Multichannel Convolutive Speech Separation with Estimated Density Models

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Abstract—We consider the separation of convolutive speech mixtures in the framework of independent component analysis (ICA). Multivariate Laplace distribution is widely used for such tasks. But, it fails to capture the fine structures of speech signals, and limits the performance of separation. Here, we first time show that it is possible to efficiently learn the derivative of speech density with universal approximators like deep neural networks by optimizing certain proxy separation related performance indices. Specifically, we consider neural network density models for speech signals represented in the time-frequency domain, and compare them against the classic multivariate Laplace model for independent vector analysis (IVA). Experimental results suggest that the neural network density models significantly outperform multivariate Laplace one in tasks that require real time implementations, or involve the separation of a large number of speech sources.

Index Terms—Independent component analysis (ICA), independent vector analysis (IVA), convolutive speech separation, speech probability density, neural network.

I. INTRODUCTION

Speech separation, also known as the cocktail problem, is a fundamental signal processing task, and could have many potential applications. Single channel separations [1], [2], [3], [4], especially the supervised deep learning based methods, attract a lot of attentions recently. However, such methods typically require prior knowledge like the number of sources, and can be too complicated for real time applications deployed on end devices. The traditional independent component analysis (ICA) based multichannel blind speech separation algorithms, e.g., Infomax [5] and independent vector analysis (IVA) [6], [7], [8], are still attractive due to their simplicity and low complexity, and the wide availability of multichannel recordings on end devices like smart phones, tablets, personal computers, smart speakers, and many more internet of things (IoT) devices. Probability density function (pdf) of speech signal is the key component driven the separation of mixtures in such frameworks. There are several choices for modeling the speech distribution, e.g., generalized Gaussian and multivariate Laplace distributions, either in the time or frequency domain [9], [10], [11]. However, none of them can capture the fine structures of real world speech signals, e.g., harmonics of vowels and the distinct spectrogram patterns in vowels and consonants. Hence, such simple density models generally can only produce reasonable separation results in less challenging scenarios like a causal mixing process or a very small number of speech sources. Density estimation is known to be a hard problem, especially for multivariate random variable due to the curse of dimensionality. Fortunately, as in most maximum likelihood (ML) estimation problems, ICA for speech separation only requires the derivative of density, which could be estimated with less difficulty in practice. Here, we consider the separation in the frequency domain. This turns the original time domain convolutive ICA problem into a set of frequency domain dependent instantaneous separation problems, i.e., IVA. In the training phase, neural networks are used to approximate the derivative of speech density in the frequency domain by optimizing certain proxy separation related objectives. Test results suggest that such learned neural network density models can greatly accelerate the convergence rate and improve the steady-state performance for online and offline speech separations, respectively.

II. BACKGROUND: MIXING MODELS AND IVA

A. Mixing and Separation Models

We assume that there are \( N \geq 2 \) speech sources and microphones. Recording of the \( m \)th microphone can be expressed as

\[
x_m(i) = \sum_{n=1}^{N} L \sum_{j=0}^{L} a_{mn}(j) s_n(i-j), \quad 1 \leq m \leq N
\]

where \( i \) and \( j \) are two discrete time indices, \( a_{mn}(i) \) the room impulse response (RIR) from the \( n \)th source to the \( m \)th receiver, \( L + 1 \) the length of RIR, and \( s_n(i) \) the \( n \)th source signal. It is convenient to rewrite (1) compactly as

\[
x(i) = \sum_{j=0}^{L} A(j) s(i-j)
\]

where \( x(i) = [x_1(i), \ldots, x_N(i)]^T \) and \( s(i) = [s_1(i), \ldots, s_N(i)]^T \) are the microphone and source vectors, respectively. \( A(j) \) the mixing matrix at delay \( j \), and superscript \( T \) denotes transpose. Reversing the convolutive mixing process of (2) in the time domain can be computationally expensive. Hence, it is more popular to consider the mixing and separation models in the frequency domain as

\[
X(\omega, t) = H(\omega_k) S(\omega, t),
\]

\[
Y(\omega, t) = W(\omega_k) X(\omega, t), \quad 1 \leq k \leq K
\]

where \( K \) is the number of frequency bins, \( \omega_k \) and \( t \) the discrete angular frequency and frame indices, respectively, \( H(\omega_k) \) and \( W(\omega_k) \) the mixing and separation matrices, respectively, and

\[
S(\omega, t) = [S_1(\omega, t), \ldots, S_N(\omega, t)]^T
\]

\[
X(\omega, t) = [X_1(\omega, t), \ldots, X_N(\omega, t)]^T
\]

\[
Y(\omega, t) = [Y_1(\omega, t), \ldots, Y_N(\omega, t)]^T, \quad 1 \leq k \leq K
\]
the time-frequency representations of source signals, microphone recordings, and separated outputs, respectively. Clearly, the frequency resolution need to be high enough in order to well approximate the linear convolution of each instantaneous mixing operation in 

