# BLIND SEPARATION OF MORE THAN TWO SOURCES BASED ON HIGH-CONVERGENCE ALGORITHM COMBINING ICA AND BEAMFORMING

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**ABSTRACT**

We propose a new blind source separation (BSS) algorithm for multiple source signals. In the proposed algorithm, independent component analysis (ICA) and beamforming are combined to resolve the slow-convergence problem through optimization in ICA. The proposed method consists of the following three parts: (a) frequency-domain ICA with direction-of-arrival (DOA) estimation using a Lloyd clustering algorithm, (b) null beamforming based on the estimated DOA, and (c) integration of (a) and (b) based on the algorithm diversity in both iteration and frequency domain. The separation matrix obtained by ICA is temporally substituted by the matrix based on null beamforming through iterative optimization, and the temporal alternation between ICA and beamforming can realize fast- and high-convergence optimization. The results of the source separation experiments reveal that the source-separation performance of the proposed algorithm is superior to that of the conventional ICA-based BSS method, even under reverberant conditions.

## 1. INTRODUCTION

Blind source separation (BSS) is an approach for estimating original source signals only from the information of the mixed signals observed in each input channel. This technique is applicable to high-quality hands-free speech recognition systems. Many BSS methods based on independent component analysis (ICA) [1] have been proposed for the acoustic signal separation [2, 3, 4, 5]. In this paper, we address the complex-valued ICA i.e., frequency-domain ICA (FDICA) [2]. The FDICA-based BSS is one of the promising approach for sound segregation. There exists, however, a slow-convergence problem which is due to the nonlinear optimization inherent in ICA [5].

We have solved this problem in a specific case of two sources and two microphones by introducing the fast-convergence algorithm combining ICA and beamforming [6, 7]. However, this algorithm cannot be extended to the source-separation problem of multiple sources and multiple microphones (more than 2 sources with more than 2 microphones). In order to solve this problem, this paper describes a new extended algorithm in which ICA and beamforming are combined for the blind separation of multiple sources. The proposed algorithm consists of the following procedures: (a) frequency-domain ICA with estimation of the DOA of the sound source using a Lloyd clustering algorithm [8], (b) null beamforming based on the estimated DOA, and (c) integration of (a) and (b) based on the algorithm diversity in both ICA iteration and frequency subband. The temporal utilization of null beamforming through ICA iterations achieves fast- and high-convergence optimization. The signal separation experiments with 3 sources and 3 sensors show that the proposed algorithm outperforms the conventional ICA-based BSS method, and the utilization of null beamforming in ICA is effective for improving both the convergence speed and SNR, even under reverberant conditions.

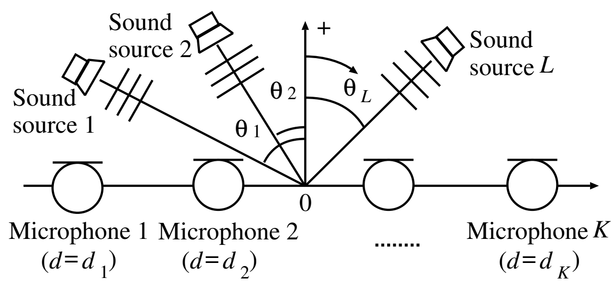


Figure 1: Configuration of a microphone array and source signals.

## 2. CONVENTIONAL FDICA

### 2.1 Sound Mixing Model of Microphone Array

The coordinates of the microphones are designated ad $d_k$ ($k = 1, \cdots, K$), and the directions of arrival of multiple sound sources are designated $\theta_l$ ($l = 1, \cdots, L$) (see Fig. 1). $K$ is the number of array elements (microphones), and $L$ is the number of sound sources.

