Independent Low-Rank Matrix Analysis Based on Parametric Majorization-Equalization Algorithm

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Abstract—In this paper, we propose a new optimization method for independent low-rank matrix analysis (ILRMA) based on a parametric majorization-equalization algorithm. ILRMA is an efficient blind source separation technique that simultaneously estimates a spatial demixing matrix (spatial model) and the power spectrograms of each estimated source (source model). In ILRMA, since both models are alternately optimized by iterative update rules, the difference in the convergence speeds between these models often results in a poor local solution. To solve this problem, we introduce a new parameter that controls the convergence speed of the source model and find the best balance between the optimizations in the spatial and source models for ILRMA.

I. INTRODUCTION

Audio source separation is a technique for estimating individual audio sources from a mixture signal. In the last decade, nonnegative matrix factorization (NMF) [1], [2], [3] has been utilized to solve the audio source separation problem for single-channel signals. In particular, Itakura–Saito NMF (ISNMF) has a special interpretation of a generative model that justifies the decomposition of power spectrograms [4], and it has been extended to a multichannel format, which is known as multichannel NMF (MNMF) [5], [6], [7], [8]. In a fully blind situation, blind source separation (BSS) has been well investigated, where the separated signals are estimated without knowing any prior information about the mixing conditions or the characteristics of the sources. In the BSS problem, methods based on statistical independence, such as frequency-domain independent component analysis (ICA) [9], [10], [11] and independent vector analysis (IVA) [12], are widely used.

In these works, parameters are often estimated by an auxiliary function technique, which is a computer-intensive method for iteratively solving various optimization problems with a full guarantee of the monotonic convergence. This includes the majorization-minimization (MM) algorithm [13] that is a generalized scheme of a well-known EM algorithm, and its improved majorization-equalization (ME) algorithm [14]. For example, MM- and ME-algorithm-based multiplicative update rules have been derived for ISNMF, and it has been reported that the optimization based on the ME algorithm results in faster convergence than that based on the MM algorithm [14], [15], [16]. For the BSS methods, the MM algorithm has been utilized to derive fast and stable update rules of ICA [17] and IVA (AuxIVA) [18].

Recently, a unified algorithm of IVA and ISNMF for BSS, independent low-rank matrix analysis (ILRMA) [19], [20], has been proposed. In this method, parameters of a spatial demixing matrix (spatial model) and NMF variables that represent the power spectrograms of each source (source model) are alternately optimized in the separate MM algorithms. From a mathematical viewpoint, this scheme is classified into the coordinate descent method and needs special care for control of each separated optimization because the ILRMA’s problem is non-convex. It is empirically known that the convergence speed of the spatial model is much higher than that of the source model, and this difference may result in unstable source separation owing to the existence of local minima in the cost function. Therefore, the convergence speeds of these models should be controlled by introducing a new parameter to find the best balance between the optimizations in the spatial and source models.

In this paper, we propose a new optimization method for ILRMA that is based on the parametric ME algorithm with the additional parameter that controls the convergence speed of the source model. Our new findings on the parametric surrogate function for an arbitrary power term enable us to construct various types of auxiliary functions that can be solved with a closed form in the ME algorithm step. It would be of great interest in BSS that the proposed method is a generalization of the conventional optimization algorithms used in ILRMA and NMFs; indeed our algorithm includes conventional ILRMA as a special case. Also, the optimal balance between the convergence speeds is experimentally confirmed by BSS experiments using music signals.

