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A New Ambiguity Elimination Method for BSS Block Signals in Time Domain

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Abstract

This paper deals with the ambiguity problem of blind source separation (BSS) in the case where continuously received mixture signals are split in time and processed block by block. Due to the inherent permutation and scaling ambiguities of BSS, tying the separated components at each adjacent time blocks doesn't recover the original source signals correctly in general. Inspired by the Permutation Method of reconstructing source signal blocks in time domain, a new ambiguity elimination approach is proposed in this paper. This method aims to concatenate the separated components in adjacent blocks by artificially setting contrast blocks for each adjacent time blocks. The core idea of this method is to utilize the associativity between components recovered from contrast blocks and corresponding adjacent blocks. Compared with Permutation Method, the main advantage of this new method consists in the fact that it is much more efficient in terms of separation quality and computational speed. Besides, a tradeoff can be adjusted between separation quality and computational speed by choosing different length of contrast blocks. Real-life experiments are performed to validate the performance of this method on the wireless communication system with two transmitting and receiving antennas.

Keywords: *Blind source separation; permutation and scaling ambiguities; adjacent signal blocks; contrast blocks*

1. Introduction

In recent decades, blind source separation (BSS) has been applied in a wide variety of fields such as array processing, passive sonar, seismic exploration, speech processing, multi-user wireless communications, *etc* [1]. In the case of a linear multi-input/multi-output (MIMO) instantaneous system, BSS corresponds to independent component analysis (ICA), which is now a well recognized concept [2].

However, for BSS one problem is inhered from the property of the following ambiguities as presented in [3]. The first ambiguity is the existence of the unknown complex scaling factor, which results in the ambiguous phase and amplitude in separated signals. The other ambiguity is the permutation of the separated signals. These ambiguities cause problems when continuously incoming measurement data is split in time and when they are processed block by block. Tying components at adjacent blocks without permutation and rescaling does not recover the original signals correctly. In order to solve the problem, several methods have been contrived as follows.

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Scaling ambiguity, *i.e.*, amplitude and phase indeterminacies can be solved using split spectrum introduced by Murata *et. al.*, [4]. For the permutation problem, there have been tried a method using similarities between separate spectra [5], a method substituting the initial weights at a frequency by those learned at its adjacent frequency [6] and a method taking advantage of directivity of array microphones [7-8]. Above all, FastICA [6, 9] proposed by Hyvarinen is expected to relax the permutation problem, because it separates the signal in order of large non-Gaussianity. DOA type [3], [10] methods tie signal blocks with similar DOA and require an array manifold. Since it requires an array manifold, it degrade permutation accuracy by calibration error. Correlation based methods [11, 4] compute the correlation coefficient of all possible combination of separated signals in adjacent blocks. But they are not appropriately used in practical application in terms of computational resource.

Recently, a new permutation method for ICA separated source signal blocks in time domain has been proposed in [12], which utilizes the associativity in column vectors of an estimated mixing matrix and a tracking filter. It has advantages of no required array calibration, efficient computation and real time updatability, which are highly beneficial for radar or communication system type applications. However, the tracking filter is difficult to control and complex to design, which affects the estimated accuracy. Besides, when the number of blocks is large, the tracking process is very time consuming.

Inspired by the permutation method in [12], a similar ambiguity elimination method is proposed in this paper. We propose to set contrast blocks for each adjacent signal blocks, and utilize the associativity between separation signals recovered from contrast blocks and corresponding adjacent blocks to eliminate the permutation and scaling ambiguities. Compared with permutation method in [12], our method is more efficient in terms of separation quality and computational speed, which is significantly striking with large number of blocks. Besides, a tradeoff can be adjusted between separation quality and computational speed by choosing appropriate length of contrast blocks. Realistic experiments based on the wireless communication system validate the performance of our proposed method.

This paper is organized as follows. System model and assumptions are shown in Section 2. Our proposed new ambiguity elimination method is introduced in Section 3. Experimental results are illustrated in Section 4. Section 5 concludes this paper.

2. System Model and Assumptions

2.1. System Model

In this paper, we consider a N-dimensional complex-valued source signal denoted by $\mathbf{s}(t) = [s_1(t), \cdots, s_N(t)]^T = [s_{1r}(t) + is_{1i}(t), \cdots, s_{Nr}(t) + is_{Ni}(t)]^T$, where T means the transpose. A M-dimensional observation signal results from the linear mixture of sources, denoted by $\mathbf{x}(t) = [x_1(t), \cdots, x_M(t)]^T = [x_{1r}(t) + ix_{1i}(t), \cdots, x_{Mr}(t) + ix_{Mi}(t)]^T$. The input-output relationship can be described as:

$$\mathbf{x}(\mathrm{t}) = \mathbf{A}\mathbf{s}(\mathrm{t}) \tag{1}$$

where A is the mixture matrix of $M \times N$, representing the linear mixing system, which is composed of M row complex-valued vectors, *i.e.*, $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_M]^T$.