In general, the observed signals in which multiple source signals are mixed linearly are given by the following equation in the frequency domain:

$$\boldsymbol{X}(f) = \boldsymbol{A}(f)\boldsymbol{S}(f), \tag{1}$$

where $\boldsymbol{X}(f)$ is the observed signal vector, $\boldsymbol{S}(f)$ is the source signal vector, and $\boldsymbol{A}(f)$ is the mixing matrix; these are given as

$$\boldsymbol{X}(f) = [X_1(f), \cdots, X_K(f)]^{\mathrm{T}}, \tag{2}$$

$$\boldsymbol{S}(f) = [S_1(f), \cdots, S_L(f)]^{\mathrm{T}}, \tag{3}$$

$$\boldsymbol{A}(f) = \begin{bmatrix} A_{11}(f) & \cdots & A_{1L}(f) \\ \vdots & & \vdots \\ A_{K1}(f) & \cdots & A_{KL}(f) \end{bmatrix}. \tag{4}$$

$\boldsymbol{A}(f)$ is assumed to be complex-valued because we introduce a model to deal with the arrival lags among each of the elements of the microphone array and room reverberations.

### 2.2 FDICA-Based BSS [2]

In FDICA, first, the short-time analysis of observed signals is conducted by frame-by-frame discrete Fourier transform (DFT). By plotting the spectral values in a frequency bin of each microphone input frame by frame, we consider them as a time series. Hereafter, we designate the time series as $\boldsymbol{X}(f,t) = [X_1(f,t), \cdots, X_K(f,t)]^{\mathrm{T}}$. Next, we perform signal separation using the complex-valued inverse of the mixing matrix, $\boldsymbol{W}(f)$, so that the $L$ time-series output $\boldsymbol{Y}(f,t)$ becomes mutually independent; this procedure can be given as

$$\boldsymbol{Y}(f,t) = \boldsymbol{W}(f)\boldsymbol{X}(f,t), \tag{5}$$

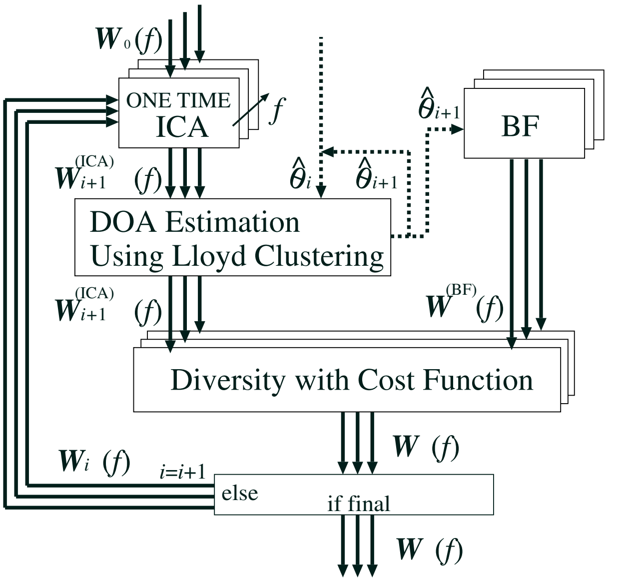


Figure 2: Proposed algorithm combining frequency-domain ICA and beamforming.

where

$$\boldsymbol{Y}(f,t) = [Y_1(f,t),\cdots,Y_L(f,t)]^{\mathrm{T}}, \tag{6}$$

$$\boldsymbol{W}(f) = \begin{bmatrix} W_{11}(f) & \cdots & W_{1K}(f) \\ \vdots & & \vdots \\ W_{L1}(f) & \cdots & W_{LK}(f) \end{bmatrix}. \tag{7}$$

We optimize $\boldsymbol{W}(f)$ using ICA algorithm based on the minimization of Kullback-Leibler divergence as follows:

$$\boldsymbol{W}_{i+1}(f) = \alpha\Big[\boldsymbol{I} - \Big\langle \boldsymbol{\Phi}\big(\boldsymbol{Y}(f,t)\big)\boldsymbol{Y}(f,t)^{\mathrm{H}}\Big\rangle_t\Big]\boldsymbol{W}_i(f) + \boldsymbol{W}_i(f), \tag{8}$$

where $\langle\cdot\rangle_t$ denotes the frame-averaging operator, $i$ is used to express the value of the $i$ th step in the iterations, and $\alpha$ is the step-size parameter. We use the nonlinear vector function $\Phi(\cdot)$ [4] as