II. CONVENTIONAL METHODS

A. Blind Source Separation in Frequency Domain

Let $N$ and $M$ be the numbers of sources and microphones, respectively. The complex-valued short-time Fourier transform (STFT) coefficients of source signals, observed signals, and separated signals are defined as $s_{ij} = (s_{ij,1}, \ldots, s_{ij,n}, \ldots, s_{ij,N})^T$, $x_{ij} = (x_{ij,1}, \ldots, x_{ij,m}, \ldots, x_{ij,M})^T$, and $y_{ij} = (y_{ij,1}, \ldots, y_{ij,n}, \ldots, y_{ij,N})^T$, where $i = 1, \ldots, I$; $j = 1, \ldots, J$; $n = 1, \ldots, N$; and $m = 1, \ldots, M$ are the integral indexes of the frequency bins, time frames, sources, and channels, respectively, and $^T$ denotes a transpose. When the window length in the STFT is sufficiently longer than the impulse responses between sources and microphones, the following instantaneous mixture model in a frequency domain holds:

$$x_{ij} = A_i s_{ij},$$  

(1)
ILRMA is a method unifying IVA and ISNMF, which allows us to simultaneously model the statistical independence between sources and the source-wise time-frequency structure. Whereas IVA employs source-wise frequency vectors [12], ILRMA estimates source-wise power spectrograms that are approximated modeled by the NMF variables. The demixing matrix $W_i$ and the separated signal $y_{ij}$ are optimized so that the spectrogram of each source tends to be a low-rank matrix. This separation mechanism of ILRMA is shown in Fig. 1, where $T_n \in \mathbb{R}^{L \times L}$ and $V_n \in \mathbb{R}_{\geq 0}^{L \times L}$ are the basis and activation matrices for the $n$th estimated source, respectively, and $l = 1, \ldots, L$ is the integral index of the bases. $W_i$, $T_n$, and $V_n$ can consistently be estimated in a fully blind manner. Note that ILRMA is theoretically equivalent to conventional MNMF only when the rank-1 spatial model (1) is assumed, which yields a more stable and more efficient algorithm.

The BSS problem is to estimate $W_i$ using only $x_{ij}$.

**B. ILRMA**

**Fig. 1.** Conceptual model of ILRMA.

where $A_i$ is the mixing matrix. This assumption of the mixing system is often called a rank-1 spatial model [21]. If the number of sources equals the number of channels ($M = N$), the demixing matrix $W_i = (w_{i,1}, \ldots, w_{i,N})^H = A_i^{-1}$ can be defined, where $^H$ denotes a Hermitian transpose, and the separated signals are represented as

$$y_{ij} = W_i x_{ij}. \quad (2)$$

The BSS problem is to estimate $W_i$ using only $x_{ij}$.

**B. Auxiliary-Function-Based Iterative Optimization**

In this subsection, we briefly introduce the mechanism in optimization based on the auxiliary function technique, which includes the MM and ME algorithms. We consider an optimization problem to minimize a cost function $Q(\theta)$ that is difficult to directly minimize, where $\theta$ belongs to an arbitrary parameter space $S$. In such a case, we can use an auxiliary-function-based iterative optimization approach. In this method, we first define an auxiliary function of $Q(\theta)$ as $Q^+(\theta|\theta)$ that satisfies

- $Q(\theta) = Q^+(\theta|\theta)$ for all $\theta \in S$,
- $Q(\theta) \leq Q^+(\theta|\theta)$ for all $\theta, \theta \in S$,

where $\hat{\theta}$ is called the auxiliary variable for $\theta$. In the MM algorithm, we replace the minimization of $Q(\theta)$ with the minimization of the auxiliary function $Q^+(\theta|\theta)$. The parameter $\theta$ is updated as

$$\theta^{(c+1)} = \arg \min_{\theta' \in S} Q^+(\theta'|\theta^{(c)}), \quad (4)$$

where $\theta^{(c)}$ is the parameter at the $c$th iteration. On the other hand, in the ME algorithm, we find a parameter $\theta^{(c+1)}$ that satisfies

$$Q^+(\theta^{(c+1)}|\theta^{(c)}) = Q^+(\theta^{(c)}|\theta^{(c)}). \quad (5)$$

**C. Derivation of New Parametric Auxiliary Function**

To control the convergence speed of the NMF variables in ILRMA, we design a new parametric auxiliary function with the parameter $p$. First, we give a brief proof of the following lemma.

