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A Comprehensive Survey on Blind Source Separation for Wireless Adaptive Processing: Principles, Perspectives, Challenges and New Research Directions

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ABSTRACT With the rapid proliferation of wireless services, the frequency spectrum has become increasingly crowded, and the interferences and composite signals will be ubiquitous in the wireless receiver. For deeply dissecting and detecting the expected signals, the research community has to investigate the smart signal processing technology to resisting the influence of detrimental signals. For this purpose, blind source separation has been shown to be a promising method for achieving simultaneous spectrum utilization and wireless adaptive interference cancellation. The attractive features and appealing advantages of blind source separation make it an attractive theory for source extraction or recovery, which plays a crucial role in helping realize intelligent signal processing for wireless communication. It can recover the unobserved sources only from the wireless received mixed signals based on the features of the source signal exempted from channel estimation and synchronization manipulation. Wireless communication systems can benefit the high spectrum efficiency, strong anti-interference, and adaptive signal processing through the blind separation mechanism. So far, numerous researchers have made tremendous efforts to investigate this field for enhancing spectrum efficiency, anti-interference ability, and signal detection performance through employing the philosophy of blind separation. These meaningful and appealing research works motivate us to make a comprehensive survey with regard to this area. In this paper, the fundamental principle of the blind separation mechanism, involving independent component analysis, sparse component analysis, non-negative matrix factorization, and bounded component analysis will be reviewed briefly, and then, the critical technologies applied in various wireless communication systems will be overviewed, such as in direct-sequence code division multiplexing access, frequency hopping, orthogonal frequency-division multiplexing, multiple input multiple output, wireless sensor networks, cognitive radio networks, radio frequency identification devices, and communication security. In addition, the important research challenges and meaningful research directions pertaining to the area of blind separation applied in wireless communications systems are also discussed.

INDEX TERMS Adaptive signal processing, blind source separation, wireless communication systems, independent component analysis, sparse component analysis, bounded component analysis, artificial intelligence, machine learning.

I. INTRODUCTION

With the advent of artificial intelligence (AI) era, the blind source separation as a significant machine learning theory will be a powerful tools and hot research topic with substantial potential application areas, such as seismic monitoring, stock prediction, text document analysis, audio signal separation, image and biomedical signal processing, wireless communication systems, and so on [1]–[4]. As is well-known, this appealing theory traced its origins to the cocktail party problem which had captured tremendous attention in last decades. The cocktail party problem hints that if you are at a cocktail party, where numerous people are chatting simultaneously, you can try to focus on one of the discussions by means of ear. As shown in figure 1, a few persons are chatting simultaneously, one person can adaptively extract one of the interested contents from their conversations or focus on one of persons' talk. This cocktail party effect motives and spurs the research field of blind source separation, which is envisioned to simulate the function of human ears with intelligent processing mechanism. The goal of blind source separation is to separate or extract the desired signal only from the observed/received mixed signals with minimal a priori information about the source signals and their mixtures. Employing blind characteristic contributes significantly to implementing blind estimation, blind equalization and adaptive signal processing in wireless communication systems.

FIGURE 1. Cocktail party problem.

Blind separation theory has become a powerful and flexible technology for wireless communication systems. Utilizing BSS for wireless receiving processing can possess a series of significant functions, as shown in figure 2. First of all, BSS can exempt from saturating network with pilot symbols, avoiding a detrimental effect known as pilot contamination. Consequently, the spectrum efficiency can be enhanced because of saving frequency resource. Secondly, the requirements of channel state information and synchronization parameter will become weaken by exploiting BSS technology. In addition, BSS is a promising scheme for anti-inference, especially the external malignant interference. Lastly, the BSS method can easily combine with the traditional signal processing methods to promote the performance refinement. All of those functions will contribute to achieve blind adaptive processing which is important for the next generation wireless communications.

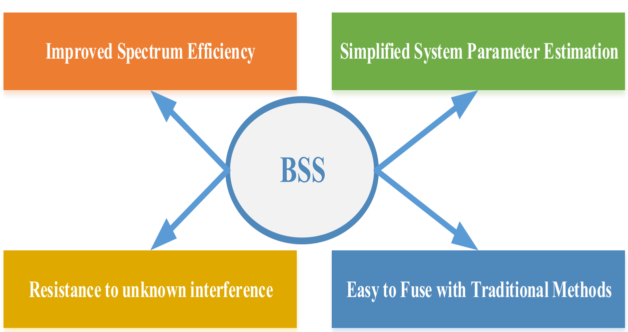

FIGURE 2. Advantages of BSS in Wireless Communication Systems.

So far, a great deal of famous and prominent algorithms related to blind source separation have been proposed and reported, and these algorithms play critical roles in many disciplines and fields. Generally, these numerous developed algorithms can be categorized into four ways from the perspective of the source separation condition or the restricted source features, including independent component analysis (ICA) [1], [3], [5], [6], sparse component analysis (SCA) [3], [7], [8], non-negative matrix factorization (NMF) [3], [9], [10] and bounded component analysis (BCA) [3], [11]–[14] respectively. As shown in firgure 3, the fundamental principles of BSS are revealed, and the occupied investigation position in the context of BSS research field is also illustrated.

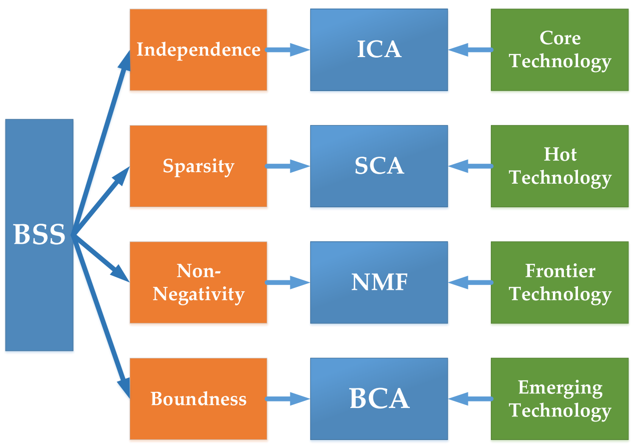

FIGURE 3. Four BSS theories based on different restricted source features.

The first type is ICA which is a classical blind separation technology based on the statistical independence of source signals. ICA is a mainstream technology of BSS that has sprung up a number of representative algorithms, such as SOBI, FastICA, JADE, EASI, INFOMAX, and so on [1], [3]. The second category is SCA which is a hot blind separation technology based on the sparsity of source signals. If the source signals are inherent sparseness or sparse in their transform domain, and their mixtures can be unmixed using the SCA algorithms. The typical representative algorithms are time frequency ratio of mixtures (TIFROM) and degenerate unmixing estimation technique (DUET). Due to that SCA is closely linked with compressive sensing technology and suitable for implementing underdetermined BSS, it has been a hotspot in contemporary research orientation. The third kind is NMF which is a cutting-edge blind separation technology dependent on the non-negative of source signals and mixing matrix. Although NMF is appropriate for speech separation and image processing due to its technical characteristic, it also be promising candidate for wireless receiving processing through its variant. The fourth type is BCA which is an emerging blind separation technology on the basis of the bounded condition of original signals. BCA can be regarded as an extended ICA, which exploits the bounded constraint of sources as a substitute of source independence condition with a weaker assumption. Therefore, BCA can form a more extensive framework to separate independent and even dependent sources under bounded constraint. Extraordinary, BCA is fit for separating communication mixed signals because the communication signals have the properties of finite alphabet and constant modulus which are typical boundedness criterions. Therefore, BCA may be a very positive scheme for extracting the desired signals from the received mixtures.

Blind source separation has been a research hotspot in the area of neural network and signal processing, which has been extensively and deeply utilized in wireless communications. In the field of wireless communication, the increasing mixed signals appear in receiver even same frequency so that a huge challenge to the classical filtering signal processing is posed with. Therefore, other meaningful methods should be sought for helping dispose of this problem. It is noticed that the fundamental received signals model in wireless communications has close relationship to the BSS model so that problems in wireless communications can be dealt with through BSS perspective. As shown in figure 4, a typical communication circumstance of the mixed received signals is demonstrated. Figure 4 shows that the receiving signals are bound to be the composite signals in complex electromagnetic environment. This is a widespread phenomenon in wireless communication.

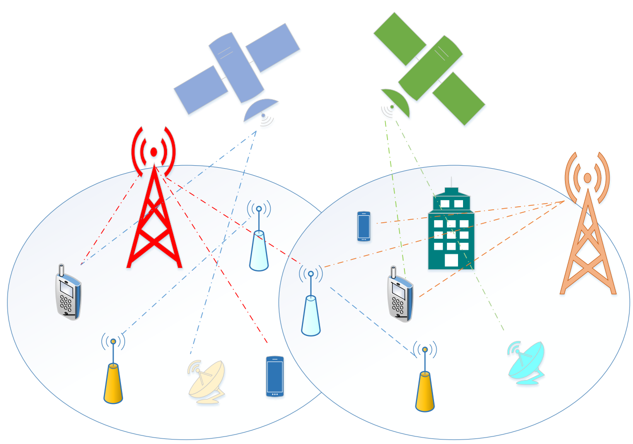

FIGURE 4. Mixed signals scene in wireless communications.

In this paper, BSS applications in different wireless communications areas, such as direct-sequence code division multiple access (DS-CDMA), frequency hopping (FH) systems orthogonal frequency division multiplexing (OFDM), multiple input multiple output (MIMO) systems, wireless sensor networks (WSNs), cognitive radio network (CRNs) radio frequency identification (RFID) systems and communication security are discussed [3], [4]. The adaptive processing mechanism and the relaxed prior information limitation of BSS make a significant contribution to optimizing wireless communications for realizing various purposes. The different goals of BSS applied in wireless communication systems are portrayed in figure 5. In the figure, it illuminates that BSS contribute significantly to achieving the extraction signal of interest, automatic modulation classification, suppression of inter symbol interference (ISI), interference elimination, direction of arrival (DOA) estimation, multi-objects detection, spectrum sensing and anti-collision, and so on.

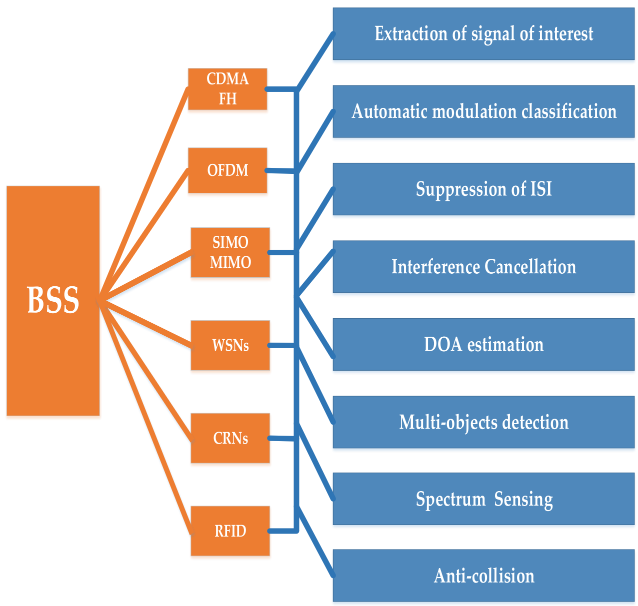

FIGURE 5. Different purposes of BSS applied in wireless communication systems.

Up to now, although a substantial of works related to BSS applied in wireless receiving systems are published and reported, a comprehensive of survey work regarding to this aspect is scarce. Therefore, this motives us to carry out this overview work for supplement. In addition, we hope ones who are interested in this area can get help and be quickly familiar with the research situations and trends of this field. Last but not least, this paper is eager to promote BSS linking to artificial intelligence which will exert tremendous role in facilitating the development of intelligent signal processing for wireless communications.

The main contribution of this manuscript is as follows. In this paper, an overview of numerous existing publicly reported literatures regarding BSS utilized in wireless receiving processing is presented. The technical restrictions and challenges concerning wireless receiving systems assisted by BSS theory are deeply analyzed for providing enlightening discussion and investigation guidance. The meaningful future research areas regarding wireless receiving processing with BSS assistance are suggested. The main contents of this paper are given as follows,

(1) Review of principles of BSS theories for ICA, SCA, NMF and BCA.
(2) Analyzing the existing literature pertaining to wireless receiving processing assisted by BSS.
(3) Recommendations on a series of research point including BSS mechanism areas and BSS application areas.

