A Novel Approach to Eliminating the Permutation and Scaling Indeterminacies of Block BSS

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Abstract: - This paper considers the permutation and scaling indeterminacy problem of blind source separation (BSS) in the case that the continuously mixing signals are split in time and processed block by block. When tying the separated signals in each time block, the recovered whole signals differ from the original sources up to permutation and scaling indeterminacies. Inspired by previous Permutation Method of reconstructing source signals in time domain, a novel approach is proposed to eliminate the inherent permutation and scaling indeterminacies when the block BSS is considered. This new method reformulates the mixing signals by overlapping adjacent signal blocks partially and utilizes the dependent correlation of the overlapping signals in each adjacent block to adjust the permutation and scaling parameters. Compared with the Permutation Method, this new method is more efficient in terms of separation quality and is much quicker in terms of execution speed. The performance of this novel approach is confirmed by computer simulations and realistic experiments performed on wireless communication system.

Key-Words: - blind source separation; independent component analysis; permutation and scaling indeterminacies; adjacent time blocks; overlapping signals; permutation method

1 Introduction

For the recent decades, blind source separation (BSS) has received considerable attention, mainly due to its wide panel of potential applications such as image recognition, audio processing, biology, wireless communications, etc [1]. BSS shows significant advantages in recovery of unknown source signals over other frameworks where techniques strongly depend on the information of signal diversity, transfer functions and so on. In the case where source signals are linearly and instantaneously mixed, BSS corresponds to independent component analysis (ICA). The core assumption in ICA is reduced to the statistical mutually independence between sources [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.

DOA type [3], [4] methods tie signal blocks with similar DOA and require an array manifold. Since it requires an array manifold, it degrades permutation accuracy by calibration error. Correlation based methods [5], [6] 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 permutation alignment scheme based on microphone array directivity patterns for speech signals is proposed in [7], where interesting connections between BSS and ideal beamforming is explored. A permutation method based upon the similarity of the column vectors of the mixing matrix and tracking filters is proposed to concatenate ICA separated source signal time blocks [8]. However, the tracking filter is difficult to control and complex to design. A contrast function for ICA without permutation ambiguity is proposed in [9], [10]. It is proved that a linear combination of the separator output fourth-order marginal cumulants is a valid contrast function for ICA under prewhitening if the weights have the same sign as the source kurtosis [11]. If, in addition, the source kurtosis are different and so are the linear combination weights, the contrast eliminates the permutation ambiguity typical to ICA, as the estimated sources are sorted at the separator output according to their kurtosis values in the same order as the weights.

Inspired from the Permutation Method in [8], in this paper, we propose a novel approach to eliminate the permutation and scaling indeterminacies of BSS in the case where continuously mixing measurement data is split in time and processed block by block. We artificially reformulate the mixing signals by making adjacent signal blocks overlap partially. Taking advantage of the dependent correlation of separated components in the overlapping part of corresponding adjacent blocks, the permutation and scaling of the latter blocks are adjusted to be identical to that of the former blocks. Computer simulations and realistic experiments are performed to validate the performance of our new method.

This paper is organized as follows. The system model and assumptions are presented in Section 2. Our novel approach is introduced in Section 3. Computer simulations and realistic experiments are performed in Section 4. Section 5 concludes this paper.

2 Model and Assumptions

2.1 System model

In this paper, the BSS system model we consider is shown in Fig. 1. The source signals are denoted by $\mathbf{s}(t)=[s_1(t),\cdots,s_N(t)]^T$, where T means the transpose. The mixing signals are denoted by $\mathbf{x}(t)=[x_1(t),\cdots,x_M(t)]^T$. The relationship between source and mixture signals can be described as

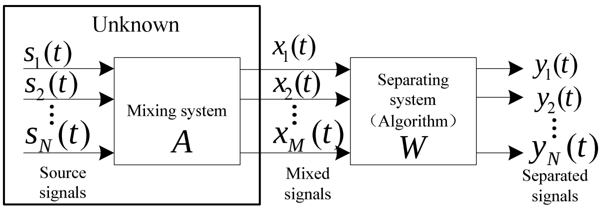

Fig. 1. BSS system model

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

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

Similarly, the recovered signals are denoted by $\mathbf{y}(\mathrm{t})=[y_1(\mathrm{t}),\cdots,y_N(\mathrm{t})]^T$. The relationship between mixture and separation signals can be described as

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

where W is the separating matrix of $M\times N$, which contains N column, i.e., $\mathbf{W}=[\mathbf{w}_1,\mathbf{w}_2,\cdots,\mathbf{w}_N]$. $\mathbf{W}^H$ means 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 model.