$$\boldsymbol{\Phi}(\boldsymbol{Y}(f,t) \equiv \big[\Phi(Y_1(f,t)),\cdots,\Phi(Y_L(f,t))\big]^{\mathrm{T}}, \tag{9}$$

$$\Phi(Y_l(f,t)) \equiv \tanh(\mathrm{abs}(Y_l(f,t)))\cdot\exp[j\cdot\mathrm{angle}(Y_l(f,t))], \tag{10}$$

where $\mathrm{abs}(Y_l(f,t))$ is an absolute value of $Y_l(f,t)$ and $\mathrm{angle}(Y_l(f,t))$ is an argument of $Y_l(f,t)$.

## 3. PROPOSED ALGORITHM

### 3.1 Motivation and Strategy

The conventional ICA often suffers a serious problem which is due to the poor convergence ability, especially when setting an invalid separation matrix as the initial value in ICA. In order to resolve the low convergence problem, we propose an algorithm including the temporal alternation of learning between ICA and beamforming; the separation matrix, $\boldsymbol{W}(f)$, obtained in ICA is temporally replaced by a null-beamforming-based matrix for a temporal initialization or acceleration of the iterative optimization.

Even in the proposed algorithm, DOA information for each source is demanded before building up the null beamformer. It was, however, too difficult to address the DOA estimation problem under ordinary BSS tasks where the number of sources, $L$, equals that of sensors, $K$. For example, the conventional DOA estimator, e.g., eigenanalysis method cannot be applied to the $K$=$L$ BSS case because of the required condition that $K > L$ for the conventional DOA estimator. In order to make the DOA estimation under $K$=$L$ possible, we introduce a novel combination, the so-called "ICA-driven null-finding-based DOA estimator," in which the DOA estimation follows one-time ICA iteration and can be done by using the separation matrix obtained from ICA. This DOA estimation method is mainly based on our preliminary finding that the directional null is steered to the DOA of the suppressed source in ICA. Thus, we can approximately estimate the DOAs only to find the null directions in the directivity patterns produced by the separation matrix of ICA.

### 3.2 Algorithm

The proposed algorithm is conducted by the following steps with respect to all frequency bins in parallel (see Fig. 2). Here we consider the general case of $K = L > 2$, unlike the previous work ($K = L = 2$) [6].

**[Step 1: Initialization]** Set the initial $\boldsymbol{W}_i(f)$, i.e., $\boldsymbol{W}_0(f)$, to a conventional delay-and-sum (DS) array, where the subscript $i$ is set to be 0.

**[Step 2: 1-time ICA iteration]** Optimize $\boldsymbol{W}_i(f)$ using the following one-time ICA iteration:

$$\boldsymbol{W}^{(\mathrm{ICA})}_{i+1}(f) = \alpha\Big[\boldsymbol{I} - \Big\langle \boldsymbol{\Phi}\big(\boldsymbol{Y}(f,t)\big)\boldsymbol{Y}(f,t)^{\mathrm{H}}\Big\rangle_t\Big]\boldsymbol{W}_i(f) + \boldsymbol{W}_i(f), \tag{11}$$

where the superscript "(ICA)" represents that the separation matrix is updated by ICA.

**[Step 3: DOA estimation]** Estimate DOAs $\vartheta = \{\theta_1,\, \cdots\, \theta_L\}$ of the sound sources by employing the directivity pattern of the array system. The directivity pattern $F_l(f,\theta)$ with respect to the $l$ th ICA output is generally given by

$$[F_1(f,\theta), F_2(f,\theta),\cdots,F_L(f,\theta)]^{\mathrm{T}} = \boldsymbol{W}^{(\mathrm{ICA})}(f)\boldsymbol{e}(f,\theta), \tag{12}$$

where $\boldsymbol{e}(f,\theta)$ is the steering vector which is defined by

$$\boldsymbol{e}(f,\theta) = \big[\exp[j2\pi(ff_s/N)d_1\sin\theta/c],\ \cdots,\exp[j2\pi(ff_s/N)d_K\sin\theta/c]\big]^{\mathrm{T}}, \tag{13}$$

where $c$ is velocity of sound, $f_s$ is a sampling frequency and $N$ is a DFT size.

