Article

Independent Vector Analysis for Blind Deconvolving of Digital Modulated Communication Signals

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Abstract: For the purpose of overcoming the random permutation ambiguity of the frequency-domain-independent component analysis (FDICA) for blind separation of convolutive mixtures, this paper proposes an independent vector analysis (IVA) detection receiver for blindly deconvolving the convolutive mixtures of digitally modulated signals for wireless communications. The foundation of IVA is through jointly carrying out separation work for different frequency bin data fusion, and the dependencies of frequency bins are exploited in solving the random permutation problem of separation signals. In addition, IVA uses multivariate prior distributions instead of the univariate distribution used in FDICA. Multivariate prior distribution is employed to preserve the interfrequency dependencies for individual sources, which can give rise to separation performance enhancement. Simulation results and analysis corroborate the effectiveness of the proposed detection method.

Keywords: independent vector analysis; independent component analysis; permutation ambiguity; digital modulation; wireless communications

1. Introduction

With the sharply exploding advent of wireless transmission data, the spectrum band resources have become increasingly urgent and congested. A multitude of mixed signals are widespread existing in wireless receivers. This phenomenon has resulted in the difficulties of the conventional receiving processing technology. The prior information of wireless channel is also especially hard to acquire. If the channel state information (CSI) is unknown, and only the received mixture signals can be utilized, the blind adaptive processing will be a promising scheme for source recovery. Thus far, this processing mechanism has received great attention and will be a promising scheme for future intelligent and green communications, known as latent data analysis or unsupervised learning methods [1,2].

Blind source separation (BSS) is a typical latent data analysis method, which has solid theoretical foundations and extensive potential applications [1,3,4]. It can achieve the latent source separation only from the received mixture signals, depending on the statistical features of source signals. One of the representative BSS methods is relying on the independent principle of source to implement separating assignment, i.e., independent component analysis (ICA). To the best of our knowledge, ICA-assisted wireless receiving processing has attracted remarkable attention from home and abroad. There are many scholars engaged in investigating these interesting areas [1,3–17]. These typical related works are given below for discussion.

In the wireless communication systems, the received signals model is always constructed as the instantaneous mixture of source signals and channel effects. Then, the ICA methods can be used for source signal separation or extraction. From the perspective of

the processing mechanism, the time-domain ICA methods are the main detection tools, such as in [6,7]. The time-domain ICA-based detection schemes are for wireless receiving mixture modulation signals. However, in real applications, suffering the multipath fading channel effects, the wireless receiving model should be established as a convolutive mixture of source signals and channel factors. In this convolutive model, direct time-domain ICA methods suffer from severe computational complexity problems with low implementation efficiency.

To overcome the above-mentioned problem, the frequency-domain ICA (FDICA) is recommended for separating each frequency bin instantaneous mixture obtained from the time frequency transformation of convolutive mixtures [5,13–17]. FDICA independently carries out ICA separation, neglecting the relationship of each frequency bin dataset, which uses univariate source component for achieving source modeling. It has been extensively used in multiple input multiple output (MIMO) and MIMO–OFDM (multiple input multiple output–orthogonal frequency division multiplexing) detection [13–17]. In reference [13], the authors investigated FDICA-based impulse interference mitigation for MIMO-OFDM systems. In reference [14], the authors proposed a blind channel estimation using correntropy FDICA for MIMO–OFDM systems. The authors in reference [15] developed an FDICA-based decoding method for massive array antenna MIMO systems. In reference [16,17], the authors proposed an FDICA-based MIMO–OFDM receiver for green communication processing. However, FDICA confronts the random permutation ambiguity problem, which will lead to the difficulty of the source recovery. In processing, the random permutation correction must be used for the further source detection.

To solve the above-mentioned problems, this paper proposes an IVA detection receiver for blind deconvolving of wireless receiving mixture data. IVA is a generation of ICA, which can not only overcome random permutation problems, but also acquires performance enhancement due to using a multivariate source model instead of a univariate source model for constructing separation function [18–22]. Experimental results and analysis corroborate the effectiveness and efficiency of the proposed IVA detection receiver.

The remainder of this paper is constructed as follows. Section 2 discusses the system model and problem formulation. Section 3 talks about the IVA detection receiver, including cost function formulation and optimization methods. Computational complexity and performance evaluation are discussed in Section 4. Section 5 conducts experiments for confirming the proposed method. Lastly, conclusions are obtained in Section 6. The math notations are illustrated as follows. Scalars, vectors, and matrices are denoted by lowercase letters, lowercase boldface letters, and uppercase boldface letters, respectively. The uppercase superscripts "T" and "H" are used for transpose and hermite transpose, respectively, and "*" denotes the convolutive operation.

2. System Model and Problem Formulation

In wireless communications, the source signals always transmit through frequency-selective fading channels. The received signals are the convolutive mixtures of source signals and channel effects. A typical system model with time-domain ICA detection receiver is illustrated in Figure 1.

