SIMO-MODEL-BASED BLIND ACOUSTIC SIGNAL SEPARATION: CONCEPT AND ITS APPLICATION

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ABSTRACT

In this paper, we describe a new framework of blind source separation (BSS), i.e., Single-Input Multiple-Output (SIMO)-model-based ICA (SIMO-ICA), and we discuss its applicability to acoustic signal processing. The term "SIMO" represents a specific transmission system in which the input is a single source signal and the outputs are its transmitted signals observed at multiple microphones. The SIMO-ICA consists of multiple ICAs and a fidelity controller, and each ICA runs in parallel under the fidelity control of the entire separation system. In the SIMO-ICA scenario, unknown multiple source signals which are mixed through unknown acoustical transmission channels are detected at the microphones, and these signals can be separated, not into monaural source signals but into SIMO-model-based signals from independent sources as they are at the microphones. Thus, the separated signals of the SIMO-ICA can maintain the spatial qualities of each sound source. This attractive feature of the SIMO-ICA shows the promise of applicability to many high-fidelity acoustic signal processing systems. As a good examples of SIMO-ICA's application, SIMO-ICA is applied to the extraction of the independent components from binaurally recorded signals. The experiment using a head-and-torso simulator shows that the separated SIMO signals succeed in maintaining the HRTF and spatial characteristics.

1. INTRODUCTION

Blind source separation (BSS) is the approach taken to estimate original source signals using only the information of the mixed signals observed in each input channel. This technique is applicable to various fields of signal processing such as digital communications systems, radar antenna systems, and image and acoustic signal processing systems. One promising example in acoustic signal processing is a high-quality hands-free telecommunication systems involving a microphone array [1, 2].

Independent component analysis (ICA) [3] is commonly used in the BSS framework, and various ICA-based methods have been proposed for separation of acoustical sounds which corresponds to the convolutive mixture case [4, 5, 6, 7]. However, the existing BSS methods can only separate the mixed sound sources into each *monaural* independent signal. Thus, from the practical point of view, these methods have a serious drawback in that the separated sounds cannot maintain information about the directivity, localization, or spatial qualities of each sound source. Since the above-mentioned information is essential for human hearing, the drawback prevents any BSS methods from being applied to high-fidelity audio technology, e.g., binaural signal processing [8], auditory signal processing, or sound reproduction systems [9], which construct an indispensable basis for audio virtual reality technology.

In this paper, we review a newly proposed blind separation framework for *sound scene decomposition and reconstruction*, in which Single-Input Multiple-Output (SIMO)-model-based acoustic signals are mainly treated with the extended ICA algorithm, SIMO-ICA [10]. Here the term "SIMO" represents the specific transmission system in which the input is a single source signal and the outputs are its transmitted signals observed at multiple sensors. In the SIMO-ICA scenario (see Fig. 1), unknown multiple source signals which are mixed through unknown acoustical transmission channels are detected at the microphones. Here the mixed sounds are regarded as the superposition of SIMO-model-based acoustic signals from independent sources, and can be separated, not into monaural source signals but into SIMO-model-based signals from independent sources as they are at the microphones. Thus, the separated signals of SIMO-ICA can maintain the spatial qualities of each sound source, i.e., they represent the decomposed sound scenes. Obviously the attractive feature of SIMO-ICA is highly applicable to audio virtual reality because we can separately control, modify, and reproduce each of sound scenes in this framework.

As the good example of SIMO-ICA's application, binaural-sound separation experiments [11] are carried out under a reverberant condition. The experimental results reveal that (a) the signal separation performance of the proposed SIMO-ICA is the same as that of the conventional ICA, and (b) the