The reminder of this paper is structured as follows. Section II give a discussion on the principle of BSS theories. The mixing models and fundamental principles are also presented in this section. The BSS used in different wireless receiving areas are comments in section III. Section IV talks about the technical challenges and meaningful research points in the area of BSS and its applications in wireless receiving processing. Finally, conclusion is achieved in section V. Symbols and abbreviations are presented in this paper which will be summarized in Tables 1 and 2 respectively.

TABLE 1. List of symbols.

$\boldsymbol{A}$	Mixing matrix of size $N \times M$
M	Number of source signals
$\boldsymbol{e}$	Noise vector of size $N \times 1$
$\boldsymbol{E}$	Noise matrix of size $N \times T$
N	Number of sensors or antennas
$\boldsymbol{s}$	Source signal vector of size $M \times 1$
$\boldsymbol{S}$	Source signal Matrix of size $M \times T$
T	Length of the processing data block
$\boldsymbol{W}$	Un-mixing matrix of size $M \times N$
$\boldsymbol{x}$	Mixed data vector of size $N \times 1$
$\boldsymbol{X}$	Mixed data Matrix of size $N \times T$

II. THE PRINCIPLE OF BLIND SOURCE SEPARATION

In this section, four categories of blind separation theories are briefly described. The fundamental separation principles and model are analyzed. The philosophies of the critical algorithms related to four types of blind separation theories are summarized. The detailed contents are scheduled as follows. In section 2.1, the system model and relevant framework classifications of BSS are presented. Then the fundamental principles for BSS are shown in subsection 2.2-2.5 for ICA, SCA, NMF and BCA respectively. In subsection 2.6, BSS theory used in various wireless receiving scenes are discussed.

A. FUNDAMENTAL MODEL AND CLASSIFICATION OF BSS

A fundamental BSS model in signal processing area is expressed as matrix factorization, the basic linear

TABLE 2. List of abbreviations.

AI	Artificial intelligence
BCA	Bounded component analysis
BER	Bit error rate
BSS	Blind source separation
CCI	Co-channel interference
CCFD	Co-Time Co-frequency Full-Duplex
CDMA	Code division multiple access
CFO	Carrier frequency offset
CICA	Constrained ICA
CRN	Cognitive radio network
CRSN	Cognitive radio sensor network
DOA	Direction of arrival
DS-CDMA	Direct sequence CDMA
DUET	Degenerate un-mixing estimation technique
EASI	Equivariant adaptive source separation via independence
FastICA	Fast independent component analysis
FH	Frequency hopping
FIR	Finite Impulse Response
ICA	Independent component analysis
Infomax	Information maximization
ISI	Inter-symbol Interference
JADE	Joint approximation diagonalization of Eigen matrices
MAI	Multiple access interference
MIMO	Multiple input multiple outputs
MMSE	Minimum mean square error
NMF	Non-negative matrix factorization
OFDM	Orthogonal frequency division multiplexing
PAPR	Peak-to-average power ratio
QAM	Quadrature Amplitude Modulation
RFID	Radio frequency identification devices
SCA	Sparse component analysis
SIMO	Single input multiple outputs
SIR	Signal to interference ratio
SISO	Single input single output
SNR	Signal to noise ratio
SOBI	Second Order Blind Identification
STBC	Space-time block code
TIFROM	Time frequency ratio of mixtures
WSN	Wireless sensor network
ZDMA	Zero-division multiple access

instantaneous model is described as follows,

$$X = AS + E, \quad X \in R^{N\times T}, \quad A \in R^{N\times M}, \quad S \in R^{M\times T}, \quad E \in R^{N\times T} \tag{1}$$

where N and M show the number of source signals and observed signals respectively. T denotes the length of samples. The errors are expressed as $\boldsymbol{E}$. $\boldsymbol{X}$ represents the observed mixtures, the mixing matrix $\boldsymbol{A}$ and source signals $\boldsymbol{S}$ are both unknown but have some specific characteristics. According to these features, the source signal can be extracted from the observations. Utilizing different properties of mixing matrix and source signals, the different BSS theories can be developed, namely:

(1) If source signals $\boldsymbol{S}$ are statistically independent, then the ICA method can be formed to separate signals;

(2) If source signals $\boldsymbol{S}$ are sparse in original domain or transformed domain, then the SCA method can be achieved for source extraction;

(3) All of elements of $\boldsymbol{X}, \boldsymbol{A}$ and $\boldsymbol{S}$ are nonnegative, then the NMF method can be developed for source separation;

(4) The $\boldsymbol{A}$ and $\boldsymbol{S}$ are bounded, then the BCA method can be used to extract source signals.

The basic BSS model has close relationship with numerous wireless receiving model, such as MIMO, as shown in figure 6. The wireless receiving equation can be also modeled as the model equation (1). In wireless communication scenes, the mixing matrix $\boldsymbol{A}$ is to represent the influence of the wireless channel, and the receiving signals are the composite signals which are linear combination of source signals, and the errors are always Gaussian noise signals. In conventional scheme, the channel estimation and synchronization operation need to be carried out before further source detection. The processing mechanism is non-blind and non-adaptive for wireless receiving processing. However, with the assistance of the BSS, the blind adaptive processing can be achieved for helping source detection without using pilot sequence. Blind adaptive signal processing is an promising future signal processing mechanism, which play a critical role in enhancing spectrum efficiency and data transmission rate for many communication scenes.

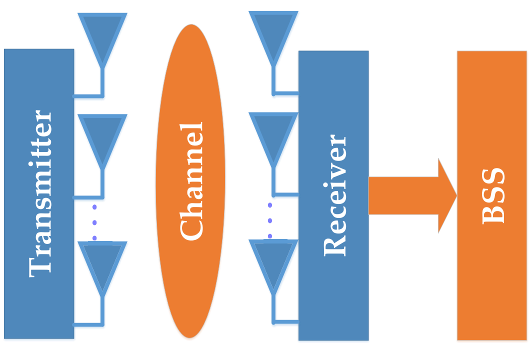

FIGURE 6. BSS adaptive processing for MIMO systems.

In view of the previous model equation (1), it is a simplest form of BSS. When other more practical factors are involved, the linear convolutive model or even non-linear model will be produced. In addition, the system model can be classified into three categories according to the numerical relationship among the number of transceiver antennas, i.e., determined model ($N = M$), underdetermined ($N < M$), and overdetermined ($N > M$). Especially, when $N = 1$ will be led to blind separation of single channel receiving model, this is an extremely meaningful and challenging problems. Moreover, according to the mixing mode and parameter properties, the different BSS problems are obtained to describe the different channel model in wireless communication systems. As illustrated in figure 7, a classification of BSS problems is shown. In general, the philosophy of BSS algorithms is constituted of the cost function (objective function or contrast function)and optimized method.

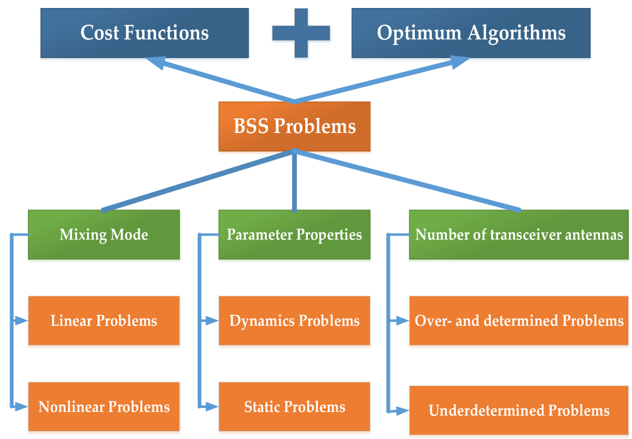

FIGURE 7. BSS classification.

The cost function of BSS is always constructed from the separation criteria according to restricted source feature. In BSS, the constructed cost function is always handled as an optimized problem. Then a suitable optimized method is chosen to execute optimization processing. The purpose of BSS is to seek a proper linear transformation matrix or separation matrix $\boldsymbol{W}$ through optimizing the cost function $\varphi(\boldsymbol{WX})$.Thereby, in process of operation, BSS separation assignment often composes of two steps. The first step is to estimate the separating matrix. The second step is to recover the source signals by exploiting the estimated separation matrix.

B. ICA FOR BSS

As a critical theory of BSS, ICA depends on statistically independent criterions to build the cost function, then to separate or extract the original signals from their linear mixtures through implementing optimization processing. ICA is a characteristic unsupervised learning method, which can directly estimate both the mixing matrix and the independent source components by using only the signal observations. ICA model always describes the linear mixture process of the original sources. In practice applications, the ICA model has to conform to the subsequent assumptions for guaranteeing effective and accurate source separation.

There are three assumptions for ICA model. First of all, the sources should be mutually statistical independence. In statistical mathematic description,

$$p(\boldsymbol{S}) = \prod_{m=1}^{M} p_m(\boldsymbol{s}_m) \tag{2}$$

Secondly, the independent source components cohere with non-Gaussian probability distribution. That is to say, the higher-order statistical of source is non-zero, such as kurtosis or fourth-order cumulant [1], [2]. Finally, the mixing matrix is a square and invertible matrix. Fortunately, in most applications, the first assumption is effortless to be valid because the sources come from different physical mechanisms that are easy to create independent condition. The second assumption discloses that ICA will be incapable for separating multi-Gaussian signals mixtures. Hence, the recovery of the source signals from their Gaussian mixtures becomes impossible. The third assumption implies that source signals should has same number as that of observations.

To coincide with BSS operation, ICA tries to find an appropriate linear transformation or a separated matrix $\boldsymbol{W}$, in order to minimize the statistical dependence of the components of $\boldsymbol{WX}$. When this achieves, the original source signals can be separated, i. e.,

$$\boldsymbol{Y} = \boldsymbol{WX} \tag{3}$$

In the previous equation, the noise influence may neglected for discussion, but in real environment, the observations always have inevitable noise term. Based on the above-mentioned illustrations, the fundamental principle of BSS composes of two parts: cost function and optimum algorithm. The cost functions of ICA algorithms are always constructed according to different metrics of statistical independent, including maximum likelihood, mutual information, convex divergence, kullback-leibler divergence, cumulant criterions, and so on. The key theories of the optimized method are always constituted of gradient descent, natural gradient and joint diagonalization, and so on. As shown in figure 8, the categorized ICA principles are briefly displayed, the right of the figure is about optimization method and the opposite is about cost functions or objective functions. More details is are not discussed in this paper for brevity, and related contents description are recommended to refer to [1], [2], and [4].

C. SCA FOR BSS

With the thriving development of ICA theory, a multitude of represented algorithms have come forth to successfully solve substantial blind adaptive processing problems of wireless communications. However, due to the restrictions of ICA theory, some prevalent and significant application scenes, such as separation of underdetermined receiving and Gaussian mixture model, has not yet to be settled well. In recent years,

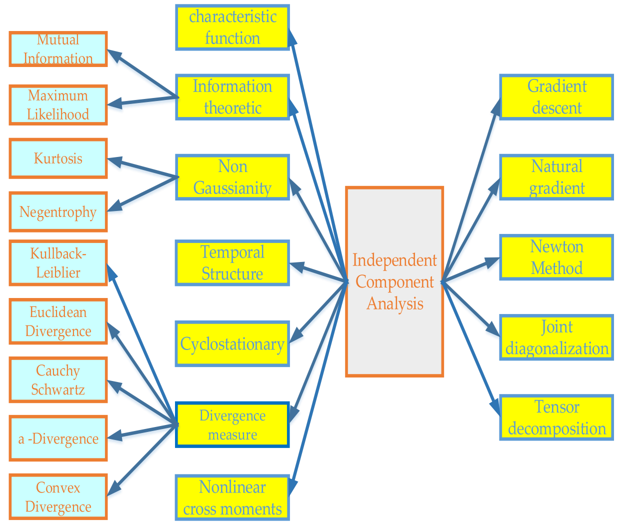

FIGURE 8. **The principle of ICA theory.**

an increasing number of scholars have come to recognize the wisdom of utilizing the sparseness of the original source signals to separate or extract signals from the receiving mixtures. Employing the sparseness of source signals can generate the promising scheme, named as sparse component analysis.