In Figure 1, the transmitted source signals are denoted as $s_l(n)$, $l = 1, \ldots, M$, $n = 1, \ldots T$, and the received signals are represented as $x_m(n)$, $m = 1, \ldots, M$, $n = 1, \ldots T$. M and T are the numbers of source signals and sample length, respectively. The number of received signals equals that of source signals. The impulse response of channel from the transmitter l to the receiver m is $a_{ml}(n)$. $z_m(n)$ represents the circularly symmetrical complex Gaussian noise term. The time-convolutive mixture contaminated by noise can be described as

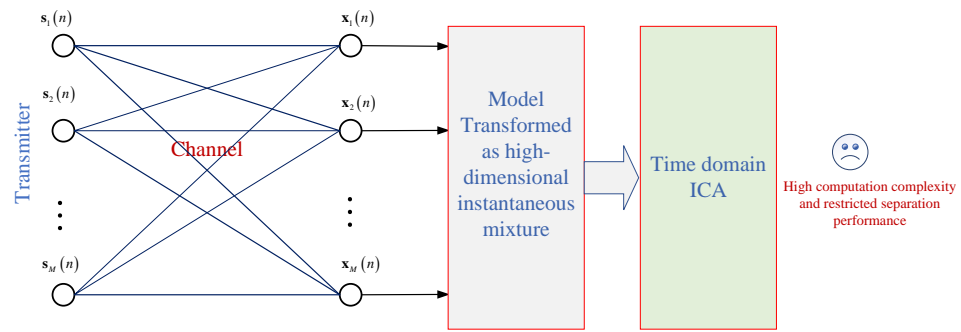$$x_m(n) = \sum_{l=1}^{M} a_{ml}(n) * s_l(n) + z_m(n). \tag{1}$$

Figure 1. Convolutive mixture model with time-domain ICA detection receiver.

In practical applications, the convolutive mixture model is always generated from two propagation influences emerged in wireless fading channels. First, the source signals reach the different receivers with delays. Second, the source signals are transmitted through multipath fading channel.

In the time-convolutive mixture model, direct ICA blind separation processing is a difficult task with high computation complexity. Therefore, the time-domain model can be transformed as a multiple-frequency-domain instantaneous mixture through discrete short-time Fourier transform (STFT). The discrete STFT of the received signal $x_m(n)$ is denoted as

$$X_m(t,f) = \sum_{t=1}^{\infty} x_m(n) win(tL - n) e^{-j2\pi f(tL-n)/F}. \tag{2}$$

where t is the frame number, and f is the frequency bin, $f = 1, \ldots, F$. The window function $win(n)$ can be chosen as a rectangular window of length L. The F-point fast Fourier transform (FFT) is implemented over the windowed section of the $x_m(n)$. The number of F is set as larger than or equal to the window length L, i.e., $F \geq L$.

Similar to the previous Equation (2), the $S_l(t,f)$ is expressed as the discrete STFT of the $s_l(n)$. For the sake of simplification, the vector form of $\mathbf{S}(t,f)$ and $\mathbf{X}(t,f)$ is defined as $\mathbf{S}(t,f) = [S_1(t,f), \ldots, S_l(t,k), \ldots S_M(t,f)]^T$, $\mathbf{X}(t,f) = [X_1(t,f), \ldots, X_m(t,f), \ldots X_M(t,f)]^T$, and $\mathbf{Z}(t,f) = [Z_1(t,f), \ldots, Z_m(t,f), \ldots Z_M(t,f)]^T$, respectively. The corresponding matrix form is $\mathbf{S}(f)$, $\mathbf{X}(f)$ and $\mathbf{Z}(f)$. After this operation, the time-convolutive mixture will be converted into frequency-domain instantaneous mixtures:

$$\mathbf{X}(t,f) = \mathbf{A}(f)\mathbf{S}(t,f) + \mathbf{Z}(t,f). \tag{3}$$

Assume that the source signal $s_l(n)$ is zero-mean, complex-valued, non-Gaussian distributed, and statistically independent. In each frequency bin, the $S_l(t,f)$ also satisfies independent condition, which is proved in Appendix A. Thus, the ICA assumptions are satisfied. Then the frequency-domain ICA is implemented in each frequency bin to separate the source signals $S_l(t,f)$ independently. Before the ICA, the whitening processing will be carried out firstly to reduce the noise effect and make the mixing matrices orthogonal. We implement the whitening processing independently in each frequency bin. Regarding the fth frequency bin ($1 \leq f \leq F$), the whitening operation is executed through the transform $\bar{\mathbf{X}}(f) = \mathbf{V}(f)\mathbf{A}(f)\mathbf{S}(f) + \mathbf{V}(f)\mathbf{Z}(f)$, where $\mathbf{V}(f) = \mathbf{D}(f)^{-1/2}\mathbf{U}(f)^H$, $\mathbf{D}(f) = diag\left(\lambda_1^f - \sigma(f)^2, \ldots, \lambda_M^f - \sigma(f)^2\right)$, and $\lambda_i^f (i = 1, \ldots, M)$ is the ith largest eigenvalue of the covariance matrix $\mathbf{R}(f) = E\left(\mathbf{X}(f)\mathbf{X}(f)^H\right)$, $\mathbf{U}(f)$ is a $M \times M$ matrix constructed by the corresponding eigenvectors, and $\sigma(f)^2$ is the variance of the noise. In practice, in order to estimate the noise variance, the number of receiver sensors is set as larger than that of the source signals. Thus, the noise variance can be estimated by averaging the difference in value of the smallest eigenvalue. The whitening operation can make the orthogonal property of the mixing matrices, i.e., it will satisfy the condition $\mathbf{V}(f)\mathbf{A}(f)(\mathbf{V}(f)\mathbf{A}(f))^H = \mathbf{I}_M$.