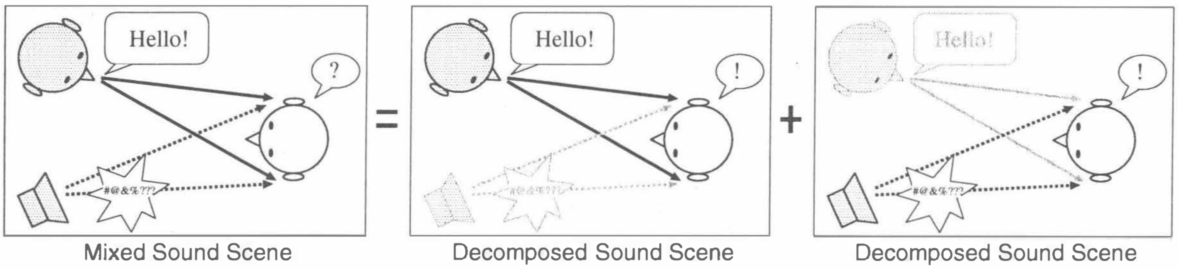

Fig. 1. Typical relation in sound scene decomposition processing. Mixed sounds are regarded as the superposition of Single-Input Multiple-Output (SIMO)-model-based acoustic signals from independent sources, and each SIMO component is separated and reproduced in SIMO-ICA framework.

sound quality of the separated signals in SIMO-ICA is remarkably superior to that in the conventional ICA, particularly for the spatial quality.

2. MIXING PROCESS AND CONVENTIONAL BSS

2.1. Mixing Process

In this study, the number of array elements (microphones) is K and the number of multiple sound sources is L. In general, the observed signals in which multiple source signals are mixed linearly are expressed as

$$\boldsymbol{x}(t) = \sum_{n=0}^{N-1} \boldsymbol{a}(n)\boldsymbol{s}(t-n) = \boldsymbol{A}(z)\boldsymbol{s}(t), \qquad (1)$$

where $\boldsymbol{s}(t)$ is the source signal vector, $\boldsymbol{x}(t)$ is the observed signal vector, $\boldsymbol{a}(n)$ is the mixing filter matrix with the length of N, and $\boldsymbol{A}(z)$ is the z-transform of $\boldsymbol{a}(n)$; these are given as

$$\boldsymbol{s}(t) = [s_1(t), \cdots, s_L(t)]^{\mathrm{T}}, \qquad (2)$$

$$\boldsymbol{x}(t) = [x_1(t), \cdots, x_K(t)]^{\mathrm{T}}, \qquad (3)$$

$$\boldsymbol{a}(n) = \begin{bmatrix} a_{11}(n) & \cdots & a_{1L}(n) \\ \vdots & \ddots & \vdots \\ a_{K1}(n) & \cdots & a_{KL}(n) \end{bmatrix}, \qquad (4)$$

$$\boldsymbol{A}(z) = [A_{ij}(z)]_{ij} = \left[\sum_{n=0}^{N-1} a_{ij}(n) z^{-n}\right]_{ij}, \qquad (5)$$

where z^{-1} is used as the unit-delay operator, i.e., $z^{-n} \cdot x(t) = x(t-n)$, a_{kl} is the impulse response between the k-th microphone and the l-th sound source, and $[X]_{ij}$ denotes the matrix which includes the element X in the i-th row and the j-th column. Hereafter, we only deal with the case of $K = L$ in this paper.

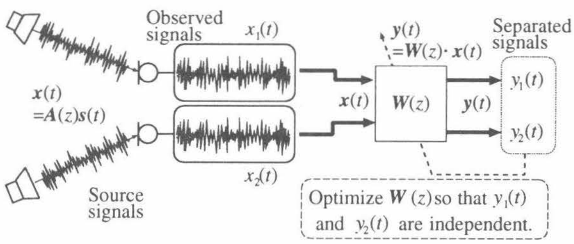

Fig. 2. Configuration of conventional TDICA, in which each element of the separation matrix is represented as an FIR filter. The separation filter matrix is optimized so that the output signals become mutually independent.

2.2. Conventional ICA-Based BSS Method

As the conventional ICA algorithm, we consider the time-domain ICA (TDICA), in which each element of the separation matrix is represented as an FIR filter. In the TDICA, we optimize the separation matrix by using only the fullband observed signals without subband processing (see Fig. 2). The separated signal $\boldsymbol{y}(t)$ is expressed as

$$\begin{aligned} \boldsymbol{y}(t) &= [y_1(t), \cdots, y_L(t)]^{\mathrm{T}} \\ &= \sum_{n=0}^{D-1} \boldsymbol{w}(n)\boldsymbol{x}(t-n) = \boldsymbol{W}(z)\boldsymbol{x}(t) \\ &= \boldsymbol{W}(z)\boldsymbol{A}(z)\boldsymbol{s}(t), \end{aligned} \qquad (6)$$

where $\boldsymbol{w}(n)$ is the separation filter matrix, $\boldsymbol{W}(z)$ is the z-transform of $\boldsymbol{w}(n)$, and D is the filter length of $\boldsymbol{w}(n)$. In our study, the separation filter matrix is optimized by minimizing the Kullback-Leibler divergence (KLD) between the joint probability density function (PDF) of $\boldsymbol{y}(t)$ and the product of marginal PDFs of $y_l(t)$. The iterative learning rule is