B. ML Separation Matrix Estimation

Let us introduce the following two column vectors

\[ \mathbf{S}_n(t) = [S_n(w_1, t), S_n(w_2, t), \ldots, S_n(w_K, t)]^T \]

\[ \mathbf{Y}_n(t) = [Y_n(w_1, t), Y_n(w_2, t), \ldots, Y_n(w_K, t)]^T, \quad 1 \leq n \leq N \]

Note that \( \mathbf{S}_n(t) \) and \( \mathbf{S}_n(t) \) are two independent complex valued source vectors for \( 1 \leq m \neq n \leq N \), hence the name IVA. IVA further assumes that \( \mathbf{S}_n(t_1) \) and \( \mathbf{S}_n(t_2) \) are independent for \( t_1 \neq t_2 \), although this might not be true in reality. Then, we can write the pdf of observed mixtures as

\[
p_X(\omega_1, \ldots, \omega_K) = \frac{\prod_{n=1}^{N} p_S(\mathbf{S}_n)}{\prod_{k=1}^{K} \det[\mathbf{H}(\omega_k)]} \tag{4} \]

where \( \det(\cdot) \) denotes the absolute determinant of a square matrix, \( p_S(\cdot) \) the pdf of speech signal in the frequency domain, and we have omitted the frame index \( t \) to simplify our writing. Hence, ML estimation for the separation matrices are given by the minimum of the following expected negative logarithm likelihood (NLL) function

\[
J(\mathbf{W}(\omega_1), \ldots, \mathbf{W}(\omega_K)) = E[-\log p_X(\mathbf{X}(\omega_1), \ldots, \mathbf{X}(\omega_K)|\mathbf{W}(\omega_1), \ldots, \mathbf{W}(\omega_K)])
\]

\[
= E[-\sum_{n=1}^{N} \log p_S(\mathbf{Y}_n) - \sum_{k=1}^{K} \log \det[\mathbf{W}(\omega_k)]^2] \tag{5} \]

One popular density model for speech separation is the multivariate Laplace one, i.e., \( p_S(\mathbf{Y}_n) \propto \exp(-\|\mathbf{Y}_n\|) \), where \( \| \cdot \| \) denotes the norm of a vector.

III. IVA with Estimated Density Model

A. On the Density of Speech

Let us suppress indices \( n \) and \( t \), and simply write the density of \( \mathbf{S} = [S(\omega_1), \ldots, S(\omega_K)]^T \) as \( p(\mathbf{S}) = p[S(\omega_1), \ldots, S(\omega_K)] \). It is reasonable to impose two regularities on the possible forms of \( p(\mathbf{S}) \). First, \( \mathbf{S} \) must be circular in the sense that \( p(\mathbf{S}) \) only depends on the amplitudes of \( S(\omega_k) \) for \( 1 \leq k \leq K \), but not their phases. Second, \( \mathbf{S} \) must be sparse, i.e., \( \partial p(\lambda \mathbf{S})/\partial \lambda \leq 0 \) for any \( \mathbf{S} \) and \( \lambda > 0 \). Then, \( p(\mathbf{S}) \) can only have form

\[
-\log p(\mathbf{S}|\theta) = F(|S(\omega_1)|^2, \ldots, |S(\omega_K)|^2, \theta) \tag{6} \]

where \( \theta \) is a pdf parameter vector, and \( F(\cdot) \) is a properly chosen function. Indeed, any such \( F(\cdot) \) can define a valid pdf as long as \( \exp(-F) \) is integrable. The sparsity regularity requires that

\[
\frac{\partial F(|S(\omega_1)|^2, \ldots, |S(\omega_K)|^2, \theta)}{\partial |S(\omega_k)|^2} \geq 0, \quad 1 \leq k \leq K \tag{7} \]

Notice that minimizing the NLL in (5) only requires derivative

\[
-\frac{\partial \log p(\mathbf{S}|\theta)}{\partial S^*(\omega_k)} = \frac{\partial F(|S(\omega_1)|^2, \ldots, |S(\omega_K)|^2, \theta)}{\partial |S(\omega_k)|^2} S(\omega_k) \tag{8} \]

where superscript * denotes conjugate. Thus, all we need are the \( K \) derivatives in (7), which could be approximated using a feedforward neural network (FNN) with \( K \) nonnegative outputs.