Due to the inherent ambiguity problem of BSS, the independent ICA will give rise to the random permutation ambiguity problem. The convolutive mixture model with frequency-domain ICA detection receivers is shown in Figure 2. It is not easy to solve, which will directly affect the following source recovery assignment.
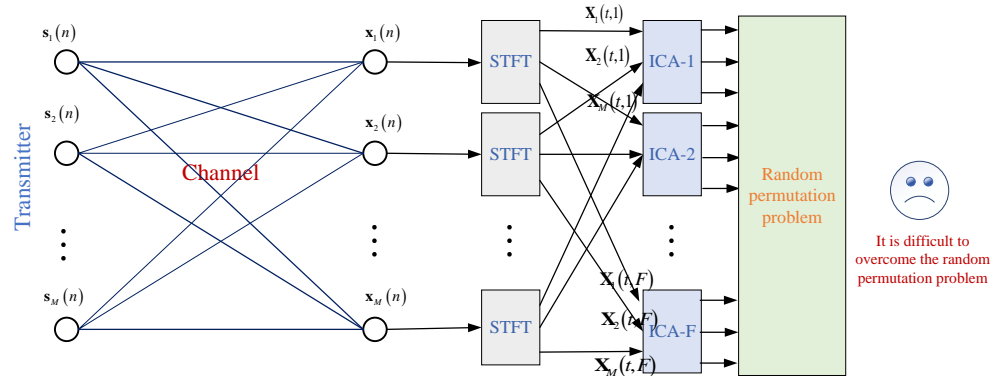

Figure 2. Convolutive mixture model with frequency-domain ICA detection receiver.

3. IVA Detection Receiver

In the separation of mixture model, the ICA methods used for each frequency bin mixture data suffer from the random permutation problem. IVA can provide a natural solution to this issue by acquiring the inherent dependencies of the transmitted digital modulation signals. Therefore, it can solve the random permutation problem and implement the separation of sources for adaptive wireless receiving processing. Regarding the used independent mechanisms in ICA and IVA that have differences, as shown in Figure 3, in IVA, the multivariate source vector is used to replace the univariate source component for modeling the source prior. The proposed IVA detection model is evolved from the conventional FDICA scheme, which is demonstrated in Figure 4. In the following, the fundamentals of IVA will be explained.
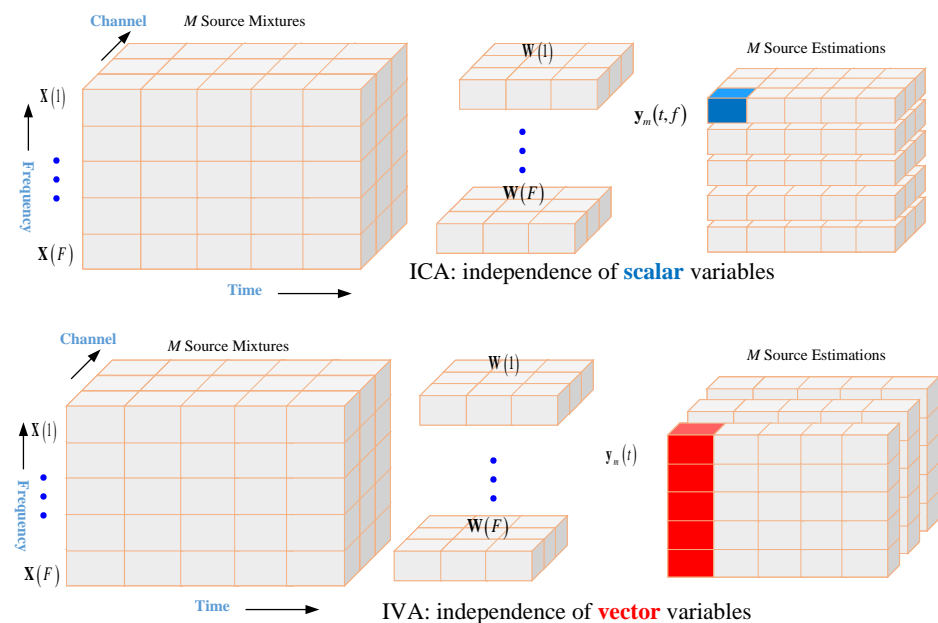

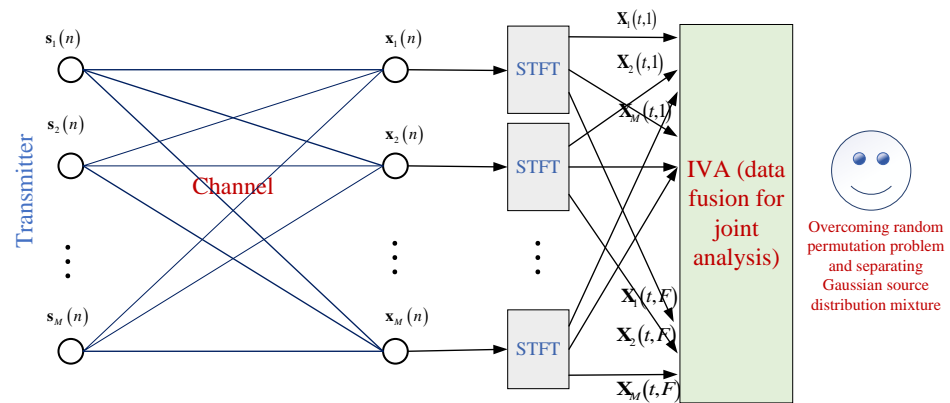**Figure 3.** IVA mechanism versus ICA mechanism.