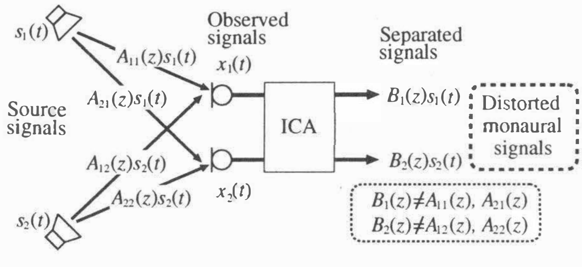

Fig. 3. Input and output relations in conventional ICA. Since $B_l(z)$ is possible to be an arbitrary filter ($B_l(z) \neq A_{kl}(z)$), the separated signals include the spectral distortions.

given by [6]

$$
\begin{aligned}
&w^{[j+1]}(n) \\
&= w^{[j]}(n) \\
&\quad - \alpha \sum_{d=0}^{D-1} \left\{ \text{off-diag} \left\langle \varphi(y^{[j]}(t)) y^{[j]}(t-n+d)^{\mathrm{T}} \right\rangle_t \right\} \\
&\quad \cdot w^{[j]}(d),
\end{aligned} \tag{7}
$$

where α is the step-size parameter, the superscript $[j]$ is used to express the value of the j-th step in the iterations, $\langle \cdot \rangle_t$ denotes the time-averaging operator, and off-diag$W(z)$ is the operation for setting every diagonal element of the matrix $W(z)$ to be zero. Also, we define the nonlinear vector function $\varphi(\cdot)$ as

$$
\varphi(y(t)) = [\tanh(y_1(t)), \cdots, \tanh(y_L(t))]^{\mathrm{T}}. \tag{8}
$$

2.3. Problems in Conventional ICA

The conventional ICA is basically a means of extracting each of the independent sound sources as a monaural signal (see Fig. 3). In addition, the quality of the separated sound cannot be guaranteed, i.e., the separated signals can possibly include spectral distortions because the modified separated signals which convolved with arbitrary linear filters are still mutually independent. As shown in Fig. 3, $y_l(t) = B_l(z)s_l(t)$, where $B_l(z)$ ($\neq A_{kl}(z)$) is an arbitrary filter, is a possible solution obtained from the conventional ICA using (7). Therefore, the conventional ICA has a serious drawback in that the separated sounds cannot maintain information about the directivity, localization, or spatial qualities of each sound source. In order to resolve the problem, particularly for the sound quality, Matsuoka et al. have proposed a modified ICA based on the Minimal Distortion Principle [12]. However, this method is valid only for monaural outputs, and the fidelity of the output signals as SIMO-model-based signals cannot be guaranteed.

3. SIMO-MODEL-BASED ICA: ALGORITHM

In order to solve the above-mentioned problems, a new SIMO-model-based ICA algorithm, *SIMO-ICA*, has been recently proposed [10]. SIMO-ICA consists of $(L-1)$ ICA parts and a *fidelity controller*, and each ICA runs in parallel under the fidelity control of the entire separation system (see Fig. 4). The separated signals of the l-th ICA ($l = 1, \cdots L-1$) in SIMO-ICA are defined by

$$
y_{(\mathrm{ICA}l)}(t) = \sum_{n=0}^{D-1} w_{(\mathrm{ICA}l)}(n) x(t-n), \tag{9}
$$

where $w_{(\mathrm{ICA}l)}(n) = [w_{ij}^{(\mathrm{ICA}l)}(n)]_{ij}$ is the separation filter matrix in the l-th ICA. Regarding the fidelity controller, we calculate the following signal vector, in which the all elements are to be mutually independent,

$$
y_{(\mathrm{ICA}L)}(t) = x(t-D/2) - \sum_{l=1}^{L-1} y_{(\mathrm{ICA}l)}(t). \tag{10}
$$

