

A Novel and Efficient Wireless Communication System

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Abstract

This paper aims to construct a novel wireless communication system, in which source signals are transmitted simultaneously in the same frequency band. The transmitted signals are only required to be statistically independent or statistically distinguished. Therefore, the source signals can be recovered at the receiver by utilizing the classical algorithms of blind source separation (BSS) and independent component analysis (ICA) such as the fast fixed-point algorithm (FastICA). On the one hand, because the source signals are transmitted simultaneously in the same frequency band, the spectrum efficiency of this novel system is much higher than those of time division multiplexing (TDM), frequency division multiplexing (FDM), and code division multiplexing (CDM) systems, in which TDM, FDM and CDM signals are limited in time interval, frequency band and code. On the other hand, inspired by recently proposed reference-based schemes, the reference signals are introduced to the classical separation algorithms of BSS and ICA, which makes this novel system much more efficient than classical ones in terms of computational speed. The performance of this new system is validated through realistic experiments. Additionally, it is theoretically shown that the information content of all the source signal inputs can be recovered by this novel wireless communication system.

Keywords: Time division multiplexing; frequency division multiplexing; code division multiplexing; statistically independent; blind source separation; independent component analysis; FastICA; reference signals

1. Introduction

With the high-speed development of the modern society, exploitation and utilization of the natural resource, especially efficient exploitation and utilization of the finite natural resource has become one of the most important research fields [1]. The electromagnetic radio spectrum is a critical natural resource in informationized society. With each passing day, more people are subscribing to one of the plethora of wireless services currently available on the market. As a result of this rapid growth in the wireless services industry, the demand for additional bandwidth is steadily increasing despite the fact that frequency spectrum is a finite natural resource. Thus, to avoid a potential spectrum scarcity problem, both spectrum policy makers and wireless technology specialists are united in seeking solutions that would help efficiently exploit and utilize the finite natural resource in order to accommodate this rapid growth [2]-[4].

A communications resource represents the time and bandwidth that is available for communication signaling associated with a given system. For the efficient development of a communication system, it is important to plan out the resource allocation among system users, so that no communications resource is wasted, and so that the users can share the

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resource in an equitable manner [5]. The traditional ways of distribution the communications resource are as follows:

- Frequency division multiplexing (FDM). Specified sub-bands of frequency are allocated.
- Time division multiplexing (TDM). Periodically recurring time slots are identified.
- Code division multiplexing (CDM). Specified numbers of a set of orthogonal or nearly orthogonal spread spectrum code are allocated.

However, since TDM and FDM carve up the signaling dimensions orthogonally, there is a hard limit on how many orthogonal channels can be obtained. This is also true for CDM using orthogonal codes. If non-orthogonal codes are used, there is no hard limit on the number of channels that can be obtained [6]. Actually, because non-orthogonal codes cause mutual interference between users, the more users that simultaneously share the system bandwidth using non-orthogonal codes, the higher the level of interference, which degrades the performance of the whole system [7]. A non-orthogonal CDM scheme also requires power control in the uplink to compensate for the near-far effect. Hence, the TDM, FDM and CDM signal is limited in time interval, or frequency band or code.

In 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 [8]. In the case where source signals are linearly and instantaneously mixed, BSS corresponds to independent component analysis (ICA) [9]. In a linear multi-input/multi-output (MIMO) system, the problem of BSS has found interesting solutions through the optimization of so-called contrast functions, which are generally treated as separation criteria. Recently, a novel family of contrast functions referred to as “reference-based” has been proposed in [10] and [11], which are based on cross-statistics or cross-cumulants between the estimated outputs and reference signals [10-12]. And they have an appealing feature in common: the corresponding optimization algorithms are quadratic with respect to the searched parameters.

This paper proposes a novel wireless communication system, which transmits source signals simultaneously in the same frequency band over wireless channel and recovers the source signals at the receiver by utilizing the statistical characteristics of source signals and broadcasting characteristics of wireless channel. Therefore, the source signals can be recovered by using the classical algorithms of BSS and ICA [13-15], which leads to higher spectrum efficiency of our new system compared with TDM, FDM and CDM. In addition, we apply the reference-based idea to the classical algorithms of BSS and ICA, which makes our system much more efficient in terms of computational speed than classical ones. The performance of our novel system is validated through realistic experiments. Note that, given the present challenge and complexity of this topic in the communications field, we only consider the case that there are two transmitting and receiving antennas in the wireless communication system in this paper.

This paper is organized as follows. Section 2 introduces our system model and assumptions. The theoretical analysis of information content of our system is shown in Section 3. Separation criteria are presented in Section 4. Realistic experiments are performed in Section 5. Section 6 concludes this paper.

2. Model and Assumptions

2.1. System Model

In this paper, we construct a two-input/two-output (TITO) wireless communication system, which is shown in Figure 1. For simplicity, we assume the carrier frequencies of

the transmitters and the local frequencies of the receivers are same, *i.e.*, $\omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_0$. The synchronous and carrier frequency offset problems will be included in our future work.

