REGULARIZED FAST MULTICHANNEL NONNEGATIVE MATRIX FACTORIZATION WITH ILRMA-BASED PRIOR DISTRIBUTION OF JOINT-DIAGONALIZATION PROCESS

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ABSTRACT

In this paper, we address a convolutive blind source separation (BSS) problem and propose a new extended framework of FastMNMF by introducing prior information for joint diagonalization of the spatial covariance matrix model. Recently, FastMNMF has been proposed as a fast version of multichannel nonnegative matrix factorization under the assumption that the spatial covariance matrices of multiple sources can be jointly diagonalized. However, its sourceseparation performance was not improved and the physical meaning of the joint-diagonalization process was unclear. To resolve these problems, we first reveal a close relationship between the jointdiagonalization process and the demixing system used in independent low-rank matrix analysis (ILRMA). Next, motivated by this fact, we propose a new regularized FastMNMF supported by IL-RMA and derive convergence-guaranteed parameter update rules. From BSS experiments, we show that the proposed method outperforms the conventional FastMNMF in source-separation accuracy with almost the same computation time.

Index Terms— blind source separation, spatial covariance model, joint diagonalization

1. INTRODUCTION

Blind source separation (BSS) [1] is a technique that separates sound sources from observed mixtures without any prior information about the sources or mixing system. For a determined or overdetermined situation, when the sources are point sources and reverberation is sufficiently short (referred to as the *rank-1 spatial model*), frequency-domain independent component analysis [2, 3], independent vector analysis [4, 5, 6], and independent low-rank matrix analysis (ILRMA) [7, 8] have been proposed. In particular, ILRMA is a BSS technique assuming statistical independence between the sources and the low-rank structure of source spectrograms, and provides high-accuracy separation with a short computation time. However, the rank-1 spatial model cannot hold in the case of spatially spread sources or strong reverberation.

Multichannel nonnegative matrix factorization (MNMF) [9, 10] is an extension of nonnegative matrix factorization (NMF) [11] to the multichannel case, which estimates the spatial covariance matrices of each source. MNMF employs full-rank spatial covariance matrices [12] and this model can simulate situations where, e.g.,

the reverberation is longer than the length of time-frequency analysis. However, it has been reported that MNMF has a huge computational cost and its performance strongly depends on the initial values of parameters [7]. To accelerate the parameter estimation, Ito and Nakatani have proposed *FastMNMF* [13], which is an improved algorithm of MNMF under the assumption of jointly diagonalizable spatial covariance matrices. It has been reported that, although the computation time of the algorithm is greatly reduced, its source-separation performance is still sensitive to the parameter initialization and not always improved (indeed, it is almost the same as that of the original MNMF) [14]. In addition, the physical meaning of the joint-diagonalization process in FastMNMF is unclear; consequently, prior information cannot be introduced into the parameter optimization to achieve further improvement.

To resolve the above-mentioned problems, we provide three contributions in this paper, namely, a new FastMNMF framework with physically reasonable prior information, its parameter optimization algorithm based on a new type of coordinate descent, and an experimental evaluation of the proposed FastMNMF. First, we reveal that the joint-diagonalization process in FastMNMF is closely related to the demixing system used in ILRMA. Motivated by this fact, we propose a new regularized FastMNMF with the prior distribution of the joint-diagonalization matrix supported by ILRMA. Next, we derive parameter update rules on the basis of vectorwise coordinate descent (VCD) [15] that guarantees a monotonic nonincrease in the cost function. Finally, we conduct BSS experiments under reverberant conditions, showing that the proposed FastMNMF outperforms the conventional FastMNMF as well as ILRMA in source-separation accuracy while maintaining similar computational efficiency.

