Underdetermined blind separation of adjacent satellite interference in modern satellite communication systems

Chengjie Li\textsuperscript{(a)}, Lidong Zhu\textsuperscript{(b)}, and Zhen Zhang\textsuperscript{(c)}

\textsuperscript{1} National Key Laboratory of Science and Technology on Communication, University of Electronic Science and Technology of China, No. 2006, Xiyuan Ave, West Hi-Tech Zone, Chengdu, China
\textsuperscript{2} NCS Pte. Ltd. of Singapore Telecommunications Limited, Ang Mo Kio Street 62, NCS Hub, Singapore

\textsuperscript{(a)} junhongabc@126.com
\textsuperscript{(b)} zld@uestc.edu.cn
\textsuperscript{(c)} zhangzhen@ncsi.com.cn

Abstract: In this paper, a novel underdetermined blind source separation algorithm guided by particle swarm optimizer (PSO) is proposed for adjacent satellite interference in modern satellite communication systems. Different from traditional methods, we formulate the separation problem as clustering problem. Due to our algorithm is affected by the sparsity of source signals and the density of mixed vectors, our algorithm is motivated by the assumption is held that the distance between two arbitrary mixed signal vectors is less than the doubled sum of variances of distribution of the corresponding mixtures. In our method, we accomplish the underdetermined blind source separation by computing the Short Time Fourier Transform (STFT) to segment received mixtures and we use some estimates to separate the mixed source signals by PSO where the number of the mixed signals is unknown. In PSO, we define new parameters \textit{gather} in formula (8) and \(c_j\) in formula (11). We verify the proposed method on several simulations. The experimental results demonstrate the effectiveness of the proposed method.

Keywords: adjacent satellite interference, blind source separation, particle swarm optimizer, Short Time Fourier Transform, sampling point

Classification: Fundamental Theories for Communications

References

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1 Introduction

Adjacent satellite interference is same frequency interference caused by satellites in nearby orbital location. Though people can reduce the influence by isolating wave beam coverage area/frequency or reducing the antenna sidelobe etc., such cases of interference happen more and more frequently due to synchronous orbit traffic get heavier, especially for Ultra Small Aperture Terminal (USAT). Adjacent satellite interference framework is shown in Fig. 1, the solid line is useful signal and the dotted line is the adjacent satellite interference signal. For many years, researches on adjacent satellite interference has been an important subject. In 1999, SLivieratos etc. adopted Crane model for adjacent interference of satellite communication links [1].

Blind source separation (BSS) is a major research area in signal processing and machine learning, and that has a large scope of applications in many fields, such as image recognition, speech enhancement, biomedical signal processing, wireless communications etc. [2, 3, 4] BSS aims to extract individual components from their mixture samples where there is very limited, or no, prior information on mixture samples nature or the mixing process. Recently, many BSS methods are based on Independent Component Analysis with the assumption that the sources are independent signals. However, if initial parameters are not given, those methods will...
produce a poor solution. And a suitable initial parameters is unlikely to be open information because of the blind hypothesis. Consequently, some accurate, efficient and robust BSS algorithms are desired.

We focus on BSS problem for adjacent satellite interference. To overcome the above difficulties, this article proposes a novel particle swarm optimizer (PSO) mechanism for identifying the exact mixing vector. In this article, we formulate the separation problem as clustering problem. Due to our algorithm is affected by the sparsity of source signals and the density of mixed vectors, our algorithm is motivated by the fact that the assumption that the distance between two arbitrary mixed signal vectors is less than the doubled sum of variances of distribution for the corresponding mixtures is held.

The rest of this paper is organized as follows. In Section II, we introduce the preparatory work of this article. In Section III, we introduce the novel BSS algorithm with PSO. In Section IV, we introduce and discuss the experimental results. Finally, the conclusion is drawn in Section V.

2 Preparatory work

In this section, we introduce the related preparatory work of Density Clustering algorithm (DC-algorithm).

2.1 BSS model

BSS aims at separating a set of $N$ unknown sources from a set of $M$ observations. Usually, the observations are obtained from $M$ sensors, each sensor receives a mixture of those sources. In this article, we only consider linear instantaneous mixtures model, each observation is described as below [5]:

$$y_j(t) = \sum_{i=1}^{N} a_{ij} s_j(t) + n_i(t), \quad j = 1, 2, \cdots, M$$

(1)

