THE SOURCE MODEL TOWARDS MAXIMIZING THE OUTPUT SIGNAL-TO-INTERFERENCE RATIO FOR INDEPENDENT VECTOR ANALYSIS

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ABSTRACT

In this paper, the optimal source model for the independent vector analysis (IVA) algorithm towards maximizing the output signal-to-interference ratio (SIR) is mathematically derived, and the corresponding optimal weighted covariance matrix is proved to be the covariance matrix of interference signals. A new algorithm framework called minimum variance IVA (MVIVA) is further proposed, where the deep neural network-based estimation of the interference covariance matrix is combined with the IVA-based estimation of the demixing matrix. Experimental results show the superiority of the proposed source model, and the MVIVA algorithm outperforms the original IVA algorithm by 9.6 dB in SIR and 5.8 dB in signal-to-distortion ratio (SDR) on average.

Index Terms—Blind source separation, independent vector analysis, deep neural network, source model

1. INTRODUCTION

Blind source separation (BSS) technology\textsuperscript{11} aims at determining the original source signals from the observed mixtures with minimal prior knowledge about the mixing process, which has found prominent applications in speech communication and speech-based human-machine interaction systems\textsuperscript{2,3,4,5,6,7}. For BSS in the determined case (equal number of microphones and sources), the IVA algorithm is one of the most fundamental method and has a remarkable advantage to overcome the well-known permutation problem\textsuperscript{4,5,7,8,9}. IVA needs to model and process all the frequency components in each source simultaneously, and the choice of source model is crucial to its separation performance.

Consequently, many research efforts have been reported on developing new source model for IVA. The generalized super Gaussian source model and Gaussian source model with time-varying variance are presented in\textsuperscript{10}. The multivariate Student’s t source prior is also adopted\textsuperscript{11} and yields improved separation performance and convergence speed. But these spherical source models are incapable of modeling the spectral structure of the source signals, such as the harmonic structure of speech or music. To address this problem, the independent low-rank matrix analysis (ILRMA) algorithm is proposed\textsuperscript{12} with a flexible source model of nonnegative matrix factorization (NMF) decomposition, which performs well in separating sources with the low-rank time-frequency structures but fails to efficiently models the sources with more complex spectral structures\textsuperscript{13}.

More recently, deep neural network (DNN) is utilized to model the source spectral characteristics\textsuperscript{13,14,15,16,17,18} given its powerful modeling ability. In\textsuperscript{13,14,15,16}, the supervised learning of the source spectrogram is presented, which is further combined with the ILRMA-based blind estimation of the demixing matrix and is referred as independent deeply learned matrix analysis (IDLMA). Due to the complexity of directly estimating the source spectrogram, the DNN-based supervised update of the source variance is then incorporated into the framework of IVA\textsuperscript{17}. Taking advantage of the iterative source steering updates, the work in\textsuperscript{18} proposes to determine the source model parameters by backing propagate the permutation invariant separation loss through multiple iterations of IVA. These DNN models\textsuperscript{13,14,15,16,17,18} can accurately estimate the parameters of the given source model. However, they need to update the source model parameters with DNN iteratively, leading to the expensive computational cost and the mismatch between training and testing data. Because these DNN models are trained with mixture signals, but is applied for the intermediate estimated results repeatedly until convergence. Moreover, the design of the source model is still problematic. The previous studies normally chose the source model heuristically without strict theoretical derivation.

In this paper, we first formulate the source model selection as an optimization problem. With the output SIR as the objective function, the optimal source model is derived whose corresponding weighted covariance matrix is proved to be the covariance matrix of interference signals. Accordingly, we further propose a new BSS method called minimum variance IVA (MVIVA), where DNN is utilized to directly estimate the interference covariance matrix from the mixtures without iterations, which in turn is used to compute the demixing matrix.
following the update rules of IVA. Experimental results under various conditions confirm the superiority of the suggested source model and the effectiveness of the MVIVA algorithm.

2. INDEPENDENT VECTOR ANALYSIS

2.1. Problem Formulation

We address the determined BSS problem where $K$ sources are observed by $K$ microphones ($K \geq 2$). The short-time Fourier Transform (STFT) coefficients of the source, the observed, and the estimated signals are denoted as $s_k(f, t), x_k(f, t)$ and $y_k(f, t)$, respectively, where $t = 1, ..., N_f; f = 1, ..., N_f; k = 1, ..., K$ are the indexes of the time frames, frequency bins and sources (or channels), respectively. For the reverberant mixtures, the mixing process can be assumed as

$$x_k(f, t) = A(f)s(f, t),$$  \hspace{1cm} (1)

where $d(f, t) = [d_1(f, t), d_2(f, t), \cdots, d_K(f, t)]^T \in \mathbb{C}^K (d \in \{s, x, y\})$ denotes the vector representation and

$$A(f) = [a_1(f), a_2(f), \cdots, a_K(f)] \in \mathbb{C}^{K \times K},$$  \hspace{1cm} (2)

is the mixing matrix containing the acoustic transfer functions from the source positions to the microphones, and the superscript $T$ denotes the transpose.