2. CONVENTIONAL METHODS

2.1. Formulation

Let the numbers of sources and channels be N and M, respectively. The short-time Fourier transforms (STFTs) of the multichannel source, the observed signal, and the separated signal are defined as

$$\boldsymbol{s}_{ij} = (s_{ij,1}, \dots, s_{ij,N})^{\mathsf{T}} \in \mathbb{C}^N, \tag{1}$$

$$\boldsymbol{x}_{ij} = (x_{ij,1}, \dots, x_{ij,M})^{\mathsf{T}} \in \mathbb{C}^{M},$$
(2)

$$\boldsymbol{y}_{ij} = (y_{ij,1}, \dots, y_{ij,N})^{\mathsf{T}} \in \mathbb{C}^{N},$$
(3)

where i = 1, ..., I, j = 1, ..., J, n = 1, ..., N, and m = 1, ..., M, are the indices of the frequency bins, time frames,

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sources, and channels, respectively, and \cdot^{T} denotes the transpose.

2.2. ILRMA [7]

When the window size in an STFT is sufficiently longer than the impulse responses between the sources and the microphones and the sources are point sources, we can represent the observed signal as

$$\boldsymbol{x}_{ij} = \boldsymbol{A}_i \boldsymbol{s}_{ij}, \tag{4}$$

where $A_i = (a_{i1}, \ldots, a_{iN}) \in \mathbb{C}^{M \times N}$ is a frequency-wise mixing matrix and a_{in} is the steering vector for the *n*th source. If M = N and the mixing matrix A_i is invertible, we can estimate the separated signal as

$$\boldsymbol{y}_{ij} = \boldsymbol{W}_i \boldsymbol{x}_{ij}, \tag{5}$$

where $W_i = (w_{i1}, \ldots, w_{iN})^{\mathsf{H}} = A_i^{-1}$ is the demixing matrix and \cdot^{H} denotes the Hermitian transpose. ILRMA assumes that the separated signals $y_{ij,n}$ $(n = 1, \ldots, N)$ are statistically independent of each other, i.e.,

$$p(\boldsymbol{y}_{ij}) = \prod_{n} p(y_{ij,n}), \tag{6}$$

and each $y_{ij,n}$ follows the complex Gaussian distribution whose mean is zero and variance is $r_{ij,n}$. The source model $r_{ij,n}$ is a spectrogram of the *n*th source at the *i*th frequency and *j*th time frame, having a low-rank spectral structure represented by NMF. From (5) and (6) the negative log-likelihood of the observed signal, which is a cost function to be minimized, is given by

$$\mathcal{L}_{\mathrm{I}} \stackrel{c}{=} \sum_{i,j,n} \left[\frac{|\boldsymbol{w}_{in}^{\mathsf{H}} \boldsymbol{x}_{ij}|^2}{r_{ij,n}} + \log r_{ij,n} \right] - 2J \sum_{i} \log |\det \boldsymbol{W}_i|, \quad (7)$$

where $\stackrel{c}{=}$ denotes equality up to a constant. Since (7) w.r.t. the source model parameter $r_{ij,n}$ is the Itakura–Saito-divergence-based cost function, the parameter is updated by the auxiliary function technique [16], similarly to Itakura–Saito NMF [17]. Regarding the demixing matrix W_i , the cost function (7) is the sum of the quadratic form of w_{in} and the negative log-determinant of W_i . This type of cost function can be minimized by iterative projection (IP) [18], which guarantees a monotonic nonincrease in the cost function. The demixing matrix W_i can be optimized so as to make separated signals mutually independent. Details of these update rules are described in [7].

2.3. FastMNMF [13, 19]

In convolutive BSS, the frequency-domain instantaneous mixing process is translated into a model using a rank-1 spatial covariance matrix $a_{in}a_{in}^{H}$ for each source. In this case, the observed signal x_{ij} is modeled as follows:

$$\boldsymbol{x}_{ij} \sim \mathcal{N}(\boldsymbol{0}, \sum_{n} r_{ij,n} \boldsymbol{a}_{in} \boldsymbol{a}_{in}^{\mathsf{H}}).$$
 (8)