Figure 4. Convolutive mixture model with IVA detection receiver.

With regard to the model (3), this problem is tackled through defining dependence between multiple components and developing a method for IVA directly. Without loss of generality, the noise effect term is not always considered for deriving the IVA method for simplicity. This consideration is reasonable due to that the whitening processing will be used for removing the noise effect in the process of before IVA, which is similar to that of the existing ICA processing.

According to the previous model (3), frequency bin datasets containing samples are formed from linear mixtures of independent latent sources,

$$\mathbf{X}(t, f) = \mathbf{A}(f)\mathbf{S}(t, f) + \mathbf{Z}(t, f), 1 \leq t \leq T, 1 \leq f \leq F. \tag{4}$$

where each frequency bin dataset $\mathbf{X}(t, f)$, $f = 1, \ldots, F$ is a linear instantaneous mixture of M independent sources.

The invertible mixing matrices $\mathbf{A}(f) \in \mathbb{C}^{M \times M}$ are to be estimated as unknown complex-valued matrix. $\mathbf{S}(t, f) = [s_1(t, f), s_2(t, f), \ldots, s_M(t, f)]^T$ is the latent random complex-valued source vector of source matrix $\mathbf{S}(f)$, in which superscript T denotes transpose operations. In the IVA data model, the source components in each dataset are assumed to be independent statistically, while in different datasets they have dependence connections. For formulating the dependence function across source components, the source component vector (SCV) can be collected by vertically concatenating the nth source from every dataset as follows:

$$\mathbf{S}_n(t) = [s_n(t, 1), s_n(t, 2), \ldots, s_n(t, F)] \in \mathbb{C}^F. \tag{5}$$

The related source component matrix (SCM) is illustrated in Figure 5 through concatenating the mth row of each $\mathbf{S}(f)$. The SCVs are mutual statistically independent random vectors. The probability distribution function (PDF) of the concatenated source vector can be denoted as $p(\mathbf{S}) = \prod_{m=1}^M p_m(\mathbf{S}_m)$.

The purpose of IVA is to seek F separation matrices and the corresponding source vector estimation for each dataset, with the fth estimations indicated as $\mathbf{W}(f) \in \mathbb{C}^{M \times M}$. The source estimations are represented as

$$\mathbf{Y}(t, f) = (\mathbf{W}(f))^H \mathbf{X}(t, f). \tag{6}$$

The estimation of the mth component from the fth dataset is denoted as $y_m(f) = (\mathbf{w}_m(f))^H \mathbf{x}(f)$, in which superscript H indicates the complex conjugate transpose, $(\cdot)^*$ is the complex conjugate operator, $\mathbf{w}_m(f)$ is the mth column of $\mathbf{W}(f)$, and $w_{n,l}(f)$ is the element in the nth row and lth column of $\mathbf{W}(f)$. The estimation of the mth SCV is described as $\mathbf{y}_m^T = [y_m(1), \ldots, y_m(F)]$. The mixing matrices mean the influence of wireless channels, which are potentially distinct for each dataset and are not necessarily related.
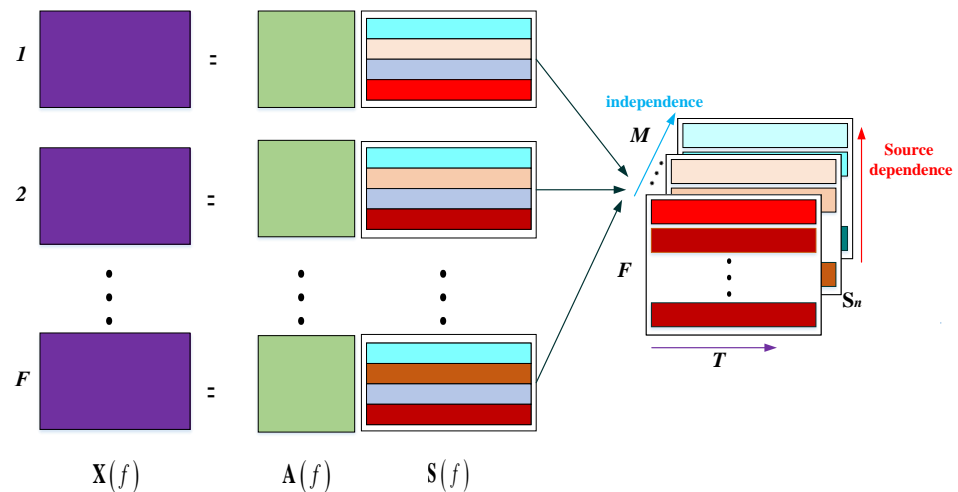
Figure 5. IVA structure based on SCV.

The cost function of IVA is obtained in the same formation as that of ICA, i.e., minimum mutual information (MMI) or maximum likelihood (ML) [20,21]. Compared with just estimating single separation matrices in ICA, the purpose of IVA requires to estimate F separation matrices $\mathbf{W}(1), \ldots, \mathbf{W}(F)$ to achieve source estimations.