Similarly, we consider a N-dimensional recovered signal to estimate the sources, which is denoted by $\mathbf{y}(\mathrm{t}) = [y_1(\mathrm{t}), \cdots, y_N(\mathrm{t})]^T = [y_{1r}(t) + iy_{1i}(t), \cdots, y_{Nr}(t) + iy_{Ni}(t)]^T$. The separator can be described as:

$$\mathbf{y}(\mathrm{t}) = \mathbf{W}^H\mathbf{x}(\mathrm{t}) \tag{2}$$

where W is the separation matrix of $M \times N$, representing the linear separating system, which contains N column complex-valued vectors, *i.e.*, $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_N]$. $\mathbf{W}^H$ stands for the Hermitian of $\mathbf{W}$, that is $\mathbf{W}$ is transposed and conjugated. Without loss of generality and for simplicity, we assume the number of sources equal to that of observed signals, *i.e.*, $N = M$ in this paper.

2.2. Assumptions on the Model

In order to recover the source signals blindly and successfully, we make two assumptions on the BSS system.

A1. The source signals are stationary and statistically independent, and they have zero-mean and unit variance and uncorrelated real and imaginary parts of equal variances.

A2. The mixing channel is linear and instantaneous without frequency selective fading and environmental noise.

3. New Ambiguity Elimination Method

3.1. Permutation and scaling ambiguities

In order to introduce our new approach more generally, we consider *P* sources and *Q* estimations and assume *P*=*Q*=*N* for simplicity in this section. We choose $\mathbf{G} = \mathbf{W}^H \mathbf{A}$ as the mixture/separation matrix, in which the elements are:

$$\mathbf{G} = \begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1N} \\ g_{21} & g_{22} & \cdots & g_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1} & g_{N2} & \cdots & g_{NN} \end{pmatrix} \tag{4}$$

The recovered signals are the estimations of sources up to permutation and scaling ambiguities, *i.e.*, $\mathbf{y} = \mathbf{G}\mathbf{s}$

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1N} \\ g_{21} & g_{22} & \cdots & g_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1} & g_{N2} & \cdots & g_{NN} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{5}$$

where $y_i = g_{ij} s_j = \left| g_{ij} \right| e^{\varphi_{g_{ij}}} s_j, i, j = 1, 2, \cdots, N$. The permutation ambiguity exists when $i \neq j$ and the scaling ambiguity, amplitude and phase indeterminacies, exist when $\left| g_{ij} \right| \neq 1$ or $\varphi_{g_{ij}} \neq 0$. The ambiguities are common to all BSS methods; fortunately, they are insignificant in most applications.

However, when the mixing data is split in time and processed block by block, tying the separated signals in each time block may not recover the original sources correctly. More precisely, the separated signals of each adjacent block may differ in permutation, amplitude and phase, which may lead to indeterminacy when they are tied together. As shown in Figure 1, it can be seen obviously that the ambiguity problem exists between source signals and recovered signals when tying recovered components block by block.

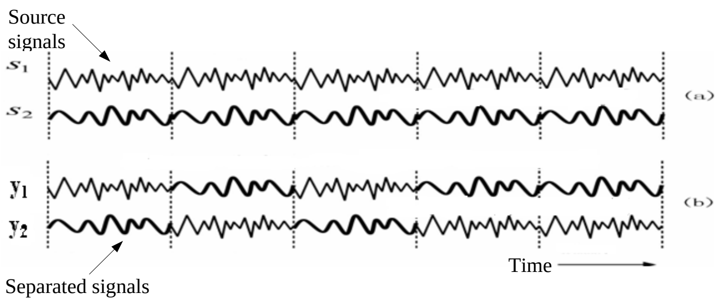

Figure 1. Ambiguities between Source Signals and Recovered Signals

3.2. Contrast Blocks

In this paper, we assume that the length of each time block is T. We denote the i-th block of mixture signals by $\mathbf{x}^i = \mathbf{x}^i(1:T) = [\mathbf{x}^i(1), \mathbf{x}^i(2), \cdots, \mathbf{x}^i(T)]$ and the corresponding separated signal is $\mathbf{y}^i = \mathbf{y}^i(1:T) = [\mathbf{y}^i(1), \mathbf{y}^i(2), \cdots, \mathbf{y}^i(T)]$. According to above analysis, we have $\mathbf{y}^i = \mathbf{G}^i\mathbf{s}$ as:

$$\begin{pmatrix} y_1^i \\ y_2^i \\ \vdots \\ y_N^i \end{pmatrix} = \begin{pmatrix} g_{11}^i & g_{12}^i & \cdots & g_{1N}^i \\ g_{21}^i & g_{22}^i & \cdots & g_{2N}^i \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1}^i & g_{N2}^i & \cdots & g_{NN}^i \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{6}$$