A rank-1 spatial covariance model, however, is inappropriate when reverberation is strong or the sources are not regarded as point sources. In the MNMF model, it is assumed that a spatial covariance matrix is full rank and denoted as G_{in} instead of the rank-1 spatial model $a_{in}a_{in}^{H}$. Under this assumption, the observed signal is represented as

$$\boldsymbol{x}_{ij} \sim \mathcal{N}(\boldsymbol{0}, \sum_{n} \sigma_{ij,n} \boldsymbol{G}_{in}),$$
 (9)

where $\sigma_{ij,n}$ is a source spectrogram. It is also assumed that $\sigma_{ij,n}$ has a low-rank structure, i.e.,

$$\sigma_{ij,n} = \sum_{k} t_{ik} v_{kj} z_{kn}, \tag{10}$$

where $k = 1, \ldots, K$ is the index of the NMF basis, and $t_{ik} \in \mathbb{R}_{\geq 0}$ and $v_{kj} \in \mathbb{R}_{\geq 0}$ represent the *i*th frequency component of the *k*th basis and the *j*th time-frame activation component of the *k*th basis, respectively. In addition, $z_{kn} \in \mathbb{R}_{\geq 0}$ is a latent variable that indicates whether the *k*th basis belongs to the *n*th source. In MNMF, we can estimate G_{in}, t_{ik}, v_{kj} , and z_{kn} by minimizing the negative loglikelihood of \mathbf{x}_{ij} , but this consumes a huge amount of computation.

To reduce the computational cost of the update algorithm, FastMNMF additionally assumes that the spatial covariance matrices G_{i1}, \ldots, G_{iN} are jointly diagonalizable by $Q_i = (q_{i1}, \ldots, q_{iM})^{\mathsf{H}}$ as

$$\begin{cases} \boldsymbol{Q}_{i}\boldsymbol{G}_{i1}\boldsymbol{Q}_{i}^{\mathsf{H}} = \boldsymbol{\mathcal{G}}_{i1} \\ \vdots \\ \boldsymbol{Q}_{i}\boldsymbol{G}_{iN}\boldsymbol{Q}_{i}^{\mathsf{H}} = \boldsymbol{\mathcal{G}}_{iN}, \end{cases}$$
(11)

where \mathcal{G}_{in} is a diagonal matrix. From (9) and (11), the negative log-likelihood of the observed signal is given by

$$\mathcal{L}_{\rm F} \stackrel{c}{=} \sum_{i,j,m} \left[\frac{|\boldsymbol{q}_{im}^{\rm H} \boldsymbol{x}_{ij}|^2}{\sum_{n,k} t_{ik} v_{kj} z_{kn} \tilde{g}_{inm}} + \log \sum_{n,k} t_{ik} v_{kj} z_{kn} \tilde{g}_{inm} \right] - 2J \sum_{i} \log |\det \boldsymbol{Q}_i|, \tag{12}$$

where \tilde{g}_{inm} is the *m*th diagonal element of \mathcal{G}_{in} . Similarly to IL-RMA, Q_i in (12) can be optimized via IP and the remaining parameters are updated by using the auxiliary function technique [19]. After the update, we can estimate the separated signals via the multichannel Wiener filter.

3. PROPOSED METHOD

3.1. Motivation and strategy

The joint-diagonalization matrix Q_i of FastMNMF makes the observed signal x_{ij} uncorrelated because x_{ij} follows the multivariate complex Gaussian distribution. When we consider the rank-1 spatial model, the demixing matrix W_i in ILRMA is regarded as one of the decorrelation matrices. From the definition of W_i , the spatial covariance matrix $a_{in}a_{in}^{H}$ multiplied by the demixing matrix W_i on both sides becomes

$$\begin{cases} \boldsymbol{W}_{i}\boldsymbol{a}_{i1}\boldsymbol{a}_{i1}^{\mathsf{H}}\boldsymbol{W}_{i}^{\mathsf{H}} = \boldsymbol{e}_{1}\boldsymbol{e}_{1}^{\mathsf{H}} \\ \vdots \\ \boldsymbol{W}_{i}\boldsymbol{a}_{iN}\boldsymbol{a}_{iN}^{\mathsf{H}}\boldsymbol{W}_{i}^{\mathsf{H}} = \boldsymbol{e}_{N}\boldsymbol{e}_{N}^{\mathsf{H}}, \end{cases}$$
(13)