3.1. Cost Function for IVA

The fundamental principle of IVA is to maximize the independence of all of SCVs, which can be acquired through minimizing the mutual information among the source component vectors. A set of separation matrices needs to be estimated that can be organized as a three-dimensional array or tensor $\mathcal{W} \in \mathbb{C}^{M \times M \times F}$. The essential cost function of IVA based on the MMI principle is represented as [18–22]:

$$
\begin{aligned}
C_{IVA}(\mathcal{W}) &\triangleq \mathcal{I}\{\mathbf{y}_1; \ldots; \mathbf{y}_M\} \\
&= \sum_{m=1}^{M} \mathcal{H}\{\mathbf{y}_m\} - \mathcal{H}\{\mathbf{y}_1, \ldots, \mathbf{y}_M\} \\
&= \sum_{m=1}^{M} \mathcal{H}\{\mathbf{y}_m\} - \mathcal{H}\left\{(\mathbf{W}(1))^H \mathbf{x}(1), \ldots, (\mathbf{W}(F))^H \mathbf{x}(F)\right\} \\
&= \sum_{m=1}^{M} \mathcal{H}\{\mathbf{y}_m\} - 2 \sum_{f=1}^{F} \log|\det(\mathbf{W}(f))| - C_1
\end{aligned}
\tag{7}
$$

in which $\mathcal{H}\{\mathbf{y}_m\}$ illustrates the differential entropy of the estimated mth SCV, and the term C_1 denotes a constant parameter $\mathcal{H}\{\mathbf{x}(1), \ldots, \mathbf{x}(F)\}$, where it is regarded as a constant in the subsequent optimization implementation. Particularly noteworthy is that the entropy of a linear invertible transformation, $\mathbf{W}^H \mathbf{x}$, in the complex domain is given by $2 \log|\det(\mathbf{W})| + \mathcal{H}\{\mathbf{x}\}$, and the determinant of a block diagonal matrix is a product of the determinants of the individual blocks. The $\log|\det(\mathbf{W}(f))|$ is a regularization term that penalizes separation matrices with small determinants and restricts separation matrices to be unitary when the penalty term becomes fixed.

By definition, $\mathcal{H}\{\mathbf{y}_m\} = \sum_{f=1}^{F} \mathcal{H}\{y_m(f)\} - \mathcal{I}(\mathbf{y}_m)$, where $\mathcal{I}(\mathbf{y}_m)$ is the mutual information within the mth SCV, which sheds light on the dependence within components of an SCV. Thus, Equation (7) can be obtained as follows after replacing of $\mathcal{H}\{\mathbf{y}_m\}$:

$$
C_{IVA}(\mathcal{W}) = \sum_{m=1}^{M} \left(\sum_{f=1}^{F} \mathcal{H}\{y_m(f)\} - \mathcal{I}(\mathbf{y}_m) \right) - 2 \sum_{f=1}^{F} \log|\det(\mathbf{W}(f))| - C_1.
\tag{8}
$$

The previous mathematical description expresses that minimizing the cost function is to simultaneously maximize the mutual information within individual SCVs and minimize the entropy of all components. It is essential to point out that the mutual information $\mathcal{I}(\mathbf{y}_m)$ in the IVA cost function gives an insight for solving the random permutation ambiguity across multiple datasets.

3.2. Optimization Methods for IVA

According to [21], $\mathbf{h}_m(f)$ is defined to be a unit length vector such that $(\tilde{\mathbf{W}}_m(f))^H \mathbf{h}_m(f) = \mathbf{0}$, where $\tilde{\mathbf{W}}_m(f)$ is the $M \times (M-1)$ matrix formed by removing the mth column of the separation matrix $\mathbf{W}(f)$. Then, it can be computed as

$$|\det(\mathbf{W}(f))| = \left|(\mathbf{h}_m(f))^H \mathbf{w}_m(f)\right| S_m(f). \tag{9}$$

where $S_m(f) = \sqrt{\left|\det\left((\tilde{\mathbf{W}}_m(f))^H \tilde{\mathbf{W}}_m(f)\right)\right|}$. Clearly, the value of $S_m(f)$ is independent of $\mathbf{w}_m(f)$. The calculation of $\mathbf{h}_m(f)$ can be computed using an extension of the efficient real-valued recursive method explained in [20] to complex domain processing. By replacing (9) in (7), we obtain

$$
\begin{aligned}
C_{IVA}(\mathbf{w}_m(f)) &= \sum_{m=1}^{M} \mathcal{H}\{\mathbf{y}_m\} - 2\sum_{f=1}^{F} \log\left(\left|(\mathbf{h}_m(f))^H \mathbf{w}_m(f)\right| S_m(f)\right) - C_1 \\
&= \mathcal{H}\{\mathbf{y}_m\} - 2\log\left|(\mathbf{h}_m(f))^H \mathbf{w}_m(f)\right| + C_m(f)
\end{aligned} \tag{10}
$$

where we note that $\mathcal{H}\{\mathbf{y}_m\}$ is independent of $\mathbf{w}_m(f)$ for $m \neq n$, yielding

$$C_m^{[f]} \triangleq \sum_{m=1,m\neq n}^{M} \mathcal{H}\{\mathbf{y}_m\} - \sum_{l=1,l\neq f}^{F} 2\log|\det(\mathbf{W}(l))| - 2\log S_n(l) - C_1. \tag{11}$$

then, IVA using vector gradient descent can be denoted as

$$(\mathbf{w}_m(f))^- \leftarrow (\mathbf{w}_m(f))^{old} - 2\mu \frac{\partial C_{IVA}}{\partial(\mathbf{w}_m(f))^*}. \tag{12}$$

in which μ denotes the nonnegative step size. The IVA cost function derivative is derived with respect to the complex conjugate of $\mathbf{w}_m(f)$ as