In the simple case of $K = L = 2$, directional nulls in the directivity patterns appear in only two particular directions, and thus we can heuristically categorize the null directions $\theta_l$ into two groups "large" or "small" [6]; this corresponds not to a complicated clustering but to a simple binary quantization. This procedure has the advantage of the low computational cost, but cannot be available in $K = L > 2$. To conquer the problem, we newly introduce an extended DOA estimation algorithm based on a directional null clustering technique, which can work even in the general case of $K = L > 2$.

Under $K = L > 2$, at most $L-1$ directional nulls are produced in the $l$ th directivity pattern $F_l(f,\theta)$ at the $f$ th frequency bin. Here the set of DOAs of the directional nulls, $\Theta^{(l)}(f)$, is defined as

$$\Theta^{(l)}(f) = \Big\{\theta\big|\ \big[F_l(f,\theta) - F_l(f,\theta-\Delta\theta)\big] \le 0;\ \big[F_l(f,\theta+\Delta\theta) - F_l(f,\theta)\big] > 0\Big\}, \tag{14}$$

where $\Delta\theta$ is a positive small value, and $\{\theta|\ A;\ B\}$ refers to a set of $\theta$ which satisfies the conditions $A$ and $B$ simultaneously.

Obviously $\Theta^{(l)}(f)$ can be considered as a set of good candidates of DOAs. In order to identify the true DOAs of sources from $\Theta^{(l)}(f)$, first, we classify $\Theta^{(l)}(f)$ with all $f$ and $l$ into $L$ categories by using a Lloyd clustering algorithm [8]. Next, we calculate the centroids of these categories, and finally we identify the centroids as the estimated DOAs. The detailed classification procedure is shown below.

**(a)** Construct the full set of $\Theta^{(l)}(f)$ to be classified, as

$$\Theta = \left\{\theta_1, \theta_2, \cdots, \theta_Q\right\} = \sum_{l=1}^{L}\sum_{f=1}^{N/2} \Theta^{(l)}(f), \qquad (15)$$

where $Q$ is the total number of detected directional nulls (up to $Q = (L-1)\cdot L \cdot N/2$).

**(b)** Set initial $L$ centroids $\vartheta^{(\mathrm{C})} = \{\theta_1^{(\mathrm{C})}, \cdots \theta_L^{(\mathrm{C})}\}$ to the DOAs estimated in the previous ICA iteration, i.e., $\vartheta^{(\mathrm{C})} = \hat{\vartheta}_i$. In the first iteration ($i = 0$), we set $\vartheta^{(\mathrm{C})}$ to an arbitrary value.

**(c)** Set $L-1$ partitions $\theta_p^{(\mathrm{P})}$ ($p = 1, \cdots, L-1$) as follows:

$$\theta_p^{(\mathrm{P})} = (\theta_p^{(\mathrm{C})} + \theta_{p+1}^{(\mathrm{C})})/2, \qquad (16)$$

where $-90 < \theta_1^{(\mathrm{P})} < \theta_2^{(\mathrm{P})} < \cdots < \theta_{L-1}^{(\mathrm{P})} < 90$. Also, the terminal partitions $\theta_0^{(\mathrm{P})}$ and $\theta_L^{(\mathrm{P})}$ are fixed at $-90$ and 90, respectively, throughout the algorithm.

**(d)** Given the partitions, calculate the $L$ centroids $\theta_l^{(\mathrm{C})}$ ($l = 1, \cdots, L$) as

$$\theta_l^{(\mathrm{C})} = \frac{1}{Q_l}\Big\{\sum_{\theta_{l-1}^{(\mathrm{P})} \le \theta_q < \theta_l^{(\mathrm{P})}} \theta_q\Big\}, \qquad (17)$$

where $Q_l$ denotes the number of $\theta_q$ under $\theta_{l-1}^{(\mathrm{P})} \le \theta_q < \theta_l^{(\mathrm{P})}$.