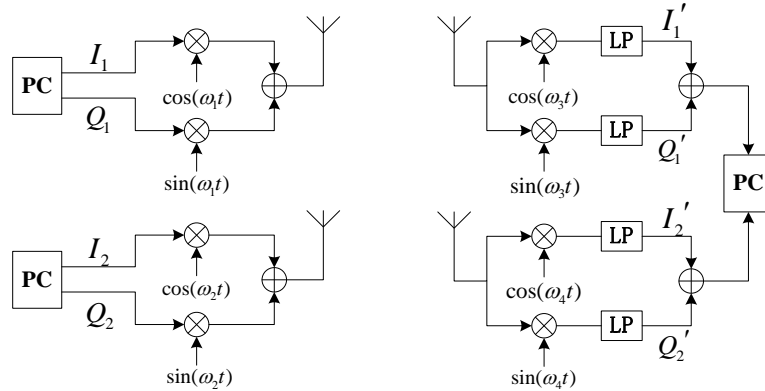


Figure 1. Our Proposed System Model

We consider the complex-valued signals with I and Q components. The two input source signals are

$$\mathbf{s} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = \begin{pmatrix} I_1 + Q_1 i \\ I_2 + Q_2 i \end{pmatrix} \quad (1)$$

The source signals after modulating are expressed as

$$s'_1 = I_1 \cos \omega_0 t + Q_1 \sin \omega_0 t \quad (2)$$

$$s'_2 = I_2 \cos \omega_0 t + Q_2 \sin \omega_0 t \quad (3)$$

The received signals result from the mixture of sources, that is

$$\mathbf{x} = \mathbf{A} \mathbf{s} \Rightarrow \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} s'_1 \\ s'_2 \end{pmatrix} \quad (4)$$

where \mathbf{A} denotes the mixing system or the wireless channel. The mixing signals are

$$\begin{aligned} x_1 &= a_{11}(I_1 \cos \omega_0 t + Q_1 \sin \omega_0 t) + a_{12}(I_2 \cos \omega_0 t + Q_2 \sin \omega_0 t) \\ &= (a_{11}I_1 + a_{12}I_2) \cos \omega_0 t + (a_{11}Q_1 + a_{12}Q_2) \sin \omega_0 t \end{aligned} \quad (5)$$

$$\begin{aligned} x_2 &= a_{21}(I_1 \cos \omega_0 t + Q_1 \sin \omega_0 t) + a_{22}(I_2 \cos \omega_0 t + Q_2 \sin \omega_0 t) \\ &= (a_{21}I_1 + a_{22}I_2) \cos \omega_0 t + (a_{21}Q_1 + a_{22}Q_2) \sin \omega_0 t \end{aligned} \quad (6)$$

After demodulating, the received signals can be simplified to

$$\begin{aligned} x_1^I &= \{(a_{11}I_1 + a_{12}I_2) \cos \omega_0 t + (a_{11}Q_1 + a_{12}Q_2) \sin \omega_0 t\} \cos \omega_0 t \\ &= \frac{1}{2}(a_{11}I_1 + a_{12}I_2) + \frac{1}{2}(a_{11}I_1 + a_{12}I_2) \cos 2\omega_0 t + \frac{1}{2}(a_{11}Q_1 + a_{12}Q_2) \sin 2\omega_0 t \end{aligned} \quad (7)$$

$$\begin{aligned} x_1^Q &= \{(a_{11}I_1 + a_{12}I_2) \cos \omega_0 t + (a_{11}Q_1 + a_{12}Q_2) \sin \omega_0 t\} \sin \omega_0 t \\ &= \frac{1}{2}(a_{11}I_1 + a_{12}I_2) \sin 2\omega_0 t + \frac{1}{2}(a_{11}Q_1 + a_{12}Q_2) + \frac{1}{2}(a_{11}Q_1 + a_{12}Q_2) \cos 2\omega_0 t \end{aligned} \quad (8)$$

$$\begin{aligned} x_2^I &= \{(a_{21}I_1 + a_{22}I_2) \cos \omega_0 t + (a_{21}Q_1 + a_{22}Q_2) \sin \omega_0 t\} \cos \omega_0 t \\ &= \frac{1}{2}(a_{21}I_1 + a_{22}I_2) + \frac{1}{2}(a_{21}I_1 + a_{22}I_2) \cos 2\omega_0 t + \frac{1}{2}(a_{21}Q_1 + a_{22}Q_2) \sin 2\omega_0 t \end{aligned} \quad (9)$$

$$\begin{aligned} x_2^Q &= \{(a_{21}I_1 + a_{22}I_2) \cos \omega_0 t + (a_{21}Q_1 + a_{22}Q_2) \sin \omega_0 t\} \sin \omega_0 t \\ &= \frac{1}{2}(a_{21}I_1 + a_{22}I_2) \sin 2\omega_0 t + \frac{1}{2}(a_{21}Q_1 + a_{22}Q_2) + \frac{1}{2}(a_{21}Q_1 + a_{22}Q_2) \cos 2\omega_0 t \end{aligned} \quad (10)$$

After low-pass filtering, the above signals are denoted by

$$I_1' = \frac{1}{2}(a_{11}I_1 + a_{12}I_2) \quad Q_1' = \frac{1}{2}(a_{11}Q_1 + a_{12}Q_2) \quad (11)$$

$$I_2' = \frac{1}{2}(a_{21}I_1 + a_{22}I_2) \quad Q_2' = \frac{1}{2}(a_{21}Q_1 + a_{22}Q_2) \quad (12)$$

Then, the relationship between the I/Q components of the original sources and the received signals after demodulating and filtering are described as

$$\begin{pmatrix} I_1' \\ I_2' \end{pmatrix} = \begin{pmatrix} a'_{11} & a'_{12} \\ a'_{21} & a'_{22} \end{pmatrix} \begin{pmatrix} I_1 \\ I_2 \end{pmatrix} \quad (13)$$

$$\begin{pmatrix} Q_1' \\ Q_2' \end{pmatrix} = \begin{pmatrix} a'_{11} & a'_{12} \\ a'_{21} & a'_{22} \end{pmatrix} \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} \quad (14)$$

where $\begin{pmatrix} a'_{11} & a'_{12} \\ a'_{21} & a'_{22} \end{pmatrix} = \frac{1}{2} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$.