It is also possible to consider the temporal dependence among successive frames from the same source signal. Specifically, for Markov sources, we have

\[
p(\mathbf{S}(t)|\mathbf{S}(t-1), \ldots, \mathbf{S}(1), \mathbf{\theta}) = p(\mathbf{S}(t)|\mathbf{h}(t-1), \mathbf{\theta}) \tag{9} \]

where \( \mathbf{h}(t) \) is a hidden state vector at time \( t \). We could use a recurrent neural network (RNN) with nonnegative outputs to model such densities as well. Examples of such neural networks are given in Section (IV-2).

B. Separation Matrix Updating with Estimated Density Model

We choose to use the natural or relative gradient descent \([12], [13]\) to update the separation matrices due to their simplicity. The estimated density model could be used along with more complicated batch optimization methods, e.g., the relative Newton method \([3]\), as well. Let us omit the frame index, and rewrite \(-\partial \log p(\mathbf{S}|\mathbf{h}, \theta)/\partial S^*(\omega_k)\) in vector form as

\[
-\frac{\partial \log p(\mathbf{S}|\mathbf{h}, \theta)}{\partial S^*} = f(|S|^2, \mathbf{h}, \theta) \circ \mathbf{S} \tag{10} \]

where \( \circ \) denotes element-wise product, \( |S|^2 = S \circ S^* \),

\[
f(|S|^2, \mathbf{h}, \theta) = [f_1(|S_1|^2, h_1, \theta), \ldots, f_K(|S_K|^2, h_K, \theta)]^T \]

is a vector of \( K \) nonnegative functions, and \( f_k(\cdot) \) is the partial derivative of \( F(\cdot) \) with respect to \( |S(\omega_k)|^2 \). Then, gradient of the NLL function in (5) with respect to \( \mathbf{W}(\omega_k) \) is given by

\[
\frac{\partial J}{\partial \mathbf{W}^*(\omega_k)} = E[g(\omega_k)\mathbf{X}^H(\omega_k) - \mathbf{W}^{-H}(\omega_k)], \quad 1 \leq k \leq K \tag{11} \]

where superscript \( H \) denotes Hermitian transpose, vector \( g(\omega_k) \) is given by

\[
[f_k(|Y_1|^2, h_1, \theta)Y_1(\omega_1), \ldots, f_k(|Y_N|^2, h_N, \theta)Y_N(\omega_1)]^T,
\]

and \( h_1 \) is the hidden state vector for the \( n \)th source estimation.

We update \( \mathbf{W}(\omega_k) \) with stochastic natural or relative gradient descent as \([12], [13]\)

\[
\mathbf{W}(\omega_k) \leftarrow \mathbf{W}(\omega_k) + \mu[I - g(\omega_k)\mathbf{Y}^H(\omega_k)]\mathbf{W}(\omega_k), \quad 1 \leq k \leq K \tag{12} \]

where \( \mu > 0 \) is the step size, and \( I \) the identity matrix. It is convenient to use the following bin-wise normalized step size

\[
\mu_k = \frac{\mu_0}{\sigma(I - g(\omega_k)\mathbf{Y}^H(\omega_k))}, \quad 1 \leq k \leq K \tag{13} \]

as it ensures that \( \mathbf{W}(\omega_k) \) is always nonsingular as long as its initial guess is invertible and \( 0 < \mu_0 < 1 \), where \( \sigma(\cdot) \) denotes the spectral norm of a square matrix. In Appendix A, we show that \( \sigma(I - g(\omega_k)\mathbf{Y}^H(\omega_k)) \geq 1 \), and a cheap but tight enough estimation for it is given by

\[
\sqrt{2 - 2 \text{Re}[g(\omega_k)\mathbf{Y}^H(\omega_k)]} + \|g(\omega_k)\|^2 \|\mathbf{Y}(\omega_k)\|^2
\]

where Re(\cdot) takes the real part of a complex variable.
C. Proxy Objective for Fitting the Derivative of Density

Section III.B suggests that vector function \( f(\cdot) \) plays the most important role in determining the trajectories of \( W(\omega_k) \) and \( Y_n(\omega, t) \). It is possible to choose a proxy performance index measuring the goodness of separation, e.g., a properly defined scaling and permutation invariant distance between \( W(\omega_k) \) and \( H^{-1}(\omega_k) \), and learn function \( f(\cdot) \) to optimize the selected proxy objective. In our experiments, we choose the following average permutation invariant absolute coherence as this objective

\[
c(\theta) = \max_{\pi} \frac{1}{NK} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{|E[Y_{\pi(n)}(\omega_k, t)S^*_n(\omega_k, t)]|}{\sqrt{E[|Y_{\pi(n)}(\omega_k, t)|^2]E[|S_n(\omega_k, t)|^2]}}
\]