SCA can break the embarrassment of ICA theory to accomplish separating the underdetermined receiving or Gaussian mixtures. SCA relays on the sparseness of source signals as substitute of independence used in ICA. In a general way, the sparseness of source signal means that S in equation (1) contains as many zeros as possible in time domain. The unique solution of SCA is always assumed that S has $(M - N + 1)$ zero components or has $N - 1$ non-zero components, namely $N - 1$ sparse. If the source signals are not inherently sparse in original domain, we can seek enough of sparseness in other transformed domains through specific transformation methods. Time-frequency and time-scale (wavelet) transformation are often utilized for this purpose.

The solution of SCA-based BSS is always represented as follows,

$$\hat{\boldsymbol{S}} = \arg\min_{S} \|\boldsymbol{S}\|_0 \ \text{ s.}t.\ \|\boldsymbol{AS} - \boldsymbol{X}\|_2^2 \le \varepsilon \tag{4}$$

In mathematics, minimization of L_0-norm of S is a NP-hard problem. Especially, it becomes computationally infeasible with the increasing of M. Furthermore, L_0-norm minimization is sensitive to noise or approximation error. Therefore, L_p-norm $(0 < L_\mathrm{p} \le 0)$ is often considered as a substitute for L_0-norm since it is convex, and provides unique solution. The algorithm steps of SCA often contain two stages: firstly, to estimate mixing matrix $\boldsymbol{A}$ by using data clustering methods; secondly, the estimated mixing matrix is employed for further source solution through L_p-norm minimization principle. If the source signals meet non-sparse in original domain, then to find transformation domain for creating sparse properties as follows,

$$T(\boldsymbol{X}) = \boldsymbol{A}T(\boldsymbol{S}) \approx \sum_{n=1}^{N} T_{s_n}\boldsymbol{\alpha}_n \tag{5}$$

Where $T(\boldsymbol{S})$ denotes the transformation form of source signals with sparseness. After that, the clustering algorithms are utilized for estimating mixing matrix from the scatter diagram of transformed measurements signals.

The SCA usually can be accomplished in time domain, frequency domain, time-frequency domain and time scale (wavelet). The principles of the representative algorithms can be categorized into two aspects. The figure 9 gives the graphic illustration.

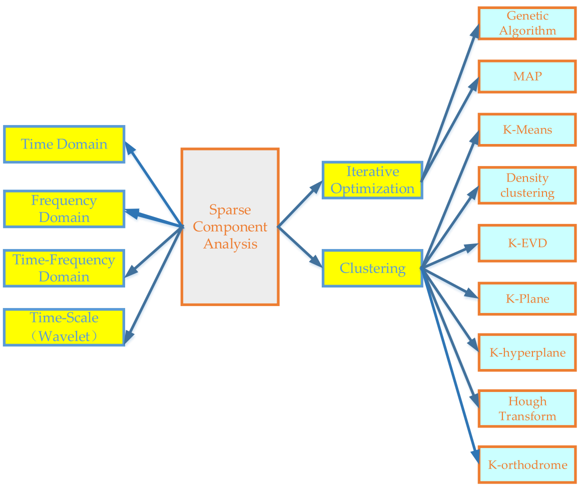

FIGURE 9. The principle of SCA theory.

D. NMF FOR BSS

NMF is essential BSS method of acquiring the data components based on non-negative constraints. In processing mechanism, NMF based BSS attaches more importance to the non-negative condition of source component while ICA and SCA play more emphasis on the independence and sparseness of source signals. Since it was put forward, NMF has received substantial attention from a multitude of scholars in many different research fields. In comparison with the classical methods, NMF provides a new perspective for implementing matrix factorization of larger-scale data. NMF possesses numerous superiorities in terms of implementation complexity, comprehensive decomposition solution and less storage requirement.

A great deal of BSS problems arising in imaging, chemo- and/or bioinformatics are described by superposition of non-negative latent variables (sources):

$$\boldsymbol{X} = \boldsymbol{AS}, \boldsymbol{X} \in R_{0+}^{N\times T}, \quad \boldsymbol{A} \in R_{0+}^{N\times M}, \quad \boldsymbol{S} \in R_{0+}^{M\times T} \tag{6}$$

Thus, solution of related decomposition problem can be obtained by imposing non-negativity constraints on $\boldsymbol{A}$ and $\boldsymbol{S}$, to narrow down number of possible decomposition of $\boldsymbol{X}$. Due to non-negativity constraints, some other constraints (statistical independence or sparseness) can be relaxed/ replaced in applications where they are not fulfilled.

The NMF problems was initially proposed by Lee-Seung' Nature paper. It was suggested to estimate $\boldsymbol{A}$ and $\boldsymbol{S}$ through alternative minimization operation of two different objective functions. This process is described as follows:

(1) set randomly initialize: $\boldsymbol{A}^{(0)}, \boldsymbol{S}^{(0)}$;

(2) For $k = 1, 2, \ldots,$ until convergence do

Step 1: $\boldsymbol{S}^{(k+1)} = \arg\min_{S_{mt}\geq 0} D_S\left(\boldsymbol{X}\,\|\boldsymbol{A}^{(k)}\boldsymbol{S}\right)_{S^{(k)}}$

Step 2: $\boldsymbol{A}^{(k+1)} = \arg\min_{a_{nm}\geq 0} D_A\left(\boldsymbol{X}\,\|\boldsymbol{AS}^{(k+1)}\right)_{A^{(k)}}$

If both cost functions denote the squared Euclidean distance (Froebenius norm) so that we obtain the alternating least square (ALS) method for implementing NMF. Then, ALS-based NMF is represented as,

$$\left(\boldsymbol{A}^*, \boldsymbol{S}^*\right) = \arg\min_{A,S} D(\boldsymbol{X}\,\|\boldsymbol{AS}) = \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{AS}\|_2^2$$
$$s.t.\,\boldsymbol{A} \geq 0, \quad \boldsymbol{S} \geq 0$$

There are two problems with above factorization. Minimization of the square of Euclidean norm of approximation error $\boldsymbol{E} = \boldsymbol{X} - \boldsymbol{AS}$ is from the maximum likelihood viewpoint justified only if error distribution is Gaussian:

$$p(\boldsymbol{X}\,|\boldsymbol{A}, \boldsymbol{S}) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{\|\boldsymbol{X} - \boldsymbol{AS}\|_2^2}{2\sigma^2}\right) \tag{7}$$

In many instances, non-negativity constraints imposed on $\boldsymbol{A}$ and $\boldsymbol{S}$ do not suffice to obtain solution that is unique up to standard BSS indeterminacies permutation and scaling. In relation to original Lee-Seung NMF algorithm, additional constraints are necessary to obtain factorization unique up to permutation and scaling. Generalization that involves constraints is given in [3],

$$D(\boldsymbol{X}\,\|\boldsymbol{AS}) = \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{AS}\|_2^2 + \alpha_S J_S(\boldsymbol{S}) + \alpha_A J_A(\boldsymbol{A}) \tag{8}$$

Where $J_S(\boldsymbol{S}) = \sum_{mt} S_{mt}$ and $J_A(\boldsymbol{A}) = \sum_{nm} a_{nm}$ are sparseness constraints that correspond with L_1-norm of $\boldsymbol{S}$ and $\boldsymbol{A}$ respectively. α_S and α_A are regularization constants. After cost functions are built, then the optimization algorithm is implemented for achieving NMF. In general, the principle of NMF theory concerning cost functions and optimization methods can be summarized in figure 10 as follows.

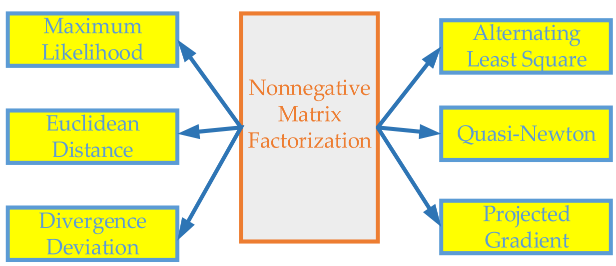

FIGURE 10. The principle of NMF theory.

E. BCA FOR BSS

BCA is a new type theory of BSS, which depends on the geometric boundedness property of source signals for the linear decomposition of the observed mixtures. In BCA, the assumption of the Cartesian decomposition and compactness of the convex support is a fundamental principle utilized for extracting source components. Different from ICA algorithms, BCA does not need the independence assumption to work, so it can successfully extract sources that are somehow dependent. The fundamental principle of BCA will be demonstrated in the following.

In the context of BCA, the samples of signal model $\boldsymbol{X}(t)$ is belong to F^N, where the field F can be real R or complex C domain is decided by the preferred chosen application. This observations can be decomposed into N signal components and a noise component $\boldsymbol{E}(t)$. The model can be produced as the following additive model,

$$\boldsymbol{X}(t) = \boldsymbol{X}_1(t) + \cdots + \boldsymbol{X}_N(t) + \boldsymbol{E}(t) \tag{9}$$

Assume that the components $\boldsymbol{X}_i(t)$ admit a rank one interpretation as

$$\boldsymbol{X}_i(t) = \boldsymbol{\alpha}_i S_i(t) \tag{10}$$

where $\boldsymbol{\alpha}_i$ denotes a finite and non-null mixing vector that determines the subspace. $S_i(t)$ has bounded property which determines the statistical structure. Without loss of generality, assume that these source components are stationary and memoryless. Therefore, the investigation can concentrate on independent identically distributed (i.i.d.) samples. To assemble together the mixing vectors in the mixing matrix $\boldsymbol{A} = (\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_M)$ and the sources in the vector $\boldsymbol{S} = (S_1, \ldots, S_M)^T$, the observations meet the previous BSS model in equation (1).

Like as the mutual independence condition in ICA, or the sparseness condition of the sources in SCA, to perform a bounded component analysis it is necessary to establish some assumptions. In terms of BCA of the observed mixtures, the subsequent properties for the sources and the mixture is necessary:

(1) The source components and the noise have bounded property.

(2) The convex support of source component $\boldsymbol{S} = (S_1, \ldots, S_M)^T$ is the Cartesian product of marginal convex support sets, i.e.

$$S_S = S_{S_1} \times \ldots \times S_{S_M} \tag{11}$$

And the joint convex support of the extended vector is $\underline{\boldsymbol{S}} = vec(\boldsymbol{S}, \boldsymbol{E})$.

(3) This assumption differs relying on whether we care in the identifiability of the mixing system $\boldsymbol{A}$ or in the separability of the sources:

(i) The mixing matrix $\boldsymbol{A}$ does not have collinear columns. (Identifiability).

(ii) The mixing matrix $\boldsymbol{A}$ is full-column rank (Separability).

(4) The critical statistics of the Gaussian noise, such as its convex support or its covariance matrix is known or can be reasonably acquired from the observed mixtures.

Up to now, BCA is considered as an emerging technique of BSS, which has developed its critical theories and principles yet many related significant investigations still require to be investigated. As far as we know, the principle of BCA can be summarized roughly as follows, as illustrated in figure 11.

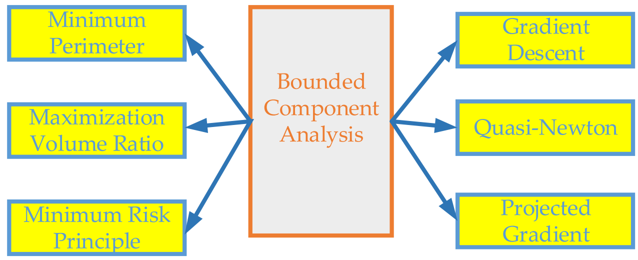

FIGURE 11. The principle of BCA theory.

BCA is on the basis of the bounded property of the source components to carry out source separation or extraction. According to geometric features, the additive decomposition of the convex set of supports the observed mixtures. The bounded nature is very attractive and promising in wireless communication system, because the transmitted signals always possess the characteristic boundedness and the additive decomposition condition can be reasonably satisfied even in small samples. Due to its promising applications in communications, BCA is strongly recommended to associate with signal processing for wireless communication fields.