At last, we get two base-band mixture signals, which are denoted by

$$\begin{aligned} x_1 &= a'_{11}I_1 + a'_{12}I_2 + (a'_{11}Q_1 + a'_{12}Q_2)i = a'_{11}(I_1 + Q_1i) + a'_{12}(I_2 + Q_2i) \\ &= a'_{11}s_1 + a'_{12}s_2 \end{aligned} \quad (15)$$

$$\begin{aligned} x_2 &= a'_{21}I_1 + a'_{22}I_2 + (a'_{21}Q_1 + a'_{22}Q_2)i = a'_{21}(I_1 + Q_1i) + a'_{22}(I_2 + Q_2i) \\ &= a'_{21}s_1 + a'_{22}s_2 \end{aligned} \quad (16)$$

These two signals can be seen as the linear mixture of source signals, from which sources can be recovered by using the separation algorithms of BSS and ICA. The recovered signals are denoted by

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

where \mathbf{W} denotes the separation operator. The separated signals are the approximate estimation of source signals.

2.2. Assumptions on the Model

In order to realize the simultaneous communication in the same frequency band, we assume the following assumptions as follows:

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

A2. The mixing system is time-invariant and unselective for frequencies without considering the multi-path and time delay effects, which means that the mixing system is linear and instantaneous.

To satisfy A1, we set the distance of two transmitters about 5 meters away to make sure the transmitted signals as independent as possible. To a certain extent, the approximate independence between sources can be well accepted, even though they are not absolutely independent.

To satisfy A2, we set the distance between transmitter and receiver about 5 meters away to ensures that the wireless channel is as approximately linear and instantaneous as possible. Although the mixing system is not absolutely linear and instantaneous, the influence caused by the frequency selective fading and noise of the wireless channel can be ignored to some extent.

3. Information Content

In this section, the information content of our new system is investigated. First of all, we define the mixing-separating matrix $\mathbf{G} = \mathbf{W}^H \mathbf{A}$, and then the relationship between sources and recovered signals can be described as

$$\mathbf{y} = \mathbf{G} \mathbf{s} \Rightarrow \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \quad (18)$$

It is widely accepted that, for random variables w, x, y, z with zero-mean, the fourth-order mutual-cumulant [13] between them can be denoted by

$$\begin{aligned} Cum\{w, x, y, z\} &= Cum\{w, x^*, y, z^*\} \\ &= E\{wx^*yz^*\} - E\{wx^*\}E\{yz^*\} - E\{wy\}E\{x^*z^*\} - E\{wz^*\}E\{x^*y\} \end{aligned} \quad (19)$$

As shown in [13]-[15], the cumulant has the following linear properties:

$$Cum(x + y) = Cum(x) + Cum(y) \quad (20)$$

$$Cum(\alpha x) = |\alpha|^4 Cum(x) \quad (21)$$

Based on the assumptions A1 and A2, the recovered signals y_1, y_2 are statistically independent. Therefore, according to (19), the fourth-order cumulant between them are

$$\begin{aligned} Cum\{y_1, y_1, y_2, y_2\} &= E\{y_1 y_1^* y_2 y_2^*\} - E\{y_1 y_1^*\}E\{y_2 y_2^*\} \\ &\quad - E\{y_1 y_2\}E\{y_1^* y_2^*\} - E\{y_1 y_2^*\}E\{y_1^* y_2\} = 0 \end{aligned} \quad (22)$$

Combined (18), (20) and (21), (22) can be simplified to

$$Cum\{y_1, y_1, y_2, y_2\} = |g_{11}|^2 |g_{21}|^2 Cum\{s_1, s_1, s_1, s_1\} + |g_{12}|^2 |g_{22}|^2 Cum\{s_2, s_2, s_2, s_2\} \quad (23)$$

It is well accepted that the realistic communication signals are almost all nongaussian so that we have $Cum\{s_i, s_i, s_i, s_i\} \neq 0, i \in \{1, 2\}$. Combined (22) with (23), it is obvious that there are two solutions as follows:

- (1) $g_{11} = 0$ and $g_{12} = 0$ or $g_{21} = 0$ and $g_{22} = 0$
- (2) $g_{11} = 0$ and $g_{22} = 0$ or $g_{21} = 0$ and $g_{12} = 0$

When the first case is considered, only one source signal is retrieved and the other one is zero, which can't satisfy the purpose of our proposed system in this paper. So the second case is chosen as the appropriate solution, in which case the matrix \mathbf{G} calls the generalized permutation matrix.

Secondly, the mutual information between source signals and recovered signals are denoted by

$$I(s_j, y_i) = \iint p(s_j, y_i) \log \frac{p(s_j, y_i)}{p(s_j)p(y_i)} ds_j dy_i, \quad \forall i, j \in \{1, 2\} \quad (24)$$

Combined (24) with above analysis, the separated signal y_i at least corresponds to one of sources, that is $y_i = g_{ij}s_j, (i, j) \in \{(1,1), (1,2), (2,1), (2,2)\}$. Therefore, we have

$$\begin{aligned} I(s_j, y_i) &= \iint p(s_j, y_i) \log \frac{p(s_j, y_i)}{p(s_j)p(y_i)} ds_j dy_i \\ &= \iint p(s_j, y_i = g_{ij}s_j) \log \frac{p(s_j, y_i = g_{ij}s_j)}{p(s_j)p(y_i = g_{ij}s_j)} ds_j dy_i \\ &= \int p(s_j) \log \frac{p(s_j)}{p(s_j)^2} ds_j = \int p(s_j) \log \frac{1}{p(s_j)} ds_j = H(s_j) \end{aligned} \quad (25)$$

Finally, we have $I(s_j, y_i) = H(s_j), i, j = \{1, 2\}$, which means that the information content of all the signal inputs can be recovered by our proposed wireless communication system.