(14)

where \( \pi \) denotes an element of the set of all possible permutations of list \([1, 2, \ldots, N]\), \( \pi(n) \) the \( n \)th element of permutation \( \pi \), and we deliberately write \( c(\theta) \) as a function of \( \theta \) to show its dependence on the parameters of \( f(\cdot) \). Clearly, \( c(\theta) \) is invariant to the scaling and permutation of separated outputs. In the training phase, the source signals are known. Thus, given the form of \( f(\cdot) \), we can optimize its parameters by maximizing the objective in (14). Such resultant density model implicitly defines a pdf suitable for the separation of speech mixtures.

IV. EXPERIMENTAL RESULTS

Training and test code reproducing the results reported below can be found at [https://github.com/lixilinx/IVA4Cocktail](https://github.com/lixilinx/IVA4Cocktail).

1) General Setup: The training speeches are from a corpus of 100 hour read LibriVox English books [13], and the test ones are from the well known TIMT corpus. All have the same sampling rate, 16,000 Hz. A short time Fourier transform (STFT) with frame size 512 and hop size 160 is used to convert the time domain signals to the frequency domain with analysis and synthesis windows designed by the method in [15]. This frequency resolution works well for separation of mixtures recorded in low to moderate reverberant environments. Higher frequency resolutions may be required for the separation of mixtures with heavier reverberations. All the separation matrices are initialized to the identity matrix.

2) Neural Networks for the Speech Density Model: A neural network usually performs the best for normalized inputs. Here, we define the normalized spectrum vector as \( \tilde{S} = S/\|S\| \). Amplitudes of its elements are further compressed with an element-wise logarithm operation. Our designed neural network density model for (10) is given by

\[
-\frac{\partial \log p(S|h, \theta)}{\partial S^*} = \log[1 + \exp(\gamma)] \odot \tilde{S}
\]

with \( \gamma \) as the output of the following three layer neural network

\[
\alpha(t) = \tanh(\Theta_1 \| \tilde{S}(t) \|; \| \tilde{S}(t) \|; \| h(t - 1); 1 \|) \\
\beta(t) = \tanh(\Theta_2 \alpha(t); 1) \\
\gamma(t) = \Theta_3 \beta(t); 1)
\]

(15)

where \( \{\Theta_1, \Theta_2, \Theta_3\} \) are the model parameters, \( \cdot ; \cdot ; \cdot \) denotes stacking column vectors vertically, and hidden state vector \( h(t - 1) \) is a subset of \( \alpha(t - 1) \). Specifically, (15) defines a FNN when \( h(t) = [] \), and a RNN otherwise. The RNN model can only be used to update the separation matrices sequentially, while the FNN one has no such limitation. We have prepared one FNN and one RNN model. Dimensions of \( \alpha \) and \( \beta \) are the same, 512. For the RNN model, the first 128 elements of \( \alpha \) serve as the hidden states.

3) The Training Environments: We always set \( N = 4 \). Four randomly selected sources are mixed as \( x(i) = \sum_{j=0}^{N-1} A(j) s(i-j)/(1+|j|) \), where all the elements in \( A(i) \) are identically distributed Gaussian random variables. The normalized learning rate in (13) is set to 0.01. The absolute coherence in the proxy objective of (13) is estimated over 128 frames. We choose to reset the mixing matrices with a probability of 0.02 after each evaluation of proxy objective. The simulation batch size is set to 64. The preconditioned stochastic gradient method in (17) is used to optimize the neural network coefficients with default step size 0.01 and a total of 20,000 iterations. The final converged average absolute coherence is about 0.8.

4) The Test Environments: The test speeches are convolutively mixed through randomly generated RIRs using the image source method [16]. Sizes of the simulated room are (Length = 5, Width = 4, Height = 3), all in meters. Locations of simulated microphones are randomly and uniformly distributed inside of a sphere with radius 0.1 and centered at (2, 2, 1.5), while the positions of simulated speech sources are also equally distributed outside of a sphere with radius 1 and the same center location. To simulate fractional delays, we first generate the RIRs with sampling rate 48,000, and then decimate them to sampling rate 16,000. The wall reflection coefficients are set to 0.25 such that the typical converged signal to interference ratio (SIR) for the separation of two sources is about 15 dB. This SIR number is also representative for IVA tested on real world mixtures of two speech sources recorded in living rooms with low to moderate reverberations.

