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An Improved Blind Spectrum Sensing Technique for Cognitive Radio Systems

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Abstract— **Cognitive radio technology has been proposed as a key solution for the problem of inefficient usage of spectrum bands. Spectrum sensing is one of the most important issues in each cognitive radio system. Classically-used spectrum sensing techniques require that the cognitive transmitter is not in operation while detecting the presence/absence of the primary signal during the sensing period. In this paper, we propose to use blind source separation algorithms such as Kurtosis metric, STFD and TALS with the aim of improving the accuracy of conventional spectrum sensing techniques based on blind source separation. Using blind source separation algorithms, cognitive radio can sense a specific spectrum band while sending its own data in this band. We also introduce a new spectrum sensing framework that combines blind source separation with conventional spectrum sensing techniques. In this way, spectrum sensing can continue to work even when the cognitive transmitter is in operation. Simulation results provided in terms of receiver operating characteristic (ROC) curves indicate that the proposed method also improves the sensing performance achieved with conventional spectrum sensing techniques.**

Keywords- Spectrum Sensing; Cognitive Radio; Blind Source Separation; Random Matrix Theory.

I. INTRODUCTION

Cognitive radio (CR) communication [1] is a promising solution to the problem of spectrum scarcity. CR users have to sense the spectrum constantly in order to detect the presence of a primary signal for avoiding any interference between the primary signal and the CR signal [2]. Therefore, making a correct decision about the presence of a primary signal is one of the most important issues in the implementation of each CR system. Spectrum sensing is usually imperfect and imposes interference on the primary network. Channel fading conditions and the so-called hidden terminal problem [3, 4], urge the CR technology to use spatial diversity and cooperation in order to achieve better performance.

In [5], a cooperative spectrum sensing method that is able to improve the achievable throughputs of the system is proposed.

The interference imposed by the CR network on the primary transmission is studied in [6] where the focus is on the interference level and appropriate sensing techniques for minimizing the interference. However, note that spectrum sensing techniques investigated in [6] are based on energy detection (ED).

Some conventional cooperative spectrum sensing methods are usually performed at the beginning of each frame with the important requirement that the cognitive transmitter does not communicate with its base station (BS) during this operation. Obviously, this requirement leads to a waste of the spectral efficiency, especially when the CR was allowed to send data in over a specified band and the decision of the current spectrum sensing is to maintain the CR transmission.

One of these kinds of spectrum sensing methods is random matrix theory (RMT) [7]. The concept of RMT is recently applied to the problem of cooperative spectrum sensing in cognitive systems. In these techniques, the eigenvalues of the matrix formed by the received samples are compared to a threshold value and a final binary hypothesis is made about the presence or the absence of the primary user signal. In RMT-based techniques, unlike other spectrum sensing methods such as likelihood ratio test [8], cyclostationary detection [9], matched filtering [10] ED [11], it is not necessary to dispose *a priori* information about the source signal.

One of the main limitations in conventional spectrum sensing techniques such as ED or RMT is that the cognitive transmitter should not be in operation during spectrum sensing. In other words, conventional algorithms have not the ability to differentiate between the primary and the secondary (cognitive) transmitted signal. Obviously, this leads to different limitations such as: i) the overall achieved throughputs are reduced, ii) the accuracy of spectrum sensing is affected, iii) an accurate synchronization technique should be used in order to synchronize CR sensing frames with primary data frames.

Blind source separation (BSS) is recently recommended for spectrum sensing in CR systems [12, 13]. For instance, in reference [12], BSS is proposed to separate the mixed signal of CR and primary user with little collision, in a multi-antenna application.

In this paper, to overcome the aforementioned limitations of conventional techniques based on ED, we propose to apply the Kurtosis metric for the BSS algorithm as an alternative to conventional techniques. Here we use the Kurtosis metric in order to indicate the properties of the separated signals. In fact, the Kurtosis metric measures the non-Gaussian property of a signal which leads us to decide about the BSS separated signals. Moreover, we apply another BSS algorithm [14] which is based on [15]. Reference [15] proposed a method for blind separation of non-stationary sources in the over-determined case. This method relies on joint diagonalization of a set of spatial time–frequency distributions (STFDs) of the whitened observations at selected time–frequency (t–f) locations. This STFD method is improved by [14]. Another BSS algorithm based on STFD is proposed in [16] which is focused on the identification of the signal source autoterms which corresponds to diagonal