In this paper, we artificially set contrast blocks for each adjacent blocks denoted by $\mathbf{\Phi}^i = \mathbf{\Phi}^i(1:T) = [\mathbf{\Phi}^i(1), \mathbf{\Phi}^i(2), \cdots, \mathbf{\Phi}^i(T)], \quad i = 1, 2, \cdots$, which is composed of last L_1/T samples of former block and first L_2/T samples of latter block. Without lose of generosity, we assume $L_1 = L_2 = L$ in this paper. For instance, $\mathbf{\Phi}^i$ is the contrast block of $\mathbf{x}^i$ and $\mathbf{x}^{i+1}$, *i.e.*,

$$\mathbf{\Phi}^i = [\mathbf{x}^i(\frac{(L-1)}{L}T+1), \mathbf{x}^i(\frac{(L-1)}{L}T+2), \cdots, \mathbf{x}^i(T), \mathbf{x}^{i+1}(1), \mathbf{x}^{i+1}(2), \cdots, \mathbf{x}^{i+1}(\frac{1}{L}T)] \tag{7}$$

for which the corresponding separation signals is denoted by $\mathbf{z}^i$, and we assume T is divisible by L in this paper. The n-and $(n+1)$th mixture blocks and corresponding nth contrast block are shown in Figure 2 with L=2, in which the overlapping signals are artificially set.

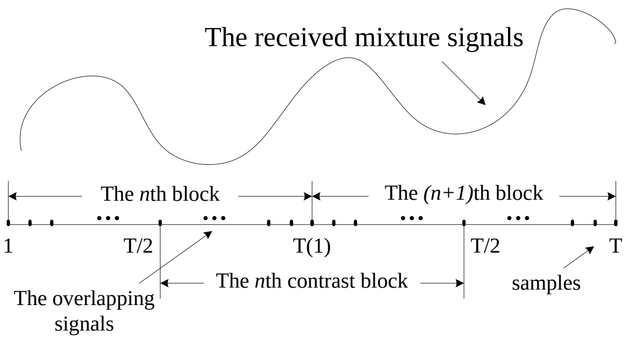

Figure 2. The *n*-and *(n+1)*th Mixture Blocks and Corresponding *n*th Contrast Block with *L*=2

3.3. Procedure of New Ambiguity Elimination Method

As we mentioned above, the permutation and scaling of separated signals may differ for each signal block, which may result in ambiguity when tying them together. Based on the assumptions A1, all the sources are zero-mean and unit variance. Therefore, we can normalize the amplitude of separated signals for all time blocks so that the amplitude ambiguity can be eliminated. The remaining permutation and phase indeterminacies will be eliminated by using our proposed method, which is shown as follows.

For $i = 1, 2, \cdots$

Step1: $\mathbf{y}^i = BSS(\mathbf{x}^i), \quad \mathbf{y}^{i+1} = BSS(\mathbf{x}^{i+1}), \quad \mathbf{z}^i = BSS(\mathbf{\Phi}^i)$

Step2:

$$\Psi^i = (\mathbf{y}^i(\frac{(L-1)}{L}T + 1 : T).*(\mathbf{z}^i(1:\frac{1}{L}T))^H) \Big/ (\frac{T}{L})$$

$$\Upsilon^i = (\mathbf{z}^i(\frac{(L-1)}{L}T + 1 : T).*(\mathbf{y}^{i+1}(1:\frac{1}{L}T))^H) \Big/ (\frac{T}{L})$$

Step3:

for $j = 1, 2, \cdots, N$

$[temp1, mark1] = \max(abs(\Psi(j,:)))$

$[temp2, mark2] = \max(abs(\Upsilon(mark1,:)))$

$\psi = y_j^{i+1}, \quad y_j^{i+1} = y_{mark2}^{i+1}, \quad y_{mark2}^{i+1} = \psi$

if $norm(y_j^i(1:T) - y_j^{i+1}(1:T)) > norm(y_j^i(1:T) + y_j^{i+1}(1:T))$

$y_j^{i+1} = -y_j^{i+1}$

end;

end;

Step4:

if $i + 1 \le B$

Go back to step1.

end;

End;

Firstly, as shown in **Step1**, $BSS(\mathbf{x})$ means to separate mixing signals using BSS algorithms. In this paper, we choose the fast fixed-point algorithms for complex-valued signals based on negentropic contrast criterion [9], which is also applied in [12].