A1. The source signals are stationary and statistically independent, and they have zero-mean and unit variance.

A2. The mixing system is linear and instantaneous.

3 New Permutation and Scaling Elimination Approach

3.1 Permutation and scaling indeterminacies

First, we set the global matrix as $\mathbf{G}=\mathbf{W}^H\mathbf{A}$. In fact, the recovered signals are the estimations of sources up to permutation and scaling indeterminacies, i.e., $\mathbf{y}=\mathbf{Gs}$

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix}=\begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1N} \\ g_{21} & g_{22} & \cdots & g_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1} & g_{N2} & \cdots & g_{NN} \end{pmatrix}\begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{3}$$

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 indeterminacy exists when $i\neq j$ and the scaling indeterminacy, amplitude and phase, exist when $\left|g_{ij}\right|\neq 1$ or $\varphi_{g_{ij}}\neq 0$. The indeterminacies 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 Fig. 2, it can be seen obviously that the ambiguity problem exists between source signals and recovered signals when tying recovered signals block by block.

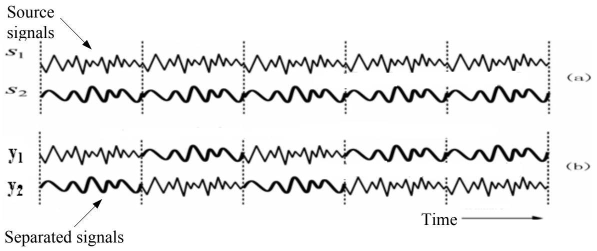

Fig. 2. Ambiguities between source signals and recovered signals

3.2 Overlapping signals

Second, we reformulate the mixing signals by overlapping adjacent time blocks partially, which is called the overlapping signals. When the samples rate is fixed, we assume the samples of each block are *T*. The *i*-th and (*i+1*)-th block of mixture signals are denoted by $\mathbf{x}^i = \mathbf{x}^i(1:T) = [\mathbf{x}^i(1), \mathbf{x}^i(2), \cdots, \mathbf{x}^i(T)]$ and

$$\begin{aligned}\mathbf{x}^{i+1} &= \mathbf{x}^{i+1}(1:T) = [\mathbf{x}^{i+1}(1), \mathbf{x}^{i+1}(2), \cdots, \mathbf{x}^{i+1}(T)] \\ &= [\mathbf{x}^i(T-L+1), \mathbf{x}^i(T-L+2), \cdots, \mathbf{x}^i(T), \\ &\quad \mathbf{x}^{i+1}(L+1), \mathbf{x}^{i+1}(L+2), \cdots, \mathbf{x}^{i+1}(T)]\end{aligned} \tag{4}$$

In (4), we can see clearly the first *L* samples $\mathbf{x}^i(T-L+1), \mathbf{x}^i(T-L+2), \cdots, \mathbf{x}^i(T)$ in the (*i+1*)-th block are the overlapping part between the *i*-th and (*i+1*)-th block, i.e., the overlapping signals. For simplicity, we assume *T* is divisible by *L* in this paper. The structural model of the *i*-th and (*i+1*)-th mixture blocks and corresponding overlapping signals is shown in Fig. 3, in which the length of overlapping signals is artificially set by *L*.

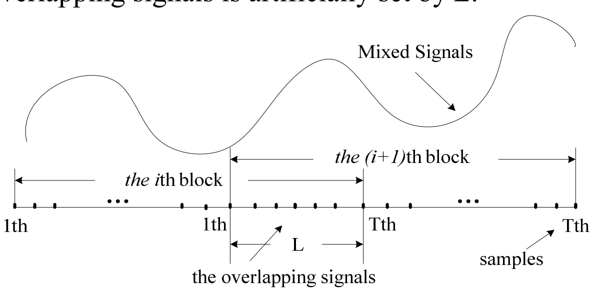

Fig. 3. The *i*-th and (*i+1*)-th mixture blocks and corresponding overlapping signals with length of *L*.