4. Separation Criteria

4.1. Contrast Functions

As we mentioned above, the problem of BSS has found interesting solutions through the optimization of so-called contrast functions, many of them rely on higher-order statistics (e.g., the kurtosis contrast function [13]) or can be linked to higher-order statistics (e.g., the constant modulus contrast function [14]). These criteria are known to provide good results. For the linear BSS model, the common and classical contrast functions are kurtosis and negentropy, so we mainly discuss them in this paper. Based on the assumptions A1 and A2, the kurtosis and negentropy can be simplified as follows:

$$J_K(\mathbf{w}) = Cum\{\mathbf{w}^H \mathbf{x}\} = E\{|\mathbf{w}^H \mathbf{x}|^4\} - 2(E\{|\mathbf{w}^H \mathbf{x}|^2\})^2 \quad (26)$$

$$J_N(\mathbf{w}) = E\{G(|\mathbf{w}^H \mathbf{x}|^2)\} \quad (27)$$

where $J_K(\mathbf{w})$ and $J_N(\mathbf{w})$ denote kurtosis and negentropy, respectively. For (27), the nonlinear function can be chosen the form of $G_1(y) = \sqrt{a_1 + y}$, $G_2(y) = \log(a_2 + y)$,

$$G_3(y) = \frac{1}{2}y^2$$

For G_1 and G_2 , a_1 and a_2 are some arbitrary constants for which values $a_1 \approx 0.1$ and $a_2 \approx 0.1$ are chosen in this paper. Of the above functions, G_1 and G_2 grow more slowly than G_3 , and thus they give more robust estimators. G_3 is motivated by kurtosis [13, 14].

4.2. Reference Signals

Recently, a class of novel contrast functions referred to as “reference-based” have been proposed, which are essentially the cross-statistics or cross-cumulants between the

estimated outputs and reference signals [10-12]. Before introducing the reference-based contrast functions, we first introduce the reference signals. Similarly to (17), we consider a separation matrix of $M \times N$ denoted by \mathbf{V} . As shown in [11], the reference signals are in the form of

$$\mathbf{z} = \mathbf{V}^H \mathbf{x} \quad (28)$$

where \mathbf{z} and \mathbf{V} have the same function with \mathbf{y} and \mathbf{W} . Note that the reference signals have direct influence on the optimization result, especially the initialization value of them.

As described in [11], the reference signals are artificially introduced in the algorithms for the purpose of facilitating the maximization of contrast functions. Actually, the reference signals are indirectly involved in the iterative optimization process. In other words, the reference signals update following the objective signals [12]. More precisely, \mathbf{V} updates following \mathbf{W} in each loop iteration step. Therefore, combined (26), (27) and (28), the reference-based contrast functions can be expressed as

$$I_K(\mathbf{w}, \mathbf{v}) = Cum\{\mathbf{w}^H \mathbf{x}, \mathbf{v}^H \mathbf{x}\} = E\{|\mathbf{w}^H \mathbf{x}|^2 |\mathbf{v}^H \mathbf{x}|^2\} - E\{|\mathbf{w}^H \mathbf{x}|^2\} E\{|\mathbf{v}^H \mathbf{x}|^2\} - E\{(\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})\} E\{(\mathbf{w}^H \mathbf{x})^* (\mathbf{v}^H \mathbf{x})^*\} - E\{(\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})^*\} E\{(\mathbf{w}^H \mathbf{x})^* (\mathbf{v}^H \mathbf{x})\} \quad (29)$$

$$I_N(\mathbf{w}, \mathbf{v}) = E\{G((\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})^*)\} \quad (30)$$

where (29) and (30) are the reference-based contrast functions based on kurtosis and negentropy, respectively.

Therefore, based on the reference-based contrast functions in (29) and (30), many optimization schemes can be chosen to separate the mixing signals in our new wireless communication system. These reference-based algorithms are quadratic with respect to searched parameters.

4.3. Separation Algorithm

Based on the reference-based contrast functions in (29) and (30), the source signals can be recovered through optimization algorithms. For the linear BSS and ICA, the most common and classical optimization algorithms are the gradient alike algorithms and fast fixed-point algorithm (FastICA) [13]-[15]. So we mainly consider them as the optimization schemes in this paper. Taking the FastICA algorithm based on negentropy for example, the efficient reference-based algorithm for our novel wireless communication system is briefly introduced as follows:

-
- Eliminate the mean value of \mathbf{x} , and prewhiten it.
 - Initialize \mathbf{W} , and normalize it.
 - (M_0) For $i = 1, 2, \dots, N$ repeat (M_0)

$$\text{Set } \mathbf{w}_0^i = \mathbf{w}_i, \mathbf{v}_0^i = \mathbf{w}_0^i$$

- (M_0') For $k = 0, 1, \dots, k_{\max} - 1$ repeat (M_0')

- ◆ Set $\mathbf{w}_{k+1}^i = E\{\mathbf{x}(\mathbf{v}^H \mathbf{x})^* g((\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})^*)\} - 2(E\{(\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})^* g'((\mathbf{w}^H \mathbf{x})(\mathbf{v}^H \mathbf{x})^*)\})\mathbf{w}$

- ◆ Normalize \mathbf{w}_{k+1}^i

- ◆ $\mathbf{w}_{k+1}^i = \mathbf{w}_{k+1}^i - \sum_{j=1}^{i-1} \mathbf{w}_j \mathbf{w}_j^T \mathbf{w}_i$