Secondly, in **Step2**, the correlation matrices between contrast blocks and corresponding adjacent blocks are denoted by Ψ^i and Υ^i, which are $\frac{T}{L} \times \frac{T}{L}$ matrices. It is well accepted that the expectation of random variable approximately equals to the mean value of all samples for one realization in time domain when the variable is stationary, *i.e.*, $E(x) = (\sum_{i=1}^{T} x(i)) \Big/ T$. Based on assumptions A1 and A2, we have following approximate estimations as:

$$\Psi^{i} \overset{\Delta}{=} E\left[\begin{pmatrix} \sum_{j=1}^{N} g_{1j}^{i} s_{j} \\ \sum_{j=1}^{N} g_{2j}^{i} s_{j} \\ \vdots \\ \sum_{j=1}^{N} g_{Nj}^{i} s_{j} \end{pmatrix} \begin{pmatrix} \sum_{j=1}^{N} g_{1j}^{\prime i} s_{j} & \sum_{j=1}^{N} g_{2j}^{\prime i} s_{j} & \cdots & \sum_{j=1}^{N} g_{Nj}^{\prime i} s_{j} \end{pmatrix}^{*}\right]$$

$$= E\begin{bmatrix} \sum_{j=1}^{N} g_{1j}^{i} s_{j} \sum_{j=1}^{N} (g_{1j}^{\prime i} s_{j})^{*} & \sum_{j=1}^{N} g_{1j}^{i} s_{j} \sum_{j=1}^{N} (g_{2j}^{\prime i} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{1j}^{i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{\prime i} s_{j})^{*} \\ \sum_{j=1}^{N} g_{2j}^{i} s_{j} \sum_{j=1}^{N} (g_{1j}^{\prime i} s_{j})^{*} & \sum_{j=1}^{N} g_{2j}^{i} s_{j} \sum_{j=1}^{N} (g_{2j}^{\prime i} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{2j}^{i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{\prime i} s_{j})^{*} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{j=1}^{N} g_{Nj}^{i} s_{j} \sum_{j=1}^{N} (g_{1j}^{\prime i} s_{j})^{*} & \sum_{j=1}^{N} g_{Nj}^{i} s_{j} \sum_{j=1}^{N} (g_{2j}^{\prime i} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{Nj}^{i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{\prime i} s_{j})^{*} \end{bmatrix} \tag{8}$$

$$\Upsilon^{i} \overset{\Delta}{=} E\left[\begin{pmatrix} \sum_{j=1}^{N} g_{1j}^{\prime i} s_{j} \\ \sum_{j=1}^{N} g_{2j}^{\prime i} s_{j} \\ \vdots \\ \sum_{j=1}^{N} g_{Nj}^{\prime i} s_{j} \end{pmatrix} \begin{pmatrix} \sum_{j=1}^{N} g_{1j}^{i+1} s_{j} & \sum_{j=1}^{N} g_{2j}^{i+1} s_{j} & \cdots & \sum_{j=1}^{N} g_{Nj}^{i+1} s_{j} \end{pmatrix}^{*}\right]$$

$$= E\begin{bmatrix} \sum_{j=1}^{N} g_{1j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{1j}^{i+1} s_{j})^{*} & \sum_{j=1}^{N} g_{1j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{2j}^{i+1} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{1j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{i+1} s_{j})^{*} \\ \sum_{j=1}^{N} g_{2j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{1j}^{i+1} s_{j})^{*} & \sum_{j=1}^{N} g_{2j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{2j}^{i+1} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{2j}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{i+1} s_{j})^{*} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{j=1}^{N} g_{Nj}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{1j}^{i+1} s_{j})^{*} & \sum_{j=1}^{N} g_{Nj}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{2j}^{i+1} s_{j})^{*} & \cdots & \sum_{j=1}^{N} g_{Nj}^{\prime i} s_{j} \sum_{j=1}^{N} (g_{Nj}^{i+1} s_{j})^{*} \end{bmatrix} \tag{9}$$

where

$$\mathbf{z}^{i} = \begin{pmatrix} g_{11}^{\prime i} & g_{12}^{\prime i} & \cdots & g_{1N}^{\prime i} \\ g_{21}^{\prime i} & g_{22}^{\prime i} & \cdots & g_{2N}^{\prime i} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1}^{\prime i} & g_{N2}^{\prime i} & \cdots & g_{NN}^{\prime i} \end{pmatrix}\begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{10}$$

$$\mathbf{y}^{i+1} = \begin{pmatrix} g_{11}^{i+1} & g_{12}^{i+1} & \cdots & g_{1N}^{i+1} \\ g_{21}^{i+1} & g_{22}^{i+1} & \cdots & g_{2N}^{i+1} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1}^{i+1} & g_{N2}^{i+1} & \cdots & g_{NN}^{i+1} \end{pmatrix}\begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{11}$$

According to assumption A1 and A2, we known all the sources are zero-mean and unit variance, and have uncorrelated real and imaginary parts of equal variances. Hence, we have:

$$\begin{aligned} E\{\sum_{i=1}^{N} s_i \sum_{j=1}^{N} s_j^*\} &= E\{(s_1 + s_2 + \cdots + s_N)(s_1^* + s_2^* + \cdots + s_N^*)\} \\ &= E\{s_1 s_1^* + s_2 s_2^* + \cdots + s_N s_N^*\} = N \end{aligned} \tag{12}$$

Thirdly, in **Step3**, we use the *Matlab* functions $[temp1, mark1] = \max(abs(\Psi(j,:)))$ and $[temp2, mark2] = \max(abs(\Upsilon(mark1,:)))$ to find the correct following component of the *j*-th separated signals in the *(i+1)*-th block, in which $\max$ means finding the maximization of a row vector and returns the value and corresponding column index as *temp* and *mark* respectively. And *abs* means the absolute value or norm value when it corresponds to be complex-valued.