The primary aim of BSS is to estimate a demixing matrix $W(f)$, so that the source signals can be recovered utilizing a linear demixing process,

$$y(f, t) = W(f)x(f, t),$$  \hspace{1cm} (3)

where

$$W(f) = [w_1(f), w_2(f), \cdots, w_K(f)]^H \in \mathbb{C}^{K \times K},$$  \hspace{1cm} (4)

and the superscript $^H$ denotes the Hermitian transpose.

2.2. IVA With Super-Gaussianity Source Model

The original IVA algorithm uses a spherical super-Gaussianity distribution as the source model, i.e.,

$$p(y_k(t)) \propto \exp \left\{ - \frac{1}{\alpha} \| y_k(t) \|^\beta \right\},$$  \hspace{1cm} (5)

$$r_k(t) = \| y_k(t) \| = \sqrt{\sum_{f=1}^{N_f} |y_k(f, t)|^2},$$  \hspace{1cm} (6)

where $\beta$ is a shape parameter ($0 < \beta \leq 2$) \cite{10}, and $\| \cdot \|$ denotes the $l_2$ norm operator, and

$$y_k(t) = [y_k(1, t), ..., y_k(N_f, t)]^T \in \mathbb{C}^{N_f}.$$  \hspace{1cm} (7)

The demixing matrix is then estimated by minimizing the Kullback-Leibler divergence-based objective function \cite{4,7}, given by

$$J(W) = \sum_{k=1}^{K} E_t \{ G(y_k(t)) \} - \sum_{f=1}^{N_f} \log | \det W(f) |,$$  \hspace{1cm} (8)

where $G(y_k(t)) = -\log p(y_k(t))$ is the contrast function, and $E_t \{ \cdot \}$ and $\det(\cdot)$ denote the expectation and determinant operator, respectively.

By introducing the auxiliary function technique \cite{8}, the fast and stable update rules can be obtained in a vector-wise iterative calculation, given by

$$w_k(f) = V_k^{-1}(f)W^{-1}(f)e_k,$$  \hspace{1cm} (9)

$$w_k(f) = w_k(f)/\sqrt{w_k^H(f)V_k(f)w_k(f)},$$  \hspace{1cm} (10)

where $e_k$ denotes the unit vector with the $k$th element unity, and $V_k(f)$ is the weighted covariance matrix and defined as

$$V_k(f) = E_t \left\{ \frac{G'(y_k(t))}{r_k(t)} x(f, t)x^H(f, t) \right\}.$$  \hspace{1cm} (11)

For all $k$ and $f$, Eqs. (3), (5), (11), (9) and (10) are applied in order until convergence, which is referred as AuxIVA \cite{8}.

3. PROPOSED METHOD

3.1. Derivation of The Optimal Source Model

In this paper, we propose to determine the source model by optimizing the output SIR. Since the source model corresponds directly to the weighted covariance matrix $V_k(f)$ given in Eq. (11), we first determine the optimal $V_k(f)$. The optimization problem is formulated as

$$\hat{V}_k(f) = \arg \max_{V_k(f)} \frac{w_k^H(f)\Phi S_k(f)w_k(f)}{w_k^H(f)\Phi N_k(f)w_k(f)},$$  \hspace{1cm} (12)

where

$$\Phi S_k(f) = E_t \{ S_k(f, t)S_k^H(f, t) \},$$  \hspace{1cm} (13)

$$\Phi N_k(f) = E_t \{ N_k(f, t)N_k^H(f, t) \},$$  \hspace{1cm} (14)

denote the covariance matrix of the source component $S_k$ and interference component $N_k$, respectively, and

$$S_k(f, t) = a_k(f)s_k(f, t),$$  \hspace{1cm} (15)

$$N_k(f, t) = x(f, t) - S_k(f, t).$$  \hspace{1cm} (16)