where e_n denotes the one-hot vector in which the *n*th element equals unity and the others are zero, and consequently $e_n e_n^H$ is a diagonal matrix. Thus, this demixing matrix W_i is one of the jointdiagonalization matrices in the rank-1 spatial model. On the other hand, when the spatial model is not rank-1, such as when the sources are still point sources but the reverberation is strong, the full-rank spatial covariance matrix \tilde{G}_{in} is defined as the sum of the covariances corresponding to the rank-1 part and the reverberation part $\sigma_{rev}\Psi_i$ [20],

$$\tilde{G}_{in} = a_{in}a_{in}^{\mathsf{H}} + \sigma_{rev}\Psi_i, \qquad (14)$$

and the demixing matrix W_i can also jointly diagonalize the first term of the right-hand side of (14), as in (13). Therefore, the jointdiagonalization matrix Q_i can be approximated by W_i estimated in ILRMA. This fact motivates us to propose a new algorithm to find the optimal Q_i around W_i that jointly diagonalizes rank-1 spatial covariance matrices. Note that, although principal component analysis (PCA) is also a typical method of decorrelation, the rotation matrix of PCA only diagonalizes the spatial covariance matrix of the observed signal x_{ij} , which is the weighted sum of the spatial covariance matrix G_{in} of each source, but does not jointly diagonalize each one. Thus, PCA is not appropriate for the joint diagonalization.

In this paper, we only consider a determined situation (M = N). If M < N, i.e., underdetermined situations, the demixing matrix W_i cannot strictly diagonalize the first term of the right-hand side of (14). However, we can still apply this method in this case because the demixing matrix W_i leads to the separated signals being independent of each other to some extent, i.e., $W_i G_{in} W_i^{H}$ (n = 1, ..., N) is close to a diagonal matrix.

3.2. Proposed regularized FastMNMF

From the discussion in Sec. 3.1, we can introduce the prior distribution of the joint-diagonalization matrix Q_i into (12), where the mean of the distribution is set to the demixing matrix W_i of ILRMA, as

$$\boldsymbol{q}_{im} \sim \mathcal{N}(\hat{\boldsymbol{q}}_{im}, (J\lambda_{im})^{-1}\boldsymbol{E}_M), \tag{15}$$

$$\hat{\boldsymbol{q}}_{im} = \boldsymbol{w}_{im}, \tag{16}$$

where λ_{im} is the weight parameter, E_M is the $M \times M$ identity matrix, and J is used to remove the dependence on the total number of time frames. Introduction of the prior distribution (15) is equivalent to the imposition of the regularization term $J \sum_{i,m} \lambda_{im} || q_{im} - \hat{q}_{im} ||^2$ on (12). Hence, the negative log-posterior of the proposed regularized FastMNMF is obtained as

$$\mathcal{L}_{\mathrm{R}} \stackrel{c}{=} \sum_{i,j,m} \left[\frac{|\boldsymbol{q}_{im}^{\mathrm{H}} \boldsymbol{x}_{ij}|^{2}}{\sum_{n,k} t_{ik} v_{kj} z_{kn} \tilde{g}_{inm}} + \log \sum_{n,k} t_{ik} v_{kj} z_{kn} \tilde{g}_{inm} \right] - 2J \sum_{i} \log |\det \boldsymbol{Q}_{i}| + J \sum_{i,m} \lambda_{im} ||\boldsymbol{q}_{im} - \hat{\boldsymbol{q}}_{im}||^{2}.$$
(17)