If we assume it just happens that there are no permutation indeterminacy between $\mathbf{y}^i$ and $\mathbf{y}^{i+1}$, then Ψ^i and Υ^i can be simplified to:

$$\begin{aligned} \Psi^i &\overset{\Delta}{=} E\begin{bmatrix} g_{11}^i (g_{11}'^i)^* |s_1|^2 & 0 & \cdots & 0 \\ 0 & g_{22}^i (g_{22}'^i)^* |s_2|^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_{NN}^i (g_{NN}'^i)^* |s_N|^2 \end{bmatrix} \\ &= \begin{bmatrix} g_{11}^i (g_{11}'^i)^* & 0 & \cdots & 0 \\ 0 & g_{22}^i (g_{22}'^i)^* & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_{NN}^i (g_{NN}'^i)^* \end{bmatrix} \end{aligned} \tag{13}$$

$$\begin{aligned} \Upsilon^i &\overset{\Delta}{=} E\begin{bmatrix} g_{11}'^i (g_{11}^{i+1})^* |s_1|^2 & 0 & \cdots & 0 \\ 0 & g_{22}'^i (g_{22}^{i+1})^* |s_2|^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_{NN}'^i (g_{NN}^{i+1})^* |s_N|^2 \end{bmatrix} \\ &= \begin{bmatrix} g_{11}'^i (g_{11}^{i+1})^* & 0 & \cdots & 0 \\ 0 & g_{22}'^i (g_{22}^{i+1})^* & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_{NN}'^i (g_{NN}^{i+1})^* \end{bmatrix} \end{aligned} \tag{14}$$

Note that there exists phase ambiguity in (13) and (14). In order to eliminate it, we reformulate the phase of the following signals by π in **Step 3**. More precisely, we only consider the case $g_{ii}^i (g_{ii}'^i)^* = \pm 1$ and $g_{jj}'^i (g_{jj}^{i+1})^* = \pm 1$, which may not satisfy the practical needs absolutely. However, note that the approximate estimation is well acceptable and suitable, when our system model and assumptions are considered in this paper. More complex phase ambiguities, $g_{ii}^i (g_{ii}'^i)^* \neq \pm 1$ or $g_{jj}'^i (g_{jj}^{i+1})^* \neq \pm 1$, will be addressed in our latter work. After adjusting the phase of separated signals for adjacent blocks, the correlation matrices become identity ones, *i.e.*, $\Psi^i = \mathbf{I}$ and $\Upsilon^i = \mathbf{I}$.

Finally, in **Step4**, *B* denotes the number of blocks, which determines when the method ends.

4. Experimental Results and Analysis

Similar to [12], a wireless communication system with two transmitting and receiving antennas is constructed in this paper, which is shown in Figure 3. For simplicity, we assume the carrier and local frequencies are the same, *i.e.*, $\omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_0$. And the synchronous and carrier frequency offset problems are not considered in this paper.

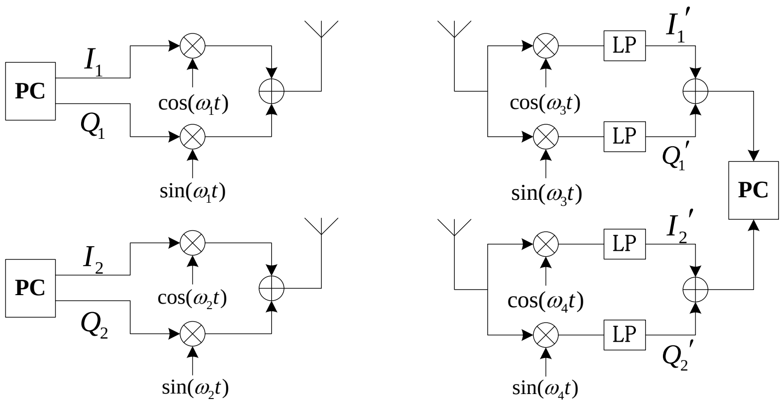

Figure 3. Wireless Communication System Model

The transmitted source signals are complex-valued, denoted by:

$$\mathbf{s} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = \begin{pmatrix} I_1 + Q_1 i \\ I_2 + Q_2 i \end{pmatrix} \tag{15}$$

As shown in Figure 3, the sources are modulated on carrier frequencies, which is send out through transmitting antennas. At the receiver, the received signals are demodulating through local frequencies.