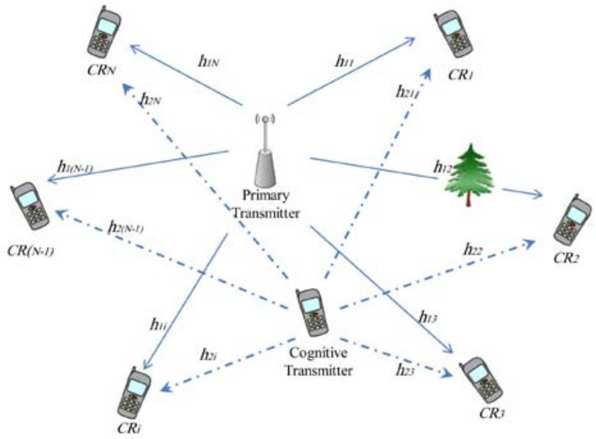

Figure. 1. Architecture of the considered cognitive radio network. In this architecture, both the primary and the cognitive networks can transmit their signals simultaneously over the same bandwidth.

STFD of sources signal with only one non-zero diagonal entry. Furthermore, by using the BSS algorithm based on the Trilinear Alternating Least Squares (TALS) [17, 18], we propose a spectrum sensing method for the case were the CR transmitter is in operation or not. These methods are classically used to separate mixed signals. As proposed in [17], the principle of alternating least squares can be used to fit the trilinear model on the basis of noisy observations. In the noiseless case, and under considerably stronger conditions, original signals can indeed be found using Eigen analysis. So, using TALS will help to separate the cognitive and the primary signals in order to detect the spectrum holes. Interestingly, by using these signal separation methods, the cognitive transmitter can continue on working during the sensing period. Recently in [19], the authors have proposed to combine conventional spectrum sensing techniques like RMT with BSS sensing algorithms in order to enhance the spectrum sensing performance, further.

However, the BSS algorithm used here is more elaborated than the BSS method used in [19]. In other words, in this paper we mainly focus on the comparison of different BSS-based spectrum sensing methods for finding the algorithm that leads to a more accurate BSS spectrum sensing technique. Note that the approach proposed in this work can be applied in part on the proposed joint spectrum sensing method introduced in [19] to enhance the performance further. We will discuss about this possibility in Section V.

The rest of this paper is organized as follows. The spectrum sensing formulation along with our main system model assumptions are presented in Section II. Section III explains the blind RMT-based spectrum sensing method as well as the BSS spectrum sensing algorithm. Section IV applies the Kurtosis metric, STFD and TALS on BSS spectrum sensing algorithm and formulates our proposed improved spectrum sensing technique. Section V provides simulation results and discussions about the performance obtained by the proposed technique. Finally, Section VI draws our conclusions.

II. Spectrum Sensing System Model

Sensing the presence of a primary transmitter inside a given frequency band is usually viewed as a binary hypothesis testing problem with hypothesis H_0 and H_1 defined as:

$$\begin{cases} H_0: & \text{primary user is not in operation,} \\ H_1: & \text{primary user is in operation.} \end{cases}$$

Obviously, in the above definition, one has to differentiate between the presence of the primary user in reality and from the CR point of view, i.e., the decision made by the spectrum sensing process. To this end, we define H_i^{PN} to denote the absence (for $i=0$) and the presence (for $i=1$) of the primary signal, respectively. Similarly, we define H_i^{CN} to indicate the decision made based on the received signals during spectrum sensing at cognitive terminals about the absence (for $i=0$) and the presence (for $i=1$) of the primary signal. The above hypotheses are usually used to define the following conditional probabilities [20]:

$$P_m = P\left(H_0^{CN} \mid H_1^{PN}\right) \tag{1}$$

and

$$P_f = P\left(H_1^{CN} \mid H_0^{PN}\right). \tag{2}$$

Equation (1) (referred to as *miss-detection* probability) is a performance metric for cases where the cognitive radio fails to detect the *presence* of the primary signal whereas Equation (2) (referred to as *false-alarm* probability) is another performance metric for cases where the CR fails to detect the *absence* of the primary signal [21].