**(e)** Go back to (c) for updating the new partitions by using the new centroids, and repeat the loop in (c)$\sim$(e) with an appropriate number of iterations. The final centroids $\vartheta^{(\mathrm{C})}$ are regarded as the resultant estimated DOAs $\hat{\vartheta}_{i+1}$ in the $(i+1)$ th iteration, i.e., $\hat{\vartheta}_{i+1} = \vartheta^{(\mathrm{C})}$.

**[Step 4: Beamforming]** Construct a beamforming-based separation matrix, $\boldsymbol{W}^{(\mathrm{BF})}(f)$, based on the null-beamforming technique where the DOA information obtained in **Step 3** is used. The matrix $\boldsymbol{W}^{(\mathrm{BF})}(f)$ is given by

$$\boldsymbol{W}^{(\mathrm{BF})}(f) = \left[\boldsymbol{e}(f, \hat{\theta}_1), \boldsymbol{e}(f, \hat{\theta}_2), \cdots, \boldsymbol{e}(f, \hat{\theta}_L)\right]^{-1}. \qquad (18)$$

**[Step 5: Diversity using cost function]** The following strategy is applied for selecting the most suitable separation matrix in each frequency bin and at each iteration point, i.e., algorithm diversity in both ICA iteration and frequency subband. As the cost function used in the diversity, we define an averaged *coherence function* among $L$ separated signals:

$$C(\boldsymbol{W}(f)) = \frac{1}{{}_L\mathrm{C}_2}\sum_{l=2}^{L}\sum_{l'<l} \frac{\left|\left\langle Y_{l'}(f,t) Y_l(f,t)^*\right\rangle_t\right|}{\sqrt{\left\langle |Y_{l'}(f,t)|^2\right\rangle_t \left\langle |Y_l(f,t)|^2\right\rangle_t}}, \qquad (19)$$

where $Y_l(f,t)$ and $Y_{l'}(f,t)$ are the distinct separated signals defined by (5). We calculate the estimated coherence function once for $\boldsymbol{W}(f) = \boldsymbol{W}^{(\mathrm{ICA})}(f)$ (i.e., $C(\boldsymbol{W}^{(\mathrm{ICA})}(f))$), and once for $\boldsymbol{W}(f) = \boldsymbol{W}^{(\mathrm{BF})}(f)$ (i.e., $C(\boldsymbol{W}^{(\mathrm{BF})}(f))$). Although the coherence function cannot measure the accurate independence among sources, we use this function to assess the source independence approximately because of the benefit of the small computational complexity.

If the expected separation performance of beamforming is better than that of ICA, then $C(\boldsymbol{W}^{(\mathrm{ICA})}(f)) > C(\boldsymbol{W}^{(\mathrm{BF})}(f))$; otherwise, $C(\boldsymbol{W}^{(\mathrm{ICA})}(f)) \le C(\boldsymbol{W}^{(\mathrm{BF})}(f))$. Accordingly, an inspection of the conditions leads to the following diversity:

$$\boldsymbol{W}_{i+1}(f) = \begin{cases} \boldsymbol{W}^{(\mathrm{ICA})}(f), \ \left(C(\boldsymbol{W}^{(\mathrm{ICA})}(f)) \le C(\boldsymbol{W}^{(\mathrm{BF})}(f))\right) \\ \boldsymbol{W}^{(\mathrm{BF})}(f), \ \left(C(\boldsymbol{W}^{(\mathrm{ICA})}(f)) > C(\boldsymbol{W}^{(\mathrm{BF})}(f))\right). \end{cases} \qquad (20)$$

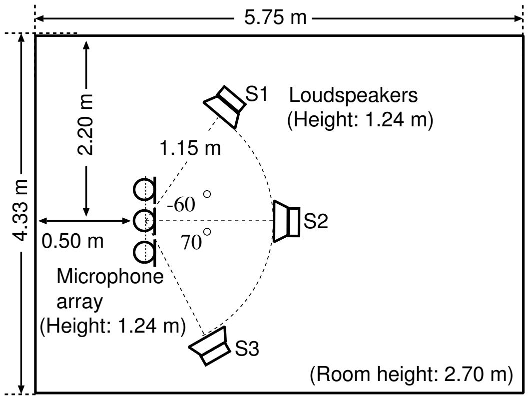

Figure 3: Layout of reverberant room used in experiment.