**Lemma 1.** For all $0 < q_1 < q_2$ or $q_2 < q_1 < 0$,

$$z_{q_1} \leq \frac{q_1}{q_2} z_{q_2} + \frac{q_2 - q_1}{q_2} z_{q_1} \quad (6)$$
From (3) and (8)–(11), we have the following auxiliary function:

\[ u_\frac{q_1}{q_2} \leq \frac{q_1}{q_2} \eta z^{-1} (u - \eta) + \eta \frac{q_1}{q_2}, \]  

where \( \eta > 0 \) and the equality holds if and only if \( u = \eta \). By substituting \( u = q_2 \eta \) and \( \eta = \xi q \), we have (6). The equality in (6) holds if and only if \( z = \xi \).

**Proof:** \( u^{q_1/q_2} \) is a concave function for \( u > 0 \) because \( 0 < q_1/q_2 < 1 \). From the tangent-line inequality, we obtain

\[ u_\frac{q_1}{q_2} \leq \frac{q_1}{q_2} \eta z^{-1} (u - \eta) + \eta \frac{q_1}{q_2}, \]  

where \( \eta > 0 \) and the equality holds if and only if \( u = \eta \). Applying Jensen’s inequality, we have

\[ \sum_{i,l,n} t_{il,n} v_{ij,n} \leq \frac{\alpha_{ij,n}^2}{\beta_{ij,n}}, \]  

Also, by applying the tangent-line inequality to the second term using an auxiliary variable \( \beta_{ij,n} > 0 \), we have

\[ \log \sum_{i,l,n} t_{il,n} v_{ij,n} \leq \frac{1}{\beta_{ij,n}} \left( \sum_{i,l,n} t_{il,n} v_{ij,n} - \beta_{ij,n} \right) + \log \beta_{ij,n}. \]  

The equalities in (8) and (9) hold if and only if

\[ \alpha_{ij,n} = \sum_{i,l,n} t_{il,n} v_{ij,n}, \]  

\[ \beta_{ij,n} = \sum_{i,l,n} t_{il,n} v_{ij,n}. \]  

From (3) and (8)–(11), we have the following auxiliary function:

\[ \mathcal{J}^+(W, T, V | \tilde{T}, \tilde{V}) = \sum_{i,j,l,n} \left[ \frac{|w_{iln}^H x_{ij}|^2 t_{il,n} \tilde{v}_{ij,n}}{\sum_{i',l',n'} t_{i'l',n'} v_{i'l',n'}} \cdot \tilde{t}_{il,n} \tilde{v}_{ij,n} \right] \]  

\[ + \sum_{i,l,n} \tilde{t}_{il,n} \tilde{v}_{ij,n} - \tilde{t}_{il,n} v_{ij,n} \]  

\[ + C, \]  

where we denote the auxiliary variables using \( \tilde{\cdot} \) to distinguish them from the original variables, and \( C \) is a term independent of \( T \) and \( V \). This auxiliary function was used in (12) to derive the update rules for \( T \) and \( V \) based on the MM algorithm. In this paper, we design a further auxiliary function parameterized by \( p \) to control the convergence speed of the update rules. By applying (12) to \( (t_{il,n} v_{ij,n})^{-1} \) and \( t_{il,n} v_{ij,n} \) in the right-hand side of (12) using auxiliary variables \( \gamma_{ij,n} > 0 \) and \( \delta_{ij,n} > 0 \), we have

\[ (t_{il,n} v_{ij,n})^{-1} \leq p \gamma_{ij,n}^{-1} \left( t_{il,n} v_{ij,n} \right)^{-1} + (1 - p) \delta_{ij,n}, \]  

\[ t_{il,n} v_{ij,n} \leq p \gamma_{ij,n}^{-1} \left( t_{il,n} v_{ij,n} \right)^{-1} + (1 - p) \delta_{ij,n}. \]  

The equalities in (13) and (14) hold if and only if

\[ \gamma_{ij,n} = \delta_{ij,n} = t_{il,n} v_{ij,n}. \]  