- ◆ Renormalize \mathbf{w}_{k+1}^i

- ◆ Set $\mathbf{v}_{k+1}^i = \mathbf{w}_{k+1}^i$

- ◆ $\mathbf{w}_i = \mathbf{w}_{k_{\max}-1}^i$

- $\mathbf{y} = \mathbf{W}^H \mathbf{x}$
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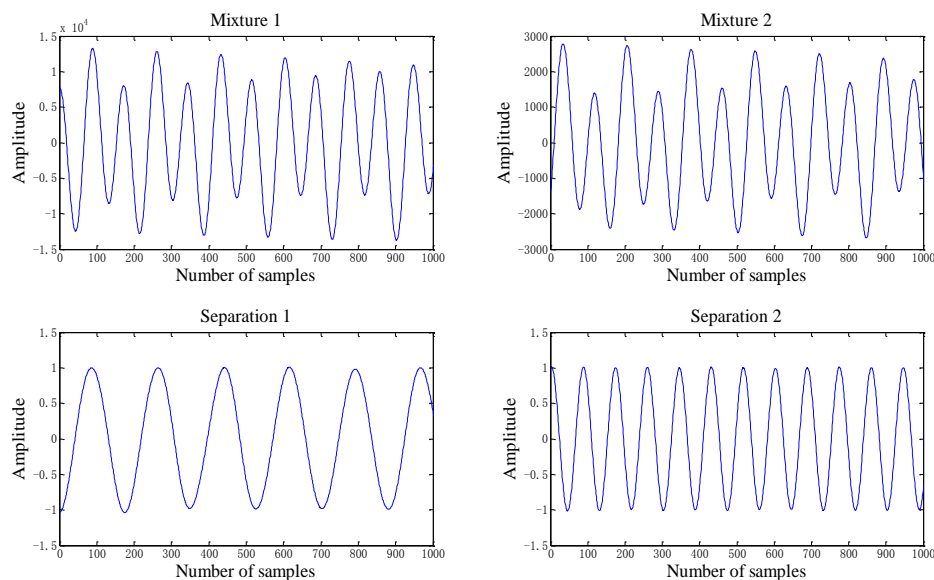
In this algorithm shown above, \mathbf{W}^0 is the initialization value of \mathbf{W} , which is chosen randomly. And we can see that the reference signals update following the objective signals, that is \mathbf{V} updates following \mathbf{W} in each loop iteration step. Note that the above algorithm is derived for extracting one component and other sources can be extracted one by one in a deflation manner. To prevent different one-dimensional optimization converging to the same maxima, a Gram-Schmidt-like decorrelation scheme [13, 14] is used in this paper. Although we only consider the FastICA algorithm based on the reference-based negentropy here, the algorithm's execution procedure can be extended to the gradient alike algorithms. Similar applications for other optimization algorithms will be investigated in our latter work. We skip the derivation process of above FastICA algorithm here for lack of space, for which details can be found in [15].

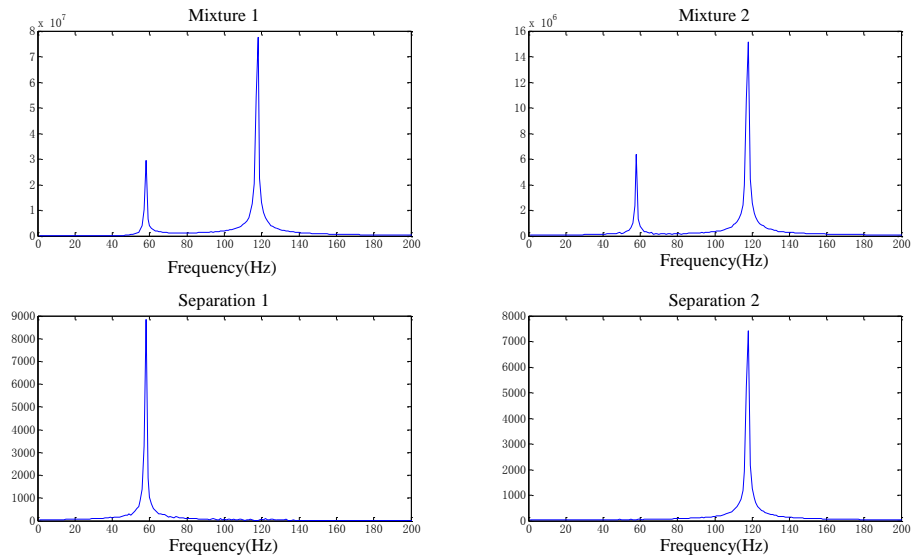
5. Experimental Results and Analysis

In order to lower the influence of nonlinear distortion caused by the power amplifier as litter as possible in the transmitters, we take two E4438C [16] as the transmitters, which can send radio signals in the form of single, AM, BPSK, speech and so on. Then, at the receivers, we use the USRP with GUN Radio [17] device to receive the RF signals.

5.1. Separability

As shown in Figure 2, two single signals are transmitted as sources, for which the carrier frequency is 30MHz. The transmitted power is 0 dBm. The number of samples is 1000 and the iteration parameter $k_{\max} = 1000$. The mixing signals after demodulating and the separating signals are shown in Figure 2, in which (a) represents the signals in time domain and (b) represents the signals in frequency domain.

