal is corresponding with the reverberation term which can be reduced by the inverse filtering. By comparing Eq. 11 and Eq. 6, it can be shown that $\sum_{l=D}^{2L_3-2} \sum_{m=1}^{M} |x_{f,\tau-l,m}|^2 G_{l,m}$ is added in the proposed model. This term is corresponding with the covariance matrix of the residual reverberation which is time-variant and cannot be reduced by the inverse filtering. In the proposed method, the residual reverberation is reduced by the multichannel Wiener filter in MMSE sense, which is a multichannel extension of a single-channel non-linear filtering. Therefore, the inverse filtering and the non-linear filtering are optimized simultaneously, and all parameters of the PRTFM can be optimized under the same likelihood function.

4. PROPOSED OPTIMIZATION SCHEME UNDER PRTFM

The optimization of parameters under the proposed PRTFM can be performed efficiently by using EM algorithm [9]. This optimization scheme is based on the semi-blind local Gaussian modeling proposed by one of authors for echo reduction problems [8]. In the Estep (the t-th iteration), the sufficient statistics for the latent variables are



Fig. 1. Experimental environment: Impulse responses were recorded by setting a loudspeaker at position "1", "2", and "3".

estimated by the following step: At first, the estimated dereverberated signal, $\boldsymbol{x}_{\text{derev},f,\tau} = \boldsymbol{x}_{f,\tau} - \sum_{l=D}^{2L_3-2} \boldsymbol{W}_{f,l}^{(t)} \boldsymbol{x}_{f,\tau-l}$, is calculated.

$$\boldsymbol{R}_{x,f,\tau} = \sum_{n=1}^{N} \boldsymbol{R}_{\boldsymbol{c}_n,f,\tau} + \sum_{l=1}^{2L_3-2} \sum_{n=1}^{M} \boldsymbol{R}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau}, \quad (12)$$

where $\mathbf{R}_{\mathbf{c}_{n},f,\tau} = v_{n,f,\tau}^{(t)} \mathbf{R}_{n,f}^{(t)}, \mathbf{R}_{\mathbf{c}_{\mathrm{rev},l,m},f,\tau} = |x_{f,\tau-l,m}|^2 \mathbf{G}_{l,m}^{(t)}.$

$$\hat{\boldsymbol{R}}_{\boldsymbol{c}_{n},f,\tau} = \boldsymbol{W}_{\boldsymbol{c}_{n},f,\tau} \boldsymbol{x}_{\text{derev},f,\tau} \boldsymbol{x}_{\text{derev},f,\tau}^{H} \boldsymbol{W}_{\boldsymbol{c}_{n},f,\tau}^{H} \\
+ (\boldsymbol{I} - \boldsymbol{W}_{\boldsymbol{c}_{n},f,\tau}) \boldsymbol{R}_{\boldsymbol{c}_{n},f,\tau},$$
(13)

$$\hat{\boldsymbol{R}}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau} = \boldsymbol{W}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau} \boldsymbol{x}_{\text{derev},f,\tau} \boldsymbol{x}_{\text{derev},f,\tau}^{H} \boldsymbol{W}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau}^{H}
+ (\boldsymbol{I} - \boldsymbol{W}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau}) \boldsymbol{R}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau}, \quad (14)$$

where $W_{\mathbf{c}_n,f,\tau} = \mathbf{R}_{\mathbf{c}_n,f,\tau} \mathbf{R}_{x,f,\tau}^{-1}$, $W_{\mathbf{c}_{\text{rev},l,m},f,\tau} = \mathbf{R}_{\mathbf{c}_{\text{rev},l,m},f,\tau} \mathbf{R}_{x,f,\tau}^{-1}$ In the M step, the parameters of the PRTFM can be updated so as to increase Q function as follows:

$$v_{n,f,\tau}^{(t+1)} = \frac{1}{M} \operatorname{tr}\{(\boldsymbol{R}_{n,f}^{(t)})^{-1} \hat{\boldsymbol{R}}_{\boldsymbol{c}_{n},f,\tau}\},$$
 (15)

$$\boldsymbol{R}_{n,f}^{(t+1)} = \frac{1}{L_T} \sum_{\tau=1}^{L_T} \frac{\hat{\boldsymbol{R}}_{\boldsymbol{c}_n,f,\tau}}{v_{n,f,\tau}^{(t+1)}},$$
(16)

$$\boldsymbol{G}_{l,m}^{(t+1)} = \frac{1}{L_T} \sum_{\tau=1}^{L_T} \frac{\hat{\boldsymbol{R}}_{\boldsymbol{c}_{\text{rev},l,m},f,\tau}}{|\boldsymbol{x}_{f,\tau-l,m}|^2}, \qquad (17)$$

$$\operatorname{vec}(\mathcal{W}_{f}^{(t+1)}) = \boldsymbol{P}^{-1}\operatorname{vec}\left(\sum_{\tau=1}^{L_{T}} \boldsymbol{R}_{x,f,\tau}^{-1} \boldsymbol{x}_{f,\tau} \boldsymbol{X}_{f,\tau}^{H}\right), \quad (18)$$

where $\boldsymbol{P} = \left(\sum_{\tau=1}^{L_T} (\boldsymbol{X}_{f,\tau} \boldsymbol{X}_{f,\tau}^H)^T \otimes \boldsymbol{R}_{x,f,\tau}^{-1}\right)$, \otimes is the operator for the Kronecker-delta multiplication of matrix, $\boldsymbol{X}_{f,\tau} = [\boldsymbol{x}_{f,\tau-D}^H \dots \boldsymbol{x}_{f,\tau-2L_3+2}^H]^H$, vec is the operator for convertion of a matrix to a vector [10], and $\mathcal{W}_f^{(t+1)} = [\boldsymbol{W}_{f,D}^{(t+1)} \dots \boldsymbol{W}_{f,2L_3-2}^{(t+1)}]$.