$$\frac{\partial C_{IVA}}{\partial(\mathbf{w}_m(f))^*} = -E\left\{\frac{\partial \log p(\mathbf{y}_m)}{\partial y_m(f)}\frac{\partial y_m(f)}{\partial(\mathbf{w}_n(f))^*} + \frac{\partial \log p(\mathbf{y}_m)}{\partial(y_m(f))^*}\frac{\partial(y_m(f))^*}{\partial(\mathbf{w}_m(f))^*}\right\} - 2\frac{\partial\left|(\mathbf{h}_m(f))^H\mathbf{w}_m(f)\right|}{\partial(\mathbf{w}_m(f))^*}. \tag{13}$$

where $E\{\cdot\}$ shows the expectation operator. Applying the complex derivative rules of Wirtinger calculus, it yields

$$\frac{\partial y_m(f)}{\partial(\mathbf{w}_m(f))^*} = \frac{\partial(\mathbf{w}_m(f))^H \mathbf{x}(f)}{\partial(\mathbf{w}_m(f))^*} = \mathbf{x}(f), \tag{14}$$

$$\frac{\partial(y_m(f))^*}{\partial(\mathbf{w}_m(f))^*} = \frac{\partial(\mathbf{x}(f))^H \mathbf{w}_m(f)}{\partial(\mathbf{w}_m(f))^*} = 0. \tag{15}$$

and

$$\frac{\partial \log\left|(\mathbf{h}_m(f))^H \mathbf{w}_m(f)\right|}{\partial(\mathbf{w}_m(f))^*} = \frac{1}{2}\frac{\mathbf{h}_m(f)}{(\mathbf{w}_m(f))^H \mathbf{h}_m(f)}. \tag{16}$$

Combining with the previous derived three gradients and assuming that

$$\phi(\mathbf{y}, f) = [\phi(\mathbf{y}_1, f), \ldots, \phi(\mathbf{y}_M, f)]^T$$
$$= -\left[\frac{\partial \log\{p(\mathbf{y}_1)\}}{\partial y_1(f)}, \ldots, \frac{\partial \log\{p(\mathbf{y}_M)\}}{\partial y_M(f)}\right]^T \cdot \tag{17}$$

we can obtain

$$\frac{\partial C_{IVA}}{\partial (\mathbf{w}_m(f))^*} = E\{\phi(\mathbf{y}_m, f)\mathbf{x}(f)\} - \frac{\mathbf{h}_m(f)}{(\mathbf{w}_m(f))^H \mathbf{h}_m(f)}. \tag{18}$$

4. Computational Complexity and Performance Evaluation

The time-domain ICA method is only theoretically feasible. However, the time-domain methods are computationally complex because of the convolutive mixture mechanism. It is not realizable to use time-domain ICA, owing to the computational need.

After time-frequency processing, it is computationally efficient to implement separation work in each frequency bin, named FDICA. This method requires F times independent ICA work for source separation, which has roughly the complexity order of $O(FTM^2)$. In contrast with ICA, the IVA requires that of $O(FTM^2 + FTM)$. It is noticeable that the sampling length T is far larger than the number of source components M and frequency bins F. Therefore, they have roughly similar computational complexity. Moreover, the FDICA needs the permutation correction processing that also will lead to some computation complexities.

In addition, due to that the inherent random permutation problem existed in the FDICA method, the permutation correction must be used for further source recovery. Otherwise, the performance will be lost severely. In IVA, the random permutation problem can be overcome. Moreover, the multivariate source models are utilized for source separation; this will be better than the independently used univariate source model for realizing the digital modulation signal model. In the next section, the simulation experiment will be conducted for performance comparison; this will confirm the effectiveness of the investigated IVA-based detection method.

5. Simulation Results and Analysis

To verify the effectiveness of the proposed IVA detection receiver, we conduct computer simulations for performance analysis. Before the application of IVA to convolutive mixtures, IVA experiments are implemented for helping set the appropriate algorithm parameters to wireless receiving detection application. Then, four different FDICA methods and the proposed IVA detection method are implemented for performance comparison in a convolutive mixture application. The joint inter-symbol interference (*jISI*) is used to as performance index. The *jISI* is derived from the conventional normalized inter-symbol interference (*ISI*) and is used to analyze performance, i.e,

$$ISI(\mathbf{G}) \triangleq \frac{1}{2M(M-1)} \left[\sum_{n=1}^{M}\left(\sum_{m=1}^{M}\frac{|g_{n,m}|}{\max_p |g_{n,p}|} - 1\right) + \sum_{m=1}^{M}\left(\sum_{n=1}^{M}\frac{|g_{n,m}|}{\max_p |g_{p,m}|} - 1\right)\right]. \tag{19}$$

where $\mathbf{G} = \mathbf{WA}$. The *ISI* can be extended to obtain the joint *ISI*, i.e., $\mathbf{G}(f) = \mathbf{W}(f)\mathbf{A}(f)$, and $|\mathbf{G}(f)|$ is the absolute value of $\mathbf{G}(f)$.

$$jISI \triangleq ISI\left(\sum_{f=1}^{F} |G(f)|\right). \tag{20}$$

The metric *jISI* measures the consistency of SCV estimation among datasets. The lower *jISI* means the better separation performance. In addition, BER performance metric is also used to evaluate the different detection methods for convolutive mixture separation in wireless receiving processing.