Here, $a_{ij}$ is the $(i, j)$th element of the mixed matrix, $n_i(t)$ is the $i$th component of the noise. Equation (2) can also be written in matrix form,

$$Y(t) = AS(t) + N(t)$$

(2)
2.2 Particle swarm optimizer (PSO) model

In PSO, a goal is to minimize an objective function \( f \), and there are three attributes, the particles’ current position \( p_i \), current velocity \( v_i \), and local best position \( P_{bi} \). Each particle in the swarm is iteratively updated according to the aforementioned attributes. In [6], a compact and workable PSO version is proposed, the new velocity of every particle is updated by the following formula,

\[
v_j(g + 1) = a_0 \cdot v_j(g) + a_1 \cdot r_1[P_{bj}(g) - p_j(g)] + a_2 \cdot r_2[G_b(j)(g) - p_j(g)]
\]

(3)

here, \( j = 1, 2, \ldots, k \) denotes the index of dimension, \( i = 1, 2, \ldots, sz \) denotes the individual of particles, \( P_{bj}(g) \) denotes the local best position of the \( j \)th dimension of the \( i \)th particle, and \( G_b(j)(g) \) denotes the global best position at the \( g \)th generation. \( v_j(g) \) is the velocity of the \( j \)th dimension of the \( i \)th particle. There are three parameters that should be predefined suitably for the better performance of PSO. \( a_0 \) is the inertia weight of velocity, \( a_1 \) and \( a_2 \) denote the acceleration coefficients, \( r_1 \) and \( r_2 \) are elements from two uniform random sequences in the range \((0, 1)\), and \( g \) is the number of generations. The new position of a particle is calculated by the following formula,

\[
p_i(g + 1) = p_i(g) + v_i(g + 1)
\]

(4)

The local best position of each particle is updated by

\[
P_{bi}(g + 1) = \begin{cases} P_{bj}(g), & \text{if } f(p_i(g + 1)) \geq f(P_{bi}(g)) \\ p_i(g + 1), & \text{otherwise} \end{cases}
\]

(5)

and the global best position \((G_b)\) found from all particles during the previous three steps is defined as

\[
G_b(g + 1) = \min_{P_{bi}} f(P_{bi}(g + 1)), \quad 1 \leq i \leq sz
\]

(6)

The evolutionary process will continuously repeat (3)–(6) until some terminative condition is reached.

3 Improved BSS algorithm with PSO

Because of only two sensors are available, the received mixtures are represented as \([Y_1(t, f), Y_2(t, f)]^T\). Since source signals are sparse, the mixtures center around the mixing vectors on the \( Y_1 - Y_2 \) coordinate plane. And \( Y_i(t, f) \) is described as follows:

\[
Y_i(t, f) = \int_0^1 y(t)h(t - \tau)e^{-j2\pi f\tau}d\tau, \quad i = 1, 2
\]

(7)

Here, \( y(t) \) is the received mixing signal, \( h(t - \tau) \) is the Hamming window function. Thus, unobservable mixing vectors could emerge from these clusters of mixtures. In fact, since local optima would reduce the performance of conventional methods or the source signals may not be sparse enough, the mixing vectors not scattered enough to be able to easily distinguished. In order to enhance BSS performance and handle more advanced conditions, the improved BSS algorithm with PSO is developed to search mixed vectors [7].
3.1 Definition of parameter

In the development of BSS algorithm with PSO, \( p = [\delta_1, \delta_2, \ldots, \delta_k] \) is a set of estimated vectors and regarded as a particle of PSO, where \( \forall \delta \in (-\frac{\pi}{2}, \frac{\pi}{2}) \) and \( k \) denotes the dimension of each particle, that is, \( k \) is the maximal number of estimated vectors. The elements of a particle represent the gathering angles of mixtures. Since \( n \) mixing vectors have to be found and \( n \) is unknown, a value \( k \) will be given, \( k \geq n \). Compared with the [8], a normal angle with one dimension replaced the original plane coordinate with two dimensions for some estimated mixing vectors. Hence, the learning complexity can be reduced and the searching range becomes definite.

Because the gathering directions of mixtures imply the location of the mixing vectors, an objective function that evaluates how close the estimated mixing vectors are to the gatherings is defined as

\[
gather = \sum_{i=1}^{N} \xi^2_i \times \Delta \theta_i \tag{8}
\]

where \( \xi_i = \sqrt{y_1^2(i) + y_2^2(i)} \) denotes the energy of the signal of the \( i \)th mixture, which is regarded as the weight of each mixture. So, a sample with a large \( \xi \) indicates a main signal that is regarded as important. \( \Delta \theta_i \) denotes the differential angle between the \( i \)th mixture vector and the nearest estimated vector and is calculated by

\[
\Delta \theta_i = \min|\theta_i - \delta_j|, \quad i = 1, 2, \ldots, N \text{ and } j = 1, 2, \ldots, k \tag{9}
\]

where \( \theta_i \) is the angle of the \( i \)th mixture vector. When all \( \delta \) approach the center of the mixture gathering, \( \Delta \theta \) will reduce integrally. So, a particle responding with the minimum of the objective function denotes its elements place exactly in the direction of a gathering of mixtures. \( \text{gather} \) values of particles are evaluated by (8). According to \( \text{gather} \) values we can update the Pb and Gb by (5) and (6).