5. EVALUATION

The proposed method is evaluated by dereverberation experiments with simulated signals convolved with recorded impulse responses. Two dry sources were used. One was a male speech, and another was a female speech. Impulse responses were recorded at a real meeting room which is shown in Fig. 1. The impulse responses were recorded by setting a loudspeaker at position "1", "2", and "3". The reverberation time RT_{60} was 430 [ms]. The experimental conditions are shown in Table 1. The evaluation measures are

 Table 1. Experimental conditions

Sampling rate	16000 [Hz]
Frame size	1024 [pt]
Frame shift	256 [pt]
Number of microphones	4
Number of speech sources	1 or 2
Length of dry source signal	about 5 [sec]
D	2 [tap]
L_3	6 [tap]

MFCC distance and NRR (Noise reduction ratio). MFCC distance is defined as the distance between the correct dereverberated signal and the estimated one in the MFCC domain. The dimension of MFCC is set to be 13. NRR is defined as $SRR_{post} - SRR_{pre}$, where SRR_{pre} is the ratio between the correct dereverberated signal and the reverved signal at a microphone, and SRRpost is the ratio between the correct dereverberated signal and the estimated dereverved signal. Smaller MFCC distance means less distortion. High NRR means high dereverberation performance. In this evaluation, average NRR and average MFCC distance of two sources were used. The correct dereverberated signal was synthesized by convolving original dry sources with trimmed impulse responses (length is P+256 [pt]). P is the peak-time index of each impulse response. The proposed method ("PROPOSED") is compared with 4 methods. "LINEAR_LGM" utilizes only the inverse filtering part of the proposed method. "LINEAR_LGM" is a representative of the conventional inverse filtering techniques weighted by the time-varying matrix (e.g. [4]). "MSLPC" is a basic multi-step linear prediction approach $V_{x,f,\tau} = I(I$ is the identity matrix). "CASCADE" is a cascading method of "MSLPC" and only the non-linear part of the proposed method. "ONLY_NLP" is only the non-linear part of the the proposed method.

The evaluation result when there is one speech source was shown in Fig. 2. In this evaluation, dereverberation performance is evaluated by two cases. In the first case, the transfer function was time-invariant. At the second case, the radiation direction changed at about 2.5 [sec] by 30 degree. Therefore, the transfer function was time-variant in this case. The number of the EM iterations was set to be 10. In the time-invariant transfer function cases, it is shown that MFCC distance of the proposed method is smallest. NRR of the proposed method is comparable to "LINEAR_LGM", although the time-invariant transfer function is desirable for inverse filtering. In the time-variant transfer function cases, it is shown that the proposed method achieves always the best performance. Therefore, it is shown that the proposed method is robust against fluctuation of the acoustic transfer function. A sample of the spectrogram of the output signal by the proposed method ("position 1", the time-variant case, female speech) is shown in Fig. 3. It can be seen that the late reverberation was effectively reduced.

Dereverberation and separation performance when there were two sources and the transfer function was time-varying are evaluated. In this evaluation, "MSLPC" was excluded, because "MSLPC" performs only dereverberation. For the other methods, the permutation problem was solved by power spectrum correlation method [11]. The number of the EM iterations was set to be 50 since convergence was slowly in the two sources case. The evaluation result is shown in Fig. 4. Except for the NRR result at the "position 1,2", the proposed method is shown to achieve the best performance.

Finally, dereverberation performance was measured for the recorded speech signal. The dereverberated signal was compared



Fig. 2. Experimental result: Evaluation of dereverberation performance under single-source condition



Fig. 3. A sample of output spectrogram by proposed method



Fig. 4. Experimental result: Evaluation of dereverberation and separation performance under two-sources condition. In "position i,j", two sources are located at "position i" and "position j".

Table 2. Evaluation result for recorded signal: Evaluation measure is MFCC distance.

	PROPOSED	LINEAR_LGM	MSLPC	CASCADE	ONLY_NLP	INPUT
position 1	22.7	25.8	27.1	24.7	29.2	32.3
position 2	19.1	22.5	24.1	21.5	25.1	29.4

with the signal recorded at the position of the loudspeaker. MFCC distance was utilized for the evaluation measure. The speaker positions were at the position 1 and 2. The wave-length was about 5 [sec]. The background noise was also mixed into the recorded signal. The evaluation result is shown in Table 2. It is shown that MFCC distance of the proposed method is the smallest.

6. CONCLUSION

In this paper, we proposed a simultaneous optimization technique of linear filtering and non-linear filtering from probabilistic perspective for dereverberation and separation of speech sources. For robustness against fluctuation of acoustic transfer functions, the proposed method is based on a novel probabilistic reverberant transfer function model (PRTFM). The proposed method is shown to be effective by evaluation in a real meeting room.

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