Hereafter, we regard $y_{(\mathrm{ICA}L)}(t)$ as an output of a *virtual* "L-th" ICA, and define its *virtual* separation filter as

$$
w_{(\mathrm{ICA}L)}(n) = I\delta(n - \frac{D}{2}) - \sum_{l=1}^{L-1} w_{(\mathrm{ICA}l)}(n), \tag{11}
$$

where I is the identity matrix, and $\delta(n)$ is a delta function. From (11), we can rewrite (10) as

$$
y_{(\mathrm{ICA}L)}(t) = \sum_{n=0}^{D-1} w_{(\mathrm{ICA}L)}(n) x(t-n). \tag{12}
$$

The reason why we use the word "*virtual*" here is that the L-th ICA does not have own separation filters unlike the other ICAs, and $w_{(\mathrm{ICA}L)}(n)$ is subject to $w_{(\mathrm{ICA}l)}(n)$ ($l = 1, \cdots, L-1$).

To explicitly show the meaning of the fidelity controller, we rewrite (10) as

$$
\sum_{l=1}^{L} y_{(\mathrm{ICA}l)}(t) - x(t-D/2) = 0. \tag{13}
$$

Equation (13) means a constraint to force the sum of all ICAs' output vectors $\sum_{l=1}^{L} y_{(\mathrm{ICA}l)}(t)$ to be the sum of all SIMO components $[\sum_{l=1}^{L} A_{kl}(z)s_l(t-D/2)]_{k1}(= x(t-D/2))$. Using (9) and (10), we can obtain the appropriate separated signals and maintain their spatial qualities as follows.

Theorem: If the independent sound sources are separated by (9), and simultaneously the signals obtained by (10) are also mutually independent, then the output signals converge on unique solutions, up to the permutation, as

$$
y_{(\mathrm{ICA}l)}(t) = \mathrm{diag}\left[A(z)P_l^{\mathrm{T}}\right] P_l s(t-D/2), \tag{14}
$$

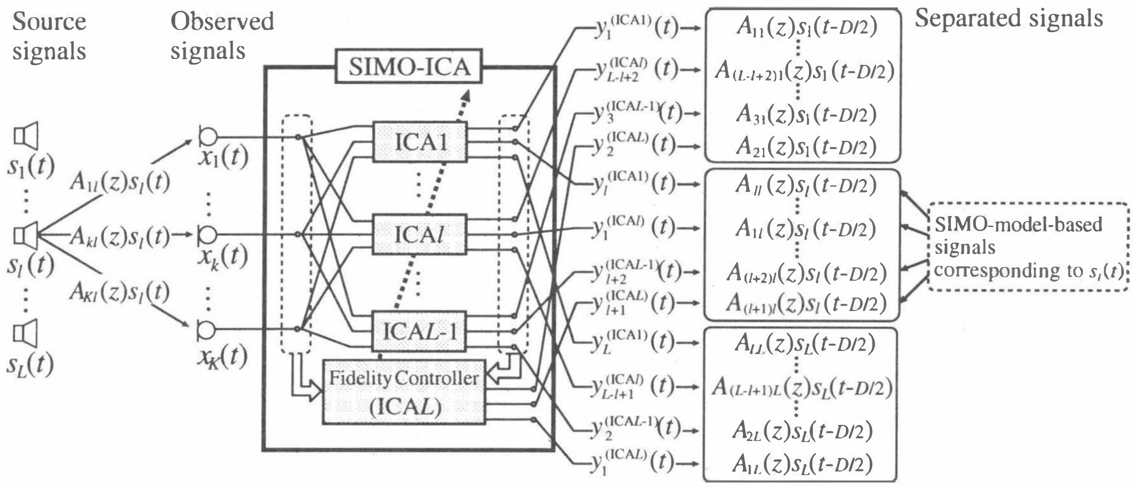

Fig. 4. Example of input and output relations in proposed SIMO-ICA, where exclusively-selected permutation matrices $\boldsymbol{P}_l$ are given by (16). The SIMO-ICA consists of multiple ICA parts and a fidelity controller, and each ICA runs in parallel under the fidelity control of the entire separation system. In this system, the separated signals maintain their spatial qualities.

where $\boldsymbol{P}_l$ $(l = 1, \cdots, L)$ are exclusively-selected permutation matrices which satisfy

$$\sum_{l=1}^{L} \boldsymbol{P}_l = [1]_{ij}. \tag{15}$$

Regarding a proof of the theorem, see [10].