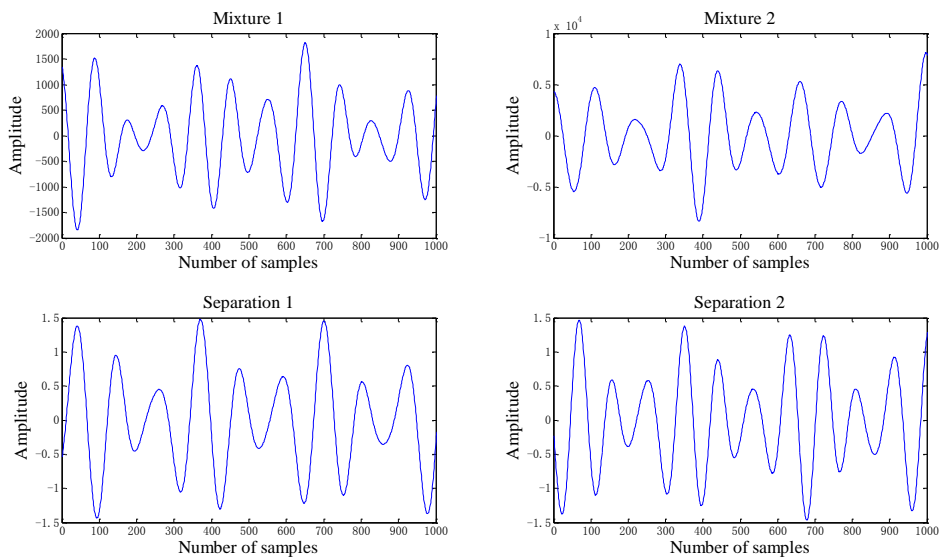




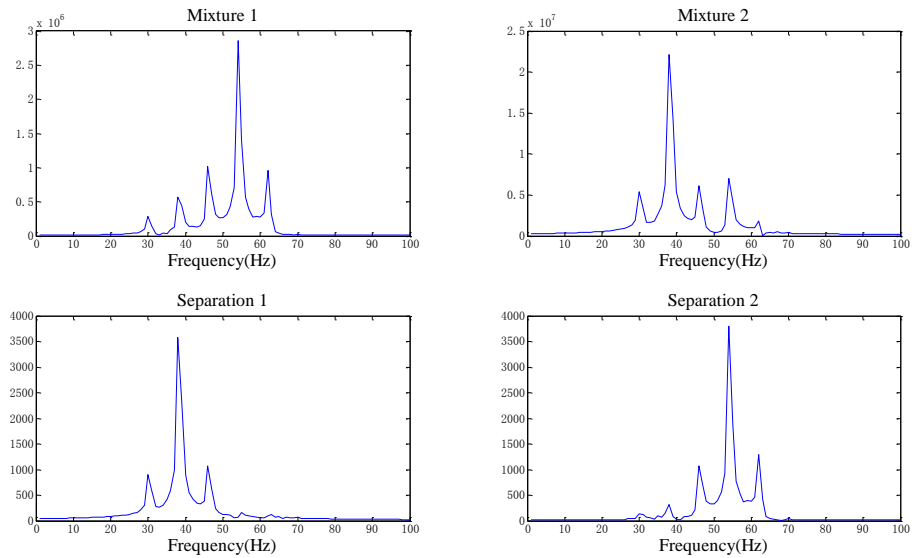
(b)

Figure 2. The Mixture and Separation Signals for Single Signals in Time and Frequency Domain

In order to distinguish the separability obviously, we choose the single signals with different frequencies. Compared the time domain signals in (a) in Figure 2, it can be seen clearly that the single source signals are recovered successfully, which can be also observed in the frequency domain in (b). However, note that, in Figure 2, the retrieved sources are with a litter distortion in the waveform, which is caused by the noise and interferences from the uncontrollable realistic wireless channel and the demodulation device.



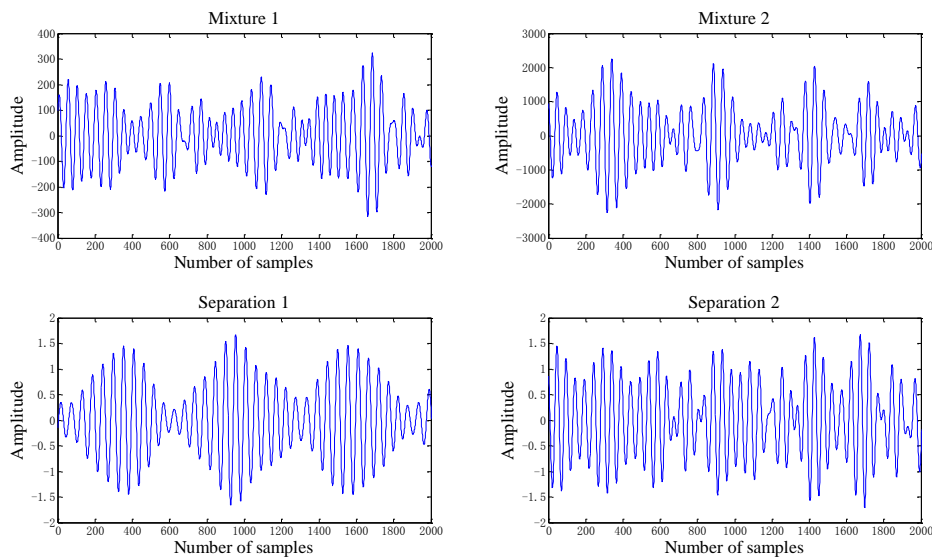
(a)



(b)

Figure 3. The Mixture and Separation Signals for Amplitude Modulated Signals in Time and Frequency Domain

In Figure 3, we perform the separation using two amplitude modulated (AM) signals, for which the carrier frequency is 30MHz. The transmitted power is 0dBm. The number of samples is 1000 and the iteration parameter $k_{max} = 1000$. Similar to Figure 2, the mixing signals after demodulating and the separating signals are shown in Figure 3, in which (a) represents the signals in time domain and (b) represents the signals in frequency domain. And in (a) and (b), the first row are received mixtures after demodulating and the second row are separated signals. Compared the mixtures and separations in time or frequency domain, *i.e.*, (a) or (b), we can see obviously that the sources are separated successfully with some distortion, which is caused by the transmitter.



(a)