After low filtering, the mixing signals can be approximately seen as the mixture of sources, which are represented as:

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} I_1' + Q_1' i \\ I_2' + Q_2' i \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \quad \Rightarrow \quad \mathbf{x} = \mathbf{A}\,\mathbf{s} \tag{16}$$

where **A** denotes the wireless channel (mixing system), which is unknown. The separating operator is given as:

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix}^H \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \quad \Rightarrow \quad \mathbf{y} = \mathbf{W}^H \mathbf{x} \tag{17}$$

where $\mathbf{y}$ is the approximate estimation of sources.

To satisfy A1, we set the distance of two transmitters about 5 meters away and make sure that they transmit signals independently. In this way, the source signals are statistically independent, even though they are not absolutely independent. However, the approximate independence between sources is accepted, which is verified by our experimental results in the following.

To satisfy A2, we set the distance between transmitters and receivers about 5 meters away, which ensures that the wireless channel is as approximately linear and instantaneous as possible. Although the mixing system is not absolutely linear and instantaneous, it is so approximate that the experimental results prove that it works well.

In order to satisfy the assumptions A1 and A2, we use two E4438C [13] as the transmitters, which can send radio signals in the form of single, AM, BPSK, speech and so on. At the receiver, we use the USRP with GUN Radio [14] device to receive the RF signals.

4.1. Performance Validity

We choose two single signals as sources. The carrier frequency is 30 MHz, *i.e.*, $\omega_0 = 30MHz$. When the sample rate is fixed, we set the number of samples of each block T=1000 and the number of blocks B=4. Here we set L=2. The transmitted power is 0 dBm and the classical algorithm in [9] is chosen as the separation method. The experimental results are shown in Figure 4, Figure 5 and Figure 6.

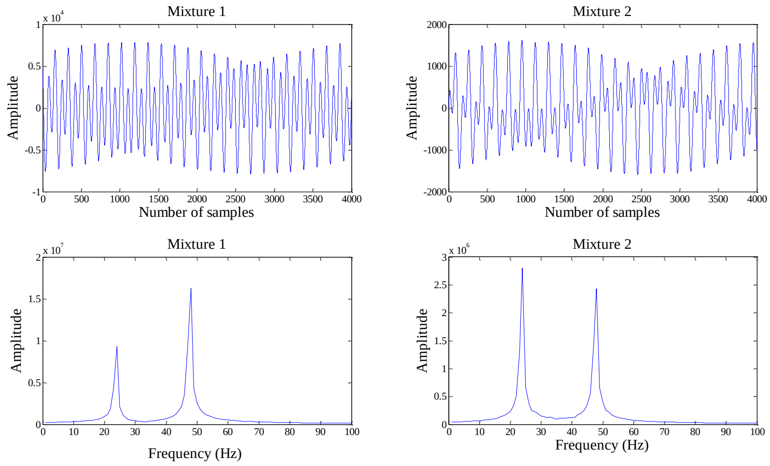

Figure 4. Mixing Signals of Four Time Blocks in Time and Frequency Domain

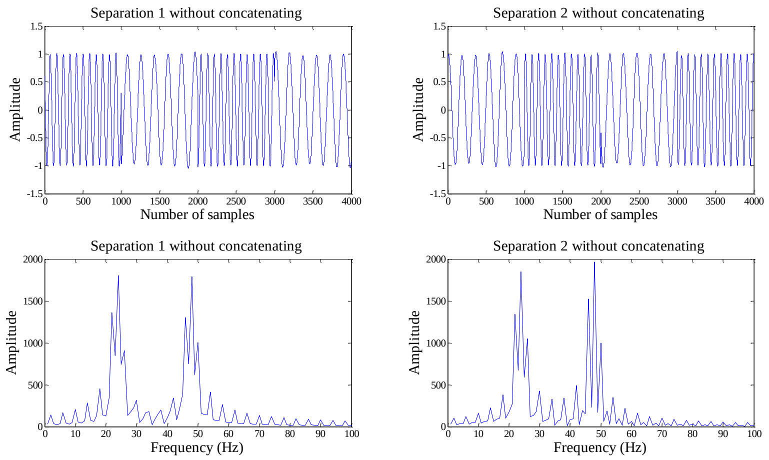

Figure 5. Separated Signals of Four Time Blocks without Concatenating Using Our Method in Time and Frequency Domain

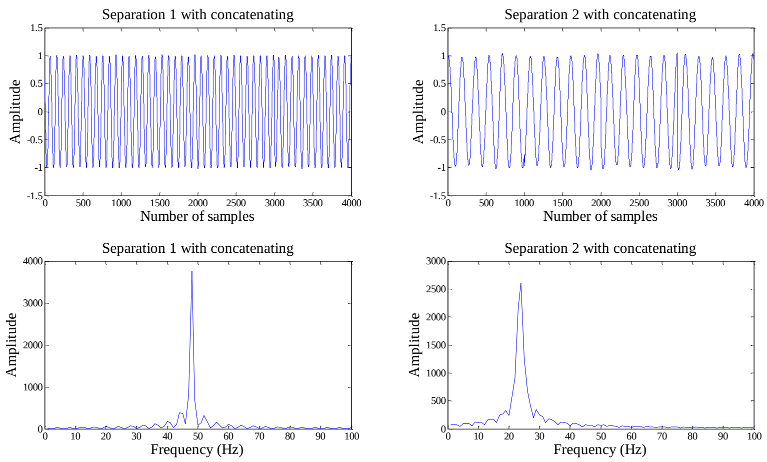

Figure 6. Separated Signals of Four Time Blocks Concatenated Using Our Method in Time and Frequency Domain