Obviously the solutions given by (14) provide necessary and sufficient SIMO components, $A_{kl}(z)S_l(t - D/2)$, for each l-th source. However, the condition (15) allows multiple possibilities for the combination of $\boldsymbol{P}_l$. For example, one possibility is shown in Fig. 4 and this corresponds to

$$\boldsymbol{P}_l = [\delta_{im(k,l)}]_{ki}, \tag{16}$$

where δ_{ij} is Kronecker's delta function, and

$$m(k,l) = \begin{cases} k+l-1 & (k+l-1 \le L) \\ k+l-1-L & (k+l-1 > L) \end{cases}. \tag{17}$$

In this case, (14) yields

$$\boldsymbol{y}_{(\mathrm{ICA}l)}(t) = [A_{km(k,l)}s_{m(k,l)}(t - D/2)]_{k1} \quad (l = 1, \cdots, L). \tag{18}$$

In order to obtain (14), the natural gradient [4] of KLD of (12) with respect to $\boldsymbol{w}_{(\mathrm{ICA}l)}(n)$ should be added to the iterative learning rule of the separation filter in the l-th ICA $(l = 1, \cdots, L-1)$. Using (11), we obtain the partial differentiation of the KLD, $\mathrm{KL}(\boldsymbol{y}_{(\mathrm{ICA}L)}(t))$, with respect to $\boldsymbol{w}_{(\mathrm{ICA}l)}(n)$ $(l = 1, \cdots, L-1)$ as

$$\begin{aligned}\frac{\partial \mathrm{KL}(\boldsymbol{y}_{(\mathrm{ICA}L)}(t))}{\partial \boldsymbol{w}_{(\mathrm{ICA}l)}(n)} &= \left[\frac{\partial \mathrm{KL}(\boldsymbol{y}_{(\mathrm{ICA}L)}(t))}{\partial w_{ij}^{(\mathrm{ICA}L)}(n)} \cdot \frac{\partial w_{ij}^{(\mathrm{ICA}L)}(n)}{\partial w_{ij}^{(\mathrm{ICA}l)}(n)}\right]_{ij} \\ &= \left[\frac{\partial \mathrm{KL}(\boldsymbol{y}_{(\mathrm{ICA}L)}(t))}{\partial w_{ij}^{(\mathrm{ICA}L)}(n)} \cdot (-1)\right]_{ij}, \end{aligned} \tag{19}$$

where $w_{ij}^{(\mathrm{ICA}L)}(n)$ is the element of $\boldsymbol{w}_{(\mathrm{ICA}L)}(n)$. Thus, the natural gradient of (19) is given as

$$\begin{aligned} &-\frac{\partial \mathrm{KL}(\boldsymbol{y}_{(\mathrm{ICA}L)}(t))}{\partial \boldsymbol{w}_{(\mathrm{ICA}L)}(n)} \cdot \boldsymbol{W}_{(\mathrm{ICA}L)}(z^{-1})^{\mathrm{T}} \boldsymbol{W}_{(\mathrm{ICA}L)}(z) \\ &= \sum_{d=0}^{D-1} \Bigg\{ \Big(\boldsymbol{I}\delta(n-d) - \Big\langle \varphi(\boldsymbol{x}(t - \frac{D}{2}) \\ &\quad - \sum_{l=1}^{L-1} \boldsymbol{y}_{(\mathrm{ICA}l)}(t)) \cdot \Big(\boldsymbol{x}(t - n + d - \frac{D}{2}) \\ &\quad - \sum_{l=1}^{L-1} \boldsymbol{y}_{(\mathrm{ICA}l)}(t - n + d)^{\mathrm{T}}\Big)\Big\rangle_t \Bigg\} \\ &\quad \cdot \Big(\boldsymbol{I}\delta(d - \frac{D}{2}) - \sum_{l=1}^{L-1} \boldsymbol{w}_{(\mathrm{ICA}l)}(d)\Big), \end{aligned} \tag{20}$$