First, we derive update rules of the joint-diagonalization matrix Q_i . We gather only the terms depending on q_{im} in (17) and rewrite the cost function as

$$\mathcal{L}_{\mathrm{R}} \stackrel{c}{=} J \sum_{i,m} \boldsymbol{q}_{im}^{\mathrm{H}} \boldsymbol{D}_{im} \boldsymbol{q}_{im} - 2J \sum_{i} \log |\det \boldsymbol{Q}_{i}| - J \sum_{i,m} \lambda_{im} (\boldsymbol{q}_{im}^{\mathrm{H}} \hat{\boldsymbol{q}}_{im} + \hat{\boldsymbol{q}}_{im}^{\mathrm{H}} \boldsymbol{q}_{im}),$$
(18)

where

$$\boldsymbol{D}_{im} = \frac{1}{J} \sum_{j} \frac{\boldsymbol{x}_{ij} \boldsymbol{x}_{ij}^{\mathsf{H}}}{\sum_{n,k} t_{ik} v_{kj} z_{kn} \tilde{g}_{inm}} + \lambda_{im} \boldsymbol{E}_{M}.$$
 (19)

Equation (18) is the sum of the quadratic form of q_{im} , the negative log-determinant of Q_i , and the *linear terms* of q_{im} . This type of problem cannot be solved by IP because of the existence of the linear terms. Instead of IP, VCD, which we previously proposed [15], can minimize (18) w.r.t. q_{im} , guaranteeing a monotonic nonincrease in the cost function. We expand the term det Q_i in (18) using $B_i = (b_{i1}, \ldots, b_{iM})$, which is the adjugate matrix of Q_i , defined as

$$[\mathbf{B}_{i}]_{mm'} = (-1)^{m+m'} \breve{\mathbf{Q}}_{i,m'm}, \qquad (20)$$

where $[B_i]_{mm'}$ is the (m, m')th element of B_i and $\hat{Q}_{i,m'm}$ is the (m', m)th minor determinant of Q_i . From a property of cofactor expansion, we obtain $|\det Q_i|^2 = |q_{im}^H b_{im}|^2 = q_{im}^H b_{im} b_{im}^H q_{im}$. Note that b_{im} is independent of q_{im} from its definition [21]. Therefore, the derivative of (18) is obtained as

$$\frac{1}{J}\frac{\partial \mathcal{L}_{\mathrm{R}}}{\partial \boldsymbol{q}_{im}^{*}} = \boldsymbol{D}_{im}\boldsymbol{q}_{im} - \frac{\boldsymbol{b}_{im}}{\boldsymbol{q}_{im}^{\mathsf{H}}\boldsymbol{b}_{im}} - \lambda_{im}\hat{\boldsymbol{q}}_{im}, \qquad (21)$$

where \cdot^* denotes the complex conjugate. By solving the equation $\partial \mathcal{L}_{\rm R} / \partial q_{im}^* = 0$, we describe the update rules of q_{im} based on VCD as follows:

$$\boldsymbol{u}_{im} \leftarrow (\boldsymbol{Q}_i \boldsymbol{D}_{im})^{-1} \boldsymbol{e}_m, \tag{22}$$

$$\hat{\boldsymbol{u}}_{im} \leftarrow \lambda_{im} \boldsymbol{D}_{im}^{-1} \hat{\boldsymbol{q}}_{im}, \tag{23}$$

$$r_{im} \leftarrow \boldsymbol{u}_{im}^{\mathsf{n}} \boldsymbol{D}_{im} \boldsymbol{u}_{im}, \tag{24}$$

$$\hat{r}_{im} \leftarrow \boldsymbol{u}_{im}^{\mathrm{H}} \boldsymbol{D}_{im} \hat{\boldsymbol{u}}_{im}, \tag{25}$$
$$(\underbrace{\boldsymbol{u}_{im}}_{im} + \hat{\boldsymbol{u}}_{im}, \tag{if } \hat{r}_{im} = 0)$$

$$\boldsymbol{q}_{im} \leftarrow \begin{cases} \sqrt{r_{im}} + \alpha_{im}, & (n+im-0) \\ \frac{\hat{r}_{im}}{2r_{im}} \left[\sqrt{1 + \frac{4r_{im}}{|\hat{r}_{im}|^2}} - 1 \right] \boldsymbol{u}_{im} + \hat{\boldsymbol{u}}_{im} \text{ (otherwise).} \end{cases}$$
(26)