It can be obviously seen from Figure 5 that the reconstructed signals doesn't recover the original signals correctly when tying the separated components at each adjacent time blocks. Besides, the fact that the original signals are not successfully rebuilt can also be observed form the frequency domain in Figure 5, which is similar to that of mixing signals in Figure 4. Compared Figure 5 and Figure 6, we can see clearly that our proposed method successfully eliminate the permutation and scaling ambiguities when tying the signals blocks together, which is especially apparent in the frequency domain of Figure 6. In order to verify the performance of our method set further, the corresponding correlation matrices are shown as follows.

$$\Psi^1 = \begin{pmatrix} -0.0071 + 0.0009i & \mathbf{0.9950 + 0.1073i} \\ \mathbf{0.6130 - 0.8291i} & 0.0032 + 0.0076i \end{pmatrix}$$

$$\Upsilon^1 = \begin{pmatrix} \mathbf{0.2308 + 0.9445i} & 0.0058 - 0.0010i \\ -0.0057 + 0.0035i & \mathbf{0.9910 - 0.1277i} \end{pmatrix}$$

$$\Psi^2 = \begin{pmatrix} -0.0048 + 0.0057i & \mathbf{0.9388 + 0.3412i} \\ \mathbf{0.3558 + 0.9587i} & 0.0006 - 0.0063i \end{pmatrix}$$

$$\Upsilon^2 = \begin{pmatrix} 0.0037 - 0.0019i & \mathbf{-0.3061 - 0.9407i} \\ \mathbf{0.7975 - 0.6110i} & 0.0000 - 0.0120i \end{pmatrix}$$

$$\Psi^3 = \begin{pmatrix} \mathbf{-0.8999 + 0.4223i} & 0.0022 + 0.0037i \\ 0.0066 + 0.0025i & \mathbf{-0.0934 - 1.0037i} \end{pmatrix}$$

$$\Upsilon^3 = \begin{pmatrix} 0.0150 + 0.0006i & \mathbf{-0.7835 + 0.6164i} \\ \mathbf{-0.6236 + 0.7836i} & 0.0054 + 0.0040i \end{pmatrix}$$

As for Ψ^1 and Υ^1, $[temp1, mark1] = [1.0007, 2]$ and $[temp2, mark2] = [0.9992, 2]$, which means that the first separated signal in *i*-th block corresponds to the second one in the corresponding overlapping signal, which in turn corresponds to the second one in the (*i+1*)-th block. Then, we can see that the separated components can't be recovered correctly when tying the *i*-th and (*i+1*)-th blocks together, which also can be clearly observed in the time domain in Figure 5.

4.2. Performance Analysis

In this section, we perform experiments to analyze the performance of our proposed method and Permutation Method in [12]. We set the number of samples of each block *T*=500 and the number of blocks *B* varies form 10 to 50. Here we set *L*=2, 4, 10, 20, 50. The source signals are two AM signals. The transmitted power is 0 dBm and the classical algorithm in [9] is chosen as the separation method. The mean value of mean square error (MSE) between sources and separations is chosen as the performance criterion of separation quality. And the execution time of concatenating all separated blocks is chosen as the measure criterion of computational speed, for which the computer is Intel (R) Core ™ 2 Duo CPU, E8400 @ 3.0GHz, 2.99GHz, 3.00 GB RAM. The experimental results are illustrated in Figure 7 and Figure 8.

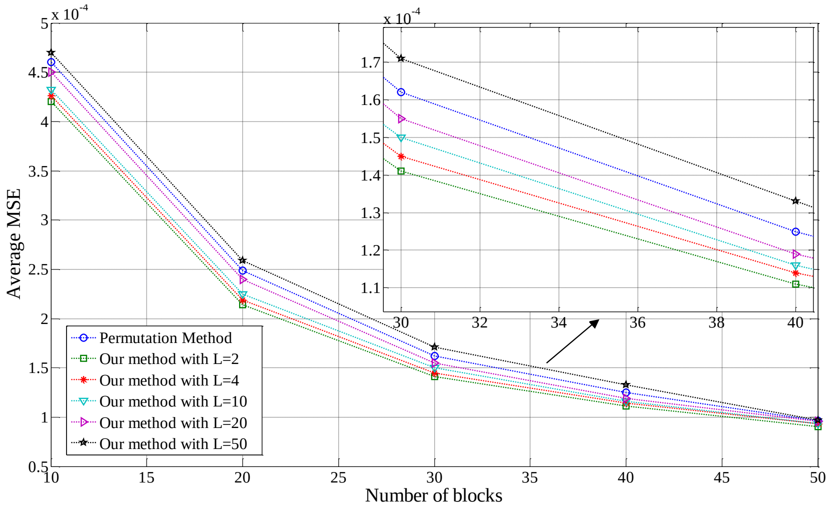

Figure 7. MSE between Sources and Separations for Permutation Method and Our Proposed Method with *L*=2, 4, 10, 20, 50 Averaged over 100 Monte-Carlo Runs