If the $(i+1)$ th iteration is the final iteration, go to **step 6**; otherwise, go back to **step 2** and repeat the iterative algorithm, inserting $\boldsymbol{W}_{i+1}(f)$ as given by (20) into $\boldsymbol{W}_i(f)$ in (11) with an increment of $i$.

**[Step 6: Ordering and scaling]** Using the DOA information obtained in **step 3**, we can detect and correct the source permutation and the gain inconsistency [5]. From the directivity patterns in all frequency bins, we approximate the interference reduction ratio by the difference between the gain at the direction of the target and that of the interferences. By comparing the degree of the estimated interference reduction, we can resolve the permutation problem. The gain inconsistency problem is resolved by normalizing the directivity patterns according to the gain in each source direction after the classification.

## 4. EXPERIMENTS AND RESULTS

### 4.1 Experimental Setup

We carried out a speech separation experiment under the condition of $K = L = 3$. The room impulse responses are measured in an ordinary room, which has the RT of 200 msec, as shown in Fig. 3. A three-element array with interelement spacing of 4.3 cm is used. Three loudspeakers are placed as the sound sources at three directions, $-60°$, $0°$, and $70°$. Two sentences spoken by two male and two female speakers are used as the original speech samples; these speech data are limited within 3 sec, and the sampling frequency is 8 kHz. Using these sentences, we obtain 12 combinations with respect to speakers and source directions. We set the DS-array-based initial value $\boldsymbol{W}_0(f)$ which steers the look directions to $-90°$, $20°$, and $90°$. The frame length is 128 msec and the frame shift is 2 msec. The step-size parameter $\alpha$ is $1.0 \times 10^{-6}$. In order to evaluate the performance, we used the *noise reduction rate* (NRR) [5], which is defined as the output signal-to-noise ratio (SNR) in dB minus input SNR in dB.

### 4.2 DOA Estimation Results

Figure 4 shows the DOA estimation results (averaged DOAs for 12 combinations) for different number of loops in the Lloyd clustering algorithm (see Sect. 3, Step 3 (e)). We compared three patterns, in which the number of Lloyd loops is 1, 5, and 10 times. These results reveal that the performances of the DOA estimation using 5 and 10 Lloyd loops are equivalent. From these results, the Lloyd clustering converges at 5 times. In the next source-separation experiment, we set the number of loops for the Lloyd clustering algorithm to be 5 times.

### 4.3 Source-Separation Result

Figure 5 shows the averaged NRRs for 12 combinations. Each curve depicted in this figure represents the following methods.

**Proposed Method** : High-convergence algorithm proposed in this paper (see Section 3).

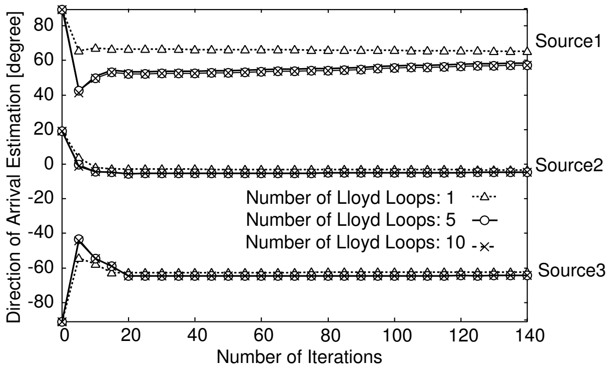


Figure 4: Results of DOAs estimated by the Lloyd clustering algorithm for different number of loops in the proposed method.