In IVA, the complex multivariate generalized Gaussian (MGGD) distribution [20,21]-based IVA is used to performance evaluation. The number is set as 5, and the sample length is 1000 vs. 10,000. The MGGD used is to generate the sub-Gaussian distribution-based SCV for simulating sub-Gaussian communication signals. The mth SCV is a zero-mean with F dimensional sub-Gaussian random vector. The different SCV structure is random correlation structure. In addition, we mainly consider the gradient iteration. We know the Newton manner is faster but with high complexity and maybe non-convergence. Therefore, the gradient is suggested in this paper. The random correlation covariance structure is defined as $\Sigma_m = C_m C_m{}^H$, where the elements of C_m are from the standard complex-valued normal distribution.

The experimental results are shown in Figure 6, which illustrates that IVA with the long sample length is better than that of the short sample length. In Figure 7, the statistical analysis of jISI for different F value is given for illustrating that the proper F values can be set as for the following joint analysis, such as $F = 16$.
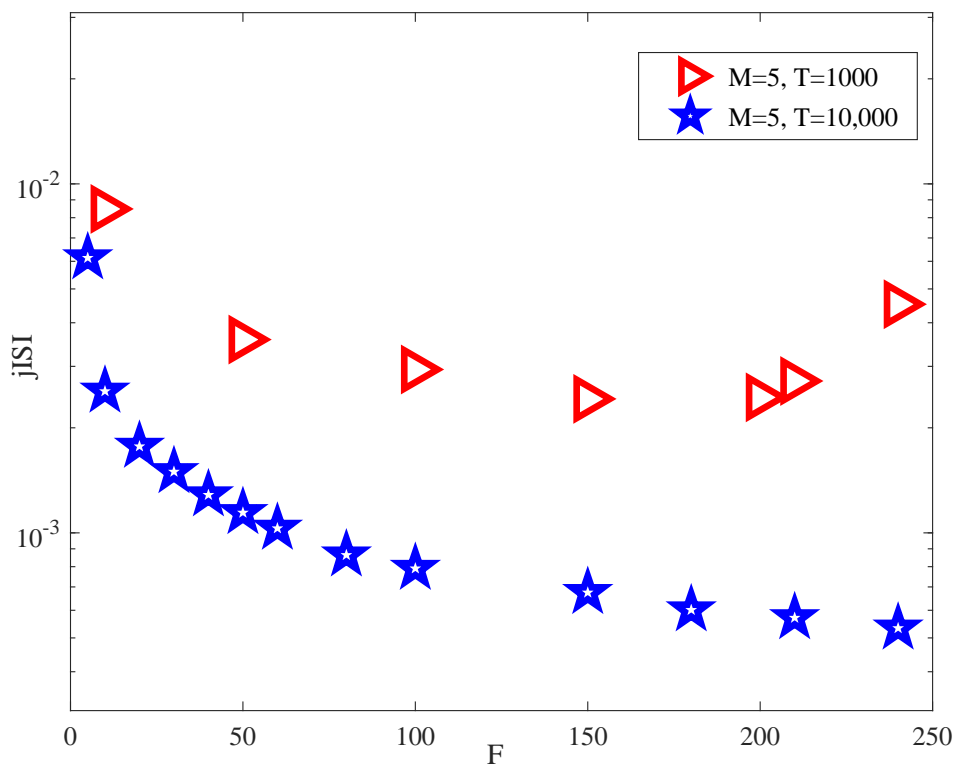

Figure 6. Performance comparison of IVA with different sample length.