For the sake of convenience, we denote the separated signals of the *i*-th block of mixture signals by $\mathbf{y}^i = \mathbf{y}^i(1:T) = [\mathbf{y}^i(1), \mathbf{y}^i(2), \cdots, \mathbf{y}^i(T)] \triangleq \mathbf{G}^i\mathbf{s}$, i.e.,

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

3.3 Our proposed method

Third, based on the assumption A1, all the sources are zero-mean and with unit variance. Hence, we can eliminate the amplitude indeterminacy by normalizing the amplitude of all the separated block signals. The remaining permutation and phase indeterminacies are eliminated by using our proposed method shown as follows:

For $i = 1, 2, \cdots$

1. $\mathbf{y}^i = BSS(\mathbf{x}^i)$, $\mathbf{y}^{i+1} = BSS(\mathbf{x}^{i+1})$

2. $\Phi^i = (\mathbf{y}^i(T-L+1:T).*(\mathbf{y}^{i+1}(1:L))^H)/L$

3. For $j = 1, 2, \cdots, N$

(a). $[temp, mark] = \max(abs(\Phi^i(j,:)))$

(b). $\psi = y_j^{i+1}$, $y_j^{i+1} = y_{mark1}^{i+1}$, $y_{mark1}^{i+1} = \psi$

(c). If $\begin{cases} norm(y_j^i(T-L+1:T) - y_j^{i+1}(1:L)) > \\ norm(y_j^i(T-L+1:T) + y_j^{i+1}(1:L)) \end{cases}$

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

end;

end;

4. If $i+1 \le B$

Go back to step **1**.

end;

In this new method, $BSS(\mathbf{x})$ in Step **1** 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 in [12], which is used in [8]. This is convenient to compare the performance of our new method with the Permutation Method in [8]. The correlation matrix of overlapping signals Φ^i in Step **2** is $L \times L$, which results from the widely accepted concept that the expectation value of random variable can be approximately represented by the mean value of all samples for one realization in time domain when the variable is stationary. Therefore, according to the assumptions A1 and A2, we have following approximate estimation.

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

$$= E\begin{bmatrix}\sum_{j=1}^{N} g_{1j}^i s_j \sum_{j=1}^{N} (g_{1j}^{i+1} s_j)^* & \cdots & \sum_{j=1}^{N} g_{1j}^i s_j \sum_{j=1}^{N} (g_{Nj}^{i+1} s_j)^* \\ \vdots & \ddots & \vdots \\ \sum_{j=1}^{N} g_{Nj}^i s_j \sum_{j=1}^{N} (g_{1j}^{i+1} s_j)^* & \cdots & \sum_{j=1}^{N} g_{Nj}^i s_j \sum_{j=1}^{N} (g_{Nj}^{i+1} s_j)^*\end{bmatrix} \tag{6}$$

In Step **3**, $[temp, mark] = \max(abs(\Phi^i(j,:)))$ in (a) is the MATLAB function that is used to find the maximization value of each row in $abs(\Phi^i(j,:))$ and return the value and corresponding column index, in which abs means the absolute value or norm value when it corresponds to complex-valued variable. The purpose of (a) is to search for the dependent component in the next block, which is based on the fact that $E\{s_i s_j^*\} = 0,\ i \neq j$ and $E\{s_i s_j^*\} = 1,\ i = j$. (b) aims to eliminate the permutation indeterminacy. When there doesn't exist permutation indeterminacy, Φ^i can be simplified as

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

$$= \begin{bmatrix} g_{11}^i (g_{11}^{i+1})^* & 0 & \cdots & 0 \\ 0 & g_{11}^i (g_{11}^{i+1})^* & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & g_{11}^i (g_{11}^{i+1})^* \end{bmatrix} \tag{7}$$

(c) aims to eliminate the phase indeterminacy. Note that we just consider to change the phase by π, which can be seen clearly in (c). More precisely, we only consider the case $g_{ii}^i (g_{ii}^{i+1})^* = \pm 1$, which may not satisfy the practical needs absolutely. However, note that it is well acceptable and suitable in the case that our system model and assumptions are considered in this paper. As for the case $g_{ii}^i (g_{ii}^{i+1})^* \neq \pm 1$, we postpone it to our future work. When there aren't permutation and scaling indeterminacies, the correlation matrix Φ^i can be simplified to be identity matrix, i.e., $\Phi^i = \mathbf{I}$.

4 Simulation and Experiment Results

4.1 Computer simulations

4.1.1 Simulation 1

In this section, we choose the sine signal, square signal and random signal as sources. The number of mixing signal block B is 5, in which sources are randomly mixed. The number of samples of each mixing signal block T is 200 and the number size of corresponding overlapping signals L is set 100. The classical algorithm in [12] is chosen as the separation method, which is similar to that in [8]. The simulation results are shown in Fig. 4.