F. BSS USED IN WIRELESS RECEIVING PROCESSING FIELDS

In the previous illustration, four BSS theories are introduced in brevity. More in-depth and intensive contents are suggested to refer to the related literatures. So far, although BSS has gained substantial attention from numerous disciplines, this paper concentrates on the BSS theories applications in wireless communications. As far as we are concerned, a great deal of technical papers have been reported and published regarding to this field. These papers can be divided into different categories according to the different BSS theories. The involved wireless communications areas consist of DS-CDMA, FH, OFDM, MIMO, MIMO-OFDM, wireless sensor networks, cognitive radio networks, RFID systems, communication security, interference coordination, digital modulation mixed signals, etc.. As depicted in figure 12, the distributed diagram shows the different occupations of four BSS theories utilized in wireless communication fields. From the figure 12, we can acquire that ICA is one of the most extensively used BSS theories applications in for wireless receiving processing across all of wireless communication aspects. SCA shares FH application with ICA for sparsity of FH signal, and NMF is gained more interests in RFID and WSNs similar with ICA. So far, BCA is few directly

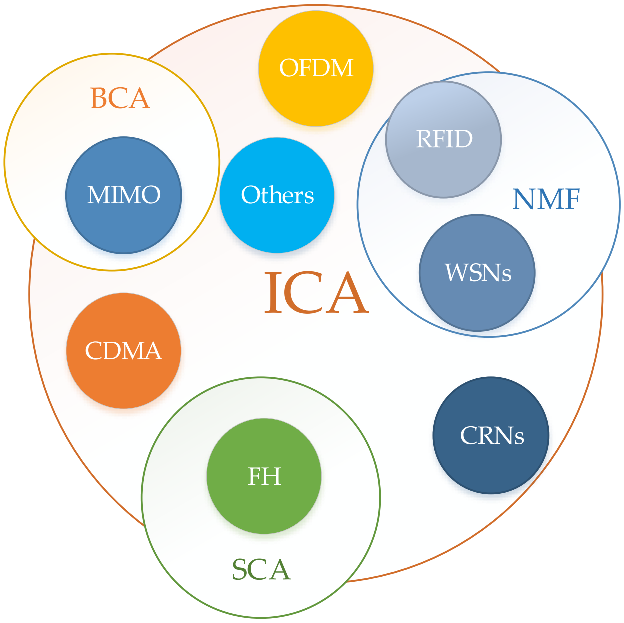

FIGURE 12. The distributed diagram of BSS theories used in wireless communication systems.

application in typical wireless communications fields, and only some simulation experiments in MIMO can be obtained from its related BCA technique papers. On top of those, other areas mainly consider to employing ICA for application.

Although ICA has been deeply and extensively utilized in wireless receiving processing due to its widely used independent condition, ICA has difficulties in tackling the underdetermined receiving model, Gaussian mixture model, dependent mixture model and large scale mixture model. However, SCA, NMF and BCA can be as wisely alternative candidates for ICA to resolve the above-mentioned interesting and valuable application requirements in wireless communication systems. Therefore, it is very worthy to investigate the BSS utilized in wireless receiving systems for performance enhancement.

III. APPLICATIONS OF BSS IN VARIOUS WIRELESS RECEIVING SYSTEMS

Due to the ever-increasing demands for higher capacity and high-efficiency frequency utilization in wireless communication systems, novel interference rejection techniques based on BSS are becoming increasingly important and attracting huge research efforts in recent years. Conventionally, co-channel interference (CCI), adjacent channel interference, and interference due to image frequencies are the three types of interference that pose major detriments on wireless transceiver design. However, using BSS can provide promising anti-interference mechanism from statistical signal processing and adaptive processing perspective. Employing BSS theory can contribute significantly to help wireless communications systems to achieve robust source recovery and enhanced spectral efficiency exempting from estimation errors and training sequence requirements.

In wireless receiving processing, BSS plays a significant role in helping execute the suppression of ISI, co-channel interference cancellation, direction of arrival (DOA) estimation, blind signal identification, multi-objects detection, and spectrum sensing, and so on. A plentiful of research literatures have investigated the BSS applications in various useful communication scenes, as depicted in figure11. These valuable and exalting applications will be surveyed and discussed in this section.

In this section, the related contents are organized as follows. In subsection 3.1 BSS applications in spread spectrum signal, DS-CDMA and FH fields are demonstrated. BSS used in OFDM, MIMO, and OFDM-MIMO scenes are overviewed in subsection 3.2. In subsection 3.3, cognitive radio networks using BSS is illustrated. BSS utilized in WSNs and RFID is illuminated in subsection 3.4 and 3.5 respectively. In subsection 3.6, the communication countermeasure and security based on BSS is introduced.

A. BSS IN SPREAD SPECTRUM SIGNAL, DS-CDMA AND FREQUENCY HOPPING SIGNAL

Application of BSS in spreading system can trace back to two pioneering literatures reported by Belouchrani and Amin [15], [16], respectively. In their works, they mainly engaged in interference cancellation based on blind separation theory for spread spectrum communication systems. Through rigorous theoretic analysis and extensive experiments illustration, the intriguing conclusion is achieved that exploiting BSS can effectively optimize the BER and anti-interference performance of spread spectrum system [15]–[17]. It is noteworthy that their works were as key components of the project of 'Time-Frequency Receiver for Nonstationary Interference Excision in Spread Spectrum Communication Systems' publicly announced in 2000. It is precisely because of this open report that has aroused the great mass fervor of scholars to embark on applications of BSS in spread spectrum systems.

During 2000 and 2008, the research actions of BSS applied in DS-CDMA systems have become very active and has received considerable critical attention. The purposes of BSS used in DS-CDMA systems often compose of blind spreading sequence estimation, blind interference cancellation and blind multiuser detections. A typical DS-CDMA system with BSS function is depicted in figure 13. In this field, the representative researchers are consisted of several famous Finland scholars, including Jyrki Joutsensalo, Tapani Ristaniemi, Karthikesh Raju and Toni Huovinen [18]–[25]. They were devoted to investigate the ICA assisted traditional detection algorithms and ICA incorporated into the existing conventional detection mechanism to tackle the dilemma of multiuser detection and external interference cancellation in DS-CDMA systems. The proposed ICA-RAKE, ICA-MMSE and ICA-SIC are verified to effectively strengthen the performance of detection and anti-interference for DS-CDMA systems [18]–[25]. In addition, the American scholars

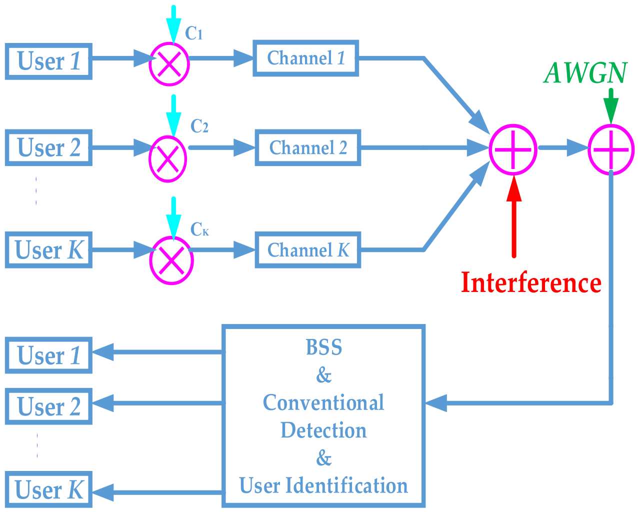

FIGURE 13. A typical DS-CDMA system model with BSS function.

David Overbye [26] and Gupta [27] also focused on studying the utilization of BSS to optimize the performance of DS-CDMA systems. David Overbye [26] explored blind multiuser detection to assist DS-CDMA receiving processing by using ICA and took advantage of prior knowledge (e.g. spreading sequence) to refine the system performance. Gupta [27] focused on investigating the ICA combined with blind multiuser detection in DS-CDMA systems for performance enhancement.

From 2008 to 2013, Chinese scholars Fu *et al.* [28], Lu *et al.* [29], Ren *et al.* [30], and Zhang *et al.* [31] have made significant efforts to undertake BSS for solving the issues of blind multiuser detection and blind spreading sequence estimation in DS-CDMA systems. After 2013, the related literatures concerning this research area reported less. Jen and Jou [32] put forward a robust blind ICA detection using second-order cone constraint condition to overcome channel estimation mismatch and Doppler spread in multicarrier CDMA. Luo and Zhu [33] proposed a blind adaptive detection method employing BSS principle in DS-CDMA systems to separate the original user signals and estimate the spreading sequences of corresponding users. The investigation results demonstrated that this conceived scheme is fit for short sample observation and low signal to noise ratio (SNR) condition. Albataineh and Salem [34] proposed four-order cumulant matrices based blind detection algorithm for implementing the multiuser symbol estimation problem in DS-CDMA systems. In this work, the proposed blind detector shows high convergence speed in extracting user symbols and outperforms ICA-based detection method in estimating the source signals from the observation mixtures. Sriyananda *et al.* [54] designed interference cancellation schemes based on blind principles for DS-CDMA system. In his work, the short code model time correlation properties of the channel is employed for BSS, and energy functions of received signal are defined in combination with using iterative fixed point rule in determining the filter coefficients. In order to solving the problem of blind multiuser equalization in the wideband WCDMA in noisy multipath propagation environment, Albataineh and Salem [35] further proposed three blind receiver schemes based on variations of ICA within several filtering structures.

In the context of blind separation of frequency hopping mixed signals, Mohammadi and Taheri [36] proposed a method for blind separation of mixed FH signals for cognitive radio systems. By exploiting this method, the cognitive radio device can identify the operational hopping behavior of the surrounding devices to adapt its operation. Chao *et al.* [37] investigated a BSS algorithm based on time frequency ratio to separate the FH signals. This method computes STFT first, and then TF ratios information of the mixed signals is utilized to localize the single source zone for estimating mixing matrix. However, the noisy model is not taken into consideration. Yu *et al.* [38] put forward a novel ICA based anti-jamming method of FH against comb jamming. The fundamental of this work is according to the statistical independence character between the FH signal and comb jamming signal. It has been shown that the proposed method can effectively enhance the anti-jamming ability of FH communications. In terms of the difficulty of dealing with correlated jamming in FH systems, Yu *et al.* [39] also investigated an ICA based receiver. It has been shown that the proposed algorithm outperforms the traditional receiver greatly.

Yu *et al.* [40] went into further research regarding blind separation of FH signals against the partial-band noise jamming (PBNJ) signal. For the purpose of sorting synchronous or asynchronous FH networks with as little as possible receiving antenna or sensors, Sha *et al.* [41] introduced an underdetermined BSS based SCA algorithm to solve this problem. Due to the time-frequency (TF) sparsity of FH signals, the problem is formulated as one of UBSS based on sparse TF representation. It has been demonstrated that the proposed method can separate FH signals efficiently and outperforms the previous methods. Lei *et al.* [42] proposed an algorithm of SPWVD to extract single-source zones of FH signals, and then an improved TIFROM algorithm proposed to separate the mixed synchronous-networking FH signals. Li *et al.* [43] proposed an underdetermined BSS for non-orthogonal frequency hopping signals based on a novel matching optimization algorithm (MOA). Zhang *et al.* [44] put forward an underdetermined blind separation of synchronous orthogonal FH signals based on single source points detection. In this work, a novel method to detect single source points in time frequency domain and an improved subspace projection method to recover signals are analyzed.

B. BSS IN OFDM, MIMO AND MIMO-OFDM

OFDM and MIMO as well as their hybrid technique MIMO-OFDM have emerged as the appealing schemes in modern high data rate wireless communication systems. It is just like as in DS-CDMA systems, the engaging interests have been motived to investigate BSS theory assisted OFDM, MIMO and MIMO-OFDM wireless receiver design. In subsequent subsection, the related literatures concerning this aspect will be shown.