For the purpose of confirming the IVA detection performance for a real communication application scheme, the following experiment is carried out. The simulation parameters are set as follows. The channel is chosen as a slowly-varying frequency-selective fading channel. This means that the channel impulse response changes slowly with the transmitted symbol period. This mixture mechanism can be described as a static mixture. The third-order convolutive mixture systems with the Gaussian distribution coefficients are used for simulation. The source signals are uniformly distributed independent differential quadrature phase shift keying (DQPSK). The number of source and received signals is 5. The sample length of the received signals is 10,000. The length of the rectangular window is 3. The points of the FFT are 16. In order to highlight the proposed IVA, different representative ICA methods are used to make performance comparisons. The simulation results are demonstrated in Figure 8.
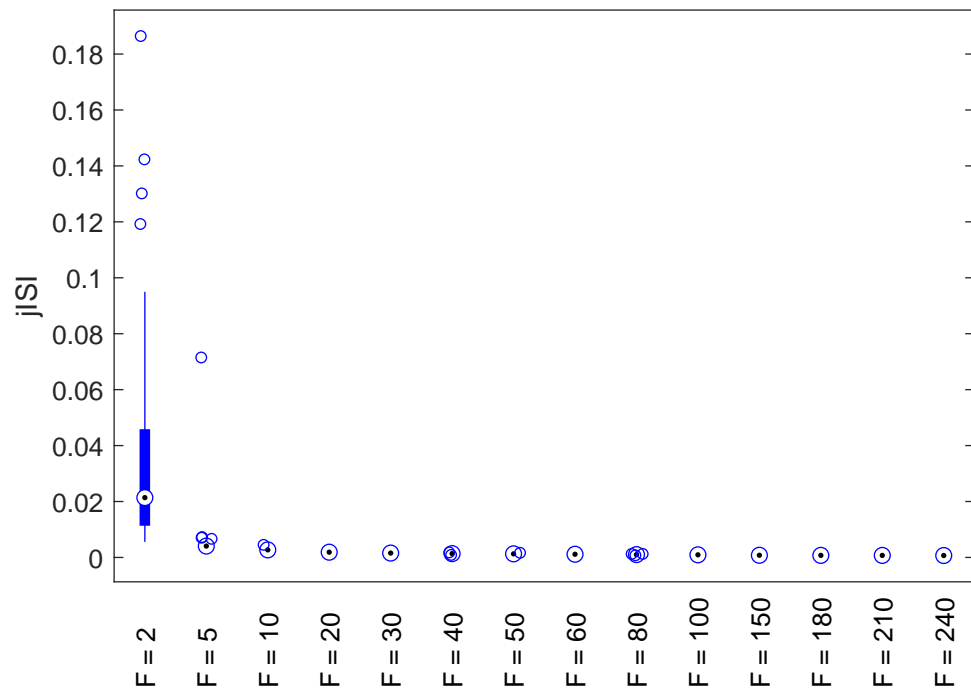
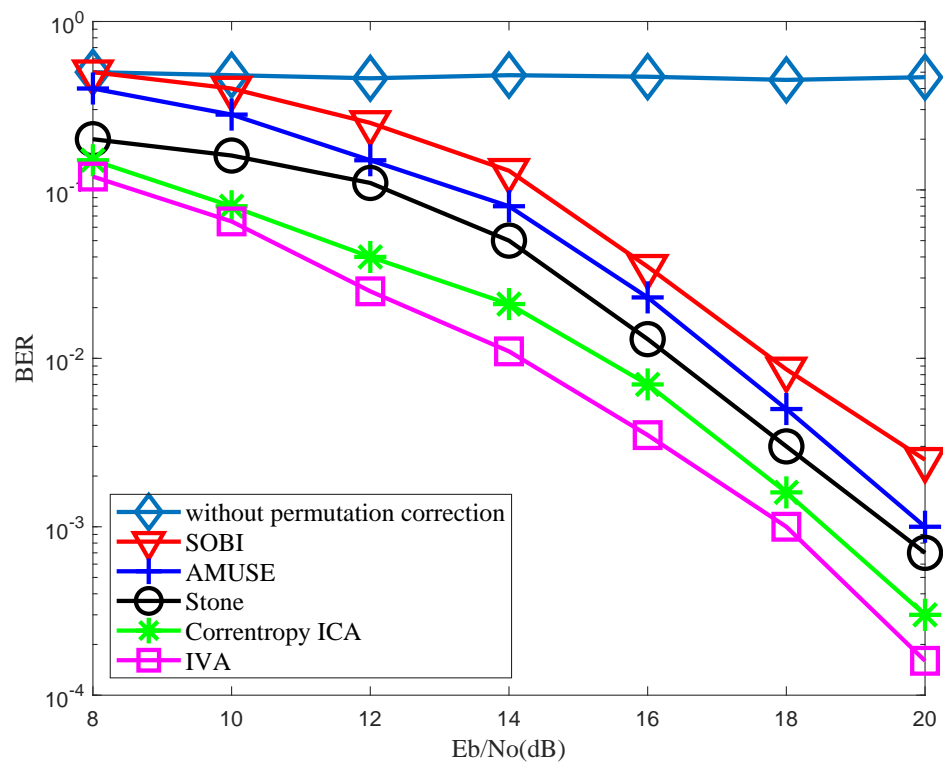**Figure 7.** Statistical performance analysis for IVA with different SCV dimension.

Figure 8. BER performance comparison for different methods.

According to the above-mentioned parameters, we simulate the IVA and four FDICA methods for performance comparison. The averaged bit error rate (BER) of the data sequence with regard to the transmission data is evaluated. In FDICA, the permutation correction scheme is from the reference [14]. In order to highlight the performance improvement, the third FDICA method without permutation corrections is also given. Simulation results are shown in Figure 8, which verify the effectiveness of applying the IVA method. The proposed IVA scheme acquires the improved BER performance.

6. Conclusions

The received wireless signals are always the convolutive mixture of the latent source signals in the unknown condition of slow frequency-selective fading channels. The main work of this paper is to propose an IVA-detection-based blind separation of convolutive signals. IVA is beneficial for conquering permutation ambiguity encountered in the conventional frequency-domain ICA model. In addition, the multivariate source models are jointly used in IVA for performance enhancement. Simulation results show that the performance of the proposed IVA detection method is better than that of the conventional FDICA detection method. In the future work, the robust IVA method is strongly recommended to be investigated for overcoming different environmental noise impact as well as dynamic channel condition impairment.

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Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BER	Bit error rate
BSS	Blind source separation
DQPSK	Differential quadrature phase shift keying
FDICA	Frequency-domain independent component analysis
ICA	Independent component analysis
IVA	Independent vector analysis
MMI	Minimum mutual information
ML	Maximum likelihood
MIMO	Multiple input multiple output
OFDM	Orthogonal frequency division multiplexing

Appendix A

According to the theorem from [23], if the two random variables x and y are independent, then the functions of these random variables $z = f(x)$ and $w = g(x)$ are also independent.

The previous theorem shows that functions of independent random variables are also independent. In the frequency bin model, the sources $s_m(n)$ are statistically independent so that their discrete STFT, $S_m(t, f)$ are linear functions of the $s_m(n)$ as

$$S_m(t,f) = \sum_{t=1}^{\infty} s_m(n) win(tL - n) e^{-j2\pi f(tL-n)/F}. \tag{A1}$$

Therefore, these frequency components $S_m(t, f)$ are also statistically independent in each frequency bin.

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