5) Test SIR Performance Comparisons: We compare the three density models, i.e., the multivariate Laplace distribution, the learned FNN and RNN models, for speech separation with IVA using natural gradient descent. The scaling ambiguity is resolved by assuming that the diagonals of \( H(\omega_k) \) are 1.

**Online processing mode**: This mode sequentially updates the separation matrices once per frame. It requires the least amount of memories, and is friendly to end devices with limited resources. The two-input-two-output (TITO) setting is possibly the most interested case for such applications. Fig. 1 shows the average SIR numbers of different density models. The learned neural network models converge about twice faster than the multivariate Laplace one, and their steady state SIRs are about 1 dB higher. The RNN model only delivers a marginal performance gain over the FNN one by providing slightly faster convergence.

**Batch processing mode**: This mode requires to buffer all the observations, and could update the separation matrices with randomly accessed \( X(\omega_k, t) \). Thus, the RNN model cannot be used here. The recording length is 10 s. Ten epochs, i.e., a total of 10,000 iterations, are performed to ensure convergence before measuring the SIR performance. The normalized step size starts from 0.1 for the first epoch, and linearly reduces to 0.01 for the last epoch. Fig. 2 shows the SIR comparison...
results between multivariate Laplace and our estimated FNN models. The FNN model consistently outperforms the multivariate Laplace one. The performance gaps between these two models tend to grow with the increase of $N$.

6) On the Capacity for Correcting Frequency Permutations: Lastly, we would like to point out that IVA with the multivariate Laplace model is inclined to local convergence [18], and thus fails to solve the frequency permutation issue. One typical error pattern is to mix one source’s high frequency band with another’s low frequency band in a single separated output. The neural network models seldom commit such errors. Unfortunately, the SIR performance index is insensitive to such errors as most speech energy locates in low frequency band. To reliably reproduce this behavior, we consider the following simple artificial mixing system consisting of low and high pass Butterworth filters

$$\left[\begin{array}{cc}
(1 + z^{-1})^2 & (1 - z^{-1})^2 \\
(1 - z^{-1})^2 & (1 + z^{-1})^2
\end{array}\right] / (1 + 0.17 z^{-2})$$

High frequency energy is emphasized by passing the outputs through filter $1 - z^{-1}$ before calculating the SIR. Fig. 3 shows the typical comparison results. Clearly, unlike the neural network models, the multivariate Laplace model fails to solve the high and low frequency bands permutation issue.

Appendix A: Spectral Norm of $I - ab^H$

It is known that the spectral norm of a square matrix $A$ is given by the square root of the maximum eigenvalue of $AA^H$. Thus, we consider the eigenvalues of matrix $B = (I - ab^H)(I - ab^H)^H = I - ab^H - ba^H + b^Hba^H$

It is clear that we have $Bz = x$ for any vector $x$ orthogonal to both $a$ and $b$. Thus, 1 is an eigenvalue of $B$ with multiplicity $N - 2$. The left two eigenvalues, $\lambda_1$ and $\lambda_2$, can be solved from the following two equations

$$\lambda_1 + \lambda_2 = \text{trace}(B) - (N - 2) = 2 - 2\text{Re}(a^Hb) + ||a||^2 ||b||^2$$

$$\lambda_1\lambda_2 = \det(B) = ||1 - a^Hb||^2$$

Since $\lambda_1 + \lambda_2 - \lambda_1\lambda_2 = 1 + ||a||^2 ||b||^2 - |a^Hb|^2 \geq 1$, we have $\lambda_1(1 - \lambda_2) \geq 1 - \lambda_2$, and thus $\max(\lambda_1, \lambda_2) \geq 1$. Hence, $\sigma(I - ab^H) = \sqrt{\max(\lambda_1, \lambda_2)}$. A cheap approximation is $\sqrt{\lambda_1 + \lambda_2}$, which is exact when $a^Hb = 1$.

V. Conclusion

Separation of speech mixtures is a longstanding challenge in signal processing problem. Speech density model is the key component in independent component analysis (ICA) based multichannel separation frameworks. In this paper, we have shown that it is possible to efficiently learn the derivative of speech density in the frequency domain with separation related proxy objectives like the absolute coherence between source signals and separated outputs. We have considered neural network speech density models with heuristic design constraints like circularity and sparsity. Experimental results confirm that these learned neural network models considerably outperform the traditional multivariate Laplace one both in convergence speed for online implementations and steady-state performance in batch processing mode.

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