Assuming that $\Phi N_k(f)$ is positive definite, we can decompose it as

$$\Phi N_k(f) = P^H P,$$  \hspace{1cm} (17)
where $P$ is the $K \times K$ invertible matrix. Substituting Eq. (15) into (13), $\Phi_{S_k}(f)$ is a rank-1 matrix given by
\[
\Phi_{S_k}(f) = \delta_k^a a_k(f) a_k^H(f),
\] (18)
where $\delta_k$ is the source power. Substituting Eq. (9) into (10), the demixing matrix can be computed with $V_k(f)$ as
\[
w_k(f) = \frac{V_k^{-1}(f) \hat{a}_k(f)}{\sqrt{\hat{a}_k(f)V_k^{-1}(f)\hat{a}_k(f)}}. \tag{19}
\]
where
\[
\hat{a}_k(f) = W^{-1}(f)e_k. \tag{20}
\]
Substituting Eqs. (17), (18) and (19) into (14), the optimization problem can be rewritten as
\[
\hat{V}_k(f) = \arg \max_{V_k(f)} \delta_k^a D^H P^{-H} a_k(f) a_k^H(f) P^{-1} D, \tag{21}
\]

where
\[
D = PV_k^{-1}(f)\hat{a}_k(f). \tag{22}
\]
According to the Cauchy-Schwarz inequality [19], the solution to Eq. (21) should satisfy
\[
\lambda P^{-H} a_k(f) = D, \tag{23}
\]
that is,
\[
\lambda \Phi_{N_k}^{-1}(f) a_k(f) = V_k^{-1}(f)\hat{a}_k(f), \tag{24}
\]
where $\lambda$ is an positive constant, and $\hat{a}_k(f)$ defined in Eq. (20) is exactly the estimation of $a_k(f)$ since the desired demixing matrix should satisfy $W(f) = A^{-1}(f)$. Therefore, the optimal weighted covariance matrix is
\[
\hat{V}_k(f) = \frac{1}{\lambda} \Phi_{N_k}(f), \tag{25}
\]
where the scale parameter $1/\lambda$ can be omitted because of the followed normalization operation in Eq. (10).

Comparing Eqs. (25) and (11), it can be seen that the optimal source model that achieves the maximum output SIR should satisfy that
\[
E_t \left\{ \frac{-(\log p(y_k(t)))'}{r_k(t)}x(f,t)x^H(f,t) \right\} \propto \Phi_{N_k}(f). \tag{26}
\]
But it is difficult to directly give its formal definition. Intuitively, the weights in Eq. (26) act like the mask to extract the interference signals from the mixture. Since only the weighted covariance matrix is required for estimating the demixing matrix, we can directly estimate $\hat{V}_k(f)$ in actual applications.

### 3.2. The MVIVA Algorithm

The key problem now is the estimation of $\Phi_{N_k}(f)$. Inspired by the success of DNNs for covariance matrix estimation in the mask-based beamformers [20][21][22], we propose to estimate the interference signal by
\[
\tilde{N}_k(f,t) = m_k(f,t)x(f,t), \tag{27}
\]
where $m_k(f,t) \in \mathbb{C}^{N_f \times T}$ is the complex-valued mask computed by the DNN and its weights are shared across channels. The estimated interference covariance matrix can then be obtained as
\[
\tilde{\Phi}_{N_k}(f) = \frac{\sum_{t=1}^{T} \tilde{N}_k(f,t)\tilde{N}_k^H(f,t)}{\sum_{t=1}^{T} m_k(f,t)m_k(f,t)}. \tag{28}
\]

Combining the DNN-based estimation of $\Phi_{N_k}(f)$ and the IVA-based estimation of the demixing matrix $w_k(f)$, the proposed MVIVA algorithm is summarized as **Algorithm 1**. It should be noted that MVIVA omits the normalization operation in Eq. (10). This simplification comes because the scale ambiguity for the separated signals will be resolved by the followed post processing. A few iterations for the update of $w_k(f)$ is still needed, but can be avoided when using the close-form update rules given in [21] for the 2-source case.

**Algorithm 1** MVIVA

1. Estimate $\Phi_{N_k}(f)$ for all $k$ and $f$ with the DNN.
2. Compute the demixing matrix for all $f$:
   ```
   for $l$ of number of iterations $L$ do
     for $k = 1, 2, ..., K$ do
       $w_k(f) = \tilde{\Phi}_{N_k}^{-1}(f)W^{-1}(f)e_k. \tag{29}$
     end for
   end for
   ```

For the DNN architecture, the deep complex convolutional recurrent network (DCCRN) [23] is adopted given its remarkable performance in speech enhancement. The multi-channel complex mixture spectrograms are stacked as input features to estimate $m_k$ for all $k$ simultaneously. For the loss function, we use the complex-domain scale-invariant signal-to-distortion ratio in [24] combined with the spectral mean square error loss to measure the estimation error of $\tilde{N}_k(f,t)$. Permutation invariant training [25] is also utilized because of the ambiguity of the output order.