With the aim of cancelling inter-carrier interference (ICI) owing to frequency offset in OFDM, Kim and Byun [45] propounded to estimate carrier frequency offset (CFO) at the time-domain by using the cyclic prefix based ICA (CP-ICA). It has been shown that the proposed scheme is more accurate than other conventional estimators under AWGN and Rayleigh flat fading channels. Liu and Mikhael [46] put forward a maximum likelihood CFO correction (ML-CFOC) approach to eliminate the detrimental effects of CFO. In this work, based on ICA mechanism, the ML-CFOC algorithm exploits the independence among the desired signals for interference cancellation. It has been demonstrated that the proposed approach is successfully executed for OFDM systems over multipath fading channels without using training sequences for spectrum efficiency enhancement.

Homayounzadeh and Shirazi [47] derived an ICI mathematical formulation from the perspective of the effect of CFO and delay dispersion as well as time variation of Channel. In this work, a blind cancellation method based more efficient ICA is proposed for ICI suppression without using CP data strictly as opposed to that of work in [45]. Shiratsuchi *et al*. [48] put forward a blind estimation of channel fading coefficients without using the pilot symbols in QAM-OFDM systems subjected to carrier frequency offset (CFO). In this work, the ICI due to CFO is formulated in the framework of ICA under a frequency selective fading channel. The permutation and scale uncertainly inherent in ICA and CFO estimation are both analyzed. Sadkhan *et al.* [49] conducted a performance analysis of SISO-OFDM system based on ICA algorithm in comparison with training sequence based Least Squares (LS) channel estimation method. The effective performance assisted by ICA principle is corroborated by simulation experiments. Jiang *et al.* [50] proposed a low-complexity orthogonal sequence based multi-CFO estimation approach and ICA based semi-blind equalization structure for the OFDM based multiuser coordinated multi-point (CoMP) system. The multiple CFOs are separated and estimated simultaneously relying on the properties of the orthogonal sequence. It has been demonstrated that the proposed scheme outperforms the CAZAC sequence based CFO estimation scheme, even has close BER performance to the ideal case with perfect CSI and no CFO using ZF and MMSE based equalizations.

Ma *et al*. [51] gave a validation of a green wireless communication system with ICA based and precoding aided semi-blind equalization through using real-time testbed consisted of the Keithley signal generator and signal analyzer. Thanks to that the good tradeoff between bandwidth and energy consumption is achieved, the precoding ICA equalization has a better BER performance compared with training data based channel equalization. Sriyananda *et al*. [52], [54] reported several interference and noise reduction schemes for OFDM using blind separation mechanism. Jiang *et al*. [53] proposed a low-complexity CFO estimation method and an ICA based semi-blind equalization structure for multiuser and coordinated multi-point OFDM systems. It has been demonstrated that the proposed semi-blind equalization structure slightly outperforms the previous pre-coding aided scheme with lower complexity. An almost same BER performance is acquired compared with the case of zero forcing (ZF) and minimum mean square error (MMSE) based equalization with perfect CSI and no CFO at the receiver. In another work, Jiang *et al*. [55] proposed a joint ICA based equalization and CFO estimation scheme for OFDMA systems. It has been shown that the proposed semi-blind ICA based scheme not only outperforms some existing CFO estimation approaches, but also provides a BER performance comparable to the ideal case with perfect CSI and no CFO. To overcome the ICI of OFDM systems subject to unknown CFO, Luo *et al*. [56], [57] developed a blind adaptive interference suppression scheme based on modified ICA. It has been shown that the proposed scheme outperforms the conventional ICA method and pilot-based scheme.

In the context of blind separation applied in MIMO systems, there are relatively affluent literatures. Liu *et al.* [58] advocated to apply ICA to blindly detect orthogonal STBC without CSI. This work highlights that the main advantage of the ICA technique is to avoid channel estimation and long training sequences. However, two prominent problems are recommended to be coped with in future work. On one hand, the convergence problems of ICA need pay more attention in the low SNR region. On the other hand, the length of the data block used should be decreased for adapting to fast variant channel. Zarzoso and Nandi [59] addressed the blind identification and equalization (BIE) of FIR channel in MIMO systems. In this work, the non-Gaussian property and statistical independence of the source data are exploited through HOS-based BSS for CCI cancellation and for joint ISI-CCI suppression. It has shown that the proposed methods are robustness, relative to Gaussian-noise, against non-Gaussian additive noise and impulsive interference. Zarsoso and Nandi [60] further considered introducing time diversity to simplify the ICA-assisted MMSE detector with improved performance and lower computational cost, by searching only for the equalization delays providing optimum MMSE for each user. It has been observed that the ICA-assisted detectors are able to improve the conventional MMSE equalizer in the situation of inaccurate channel and delay estimation. Xu *et al.* [61] exploited ICA to detect the transmitted signals blindly avoiding channel estimation. In this work, the specific models suitable to ICA are established through analyzing the essential structures of STBC and V-BLAST systems. It has been shown that the robustness against channel estimation error and flexibility of system design can be obtained by employing the ICA based scheme. Eidinger and Yeredor [62] proposed new approach for blind identification of a MIMO system, based on the Hessians of the second generalized characteristic function (GCF), evaluated at different user-specified "processing points". It has been shown that the proposed algorithm outperforms a polyspectra based algorithm, especially at moderate SNR conditions. Weikert *et al*. [63] investigated the semi-blind equalization based on ordinary complex ICA for a wireless MIMO system with frequency selective Ricean channels. A generalized Sylvester matrix is used to reduce the unknown permutations due to the reformulation of the convolutive BSS problem. It has been demonstrated that the BER of the proposed semi-blind equalization method is superior to the training based channel estimation & equalization. Castella *et al*. [64] proposed new contrast functions for blind separation of MIMO convolutive mixture of sources. The proposed approach exhibits superiority of fast and efficient for simple optimization task and iterative deflation. It has been illustrated that the proposed contrast is valid for both i.i.d and non i.i.d. source signals and very appealing in comparison with some classical contrast functions. Ranganathan *et al.* [65] reported a novel realization of the complex block adaptive ICA for the separation of complex signals with known source distributions in time-varying channel conditions. It has been verified that the proposed method exhibits superior performance to Complex FastICA.

According to the investigation work in [58], Zhang *et al*. [66] further extended at a more complicated scenario of the multiuser MIMO system, and a more robust algorithm to restore the correct order from the ICA results was proposed for CCI suppression. Cavalcante *et al*. [67] conceived a multiuser processing mechanism for exploiting BSS theory. The paper indicates that Multiuser processing is a set of fundamental techniques for the improvement of the performances of the modern wireless communications systems. For this task, information-theoretic based criterion and algorithm can be proposed for blind separation of the number of active users in the system. Routtenberg and Tabrikian [68] investigated the problem of BSS and system identification for MIMO-AR mixtures. In this work, two new time-domain methods are proposed based on the Gaussian mixture model (GMM) of source distribution and generalized expectation-maximization (GEM). Chabriel and Barrère [69] highlighted the problem of non-symmetrical joint zero-diagonalization (NSJZD) of a given set of matrices and its application in user interference cancellation for a new multiple-access MIMO wireless transmission scheme, referred to as zero-division multiple access (ZDMA). The fundamental of ZDMA is based on NSJAZ based blind separation of different accesses assuming a flat fading channel. Computer simulations and a full-analog ZDMA-based hardware prototype system have been carried out to demonstrate the technically feasible and effectiveness. Choqueuse *et al*. [70] put forward an ICA mechanism based blind channel estimation algorithm for STBC communications. The fundamental of this method is based on the minimization of a kurtosis-based cost function after zero forcing equalization. It has been corroborated that the proposed method is suitable for the whole class of linear STBCs whatever the code-rate and the modulation in comparison with subspace or second-order statistics equalization. Ali *et al.* [71] conducted a comparative performance analysis regarding BSS of MIMO systems by using different modulation techniques and wavelet denoising.

Fadlallah *et al.* [72] addressed the problem of detection in a MIMO interference channel system by using interference alignment (IA) scheme at the transmitters. This problem is formulated as a semi-blind source separation assisted by JADE based BSS for extracting the desired streams. It has been demonstrated that the proposed scheme not only performs close to full-CSI MIMO IC-IA schemes, but also outperforms the traditional MMSE using LS for CSI estimation method. Luo*et al*. [73] first investigated blind modulation recognition in non-cooperative STBC systems. To solve this problem, a modulation classifier based on ML is constructed on the condition of virtual channel matrix (VCM), and JADE based BSS algorithm is extended to a multidimensional case through using the block-diagonal structure of the cumulant matrices. It has been shown that this method can detect the modulations with high probability where coding information and CSI are unknown. Zhao *et al*. [74] conceived a new wireless statistical division multiplexing (SDM) communication system based on MIMO using BSS mechanism. Furthermore, the related performance validity and analysis of SDM are executed through realistic experiments. To improve the damaged capacity again and source recovery performance due to channel mismatch problem in MIMO systems, Luo *et al*. [75] investigated a blind separation based on second-order cone programming.

Iglesia *et al*. [76] utilized ICA in one subcarrier and applied a MMSE approach in MIMO-OFDM system for separating the remaining subcarriers sequentially, and resolving the permutation and scaling indeterminacy, which is intrinsic in blind separation mechanism. Wong *et al.* [77] applied ICA to every subcarrier and the permutation and scaling indeterminacy are overcome sequentially by using the estimated separating matrix in the previous subcarrier to initialize the separating matrix of the current subcarrier. Bin *et al*. [78] applied ICA to every subcarrier followed by sequential resolving of the permutation and scaling indeterminacy. Sarperi *et al.* [79] proposed a novel blind receiver structure for MIMO-OFDM systems based on ICA. In this work, a more robust reordering method than the previous three methods, which handle the indeterminacies of ICA estimates and is free from error propagation. In order to further enhance the performance, the layered space-time equalization (LSTE) is incorporated into ICA, referred to as blind LSTE.

Curnew and Ilow [80] come up with employing fractional sampling to increase the number of the received signals and improve diversity in MIMO-OFDM system. With the help of up-sampling factor of 2 fractional sampling, the number of ICA problems is doubled to aid in the recovery of the original data symbols. The additional solutions using equal gain combining improve signal-to-noise ratio (SNR) and the data recovery. Gao *et al*. [81] took into consideration of exploiting a linear pre-coding to resolve the phase and permutation ambiguity of the ICA model applied in MIMO-OFDM systems. In this work, iterative channel interpolation is employed to improve the channel estimation accuracy of ICA, and is incorporated with MMSE based equalization and layered space-frequency equalization (LSFE) to enhance the system performance. Gao *et al*. [82], [83] further investigated three peak-to-average power ratio (PAPR) reduction schemes for ICA based blind MIMO OFDM systems. The typical phase shifts and permutation introduced by PARA reduction are completely resolved by ICA based and pre-coding aided blind receiver. The proposed schemes do not need transmission of side information to avoid any spectral overhead.

Gao *et al*. [84] and Nadi *et al.* [85] conceived a blind compensation algorithm for both frequency-dependent and frequency-independent I/Q imbalance based on ICA in MIMO-OFDM systems. In this work, an efficient higher order statistics (HOS) based ICA is utilized to compensate for I/Q imbalance and equalize the received signals simultaneously. It has shown that he proposed approach can not only compensate for I/Q imbalance effectively, but also achieve frequency diversity gains and outperform the case with perfect channel state information (CSI) and no I/Q imbalance. Khosravy *et al*. [86], [87] investigated an ICA-based MIMO-OFDM system to efficiently overcome problems inherent to ICA by using a precise and robust signal reconstruction method. In this work, the predetermined characteristics of transmitted signals are exploited by a convolutional encoder to solve permutation indeterminacy, amplitude scaling ambiguity and phase distortion. It has been demonstrated that the proposed method not only makes the MIMO-OFDM system independent of channels characteristics, but also significantly outperforms the correlated MIMO channels based method. Khosravy *et al*. [90] engaged more in-depth investigation that designed an optimization problem to provide the optimum pre-filter based on the system structure and former pre-filter solution in [86].