From (12)–(15), we have

\[ \mathcal{J}^{p+}(W, T, V | \tilde{T}, \tilde{V}) = p \sum_{i,j,l,n} \left[ \frac{|w_{iln}^H x_{ij}|^2 \tilde{t}_{il,n} \tilde{v}_{ij,n}}{\sum_{i',l',n'} \tilde{t}_{i'l',n'} \tilde{v}_{i'l',n'}} \cdot \left( \tilde{t}_{il,n} \tilde{v}_{ij,n} \right)^{1/p} \right] \]  

\[ + \frac{\tilde{t}_{il,n} \tilde{v}_{ij,n}}{\sum_{i',l',n'} \tilde{t}_{i'l',n'} \tilde{v}_{i'l',n'}} \left( \tilde{t}_{il,n} \tilde{v}_{ij,n} \right)^{1/p} \]  

\[ + C', \]  

where \( C' \) is a term independent of \( T \) and \( V \). The inequality among (9), (12), and (16) can be represented as

\[ \mathcal{J}(W, T, V) \leq \mathcal{J}^{p+}(W, T, V | \tilde{T}, \tilde{V}) \leq \mathcal{J}^{p+}(W, T, V | \tilde{T}, \tilde{V}), \]  

where the equality in (17) holds if and only if \( \tilde{T} = T \) and \( \tilde{V} = V \). Therefore, when \( p \) approaches 1, \( \mathcal{J}^{p+} \) equals \( \mathcal{J}^+ \). On the other hand, as \( p \) approaches 0, \( \mathcal{J}^{p+} \) diverges from the original cost function \( \mathcal{J} \), which leads to slower update rules for the NMF variables as described in the next section.

**D. Derivation of New Update Rules for ILRMA**

The original cost function (3) can be minimized by employing the parametric auxiliary function (16) based on the ME algorithm to derive the update rules for \( T \) and \( V \). For the variables in \( T \) and \( V \), we have to solve the following equation:

\[ \mathcal{J}^{p+}(W, T, V | \tilde{T}, \tilde{V}) = \mathcal{J}^{p+}(W, \tilde{T}, \tilde{V} | \tilde{T}, \tilde{V}). \]  

By taking (18) apart and organizing the terms of \( \frac{1}{\tilde{t}_{il,n}} \) and \( \frac{1}{\tilde{t}_{il,n}} \), we obtain

\[ A \left( \frac{\tilde{t}_{il,n}}{t_{il,n}} \right)^{1/p} + B \left( \frac{t_{il,n}}{\tilde{t}_{il,n}} \right)^{1/p} + C'' = A + B + C'', \]  

where \( A = \sum_{i,j,l,n} |w_{iln}^H x_{ij}|^2 \tilde{v}_{ij,n} (\sum_{i',l',n'} t_{i'l',n'} v_{i'l',n'})^{-2}, B = \sum_{i,j,l,n} \tilde{v}_{ij,n} (\sum_{i',l',n'} \tilde{t}_{i'l',n'} v_{i'l',n'})^{-1}, \) and \( C'' \) is a term independent of \( t_{il,n} \). Equation (19) is a quadratic equation in the variable \( \frac{t_{il,n}}{\tilde{t}_{il,n}} \frac{1}{p} \), and we can factorize (19) as

\[ \left( \frac{t_{il,n}}{\tilde{t}_{il,n}} \right)^{1/p} - A \left( \frac{t_{il,n}}{\tilde{t}_{il,n}} \right)^{1/p} - 1 = 0. \]  

Fig. 3. Geometric interpretation of (6), where \( q_1 = 0.4 \) and \( \xi = 1 \). Left- and right-hand sides of (6) are depicted by black and red lines, respectively.
Finally, we can obtain the following update rule for $t_{il,n}$ as the nontrivial solution of (20), i.e., $t_{il,n} = \hat{t}_{il,n}(A/B)^p$: 

$$t_{il,n} = \hat{t}_{il,n}\left[\sum_j |w_{il,n}^H a_{ij}|^2 \hat{v}_{lj,n}(\sum_{\ell} \hat{t}_{il,\ell,n} \hat{v}_{\ell,j,n})^{-2}\right]^p. \quad (21)$$