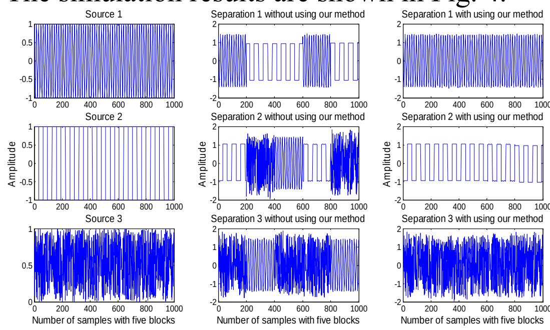

Fig. 4. Simulation results with the sine signal, square signal and random signal. The first column is source signal, the second column is the separation signal concatenated without using our method and the third column is the separation signal concatenated with using our method.

As shown in Fig. 4, it can be seen clearly that the connected separation signals in each adjacent signal block in the second column are different from corresponding source signals. This means that the source signals are not recovered successfully, which is caused by the indeterminacies in BSS. However, in the third column, it can be observed obviously that the separated components between adjacent signal blocks are concatenated successfully by using our proposed method. Therefore, our new approach is very efficient in terms of solving the permutation and scaling indeterminacies in BSS when the mixing signals are processed block by block.

4.1.2 Simulation 2

In this section, we choose three speech signals as sources because speech signals are usually not continuous in time domain. Given the fact that our new method utilizes the dependent correlation between the overlapping signals in time domain, we consider to perform simulations to validate the performance of our approach with speech signals. Moreover, the speech signals are widely used in the realistic application, especially in the wireless and mobile communication.

The number of mixing signal block B is 5, in which sources are randomly mixed. The number of samples of each mixing signal block T is 5000 and the number size of corresponding overlapping signals L is set 2500. The classical algorithm in [12] is chosen as the separation method, which is similar to that in [8]. The simulation results are shown in Fig. 5.

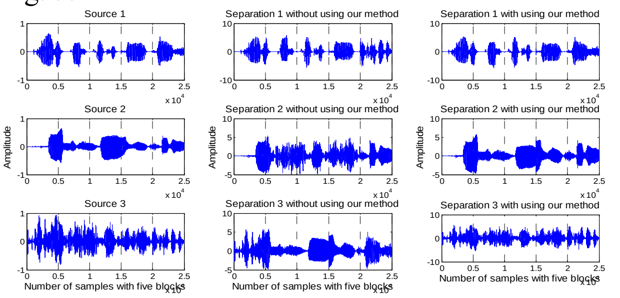

Fig. 5. Simulation results with speech signals. The first column is source signal, the second column is the separation signal concatenated without using our method and the third column is the separation signal concatenated with using our method.

Compared the concatenated separation signals in the second column with the source signals in the first column, it can be observed clearly that the separated signals in each adjacent block are not connected correctly. When our proposed method is used, the concatenated separation signals in the third column are almost the same with the sources. This means that our method succeeds in eliminating the permutation and scaling indeterminacies in the case that mixing signals are split in block and processed block by block.

4.1.3 Simulation 3

In this section, we perform simulations to analyze the performance of our indeterminacy elimination method, which is mainly compared with that in [8]. We choose the signals in Simulation 1 section as sources. In order to improve the time efficiency of our method, we set the number of samples of each block T=400 and the number of blocks B varies from 10 to 50. The length of overlapping signals changes from 20 to 400, i.e., L=20, 40, …, 400. For convenience and simplicity, we choose $\alpha = T/L$ with α =1, 2, 4, 10 and 20 as the donation. The classical algorithm in [12] is chosen as the separation method.

The mean value of mean square error (MSE) between concatenated separation signals and sources is chosen as the measure criterion for separation quality. And the execution time of concatenating all separated signal blocks is chosen as the measurement of efficiency in terms of computational speed, for which the computer is Intel (R) Core ™ 2 Duo CPU, E8400 @ 3.0GHz, 2.99GHz, 3.00 GB RAM. To ensure the validity and reliability of simulation data, 100 Monte-Carlo runs are performed independently. The simulation results are illustrated in Fig. 6 and Fig. 7.