where $\boldsymbol{W}_{(\mathrm{ICA}L)}(z)$ is the z-transform of $\boldsymbol{w}_{(\mathrm{ICA}L)}(n)$. In order to deal with the colored signals, we apply the nonholonomic constraint to (20), and then combine the modified (20) with an existing ICA algorithm [6]. The new iterative algorithm of the l-th ICA part $(l = 1, \cdots, L-1)$ in

SIMO-ICA is given as

$$
\begin{aligned}
&\boldsymbol{w}^{[j+1]}_{(\mathrm{ICA}l)}(n)\\
&= \boldsymbol{w}^{[j]}_{(\mathrm{ICA}l)}(n) - \alpha \sum_{d=0}^{D-1} \Bigg[\Bigg\{ \text{off-diag} \left\langle \varphi(\boldsymbol{y}^{[j]}_{(\mathrm{ICA}l)}(t)) \right.\\
&\left. \boldsymbol{y}^{[j]}_{(\mathrm{ICA}l)}(t-n+d)^{\mathrm{T}} \right\rangle_t \Bigg\} \cdot \boldsymbol{w}^{[j]}_{(\mathrm{ICA}l)}(d)\\
&- \Bigg\{ \text{off-diag} \left\langle \varphi(\boldsymbol{x}(t-\frac{D}{2}) - \sum_{l=1}^{L-1} \boldsymbol{y}^{[j]}_{(\mathrm{ICA}l)}(t)) \right.\\
&\left. \cdot \left(\boldsymbol{x}(t-n+d-\frac{D}{2}) - \sum_{l=1}^{L-1} \boldsymbol{y}^{[j]}_{(\mathrm{ICA}l)}(t-n+d)^{\mathrm{T}} \right) \right\rangle_t \Bigg\}\\
&\cdot \left(\boldsymbol{I}\delta(d-\frac{D}{2}) - \sum_{l=1}^{L-1} \boldsymbol{w}^{[j]}_{(\mathrm{ICA}l)}(d) \right) \Bigg], \qquad (21)
\end{aligned}
$$

where α is the step-size parameter. In (21), the updating $\boldsymbol{w}_{(\mathrm{ICA}l)}(n)$ for all l should be simultaneously performed in parallel because each iterative equation is associated with the others via $\sum_{l=1}^{L-1} \boldsymbol{y}^{[j]}_{(\mathrm{ICA}l)}(t)$. Also, the initial values of $\boldsymbol{w}_{(\mathrm{ICA}l)}(n)$ for all l should be different.

After the iterations, the separated signals should be classified into SIMO components of each source because the permutation arises. This can be easily achieved by using a cross correlation between time-shifted separated signals, $\max_n \langle y_k^{(l)}(t) y_{k'}^{(l')}(t-n) \rangle_t$, where $l \neq l'$ and $k \neq k'$. The large value of the correlation indicates that $y_k^{(l)}(t)$ and $y_{k'}^{(l')}(t)$ are SIMO components of the same sources.

4. APPLICATION OF SIMO-ICA: BINAURAL SOUND SEPARATION

4.1. Conditions for Experiments

We carried out binaural sound separation experiments [11]. In this experiment, speech signals are convolved with impulse responses which is recorded using Head and Torso Simulator (HATS by Brüel & Kjær) under the experimental room as shown in Fig. 5. The speech signals are assumed to arrive from two directions, $-30°$ and $45°$. The distance between HATS and the loudspeakers is 1.5 m. Two kinds of sentences, spoken by two male and two female speakers, are used as the original speech samples. Using these sentences, we obtain 6 combinations. The sampling frequency is 8 kHz and the length of speech is limited to 3 seconds. The length of $\boldsymbol{w}(n)$ is 512, and the initial values are inverse filters of HRTFs whose directions of sources are $\pm 60°$. The number of iterations in ICA is 5000. Regarding the conventional ICA for comparison, we used the nonholonomic ICA [6]. The step-size parameter α is changed from 1.0×10^{-8} to 2.0×10^{-6} to find the optima.