The architecture of the considered CR system is depicted in Fig. 1. In this model, when the primary user is detected to be absent, we assume that one of the cognitive users has the permission to send its data through the free sensed frequency band to the destination cognitive user. The received signal at the j-th cognitive user can be written as:

$$\mathbf{x}_j = h_{1,j}\mathbf{s^{PN}} + h_{2,j}\mathbf{s^{CN}} + \mathbf{z}_j, \tag{3}$$

where the vectors $\mathbf{x}_j = [x_{j,1},\ldots,x_{j,L}]^T$, $\mathbf{s}^{PN} = [s_1^{PN},\ldots,s_L^{PN}]^T$ and $\mathbf{s}^{CN} = [s_1^{CN},\ldots,s_L^{CN}]^T$ respectively denote the sensed symbols at the CRs, the primary transmitted symbols and the secondary transmitted symbols during the sensing period; the noise vector $\mathbf{z}_j = [z_{j,1},\ldots,z_{j,L}]^T$ is assumed to be zero-mean circularly symmetric complex Gaussian (ZMCSCG) with distribution $\mathbf{z}_j \sim CN(\mathbf{0},\sigma_{z_j}^2\mathbf{I}_L)$, and $h_{i,j}$ is the channel gain that is assumed to follow a Rayleigh distribution i.e., $h_{i,j} \sim CN(0,\sigma_h^2)$. Moreover, channel coefficients are assumed to be constant during a frame and change to new independent values from one frame to another, i.e., we assume a quasi-static channel model.

If spectrum sensing is performed while the cognitive system is in operation (i.e., under hypothesis H_0^{CN}), we get the cognitive users sensed signals as:

$$\mathbf{x_j} = \begin{cases} h_{2,j}\mathbf{s^{CN}} + \mathbf{z}_j & H_0^{PN}, \\ h_{1,j}\mathbf{s^{PN}} + h_{2,j}\mathbf{s^{CN}} + \mathbf{z}_j & H_1^{PN}, \end{cases} \tag{4}$$

whereas if spectrum sensing is performed while the cognitive system is not in operation (i.e., under hypothesis H_1^{CN}), we get:

$$\mathbf{x_j} = \begin{cases} \mathbf{z}_j & H_0^{PN}, \\ h_{1,j}\mathbf{s^{PN}} + \mathbf{z}_j & H_1^{PN}. \end{cases} \tag{5}$$

Note that (5) is widely proposed in state of the art spectrum sensing models.

Let us denote by N the number of cognitive users and by L the number of symbols used for spectrum sensing. For convenience, we also introduce the following more general system model:

$$\mathbf{X} = \mathbf{HS} + \mathbf{Z}, \tag{6}$$

where

$$\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,L} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,L} \\ \vdots & \vdots & & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,L} \end{bmatrix} = \begin{bmatrix} \mathbf{x_1}^\mathbf{T} \\ \mathbf{x_2}^\mathbf{T} \\ \vdots \\ \mathbf{x_N}^\mathbf{T} \end{bmatrix}, \tag{7}$$

$$\mathbf{S} = \begin{bmatrix} s_1^{PN} & s_2^{PN} & \cdots & s_L^{PN} \\ s_1^{CN} & s_2^{CN} & \cdots & s_L^{CN} \end{bmatrix} = \begin{bmatrix} \mathbf{s_1}^\mathbf{T} \\ \mathbf{s_2}^\mathbf{T} \end{bmatrix}, \tag{8}$$

$$\mathbf{H} = \begin{bmatrix} h_{1,1} & h_{2,1} \\ h_{1,2} & h_{2,2} \\ \vdots & \vdots \\ h_{1,N} & h_{2,N} \end{bmatrix} = \begin{bmatrix} \mathbf{h_1} & \mathbf{h_2} \end{bmatrix}, \tag{9}$$

and

$$\mathbf{Z} = \begin{bmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,L} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,L} \\ \vdots & \vdots & & \vdots \\ z_{N,1} & z_{N,2} & \cdots & z_{N,L} \end{bmatrix} = \begin{bmatrix} \mathbf{z_1}^\mathbf{T} \\ \mathbf{z_2}^\mathbf{T} \\ \vdots \\ \mathbf{z_N}^\mathbf{T} \end{bmatrix}. \tag{10}$$

In (6), all observesions of the cognitive network senesing users are collected at the cognitive network BS denoted by matrix **X**. Based on observations gathered in **X**, the spectrum sensing process in the sensing period takes place. Moreover, matrices **H** and **Z**, are Rayleigh fading channel gains and the additive ZMCSCG noise is also considered for different sensing channels (see Fig. 1).