3.2 Global best position Gb is replaced with cluster centers set C

Since mixtures gather toward the mixing vectors, cluster centers are more likely to produce a better solution than global best position (Gb). Moreover, it not only substantially improves Gb during initial generations, but also fine tunes Gb during final generations. Consequently, cluster information is the more preferable guide for particles compared to Gb. The factor Gb is replaced with cluster centers set C in (7), which could be rewritten as

\[
v_{ij}(g + 1) = a_0 \cdot v_{ij}(g) + a_1 \cdot r_1 [Pb_{ij}(g) - p_{ij}(g)] + a_2 \cdot r_2 [c_j(g) - p_{ij}(g)] \tag{10}
\]

where \( \{c_j\} j = 1, 2, \ldots, k \} \in C \) is a set of cluster centers according to Gb, and each component is evaluated by

\[
c_j = \frac{\sum_{i=1}^{cn_j}(\xi^2_i \times \theta_i)}{\sum_{i=1}^{cn_j} \xi^2_i} \tag{11}
\]

© IEICE 2017
DOI: 10.1587/comex.2016XBL0166
Received September 13, 2016
Accepted October 18, 2016
Publicized November 30, 2016
Copyedited February 1, 2017
where \( j \) denotes the index of the cluster, \( cn_j \) denotes the number of mixtures that belong to the \( j \)th estimated vector, and \( i \) is the index of mixtures. Since the involved signals are sparse, \( \xi_i \) could be regarded as a weight to the angle of the \( i \)th mixture. In other words, mixtures with a larger \( \xi \) have a greater effect upon the cluster center that it belongs to, whereas others are noisy or even voiceless.

After the above process, the cluster centers can be found. Then, every remaining sampling point is assigned to the same cluster as its nearest cluster center.

### 4 Simulation and blind source signal separation results

In this section, we verify the proposed method. In the simulation, the number of source signals is three, the number of received signals is two. We aim to separate the received mixed signals in time-frequency domain.

Each parameter is defined as follows: \( fb = 2 \times 10^5 \) Hz for sample rate, \( Rb = 10^3 \) bps for transmission bit rate, \( v = 500 \) hop/s for hopping speed, \( f_0 = 2 \times 10^3 \) Hz for modulation frequency, \( m = 8 \) for bit numbers, the original signal numbers as \( MK = 3 \), and the receiving antenna numbers as \( RK = 2 \).

Every sampling point is assigned to the nearest neighbor cluster according to its density after we find the cluster centers. The results of classification is displayed in Fig. 2. In Fig. 2, the horizontal axis and vertical axis are \( Y_1(t,f) \) and \( Y_2(t,f) \) in formula (7), respectively.

![Fig. 2. The class of the sampling points.](image)

#### 4.1 The first comparative experiment of effect

In order to show better performance of the proposed algorithm, we compare the convergence speed with other algorithms. The \( E_{ct} \) value is used. The results are shown in Fig. 3(a), the horizontal axis is iteration number and the vertical axis is the value of \( E_{ct} \), where \( E_{ct} \) is defined as:
From Fig. 3(a), we can see that the algorithm has a satisfied convergence speed than the other methods in Fig. 3(a).

### 4.2 The second comparative experiment of effect

Here, we consider two channels to fully simulate the realistic signal transmission, after the Gauss channel based transitions, we compare the source signals and the separated signals by objective evaluation and further compare the separation performance with the K-means clustering algorithm [9]. The Pearsons correlation coefficient value is used. The results are shown in Fig. 3(b), where Pearsons correlation coefficient is defined as:

$$ r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} $$

From Fig. 3(b), we can see that blind sources signals can be efficiently separated by the proposed method, and it has a better performance than the classical K-means clustering algorithm.

### 5 Conclusion

In this paper, we propose a novel blind source signal separation with PSO. First, we define new parameter and two-dimensional decision coordinate system. Then, in PSO, we replace global best Position $Gb$ with cluster centers set $C$ to separate the mixed source signals. The experiment results demonstrate the effectiveness of the proposed method.
Acknowledgments

This work is fully supported by a grant from the national High Technology Research and development Program of China (863 Program) (No. 2012AA01A502), and National Natural Science Foundation of China (No. 61179006), and Science and Technology Support Program of Sichuan Province (No. 2014GZX0004).