Meftah *et al*. [88] investigated a noisy ICA based blind method for detecting in the compound system MIMO-OFDM and in the context of CDMA. It has illustrated that the proposed method exceeds ZF and MF detectors and reaches the performance of the MMSE detector. Du *et al*. [89] carried out a comprehensive performance analysis of complex FastICA for MIMO-OFDM systems in terms of bit error rate (BER) and the convergence speed. Ranganathan *et al*. [91] proposed complex OBA-ICA algorithm to perform CFO mitigation and multiuser detection simultaneously in MIMO-OFDM systems operating in a time-variant channel environment. It has been illustrated that the proposed technique exhibits excellent convergence speed and is highly effective in reducing ISI with reasonable computational requirement. Agriman-Tosun *et al*. [92] put forward a modulation classification scheme based on ICA in conjunction with either maximum likelihood (ML) or support vector machines (SVM) for MIMO-OFDM signals over frequency selective, time varying channels. It has been shown that the proposed method performs with high probability of correct classification over realistic ITU pedestrian and vehicular channels. Alaghbari *et al.* [93] proposed a robust correntropy ICA assisted blind channel estimator for MIMO-OFDM for enhanced channel gains estimation and channel ordering and sign ambiguities resolution in non-Gaussian noise channel.

C. BSS IN COGNITIVE RADIO NETWORKS

In allusion to the conflictions of the increasing frequency utilization requirements and scarce frequency resources as well as the existing frequency underutilization mechanism, a slew of scholars and organizations from abroad and home are compelled to conceive innovative high-efficient spectrum sensing based cognitive radio networks. For this purpose, intelligent wireless network has been proposed based on machine learning technology. As key component of machine learning, BSS is highly recommended to utilized in cognitive radio networks (CRNs) and cognitive radio sensor network (CRSN) for spectrum sensing. So far, limited research works have been conducted in this field. In this subsection, the literatures related to BSS used in spectrum sensing will be illustrated.

In classical spectrum sensing, the primary user (PU) and secondary user (SU) are not allowed to share the frequency band simultaneously. Only when the PU is absent in frequency band, the SU is granted to work. This circumstance will give rise to an inherent limitation so that the cognitive radio (CR) is compelled to be synchronized with PU data transmission frames and to sense the activity of PU at the beginning part of each PU data frame. In addition, the conventional spectrum sensing methods are usually trapped in prior information utilization. However, the primary user is not obliged to notify its status to the secondary user in practice. Therefore, this activity is a non-cooperative manner in most of cases, so that blind signal processing is a highlighted scheme for spectrum sensing. Moreover, BSS can overcome primary user hiding problem. As shown in in figure 14, a typical cognitive radio scene with PU hiding issue is shown.

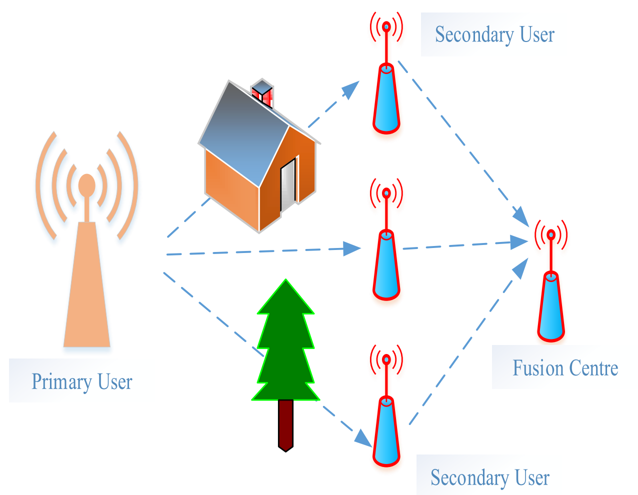

FIGURE 14. cognitive radio scene.

Primitively, Carlos and Takada [94] considered a problem of identifying interference or illegal radios in licensed communication channels. It makes use of ICA algorithm (FastICA) to separate the mixture of signals obtained from a uniform linear array (ULA) antenna for radio surveillance. A multiple-antenna based cognitive radio was constructed in [95] employing BSS (EASI) to separate the observed mixed signals with same bandwidth and modulation. In order to satisfy the real-time requirement, Liu *et al*. [96] conceived a cognitive radio (CR) scheme exploiting BSS (Max-SNR) to separate the signal mixtures from several frequency bands for performing multiple frequency spectrum detection.

With the aim of overcoming noise uncertainly, Zheng *et al.* [97] designed a cooperative spectrum sensing method based BSS (Max-SNR) for improving the reliability of sensing. To conquer the limitations of the conventional spectrum sensing, Khajavi *et al*. [98] proposed Kurtosis based BSS in combination with random matrix theory (RMT) for enhancing spectrum sensing performance. Lee and Wolf [99] presented a viewpoint that it is crucial to incorporate signal separation into cognitive radio for various purposes, and new cognitive radio physical layer architecture associated with BSS mechanism is put forward. Khajavi *et al*. [100] concentrated on designing a new spectrum sensing framework that incorporated a BSS method with conventional covariance detection based spectrum sensing, and takes advantage of Markov chain for modeling the status of PU for achieving improvement. Ivrigh *et al*. [101] developed a BSS based spectrum sensing using Kurtosis metric for separation observed mixtures and for weighed Gaussian properties of separated signals. Ivrigh and Mohammad-Sajad [102] made further investigation to introduce learning and prediction method as opposed to [101]. The BSS based spectrum sensing and variable order Markov model (VMM) is strongly recommended to combine for enhancing the performance. Ivrigh and Mohammad-Sajad [104] refined the work of Ivrigh *et al*. [101] by use of Markov model for predicting the status of PU for the purpose of achieving dynamic scenario. To strengthen the conventional BSS-based spectrum sensing algorithms, Mukherjee *et al*. [106] was devoted to combine BSS with prediction using hidden Markov model (HMM) for enhancing spectrum sensing performance. Ferreira *et al*. [105] applied ICA to identify signal sources in a broad band of frequencies and to use this information for spectrum sensing.

Saleem *et al*. [103], [107] advocated a peak detection method employing blind source separation to extract true peaks from noisy peaks for implementing wide band spectrum sensing. This method utilizes BSS to estimate the noise variance which determines the threshold value of wavelet transform to obtain true peak. To break through the time-consuming restriction of energy detection and cyclostationary analysis, a spectrum sensing method based on blind source separation and singular spectrum analysis (SSA) is explored in [108]. This work illustrates that the proposed method has lower time consumption but slightly lower sensing performance than that of cyclostationary analysis. A blind spectrum sensing algorithm for cognitive radar was put forward in [109], which use the characteristic of high-order statistics (HOS) of the received signals to carry out both separating work and deciding the presence or absence of the primary user (PU). This work indicates that fourth-order cumulants can be used as a good candidate statistical decision metric to decide the existence of PU owing to exempting from Gaussian noise influence. In [110], full-duplex cognitive radio (FD-CR) based on blind source separation was developed. In terms of the silence time problem, this proposed scheme exerts significant role in helping boost the date rate of the SU and sensing performance compared to the method in [101]. In recent, Luo *et al*. [161] propose a novel full-duplex cognitive radio method based on guided blind source separation (BSS) and non-Gaussian criterion. The functions of spectrum sensing and data transmission are designed in the same position avoiding any mismatch and resource loss in sensing information. The known secondary user in same position configuration is utilized as a guided signal to assist performing blind separation assignment. After separation, the secondary user signal is identified by correlation processing, and the other signal is recognized through non-Gaussian criterion to further deciding the status of primary user. It has been proved that this method can achieve the superior performance in computation complexity and sensing performance compared with the self-interference cancellation based spectrum sensing scheme.

D. BSS IN WIRELESS SENSOR NETWORK

In recent years, with the boom of internet of things (IOT), wireless sensor networks (WSNs) have become increasingly significant for industrial community and people's lives. A mass of sensor nodes are deployed in WSNs for sensing activity incidents of surroundings. Especially, multi-target detection and tracking using WSNs have become a research hotspot for its widespread application prospect. As illustrated in figure 15, a scene of WSN for multi-object detection and tracking is shown. It is noteworthy that signal mixtures mechanism in wireless sensor receiving scenario has posed an enormous challenge to extract multiple indistinguishable target signals accurately and simultaneously. For this reason, exploring effective methods is essential to resolve this tough issue. Lately, utilizing BSS for solving this dilemma has been highlighted and attracted extensive attention due to its superiority of discerning multiple indistinguishable targets. In this subsection, the related literatures with respect to BSS used in WSNs will be shown.

Wang *et al.* [111] indicated that the issue of detecting multiple desired targets in sensor networks from linear/nonlinear mixtures has close connection with the BSS problem. In this paper, the authors discussed the advantages and challenges of exploiting BSS in WSNs, and proposed distributed source number estimation for multiple targets detection. Chen *et al*. [112] addressed the research achievement of blind extraction of source signal for bandwidth constrained

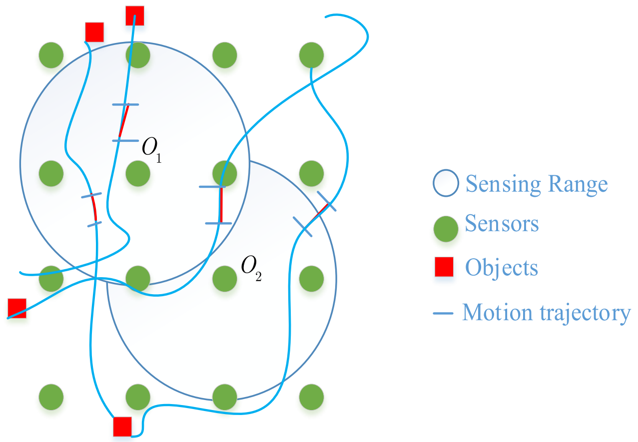

FIGURE 15. WSN for multi-object detection scene.

WSN. Cluster-based and cluster-free sensor networks are presented for investigation. Vikram [113] completed the master thesis regarding employing BSS for tracking multiple targets in WSNs. Zhu *et al.* [114], [117] studied the topologies of sensor network deployed for tracking multiple targets assisted by BSS. In his work, cluster topologies are investigated for tracking algorithms based on BSS principles. Extensive experiments have been evaluated to show that this proposed tracking algorithm can achieve comparable tracking performance in contrast with algorithms assuming single target or distinguishable targets. On the basis of the previous work, Zhu *et al.* [115] gave more in-depth investigation to propose a generic approach to track multiple indistinguishable moving targets in WSNs. This work starts with the separating the aggregate signals from multiple indistinguishable targets via BSS method. After that, both the temporal and the spatial correlation of the separated individual signals are analyzed for determining the real-time location of a target and its moving track. It has been demonstrated that the proposed method has effective performance.

Masnadi-Shirazi and Rao [116] presented a novel framework to solve the problem of tracking and separation of unknown time-varying number of microphones in a reverberant environment. In this work, the integration of a versatile and powerful ICA-based method for multiple DOA estimation with multi-target tracking is presented. Jeon *et al.* [118] investigated an adaptive noise sensing method based on NMF to enhance the speech sensing performance of speech applications operated in WSNs. The proposed algorithm composes of adaptive noise sensing and noise reduction. Adaptive noise sensing is performed by adapting a priori noise basis matrix of the NMF that then is used for the NMF decomposition of noisy speech into clean speech and background noise. Bertrand and Moonen [119] put forward a distributed canonical correlation analysis (DCCA) based BSS for WSNs. It has been shown that DCCA exhibits computationally more efficient compared to the centralized implementation. He *et al.* [120] utilized NMF based BSS for multi-target detection in WSNs. In this assignment, the number of targets is first determined using eigenvalue method, then NMF is employed for separating of signals. It has been illuminated that the proposed algorithm is effective and meaningful. Alavi and Kleijn [121] investigated a distributed robust ICA algorithm that uses a fully shared computation and can be applied over any connected graph. With the help the proposed algorithm, it enables us to facilitate a low computational load at each node as well as low data transmission rate. Alavi [122] further accomplished the Ph. D dissertation pertaining to the distributed BSS theories for WSNs in 2017.