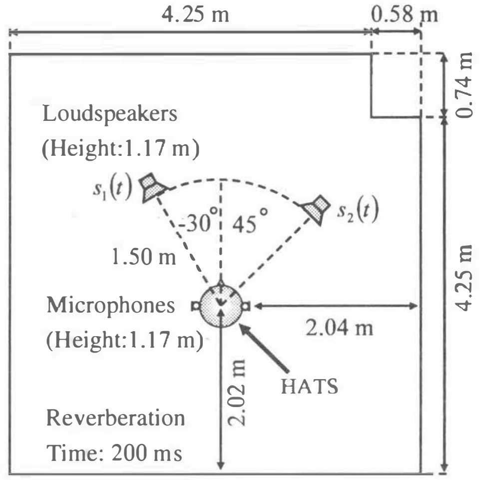

Fig. 5. Layout of reverberant room used in binaural-sound separation experiments.

4.2. Results and Discussion

SIMO-model accuracy (SA) is used as an evaluation score. The SA is defined as

$$
\mathrm{SA} = \frac{1}{K}\frac{1}{L}\sum_{k=1}^{K}\sum_{l=1}^{L} 10\log_{10} \frac{\| A_{km(k,l)}(z) s_{m(k,l)}(t) \|^2}{\| y_k^{(\mathrm{ICA}l)}(t) - A_{km(k,l)}(z) s_{m(k,l)}(t) \|^2}. \quad (22)
$$

The SA indicates a degree of the similarity between the separated signals of the ICA and real SIMO-model-based signals. Figure 6 shows the results of SA for different speaker combinations. The bars on the right of this figure correspond to the averaged results of each combination. In the averaged scores, the improvement of SA in SIMO-ICA is 9.5 dB compared with the conventional ICA. From these results, it is evident that the separated signals in the SIMO-ICA is obviously superior to that in the conventional ICA-based method. Thus, we can conclude that SIMO-ICA has the potential to decompose the mixed binaural signals into SIMO-model-based signals without loss of information about spatial qualities of each sound source.

5. CONCLUSION

In this paper, we described a new framework of SIMO-model-based ICA and its applicability to acoustic signal processing. The SIMO-ICA can separate the mixed signals into SIMO-model-based signals which can maintain the spatial qualities. As the good examples of SIMO-ICA's application, we apply SIMO-ICA to the blind source separation

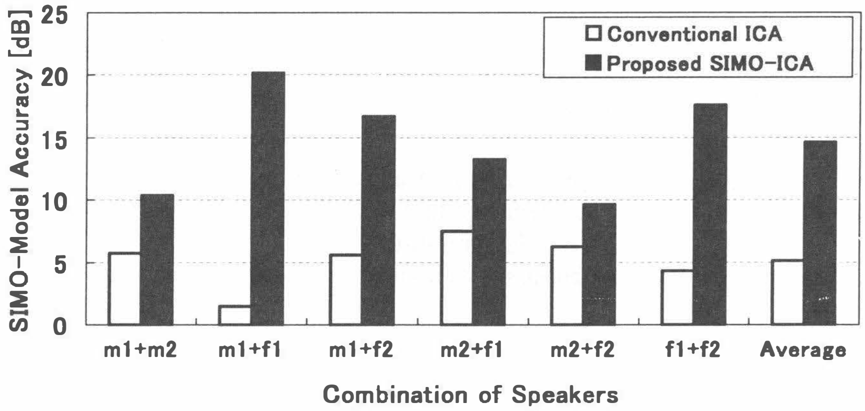

Fig. 6. Results of SIMO-model accuracy in separation experiments of binaural sounds recorded using HATS. The labels "m1" and "m2" mean two male speakers, and "f1" and "f2" mean two female speakers.

problem of the binaural sounds. The experimental results reveal that the performance of the proposed SIMO-ICA is superior to that of the conventional ICA-based method, and the separated signals of SIMO-ICA maintain the spatial qualities of each binaural sound source. This can show the promising applicability of the SIMO-ICA to various high-fidelity audio systems.

6. ACKNOWLEDGEMENT

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