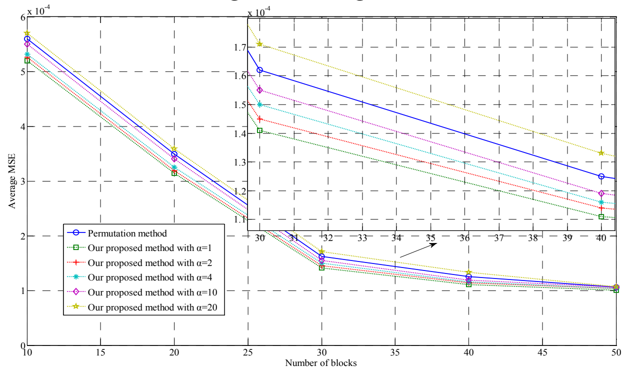

Fig. 6. MSE between sources and connected separations for Permutation Method in [8] and our proposed method with α =1, 2, 4, 10 and 20 averaged over 100 Monte-Carlo runs.

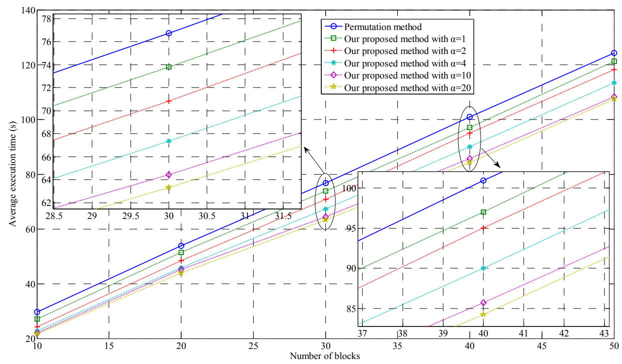

Fig. 7. Execution time of concatenating the separated sources in different number of blocks for Permutation Method and our proposed method with α =1, 2, 4, 10 and 20 averaged over 100 Monte-Carlo runs.

As shown in Fig. 6, it can be observed clearly that the MSE value of Permutation Method and our proposed method decreases with the number of blocks increasing. When the block size is fixed, the MSE of our approach differs with the length of overlapping signals changing. More precisely, when B varies from 10 to 50, our proposed method outperforms Permutation Method with α =1, 2, 4, 10, and the performance of our approach becomes slightly better and better with α decreasing. However, when α =20, our method performs worse than Permutation Method, which is caused by the fact that the number of samples of the overlapping signals 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 α is larger than 20. Since the choice of α relates to the length of signal blocks, it is difficult to determine the exact α such that our approach performs better or worse than Permutation Method.

From Fig. 7, we can see obviously that the execution time of our proposed approach with α =1, 2, 4, 10, 20 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 overlapping signals decreasing. For instance, when *B*=30, the execution time of Permutation Method is about 77s, while our method needs about 74s, 71s, 67s, 65s, 63s, respectively, for α =1, 2, 4, 10, 20. Furthermore, when *B*=40, the time of the former is about 102s, while the latter needs about 97s, 95s, 90s, 86, 84s. And it can be predicted that, when α increases, the time of our method will be less, which is not illustrated in Fig. 7.

Combined Fig. 6 and Fig. 7, we can draw the conclusion that, when the block size and corresponding length of overlapping signals 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 α = 10, the performance of our approach is not only better than Permutation Method but also only needs much less time of the latter. However, when *B*=50 and α = 20, our approach needs much less time than 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 overlapping signals. 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, α =10 to 40 is recommended.

4.2 Realistic experiments

4.2.1 Realistic wireless communication model

In this section, a wireless communication system with two transmitting and receiving antennas is constructed in this paper, which is shown in Fig. 8. For simplicity, we assume the carrier and local frequencies are the same, i.e., $\omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_0 = 30MHz$. And the synchronous and carrier frequency offset problems are not considered in this paper.