E. BSS IN RFID SYSTEMS

Similar to the WSN, as a critical component of internet of things (IoT), radio frequency identification devices (RFID) have gained great attention from industrial and academic community. With flourishing blossom of the IoT, RFID has become increasingly prevalent and plays a critical role in security, access control, transportation and supply chain management. In principle, RFID gives top priority to utilizing microelectronics and communications technology while the barcode technology places more emphasis on employing scanning technique. RFID exerts significant functions to help the efficient tracking of manufactured goods and materials conveniently. However, the tag collision has emerged as a critical issue limiting the practical application of RFID, as shown in figure 16. Consequently, great deals of researchers have been evoked to deal with this problem. Up to now, a substantial of sense ideas and attractive work has been developed and reported in this area. Traditionally, exploiting MAC level based on collision avoidance mechanism to dispose of the collision problem has been obtained tremendous attention. Nevertheless, it is noteworthy that the tag collision problem has scarcely been investigated from a signal processing perspective. In recent years, BSS is strongly recommended as a promising tool to tackle multiple-tag ID identification problems. In this subsection, the literatures related to the BSS used in RFID will be illustrated.

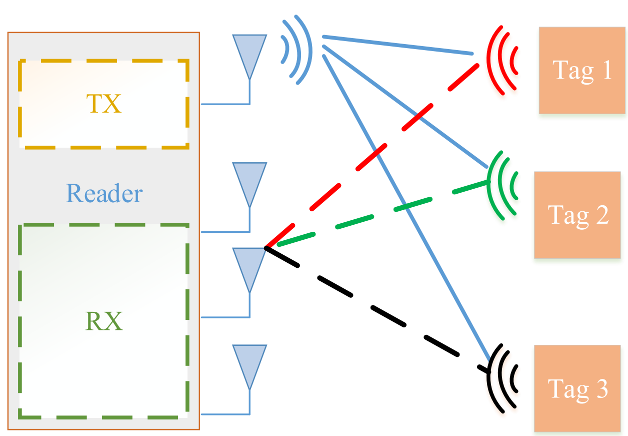

FIGURE 16. Tag collision in RFID scene.

To surmount time-consuming limitation of conventional collision avoidance algorithms, Mindikoglu and van der Vee [123] were first to make use of an antenna array associated with ICA based BSS for separating multiple overlapping tag signals simultaneously. Based on that current RFID systems do not allow readers to communicate with different tags simultaneously, Dacuna *et al*. [124] proposed a spatial multiplexing technique associated with BSS to identify multiple RFID tags at the same time. With the help of BSS, it can promote increasing the read-rate and reducing the time needed to identify large amounts of tags. Li *et al*. [125], [126] proposed a novel RFID anti-collision algorithm based on BSS and dynamic bit-slot grouping technology (BSDBG). In this work, ICA is employed to identifying several tags simultaneously at first. After that, the dynamic bit-slot tags grouping is exploited for ensuring the number of tags read by a reader at the same time. A new parameter SSR (similarity of source and results) for evaluating the separation performance is introduced. It has been shown that the proposed algorithm outperforms far more than the traditional stochastic and deterministic TDMA RFID anti-collision algorithm. Yue *et al*. [127] took into account of the case that the number of antennas in reader was less than the number of tags, and established a synchronization tag collision model of NMF based under-determined blind separation for solving the tag collision in UHF RFID system. The effective separation performance and better throughout are validated through simulation experiments and analysis.

Mu and Zhang [128] made a further investigation and presented adaptive tree grouping and BSS based anti-collision algorithm for RFID system to identify multiple tags simultaneously. It has been demonstrated that the proposed algorithm outperforms the blind separation and dynamic Bit-slot grouping (BSDBG) algorithm in terms of the tag identification speed and the tag identification rate. An under-determined blind separation based RFID collision detection algorithm is investigated in [129]. Considering the characteristics of RFID signal is not completely sparse signal, signal unit interval and a sparse set condition are employed to promote blind separation of RFID. Zhang and Jin [130] proposed a parallelizable identification anti-collision algorithm based on NMF and frame-slot for solving the under-determined receiving model. It has been shown that the proposed algorithm implements better than BSDBG algorithm using the same condition in terms of the tag identification rate and the tag identification speed.

F. BSS IN COMMUNICATION SECURITY

The physical layer security in wireless communication becomes increasingly important due to the requirements of communication security and broad foreground in applications of communication countermeasure. The philosophy of physical layer security is to guarantee a legitimate receiver with a reliable communication, while making sure that unauthorized receivers retrieve almost nothing about the transmitted information from the intercepted signals. From opposite perspective, the purpose is changed as assuring that the effective information can be extracted from the intercepted signals. Two parts of technique are mutually contradictory, but help each other promotion for achieving the respective goals. In subsection, BSS used in aspect of communication security is discussed. In addition, some typical anti-interference research literatures are also included.

In view of the philosophy behind the design of current anonymity networks is to mix traffic or to hide in crowds, Zhu and Betati [131] put forward a class of anonymity attacks based on BSS principle to both wired and wireless anonymity network. Zhang *et al*. [132] investigated a modulation identification method based on BSS for recognizing jamming signal in the normal communication channel. The JADE based ICA is used to acquire channel state information, and then the jamming signal is separated from the composite signals. The philosophy of modulation identification theory depends on the fourth-order cumulant of the jamming signal for extracting statistical characteristic. It has been shown that the proposed method has robustness performance in the presence of carrier offset. Luo and Tang [133] presented a BSS based suppression method to counter deception jamming in the single channel. In this work, the received signal is cut into 3 sections, then the mixed one is separated into two parts by the JADE algorithm. The target and deception jamming are identified by the character of phase quantization. Wang *et al*. [134] focused on investigating the issues of blind extraction of signal of interests (SOIs) in communication mixed observations. In this work, two novel iterative algorithms for extracting SOIs using spatial constraint based CICA framework are proposed. Hagstette *et al*. [135] conducted an investigation of performance analysis of three complex ICA approaches to extract a weak co-channel interfering communication signal.

Li and Hu [136], [137] gave a discussion of the physical layer security from a novel angle of perspective and designed an optimal artificial noise (AN) to resist the attack of the eavesdropper who uses the BSS methods to separate and reconstruct the hidden useful information. It has been shown that the conceived scheme has better performance than that of the white Gaussian AN to resist the BSS attacks for both the BPSK signals and speech signals. Hajisami *et al*. [138] presented an innovative BSS-based cellular communication solution for C-RANs, referred to as Cloud-BSS. A set of neighboring cells is divided into clusters that can increase the system spectral efficiency, decrease handovers, and eliminate the requirement of bandwidth-consuming for channel estimation while mitigating interference. To achieve better mitigation of both CCI and ISI, Leng *et al*. [139] proposed a new structure using generalized estimation of multipath signals in conjunction with maximal-ratio combining diversity for wireless communications over multipath channels. The proposed method can suppressed CCI significantly and extracted different time-delays and Doppler-shifts effectively due to that both space diversity gains and path diversity gains are provided by using this proposed scheme. Li *et al*. [140] designed an interference cancellation algorithm (IC-algorithm) associated with an improved FastICA algorithm with K-means cluster to extract the mixed weak object signals from the strong jamming, and then separate each weak signal from the mixed weak signals for radar systems. Li *et al*. [141] proposed two digital SIC algorithms based on ICA principle for two application scenarios of the CCFD communication systems. The proposed algorithms extract the desired signal from the received signal mixtures directly as a substitute of implementing cancellation through reconstructing self-interfering signal. Li *et al*. [142] proposed an underdetermined blind separation scheme for adjacent satellite interference cancellation based on SCA. In this work, the BSS problem is constructed as a cluster problem, and the novel density clustering is introduced for executing separation work. Based on the initial research achievement in [140], Li *et al*. [143] investigated more in-depth to develop an new blind separation of weak object signals against the unknown strong jamming method. This method breaks the priori information restriction of strong interference signal and extends the application scopes compared to that of method in [140].

IV. DISCUSSION ON SOME CHALLENGES AND FUTURE RESEARCH DIRECTIONS AND RECOMMENDATIONS

This section discusses the general and specific restrictions as well as technical challenges of BSS applied in wireless receiving processing. In addition, some meaningful future research directions concerning BSS applied in wireless communication systems are presented as follows.

A. GENERAL RESTRICTIONS AND CHALLENGES

In essence, this highly efficient and highly versatile BSS technique contributes significantly to assisting wireless receiving. Although wireless communication system can benefit a lot from utilizing BSS mechanism, some limitations and challenges still exist in the process of application. For one thing, the inherent limitation problems of BSS are the order, phase and amplitude indeterminacies. For another, the existing model always assumes that the source number is known or acquired to the BSS algorithm. However, in a practical scenario, the number of source signals are dynamic or unknown so that signals number estimation approaches must be carried out in advance for BSS algorithm. Furthermore, the wireless channel is considered as static during a single processing data block. In real cases, the channel condition may be time-varying or even nonlinear case due to complicate wireless environment. Especially, the fast and abrupt variations limit the BSS function applied in wireless communication systems. In addition, BSS has the limited capacities to separate the mixed Gaussian source signals. More than one Gaussian signal in mixtures or high power Gaussian signals in the mixtures will frustrate the BSS algorithms. Finally, the existing BSS algorithms will be trapped into for resolving the underdetermined separation problems directly. Nevertheless, the underdetermined receiving model is very widespread in wireless communications.

From the above-mentioned discussions, it can be safely concluded that the general restrictions mainly include four categories. These limitations of BSS will pose enormous challenges for the purpose of completing different application requirements. Therefore, the corresponding restrictions will give rise to respective challenges in wireless communications. Firstly, the ambiguous uncertainty issues will result in influencing the normal detection operation. In particular, the accurate order is a significant factor to helping accomplish signal detection in DS-CDMA, OFDM, MIMO, MIMO-OFDM, WSNs and RFID system as opposed to CRNs. Because CRNs gives top priority to identifying the existence of signal rather than concerns the order of separation signals. Moreover, the phase and amplitude indeterminacies can be conquered by demodulation or decoding in process of detecting signals. Secondly, compared with other schemes, sources number issue becomes more severe in the case of WSNs because of random activities. This scenario makes the separating or extracting assignment as a huge challenging problem. Thirdly, only considering the static or quasi static channel conditions may not conform to a plethora of real application requirements. Separation of source signals in abrupt and fast time variant mixing scenario has more difficult in comparison with that of in case of static channel. Last but not least, the Gaussian signals will deteriorate blind separation mechanism, even result in inseparable. The high power Gaussian signal will submerge the useful signals so that the separation work faces a dilemma in low signal to noise ratio (SNR). On top of that, the multiple Gaussian signals are mixed that will cause an inconvenience for implementing BSS work.

B. SPECIFIC LIMITATIONS AND CHALLENGES

Aiming at giving an integral illustration, the specific limitations and challenges will be discussed in this subsection as a supplement of the general case. To our best of knowledge, four types of BSS algorithms have respective speciality. ICA is reasonable for separating statistically independent or at least uncorrelated source signals, but it will be incapable to blind separation of dependent signals. However, spatially correlated sources may extensively occur in practical wireless applications. A perfect example can be found in Internet of Tings (IOT) based WSNs, in which a series of wireless sensors will be densely deployed in IOT to provide high reliability to eliminate the failure of individual sensors, and/or facilitate superior spatial localization of objects of interests. In this case, signals from adjacent sensors have inevitable cross correlated and their cross correlations are usually unknown. Certainly, the dependent signals is not alone in existing in WSNs, mutually correlated signals can also be found in MIMO wireless relay systems, and so on. In comparison with ICA, SCA depends on the sparseness of source to carry out blind separation work. Although SCA is strongly recommended to be used to separate audio signals or image signals, it is weak separation of communication signals except FH signals that is sparse in time-frequency domain. Moreover, there are few literatures reporting regarding that SCA is exploited to other communication signals apart from FH signals. The reason may be that the communication signal is sub-Gaussian without enough sparsity compared to audio signals or image signals with super-Gaussian sparsity property. Similar to SCA, NMF is often employed for separating audio signals or image signals. It is noticed that communication signals are always complex signals, which possess negative characteristic so that NMF rarely utilized wireless communication directly. However, NMF can be used to carry out separation assignment from power spectrum density perspective for communication signals. BCA is very suitable for communication signals, but its existing algorithms need higher SNR that cause a limitation for extending BCA applications in wireless communications.

C. NEW RESEARCH DIRECTIONS AND RECOMMENDATIONS

In this section, a series of meaningful future research directions of BSS applied in wireless communication systems are illustrated as follows. As illustrated in figure 17, eight aspects of future research directions are listed, which can be ranked into two categories, including BSS mechanism areas and BSS application areas.