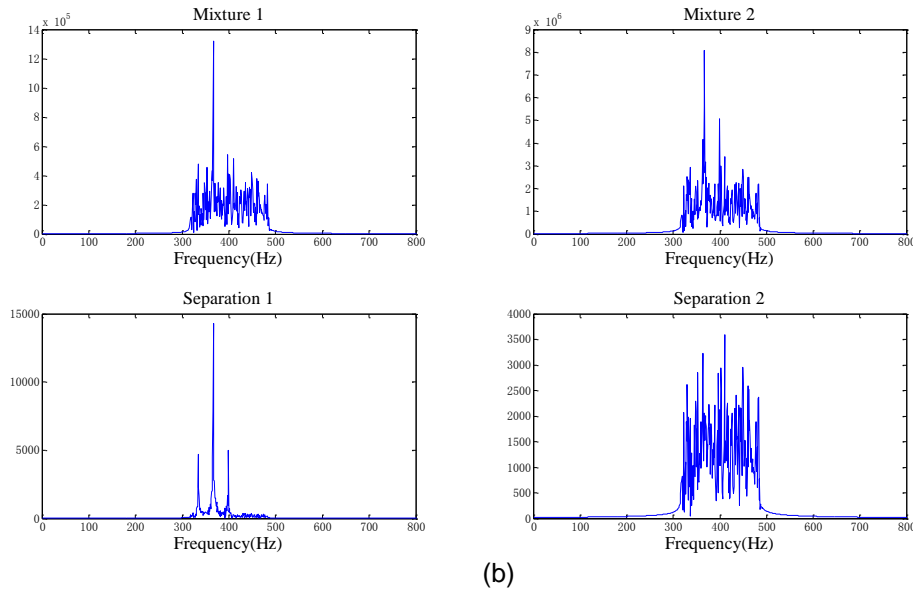


Figure 4. The Mixture and Separation Signals for Amplitude Modulated and BPSK Signals in Time and Frequency Domain

In Figure 4, we choose an AM signal and a BPSK signal as the transmitted sources, for which the carrier frequency is 30MHz. The transmitted power is 0dBm. The number of samples is 1000 and the iteration parameter $k_{max} = 1000$. Similarly, the mixing signals after demodulating and the separating signals are shown in Figure 4, in which (a) represents the signals in time domain and (b) represents the signals in frequency domain. And in (a) and (b), the first row are received mixtures after demodulating and the second row are separated signals. The first two rows are received mixtures after demodulating and the last two rows are separated signals. From the time domain in (a), we can see that the two different source signals are separated obviously, and the signals in (b) also prove this.

5.2. Efficiency

In this section, we investigate the efficiency of our proposed wireless communication system in terms of computational speed based on the reference-based algorithms by taking AM signals as sources. The carrier frequency is set 30 MHz, *i.e.*, $\omega_0 = 30MHz$. The number of samples varies from 1000 to 10000 and the transmitted power is set 0 dBm. The iteration parameter $k_{max} = 1000$. Taking the FastICA algorithm based on negentropy in [15] for example, the classical algorithms with different nonlinear functions G_1, G_2, G_3 in (28)-(30) are denoted by G1, G2 and G3 and the corresponding reference-based algorithms are denoted by G1+N, G2+N and G3+N. The mean square error (MSE) between sources and separations are chosen as the measurement criteria for separation quality, in which the MSE is mean value of MSE over all sources. And the execution time of recovering all sources is chosen as the measure criterion of efficiency. The experimental results are illustrated in Figure 4 and Figure 5.