Next, we describe update rules of the other parameters t_{ik} , v_{kj} , z_{kn} , and \tilde{g}_{inm} . The cost function \mathcal{L}_{R} in (17) w.r.t. t_{ik} , v_{kj} , z_{kn} , and \tilde{g}_{inm} is the same as \mathcal{L}_{F} in (12) because the regularization term is a function of q_{im} and independent of these parameters. Then, the update rules are given in [19] as

$$t_{ik} \leftarrow t_{ik} \sqrt{\frac{\sum_{j,n,m} \frac{|\mathbf{q}_{im}^{H} \mathbf{x}_{ij}|^{2} v_{kj} z_{kn} \tilde{g}_{inm}}{\sum_{j,n,m} \frac{(\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm})^{2}}{\sum_{j,n,m} \frac{v_{kj} z_{kn} \tilde{g}_{inm}}{\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm}}},$$
(27)

$$v_{kj} \leftarrow v_{kj} \sqrt{\frac{\sum_{i,n,m} \frac{|\mathbf{q}_{im}^{*} \mathbf{x}_{ij}|^{-t} t_{ik} z_{kn} g_{inm}}{(\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm})^{2}}}{\sum_{i,n,m} \frac{t_{ik} z_{kn} \tilde{g}_{inm}}{\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm}}}, \quad (28)$$

$$z_{kn} \leftarrow z_{kn} \sqrt{\frac{\sum_{i,j,m} \frac{|\mathbf{q}_{im}^{H} \mathbf{x}_{ij}|^{2} t_{ik} v_{kj} \tilde{g}_{inm}}{\sum_{i,j,m} \frac{t_{ik} v_{kj} \tilde{g}_{inj}}{\sum_{i,j,m} \frac{t_{ik} v_{kj} \tilde{g}_{inm}}{\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm}}}, \quad (29)$$

$$\tilde{g}_{inm} \leftarrow \tilde{g}_{inm} \sqrt{\frac{\sum_{j,k} \frac{|\mathbf{q}_{im}^{H} \mathbf{x}_{ij}|^{2} t_{ik} v_{kj} z_{kn}}{(\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm})^{2}}}{\sum_{j,k} \frac{t_{ik} v_{kj} z_{kn}}{\sum_{k',n'} t_{ik'} v_{k'j} z_{k'n'} \tilde{g}_{in'm}}}.$$
(30)

These also use the auxiliary function technique, which guarantees a monotonic nonincrease in the cost function. When $\lambda_{im} = 0$, the update rules (22) to (30) are the same as those of the conventional FastMNMF.

3.3. Scheduling of weight parameter of regularizer

The demixing matrix W_i is not an accurate solution of FastMNMF because we cannot ignore the second term of the right-hand side of (14) in the full-rank spatial covariance case. Therefore, the weight parameter of the regularizer, λ_{im} , should become smaller in the latter part of the iterations and this annealing-like approach improves the separation accuracy.

4. EXPERIMENT

4.1. Experimental conditions

We confirmed the efficacy of the proposed method by conducting music source separation experiments. We compared six methods:

	Part name	Source $(1/2)$
Music 1	Midrange/Melody 2	Piano/Flute
Music 2	Melody 1/Melody 2	Oboe/Flute
Music 3	Melody 2/Midrange	Violin/Harpsichord
Music 4	Melody 2/Bass	Violin/Cello
Music 5	Melody 1/Bass	Oboe/Cello
Music 6	Melody 2/Melody 1	Violin/Trumpet
Music 7	Bass/Melody 2	Bassoon/Flute
Music 8	Bass/Melody 1	Bassoon/Trumpet
urce 1	Source 2 (b) S	ource 1

(a)

Fig. 1. Spatial arrangements of sources and microphones.