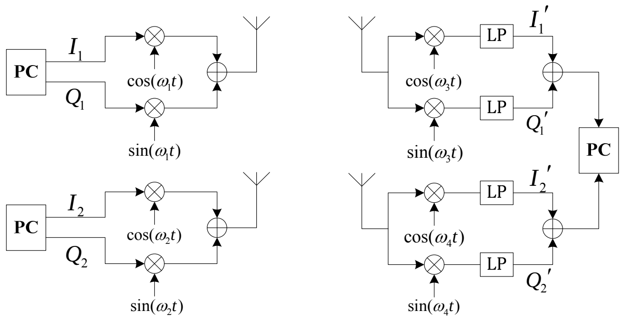

Fig. 8. Wireless communication system model

The transmitted source signals are complex-valued, denoted by

$$\mathbf{s} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = \begin{pmatrix} I_1 + Q_1 i \\ I_2 + Q_2 i \end{pmatrix} \quad (8)$$

As shown in Fig. 8, 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

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} I_1' + Q_1' i \\ I_2' + Q_2' i \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \quad (9)$$
$$\Rightarrow \quad \mathbf{x} = \mathbf{As}$$

where A denotes the wireless channel, which is unknown. The separating operator is given as

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{pmatrix}^H \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \quad (10)$$
$$\Rightarrow \quad \mathbf{y} = \mathbf{W}^H \mathbf{x}$$

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.

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.

4.2.2 Experiment 1

In this section, we choose two single signals as sources. When the sample rate is fixed, we set the number of samples of each block *T*=1000 and the number of blocks *B*=5. Here we set the length of the overlapping signals *L*=*T*/2=500. The transmitted power is 0 dBm and the classical algorithm in [12] is chosen as the separation method. The experimental results are shown in Fig. 9, Fig. 10 and Fig. 11.

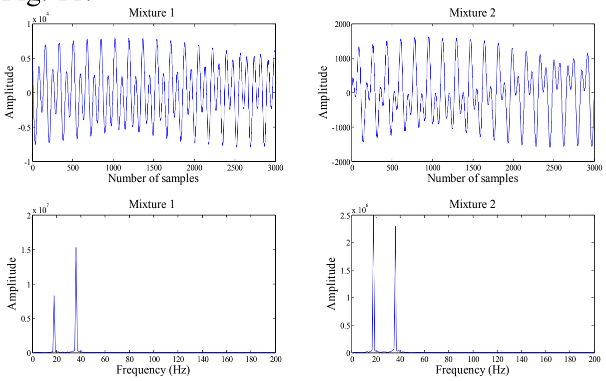

Fig. 9. Mixing signals with five blocks in time and frequency domain

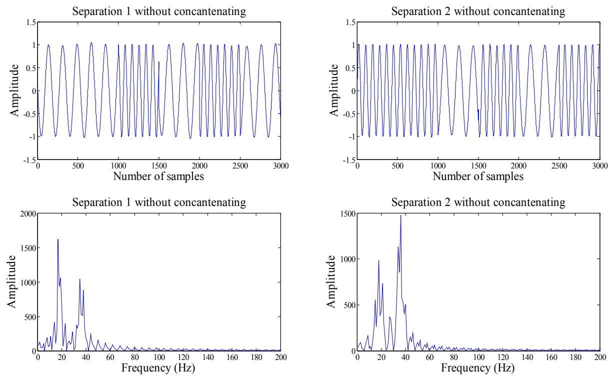

Fig. 10. Separating signals without using our proposed approach in time and frequency domain

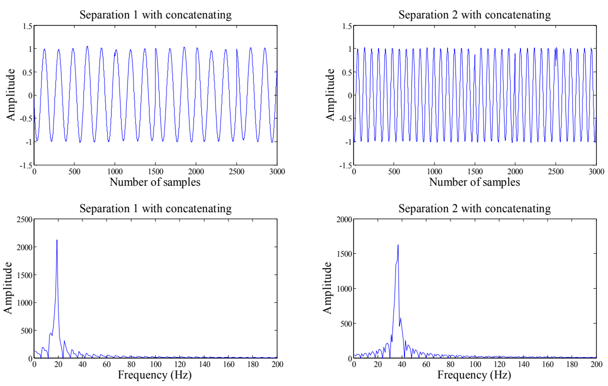

Fig. 11. Separating signals using our proposed approach in time and frequency domain

As shown in Fig. 10, the concatenated signals after separating don't recover the original sources correctly, which is more obvious in the frequency domain. Compared the frequency domain of Fig. 9 and Fig. 10, we can see that the permutation and scaling indeterminacies affect the separation quality seriously when tying each separated adjacent block together. However, note that the signals in Fig. 11 using our new approach successfully recover the original source waveform. It can be observed clearly in the frequency domain that two single signals are totally separated. Compared the time domain signals in Fig. 10 and Fig. 11, we can see that the connection ambiguity caused by permutation and scaling indeterminacies are eliminated by using our new method.