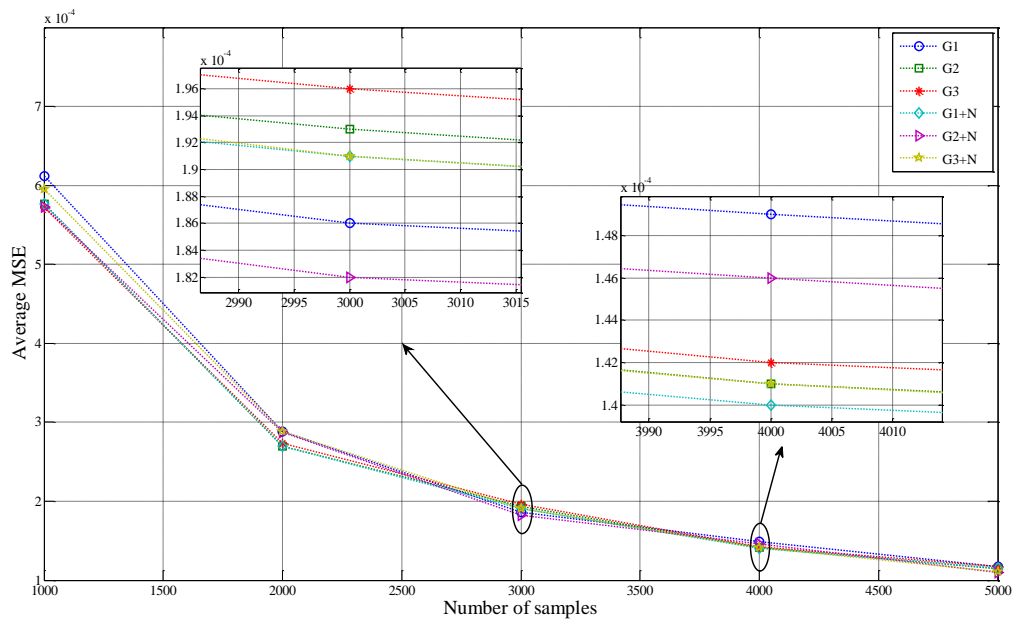


Figure 4. MSE between Sources and Separations Averaged over 100 Monte-Carlo Runs

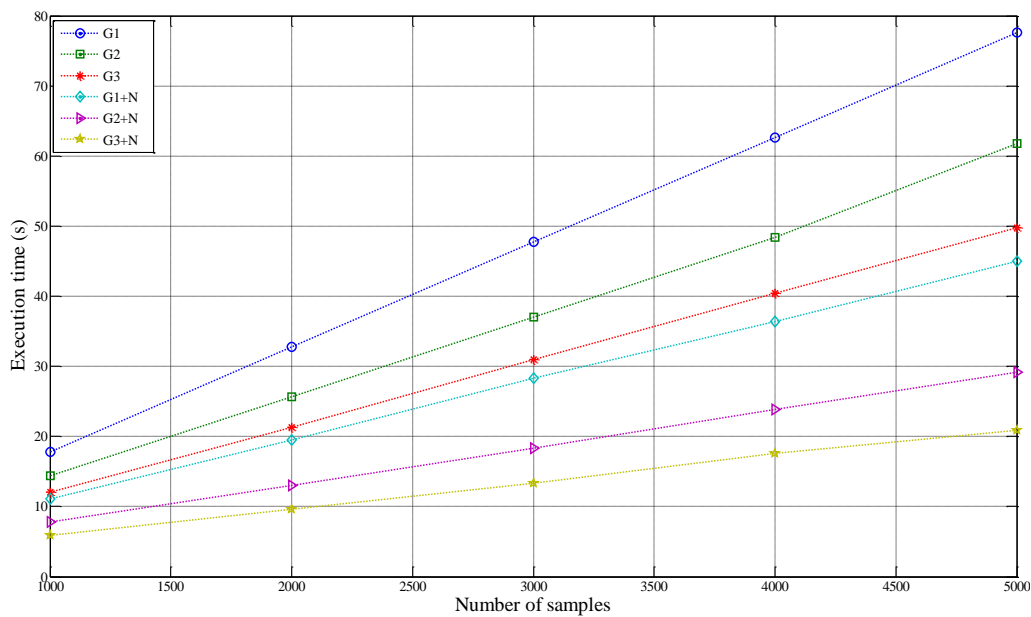


Figure 5. Execution Time of Recovering all Sources for 100 Monte-Carlo Runs

As shown in Figure 4, it is obviously observed that the MSE value between the reference-based algorithm and the classical one in [15] is very close to each other, which means that the former recovers the sources successfully and converges to the approximately identical stationary points as the latter. Considering different nonlinear functions, G_1, G_2, G_3 , we find that the separation quality provided by them for both algorithms is very similar, which is more obvious with the number of samples increasing. It can be concluded that, based on the our proposed wireless communication system, the reference-based FastICA algorithm provides the same performance as the classical one in terms of separation quality.

However, in Figure 5, it can be clearly seen that the reference-based FastICA algorithm is more efficient in terms of computational speed than the originally classical one. More precisely, G1, G2 and G3 need more execution time than G1+N, G2+N and G3+N, respectively under the same circumstance. This means that the reference-based algorithm can make our new system much quicker in terms of computational speed than the classical one, which is significantly striking with large number of samples. Therefore, combined Figure 4 with Figure 5, we can draw the conclusion that our proposed wireless communication system by using the reference-based algorithms is much efficient than that by using the classical ones in terms of computational speed. In other words, we construct a very efficient system by applying the reference-based scheme to the separation operator of our system. Note that we only consider the performance difference of reference-based and classical FastICA algorithm based on negentropy here. For lack of space, we skip the performance analysis for other optimization schemes such as the gradient algorithm based on kurtosis.

5.3. Influence of Transmitted Power

In practical applications, many effect factors can't be predicted and known beforehand for realistic communication system, especially for the wireless communication system. For example, the transmitted power of sources plays an important role in our system. Therefore, the influence of transmitted power of sources on the performance of our new system is investigated briefly, which is performed by using the FastICA algorithm based on negentropy. And we believe this is very necessary and significant for our proposed system and future work. The experimental result is shown in Figure 6, in which the transmitted power ranges from -20 dBm to 20dBm.

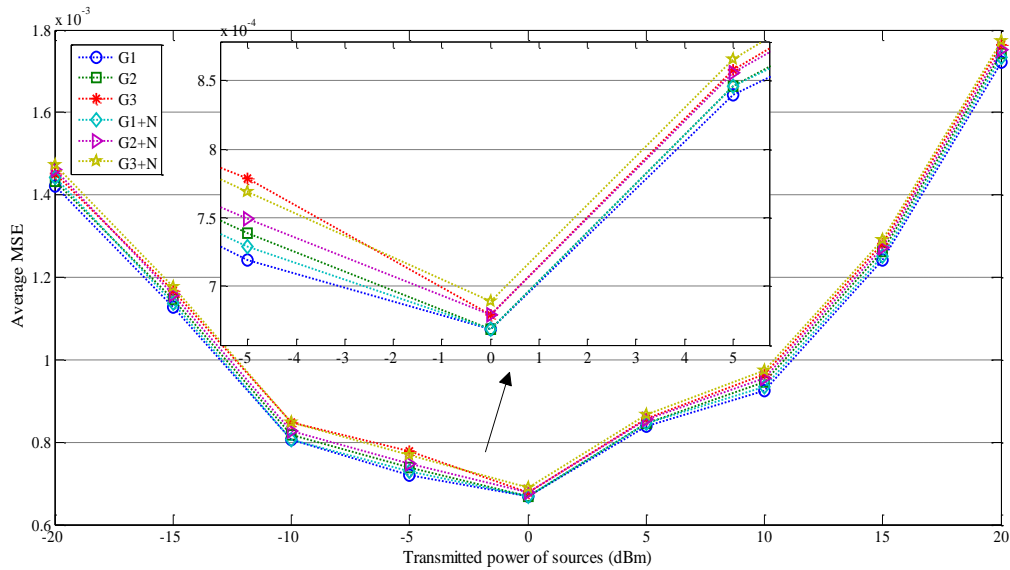


Figure 6. The Influence of Transmitted Power on the Performance of our System over 100 Monte-Carlo Runs

As observed in Figure 6, when the transmitted power increases, we can see clearly that the performance of our system in terms of separation quality doesn't become better and better monotonously, which 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 system provides good performance. Therefore, in the practical applications, the transmitted power of sources is recommended to be about 0 dBm. Although these experiments are easy and simple, we believe the experimental results are very significant, especially for future corresponding practical applications. Actually, it can be predicted that the performance results are similar.

6. Conclusion

In this paper, we construct a novel wireless communication system, which transmits source signals simultaneously in the same frequency band over wireless channel and recovers the source signals at the receiver by utilizing the statistical characteristics of source signals and broadcasting characteristics of wireless channel. The spectrum efficiency of our system is much higher than traditional ones. By applying the reference-based scheme to the classical separation algorithms, our system becomes much efficient in terms of computational speed. The performance of our system is validated through realistic experiments. Our future work includes the investigation of more complex wireless channel such as convolution channel and the extension to more transmitting and receiving antennas.

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