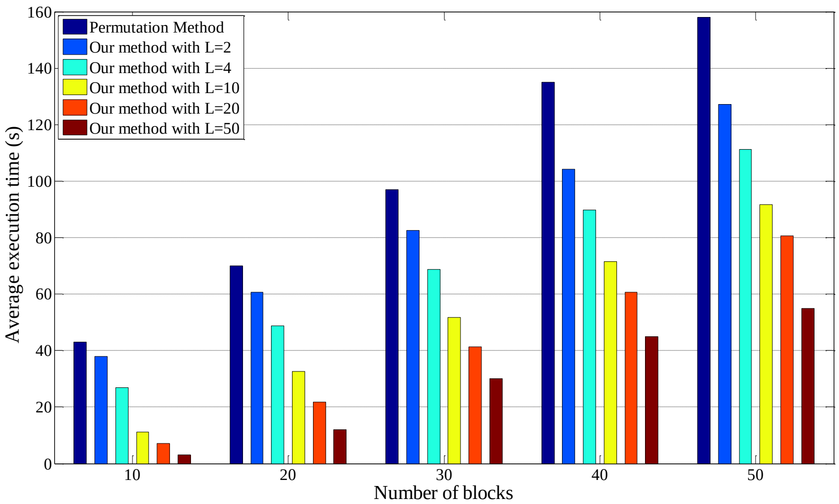

Figure 8. Execution Time of Concatenating the Recovered Sources in Different Number of Locks for Permutation Method and Our Proposed Method with *L*=2, 4, 10, 20, 50 Averaged over 100 Monte-Carlo Runs.

As shown in Figure 7, it can be observed clearly that the MSE values of Permutation Method and our proposed method decrease with the number of blocks increasing. When the block size is fixed, the MSE of our approach differs with the length of contrast blocks changing. More precisely, when B varies from 10 to 50, our proposed method outperforms Permutation Method with L=2, 4, 10, 20, and the performance of our approach becomes slightly better and better with L decreasing. However, when B=50, our method performs worse than Permutation Method, which is caused by the fact that the number of samples of the contrast blocks is not many enough. Hence, it can be predicted that, in the same condition, the performance of our method will be worse and worse when L is larger than 50. Since the choice of L relates to the length of signal blocks, it is difficult to determine the exact L such that our approach performs better or worse than Permutation Method.

From Figure 8, we can see obviously that the execution time of our proposed approach with L=2, 4, 10, 20 and 50 is less than that of Permutation Method. The advantage of our method becomes more and more apparent when the number of blocks increases and the length of contrast blocks decreasing. For instance, when B=20, the execution time of Permutation Method is about 70s, while our method needs about 61s, 50s, 32s, 22s, 10s, respectively, for L=2, 4, 10, 20 and 50. Furthermore, when B=50, the time of the former is about 158s, while the latter needs about 125s, 110s, 92s, 80, 55s. The time of our proposed method is about one third of that of Permutation Method. And it can be predicted that, when L increases, the time of our method will be less, which is not illustrated in Figure 8.

Combined Figure 7 and Figure 8, we can draw the conclusion that, when the block size and corresponding length of contrast blocks are chosen appropriately, our proposed method is more efficient than Permutation Method in terms of separation quality and computational speed. For example, when B=50 and L= 20, the performance of our approach is not only better than Permutation Method but also only needs half time of the latter. However, when B=50 and L= 50, our approach needs only one third time of Permutation Method but the performance of it is worse than the latter. Therefore, the performance of our proposed method with respect to separation quality and computational speed can be adjusted according to the choice of block size and corresponding length of contrast blocks. More analysis about the exact relationship between them in detail will be included in our latter work. In general, when the number of samples of signal blocks is about 1000, L=30 to 50 is recommended.

5. Conclusion

In this paper, a new ambiguity elimination method is proposed to solve the permutation and scaling indeterminacy problem when BSS mixture signals are split in time and processed block by block. We artificially set contrast blocks for each adjacent time blocks. By utilizing the dependent correlation between components recovered from contrast blocks and corresponding adjacent blocks, the permutation and scaling of the latter block is reformulated identical to the former. The performance of our method is confirmed through realistic experiments. Future work includes the extension of our method to convolution mixture and extension of our wireless communication system model to more transmitting and receiving antennas.

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