In order to verify the performance of our method further, we analyze the correlation matrices of the overlapping signals briefly as follows.

$$\Phi^1 = \begin{pmatrix} 0.0033+0.0062\mathrm{i} & \mathbf{1.0096+0.2094i} \\ \mathbf{0.9591-0.2855i} & -0.0078-0.0049\mathrm{i} \end{pmatrix}$$

$$\Phi^2 = \begin{pmatrix} -0.0001+0.0044\mathrm{i} & \mathbf{-0.9614+0.2796i} \\ \mathbf{-0.9382+0.3466i} & 0.0082+0.0035\mathrm{i} \end{pmatrix}$$

$$\Phi^3 = \begin{pmatrix} \mathbf{1.0156+0.1205i} & 0.0010+0.0020\mathrm{i} \\ 0.0020+0.0016\mathrm{i} & \mathbf{-0.3463+0.9376i} \end{pmatrix}$$

$$\Phi^4 = \begin{pmatrix} 0.0027+0.0037\mathrm{i} & \mathbf{0.9079-0.4437i} \\ \mathbf{0.3248+0.9507i} & -0.0082-0.0129\mathrm{i} \end{pmatrix}$$

As for Φ^1, when j=1, $[temp, mark]=[1.0311, 2]$, which means that first separated signal in the *i*-th block corresponds to the second separated component in the (*i*+*1*)-th block. Then the second signal in the *i*-th block corresponds to the first in the (*i*+*1*)-th block, which can be drawn from $[temp, mark]=[1.0007, 1]$ with j=2.

4.2.3 Experiment 2

In this section, we investigate the effect of the transmitted power of sources on the separation quality of our proposed method and Permutation Method in [8]. We choose the number of blocks *B*=10, for which the number of samples of each block *T*=1000. The length of overlapping signals changes from 20 to 400, i.e., *L*=20, 40, …, 400. For convenience and simplicity, we choose $\alpha = T/L$ with α =1, 2, 4, 10 and 20 as the donation. The transmitted power ranges from -20 dBm to 20dBm, and the classical algorithm in [12] is chosen as the separation method. The experimental results are shown in Fig. 12.

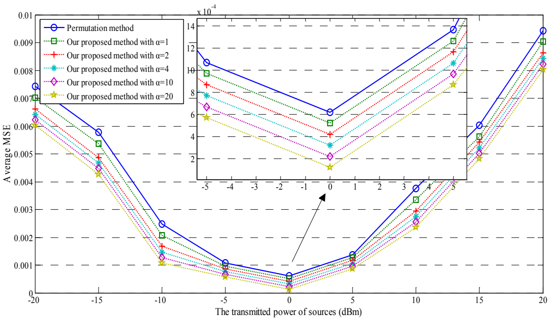

Fig. 12. MSE between sources and connected separations for Permutation Method in [8] and our proposed method with α =1, 2, 4, 10 and 20 when the transmitted power ranges from -20 dBm to 20 dBm averaged over 100 Monte-Carlo runs.

From Fig. 12, we can see clearly that the performance of our method and Permutation Method changes with the transmitted power increasing, which is different from the computer simulations. In fact, when the transmitted power increases, the performance of two methods doesn't become better and better monotonously. This is a special and interesting phenomenon for practical application. More precisely, when the transmitted power is low such as -20 dBm, the noise and interference dominate in the received signals so that the source signals can't be distinguished obviously. However, when the transmitted power is too high such as 20 dBm, the transmitters produce many other nonlinear frequency components, i.e., harmonic wave, which is caused by the nonlinear distortion of amplifiers in the transmitted devices. However, when the transmitted power is controlled appropriately such as 0 dBm, our method provides good performance. Most importantly, our method shows better performance in terms of separation quality than Permutation Method when the transmitted power changes, which can be seen clearly in Fig. 12. Although these experiments are easy and simple, we believe the experimental results are very significant, especially for future corresponding practical applications.

5 Conclusion

This paper deals with the permutation and scaling indeterminacies problem of BSS in the case where the continuously mixing signals are split in time and processed block by block. Due to the inherent indeterminacies of BSS, tying the separated signals in each adjacent time block can't recover the original sources correctly. This paper proposes a novel approach to eliminate the permutation and scaling indeterminacies by overlapping adjacent signal blocks. Simulations and realistic experiments are performed to validate the performance of our new approach. Future work includes the extension of mixture channel to convolution and nonlinear, for which more complicated realistic experiments will be performed.

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