### 4. EXPERIMENTAL RESULTS

#### 4.1. Data Preparation and Experimental Setup

We train our models on synthesized convolutive mixtures of speech. 14,400 speech samples are selected from the WSJ0 dataset [26] in total. While, 150 room impulse responses (RIRs) are generated for each of the 2-source and 3-source
Table 1. Separation performances of the different methods on the test mixing data ($K$: the number of sources).

| $K$ | Methods | SIR Improvements (dB) | SDR Improvements (dB) |
|-----|---------|-----------------------|-----------------------|
|     |         | 100ms | 200ms | 300ms | 400ms | 100ms | 200ms | 300ms | 400ms |
| 2   | AuxIVA [8] | 11.28 | 9.91  | 8.71  | 7.56  | 7.44  | 5.51  | 3.95  | 2.90  |
|     | ILRMA [12] | 16.54 | 12.03 | 10.50 | 8.83  | 11.90 | 7.02  | 4.79  | 3.27  |
|     | Kang [17] | 21.46 | 15.72 | 13.90 | 11.44 | 15.58 | 9.51  | 6.69  | 4.65  |
|     | IDLMA [13] | 20.90 | 16.14 | 14.04 | 11.89 | 16.19 | 10.13 | 6.94  | 5.01  |
|     | MVIVA    | **25.92** | **20.54** | **17.70** | **15.22** | **18.65** | **11.63** | **7.52** | **5.61** |
| 3   | AuxIVA [8] | 9.12  | 7.13  | 6.45  | 5.46  | 5.72  | 3.95  | 3.13  | 2.21  |
|     | ILRMA [12] | 12.02 | 8.57  | 7.03  | 5.41  | 8.56  | 5.14  | 3.53  | 2.08  |
|     | Kang [17] | 13.59 | 11.29 | 9.32  | 10.11 | 9.83  | 7.14  | 5.15  | 5.20  |
|     | IDLMA [13] | 17.87 | 13.51 | 9.99  | 12.26 | 13.10 | 9.06  | 5.85  | 6.57  |
|     | MVIVA    | **19.16** | **16.39** | **13.73** | **13.74** | **13.36** | **10.37** | **7.60** | **6.80** |

case using the image source method [27] in a simulated 4 m × 4 m × 3 m room. The reverberation time is chosen randomly in the 100 ms to 400 ms interval. The microphone spacing is 2 cm and the arrangement of sources is selected at random. All the models are trained for 20 epochs, and 100,000 mixtures are generated in each epoch by convolving the sources and the RIR randomly selected from the training set. Another 800 and 1,600 mixtures are generated with unseen sources and RIRs for validation and test, respectively. All the signals are sampled at 16 kHz. The STFT frame size is 4096 with half overlap. To eliminate scaling ambiguity of the separated signals, the estimated demixing matrix is rescaled based on the minimal distortion principle [28]. The other parameters are set to $\beta = 1$ and $L = 5$.

Four other algorithms are adopted for comparison, including two conventional methods (AuxIVA [8] and ILRMA [12]) and two DNN-based methods (IDLMA [13] and the method in [17] denoted as Kang method). The same DCCRN architecture and loss function are used for IDLMA and Kang method. The performances of all the methods are then evaluated by the SIR and SDR calculated by the BSS toolbox [29].

4.2. Results and Discussion

We first compare the oracle separation performances that can be achieved by these DNN-based methods. More specifically, the target spectrogram and variance of each source are directly given to IDLMA [13] and Kang method, respectively. The proposed MVIVA algorithm is also applied with the ideal interference covariance matrix. As Fig. 1 shows, MVIVA has the best oracle performance in terms of SDR and SIR under all the conditions, which confirms the superiority of the proposed source model.

Table 1 shows the SIR and SDR scores on the test set. The proposed MVIVA algorithm significantly outperforms the other methods under all the conditions. The effectiveness of the DCCRN-based interference covariance matrix estimation is therefore proved. In addition, it can be seen that MVIVA

![Fig. 1](image-url)
generally outperforms the other methods more greatly in SIR than SDR, since MVIVA aims at maximizing the output SIR. We also note that the DNN-based methods have yielded much better separation performance than the conventional methods thanks to their greater modeling ability.

5. CONCLUSION

This paper mathematically derives the source model that can achieve the maximum output SIR for IVA, where the optimal weighted covariance matrix is proved to be the covariance matrix of interference signals. The DNN model is further utilized to estimate the interference covariance matrix, which is combined with the demixing matrix update rules of IVA and achieves significant separation performance improvements. In the future work, we intend to investigate more efficient ways to estimate the interference covariance matrix and the applications in noisy environments.

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