Similar to (21), we can derive the update rule for $v_{lj,n}$ as 

$$v_{lj,n} = \hat{v}_{lj,n}\left[\sum_{\ell} |\hat{w}_{lj,\ell,n}^H a_{ij}|^2 \hat{t}_{il,\ell,n}(\sum_{\ell} \hat{t}_{\ell,l,n} \hat{v}_{\ell,j,n})^{-2}\right]^p. \quad (22)$$

These update rules coincide with those in conventional ILRMA when $p = 0.5$. By controlling this parameter in the range of $0 < p \leq 1$, we can adjust the convergence speed of the NMF variables $T_n$ and $V_n$. Note that these update rules guarantee the monotonic nonincrease in $\mathcal{J}$ for any value of $p$ in the range $0 < p \leq 1$. The similar parameterization of the MM algorithm can be derived. However, it just provides the same generalization in the range of $0 < p \leq 0.5$. Regarding the demixing matrix $W_i$, we can use the same update rule as that in conventional ILRMA called iterative projection, which was originally proposed in AutIVA [18].

IV. EXPERIMENT

A. Experimental Setup

To find the best balance between the convergence speeds, we conducted BSS experiments with two sources and two microphones. In this experiment, the observed signals were convoluted with the music sources shown in Table I obtained from the SISEC2010 professionally produced music recordings dataset [22] and the impulse response (E2A) [23] used in [19]. Also, we used uniformly produced random values of $p \in (0, 1]$ in the proposed parametric update rules (21) and (22). As the evaluation criterion, we used the signal-to-distortion ratio (SDR) [24], which indicates the overall separation quality. We performed ILRMA with the proposed parametric update rules 2000 times using different random seeds in each experiment. The other conditions are shown in Table II.

| ID | Song name Instruments |
|----|-----------------------|
| 1  | dev2 Ultimate Tour>): snap 43.61 guitar/synth |
| 2  | dev2 another dreamer-the ones we love snap 69.94 guitar/vocals |

| Table II. EXPERIMENTAL CONDITIONS |
|-----------------------------------|
| Sampling frequency                | 16000 Hz                        |
| FFT length                        | 256 ms (4096 samples)           |
| Window shift                      | 128 ms (2048 samples)           |
| Number of bases                   | \{10, 20, 40, 60\}              |
| Number of ILRMA iterations        | 200                             |
| Initial values of $T_n$, $V_n$    | Uniform random values in (0, 1) |
| Initial value of $W_i$            | $N \times N$ identity matrix    |

B. Results

Fig. 4 shows the scatter plot of SDR improvements for various values of $p$. From Fig. 4(a), we can confirm that slower update rules for the NMF variables (smaller values of $p$) provide better separation performance than faster ones (larger values of $p$). This tendency did not clearly appear in Fig. 4(b) but we can still recognize that the cluster in $p \in (0, 0.5)$ is concentrated around higher SDR values. Fig. 5 shows the average SDR improvements calculated from the 2000 separation results. When we set $L$ to a larger value, the performance of ILRMA with $p \in (0.5, 1)$ is degraded. However, by using a smaller value of $p$, ILRMA can achieve better separation even if too many bases are used in the source model, thus avoiding a poor solution.

V. CONCLUSION

In this paper, we proposed a new optimization method of ILRMA based on the parametric ME algorithm to control the optimization balance between spatial and source models, where a monotonic nonincrease in the cost function is always ensured. The experimental results showed that ILRMA with a smaller value of $p$ tends to provide better separation than conventional ILRMA, especially in the case of a large number of bases.

ACKNOWLEDGMENTS

This work was partly supported by the SECOM Science and Technology Foundation and JSPS KAKENHI Grant Numbers JP17H06101 and JP17H06572.
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