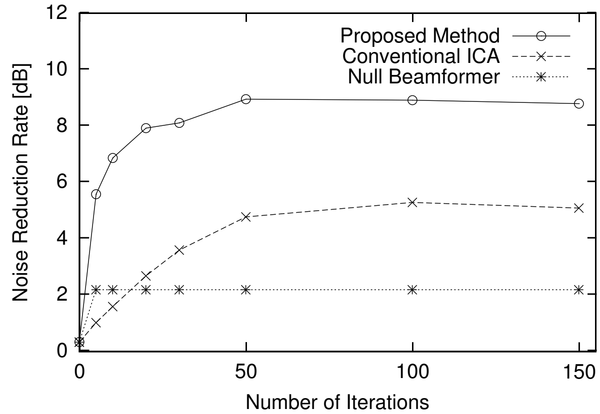


Figure 5: Noise reduction rates for different iteration points in proposed method, conventional ICA, and iteratively optimized null beamformer. These are averaged NRRs for 12 combinations.

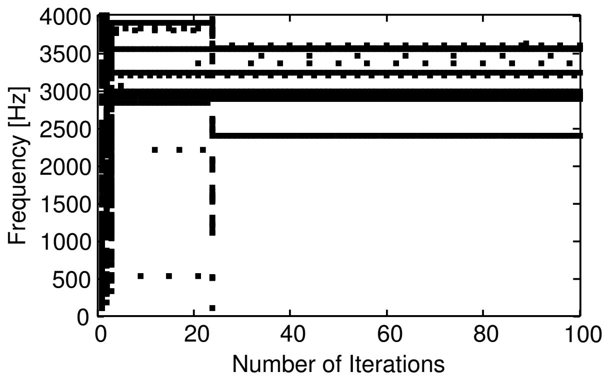


Figure 6: Result of alternation between ICA and null beamforming through iterative optimization by the proposed algorithm. The symbol "▬" indicates that the null beamforming is used at the iteration point and frequency bin.

**Conventional ICA** : The conventional ICA-based BSS method (see Section 2.2). This method is also equivalent to the specific case that ICA-based matrix is always selected in **step 5** of the proposed algorithm, i.e., always $\boldsymbol{W}_{i+1}(f) = \boldsymbol{W}^{(\mathrm{ICA})}(f)$ in (20).

**Null Beamformer** : The conventional null beamformer with the (ICA-driven) iteratively updated DOA estimator. This is also equivalent to another specific case that the null-beamformer-based matrix is always selected in **step 5** of the proposed algorithm, i.e., always $\boldsymbol{W}_{i+1}(f) = \boldsymbol{W}^{(\mathrm{BF})}(f)$ in (20).

These results indicate that the proposed method remarkably outperforms both the conventional ICA and null beamformer at every iteration point. Thus, the proposed diversity algorithm can work very well in the case of $K = L = 3$ as well as $K = L = 2$.

To investigate the proposed method's function in detail, Figure 6 shows the example of alternation results between ICA and null beamforming through iterative optimization by the proposed algorithm. The following points are disclosed.

- Early in the iterations, null beamforming is mainly used for the acceleration of learning. This is because $\boldsymbol{W}^{(\mathrm{BF})}(f)$ is a rough approximation of the separation matrix.
- After the early part of the iterations, ICA is preferred because the separation matrix can be updated more accurately in ICA.
- It is, however, very interesting that the separation matrix obtained by ICA is sometimes replaced by the null-beamforming-based matrix through all iteration points at particular frequency bins where the independence between the sources is expected to be low.

In summary, although null beamforming is not optimal for source segregation under the reverberant condition, we can confirm that the temporal utilization of null beamforming for algorithm diversity through ICA iterations is effective for improving both the convergence speed and the separation ability.

## 5. CONCLUSION

In this paper, we described a fast- and high-convergence blind separation algorithm for multiple source signals where null beamforming is temporally used for algorithm diversity through ICA iterations. The simulation results of the signal separation experiments reveal that the signal separation performance of the proposed algorithm is superior to that of the conventional ICA-based BSS method, and the utilization of null beamforming in ICA is effective for improving the separation performance and convergence, even under reverberant conditions.

## 6. ACKNOWLEDGEMENT

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