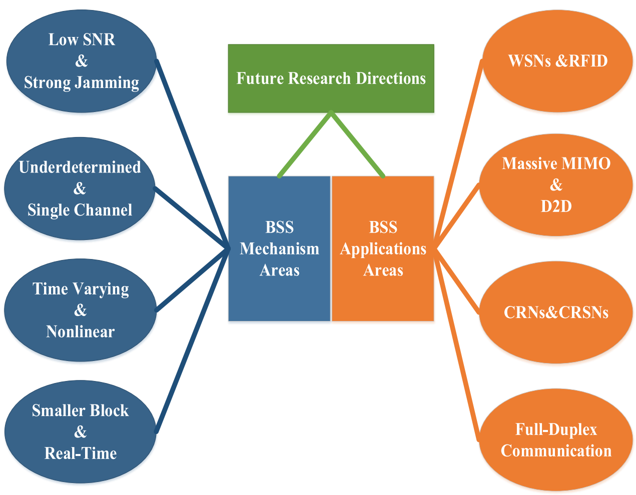

FIGURE 17. Future research directions recommendation.

1) BSS IN CONDITION OF LOW SNR OR STRONG INTERFERENCE

The wireless communication is an open system, which is easily corrupted or attacked by different electromagnetic noises or interferences. In general, the existing BSS algorithms require the moderate to high SNR gain to facilitate signal separation from the received mixtures contaminated by noises or interferences. Once the SNR gain condition is not satisfied, the separation performance may be difficult to guarantee. It must be acknowledged that the scenario of low SNR condition or strong interference often appears in wireless receiving system. Therefore, it has great of significance to investigate the blind separation of sources in low SNR or strong interference condition.

So far, limited work has been done on blind separation of communication signals in condition of low SNR or strong interference. Taking into consideration of its importance, increasingly sophisticated investigations should be evoked in the future.

2) BSS IN TIME VARYING AND NONLINEAR SCENARIO

The existing BSS algorithms are always perfectly suitable for fixed parameter and static wireless channels as well as fixed source number condition in wireless communications [144]–[146]. However, in most of case, the wireless channels have time variant characteristic and the number of source is dynamic, which will pose a big challenge for the appeared BSS theories. In terms of this case, a generalized framework is needed to further and deeply investigate BSS algorithms for time variant scenario.

Up to now, a handful of works have been published on time variant scenario assisted by BSS methods. The existing work often focuses on fixed parameter or small variations in the channel or single type of modulation. It is meaningful to study algorithms to effectively handle time variant in the channel and be adaptable for different modulation schemes. In addition, it is an essential requirement of the BSS algorithms to estimate source number in the observed mixtures. Especially, to predict the dynamic source number in a time varying channel condition will give rise to more complicated but interesting problems.

Another promising research area is about nonlinear mixed model of communication signals due to in the modeling of the complicate channel environment. The existing linear BSS technical schemes are incapable to tackle this problem. In this scenario, new technical theories are expected to be investigated for separating the original signals from their nonlinear mixture [148]. The related theories are eager to be further studied for real application requirements.

3) BSS IN CONDITION OF SMALLER DATA BLOCK LENGTHs

It is noteworthy that data block lengths have close relationship with the performance of the BSS algorithm. In general, only if the statistical information is effectively extracted from data sample, the performance of BSS can be guaranteed. Otherwise the performance of the BSS algorithm will reduce with the smaller data block lengths. Furthermore, the computation complexity will be boosted as the data block length is added, which is inconvenience for wireless communication equipment. Hence, new algorithms are strongly suggested to balance the computational complexity and bandwidth efficiency [149].

Thanks to its linking with compressive sensing, SCA may be a promising scheme for overcoming this issue. BCA is also a good candidate scheme for its recent research analysis [2].

4) BSS IN UNDERDETERMINED AND SINGLE CHANNEL RECEIVING MODEL

The existing wireless receiving model always takes into consideration of determined model so that the developed BSS algorithm can directly be applied for receiving processing. The more practical factor is considered that the antennas or sensors are difficult to being deployed in complicated geographical environment. In this case, the underdetermined receiving model is easy to formulate, so new technique should be developed for solving this problem.

In underdetermined BSS assisted wireless receiving problem, although the wireless channel information is acquired, it is still difficult to recover the original signals from the receiving mixtures. From the current situation, SCA, NMF and BCA are recommended to be reasonable and promising techniques for underdetermined problem. However, few literatures have reported investigations on these three BSS theories for underdetermined model in wireless communications.

In condition of signal channel blind separation model, the current mainstream algorithms are particle filter algorithm, per-survivor processing (PSP) algorithm, and its improved algorithm. These algorithms are computationally intensive and their complexity increases exponentially with the modulation order. Therefore, the current single channel blind separation algorithms will face a bottleneck, and the critical issue is determined how to break through the high complexity constraints. The promising processing principles may be to utilize the intrinsic feature of communication modulation signals for implementation, such as constant module (CM) character and finite character set, and so on. More sophisticated works are desired to be investigated for this significant problem [147].

5) BSS IN CRN AND CRSN

To our best knowledge, BSS has been strongly recommended to be utilized for spectrum sensing in CRNs and CRSNs. Employing BSS can overcome static sensing problem in existing half-duplex spectrum sensing mechanism to fulfil simultaneous transmission and sensing for enhancing throughput or data efficiency of the secondary user. However, limited work has been done in this field of BSS application in spectrum sensing. Innovative models and algorithms are needed to be developed as a supplement of the existing researches [150]–[154].

6) BSS IN WSN AND RFID

As a key component of the internet of thing (IOT), WSNs and RFID have captured enormous attention for their extensive applications [155]. From the present investigation situations, we can easily acquire that BSS in WSNs and RFID has been emerged as a heated topic for multi-object detection and anti-collision. For this reason, more sensible ideas and sophisticated research work are strongly encouraged to carry out.

Some papers have conducted initial work in WSNs for source number estimation and multi-object tracking and orientation. The emerging trend is to develop distributed blind separation theory to adapt the topology structure of mobility WSNs no matter how the connectivity of deployed sensors. In RFID, ICA and NMF based BSS have been utilized to execute anti-collision assignment from signal processing perspective rather than network notion. This is new attempt to develop anti-collision for algorithms improving the existing avoidance collision mechanism.

7) BSS IN MASSIVE MIMO AND D2D

BSS has been extensive applications in MIMO, MIMO-OFDM, and so on. From signal processing mechanism, we can know that BSS can be also extended to other emerging communication systems, such as massive MIMO and D2D for co-channel channel interference cancellation and multiuser detection. In [145], the rudimental investigation of BSS assisted massive MIMO detection problem and performance analysis is implemented. There has a tough problem about how to separate the large scale multi-dimension signal mixtures. It must be acknowledge that to separate large scale dimension of matrix is a challenge issue, but it is very meaningful for massive MIMO as well as data mining for big data analysis [156]–[159].

8) BSS IN CO-TIME CO-FREQUENCE FULL-DUPLEX COMMUNICATIONS

As critical technology of full-duplex communications, self-interference cancellation (SIC) plays an indispensable role in determining the performance of full-duplex systems. The existing SIC algorithms are sensitive to channel estimation error and the hardware imperfections (the Phase Noise and the Non-linear Distortion (NLD)) that will give rise to the residual self-interference (RSI) problem. To improve the performance of full-duplex communications, BSS may be a promising candidate technology for overcoming remnant self-interference problem, for example the work in [141] and [160].

D. THE PRACTICAL APPLICATIONS OF BLIND SOURCE SEPARATION IN FUTURE WIRELESS COMMUNICATIONS

Blind source separation is an important unsupervised learning technique of machine learning, which is helpful to realize the adaptive data processing for wireless communications. Adaptive signal processing has many potential advantages, which has been awarded as a the next generation solution that is a very promising technique for practical wireless receiving applications, such as in figure 18, including military and satellite communication, RFID systems, wireless sensor network and cognitive radio. With the swift development of wireless communication combined with artificial intelligence, the fusion of both will be increasingly close.

In science processing and engineering, the essential problem are considered as a data processing issue. The purpose is to acquire the interested and meaningful data information.

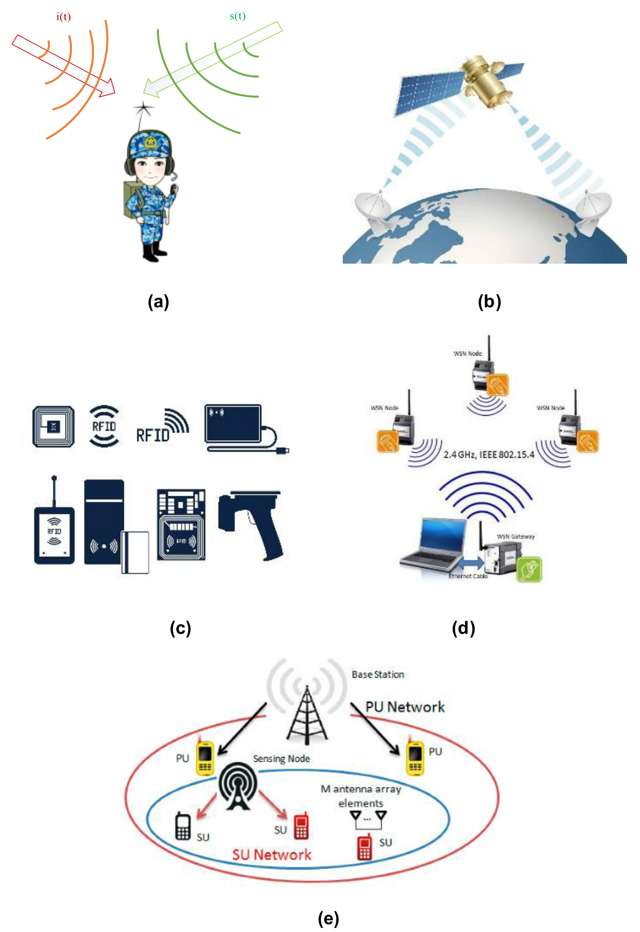

FIGURE 18. BSS Applications in Wireless Communication Systems. (a) military communications. (b) satellite communications. (c) RFID systems. (d) wireless sensor networks. (e) cognitive radio systems.

However, the expected data information is hidden in data mixtures. It is necessary to separate and extract the useful data information from these mixtures using latent component analysis, i.e., blind source separation.

In comparison with that the classical filtering methods are intractable to separate the co-frequency signal interference, BSS can effectively implement this job without occupying other communication resources. With the help of BSS, the severe problem of the scarce frequency resource can be alleviated and the requirement of the high power resources can be relaxed. Consequently, it is great of significance for achieving green communication goal. To develop efficient BSS theories can be conducive to promote the adaptive receiving processing and intelligent signal processing.

V. CONCLUSIONS

In this paper, a comprehensive overview of the application of BSS principle in wireless receiving systems is presented. From our perspectives, BSS can be categorized into four types according to different restricted conditions of source signals, including ICA, SCA, NMF and BCA respectively. From views of cost function and optimization algorithms, the fundamental principles of these four types of BSS are discussed in brevity. As a versatile method, BSS has numerous advantages and functions for wireless communications. With the assistance of the BSS technology, the boring channel estimation operation, synchronization work and plethoric prior information can be avoided. The related technical literatures regarding BSS applied in wireless receiving processing are overviewed, involving applications in DS-CDMA, FH, OFDM, MIMO, MIMO-OFDM, WSNs, RFID, CRNs and communication security. In addition, some general and specific limitations and technical challenges of BSS and its application in signal processing for wireless communication are discussed in this paper. After that, a series of meaningful research directions are presented to intensively encourage the increasing scholars to conceive innovative ideas and develop sophisticated methods. In the future work, blind source separation will emphasize attaching more importance to conceive interested ideas and methods in condition of Low SNR and Strong Jamming, underdetermined or Single channel receiving model, time varying and nonlinear model, small block and real time processing. Influenced by artificial intelligence, blind source separation also will be gained more attention applications in full-duplex communication, cognitive radio sensor network, device to device, to name a few. It is promising to exploit blind adaptive processing mechanism application in wireless receiving processing to promote the performance enhancement and refinement.

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