ILRMA [7], the conventional FastMNMF with E_M initialization for Q_i (FastMNMF w/ E_M init.) [13], the conventional FastMNMF with PCA initialization for Q_i (FastMNMF w/ PCA init.) [19], FastMNMF with W_i initialization for Q_i (FastMNMF w/ W_i init.) as a reference, the proposed regularized FastMNMF without weight scheduling (proposed regularized FastMNMF 1), and the proposed regularized FastMNMF with weight scheduling (proposed regularized FastMNMF 2). We used monaural dry music sources of four melody parts [22]. Eight combinations of instruments with different melody parts were selected as shown in Table 1. To simulate reverberant mixing, the two-channel mixed signals were produced by convoluting the impulse response E2A $(T_{60} = 300 \,\mathrm{ms})$ in the RWCP database [23]. Fig. 1 shows the recording conditions of E2A used in our experiments. In these mixtures, the input signal-to-noise ratio was 0 dB. The sampling frequency was 16 kHz and an STFT was performed using a 64 ms Hamming window with a 16 ms shift (T_{60} is longer than the window length, i.e., the spatial covariance matrices are full rank). The total number of bases in the low-rank source model was K = 20. The initializations of the source model parameters (t_{ik}, v_{kj}, z_{kn}) and the spatial covariance matrix G_{in} in FastMNMF were random values and the identity matrix, respectively. The initialization of Q_i in the proposed methods was the identity matrix. The weight parameter of the proposed regularized FastMNMF 1 was set to 10^{-7} and that of the proposed regularized FastMNMF 2 in the *l*th iteration was set to $\lambda_{im}(l) = \lambda_0 (\lambda_{end}/\lambda_0)^{l/L}$, where *L* is the total number of iterations, λ_0 is 10^{-6} , and λ_{end} is 10^{-13} . The number of iterations in the proposed and conventional methods was 300 and that of IL-RMA conducted before the proposed methods was 50. We used the source-to-distortion ratio (SDR) improvement [24] to evaluate the total separation performance.

4.2. Experimental results for source-separation accuracy

Fig. 2 shows the average SDR improvements over the recording conditions, the source pairs, and 10-trial initialization. Compared with ILRMA, conventional FastMNMF w/ E_M init. and FastMNMF w/ PCA init. provide better SDR improvements to some extent. The SDR improvement of FastMNMF w/ W_i init. is slightly lower than those of the conventional methods. On the other hand, the proposed regularized FastMNMF 1 and regularized FastMNMF 2 markedly outperform the conventional FastMNMF methods and ILRMA. This



Fig. 2. Resultant SDR improvement for each method.



Fig. 3. Average computation time per iteration for "Music 1".

suggests that the initialization of Q_i with W_i is not sufficient, showing the importance of introducing the new prior distribution for Q_i .

In addition, the proposed regularized FastMNMF 2 outperforms the proposed regularized FastMNMF 1. This is because the jointdiagonalization matrix Q_i of the proposed regularized FastMNMF 1 is exceedingly restricted by the demixing matrix W_i in ILRMA in the latter part of the iterations, which does not provide the best separation result as described in Sec. 3.3.

4.3. Experimental results for computation time

We measured the average computation time per iteration for "Music 1". We compared three methods: the conventional MNMF [10], the conventional FastMNMF w/ E_M init., and the proposed regularized FastMNMF 2. Fig. 3 shows that the proposed regularized FastMNMF and the conventional FastMNMF are much faster than the conventional MNMF. The proposed FastMNMF 2 is slightly slower than the conventional FastMNMF because of the VCD update (22) to (26), but the difference is not significant.

5. CONCLUSION

In this paper, we first revealed that the joint-diagonalization matrix Q_i in FastMNMF is closely related to the demixing matrix W_i in ILRMA. Next, motivated by this fact, we proposed a new regularized FastMNMF that includes the prior distribution of Q_i augmented with W_i . Also, we derived the parameter update rules of Q_i on the basis of VCD that guarantees a monotonic nonincrease in the cost function. From the source-separation experiments, we showed that the proposed method outperformed the conventional FastMNMF methods in SDR improvement with almost the same computation time.

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