III. Conventional Spectrum Sensing Based on Random Matrix Theory and Blind Source Separation

A. Random Matrix Theory Spectrum Sensing

Classical spectrum sensing techniques based on energy detection compare the sensed signal energy in the sensing period with a known threshold derived from the statistics of the noise and channel [11, 20]. The following equation is considered to be the decision rule at the *j*-th cognitive user:

$$\hat{\theta}_j^{ED} = \begin{cases} H_1 & \text{if} \quad E_j \geq \zeta_j, \\ H_0 & \text{if} \quad E_j < \zeta_j, \end{cases} \tag{11}$$

where ζ_j is the energy threshold applied at the *j*-th cognitive user to differentiate between the two hypotheses H_0 and H_1. Moreover, we have:

$$E_j = \frac{1}{L}\sum_{i=1}^{L} | h_j s_i + z_{i,j} |^2, \tag{12}$$

where h_j for $j \in \{1,\ldots,N\}$ is the sensing channel coefficient, N is the number of cognitive users (see Fig. 1) and s_i for $i \in \{1,\ldots,L\}$ is the *i*-th primary user signal. The cooperative spectrum sensing using ED makes its final decision about the presence of primary signal using a logical OR rule.

In the sequel, we briefly introduce the RMT spectrum sensing method. As proposed in [7], the received symbols at each cognitive user is transmitted to the cognitive BS leading to a signal model similar to (7). The RMT based spectrum sensing is done based on the maximum (denoted by λ_{max}) and minimum (denoted by λ_{min}) eigenvalues of the empirical covariance matrix $\mathbf{XX}^H/N$. Assuming the noise variance is known at the CR, the cooperative decision rule is [7]:

$$\hat{\theta}^{RMT} = \begin{cases} H_1 & \text{if} \quad \lambda_{max} \geq \kappa, \\ H_0 & \text{if} \quad \lambda_{max} < \kappa, \end{cases} \tag{13}$$

where κ is the spectrum sensing threshold applied at the cognitive BS to make decision about the presence of the primary network. Furthermore, if the noise variance is not available (blind scenario), the RMT based cooperative decision is [7]:

$$\tilde{\theta}^{RMT} = \begin{cases} H_1 & \text{if} \quad \dfrac{\lambda_{max}}{\lambda_{min}} \geq \xi, \\ H_0 & \text{if} \quad \dfrac{\lambda_{max}}{\lambda_{min}} < \xi, \end{cases} \tag{14}$$

where ξ is the blind RMT based method threshold and is chosen to satisfy the desired false-alarm probability.

B. Blind Source Separation Spectrum Sensing

In this section, we introduce the spectrum sensing based on the BSS approach. To separate two independent sources from two or more dependent observation vectors, we will apply the independent component analysis (ICA) method [22]. The goal is to recover the original source signal vectors $\mathbf{s}_1$ and $\mathbf{s}_2$ (i.e., matrix $\mathbf{S}$), by choosing the best value for matrix $\mathbf{W}$, blindly:

$$\mathbf{Y} = \mathbf{WX} \tag{15}$$

where

$$\mathbf{Y} = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,L} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,L} \end{bmatrix} = \begin{bmatrix} \mathbf{y_1}^{\mathbf{T}} \\ \mathbf{y_2}^{\mathbf{T}} \end{bmatrix} \tag{16}$$

is the best approximation of the matrix $\mathbf{S}$ and

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N} \end{bmatrix} = \begin{bmatrix} \mathbf{w_1}^{\mathbf{T}} \\ \mathbf{w_2}^{\mathbf{T}} \end{bmatrix}. \tag{17}$$

The Fast ICA algorithm [22], [23], is used to find the separated signals ($\mathbf{Y}$) using an approximation of the negentropy [24]. In order to find a metric to make a decision, different metrics such as correlation and negentropy are used to measure the nongaussianity of the separated signals. Then, the measured nongaussianity is compared to a predefined threshold to make a decision about the presence/absence of the primary signal in the sensing period of a frame. The decision is then applied to the rest of the sensed frame.

There are several methods for estimating the mixing matrix **H** such as ICA [19], STFD [15] and TALS [18, 19]. These methods are performed in the way of finding the matrix **W** in order to compensate the effect of the mixing matrix **H** and for reconstructing the original signals.

IV. Improved Blind Spectrum Sensing

In this section, we propose our new spectrum sensing method. We investigate the spectrum sensing problem by considering the two following scenarios. In the first scenario, we suppose that the cognitive transmitter is not in operation. In this case, the primary network signal is absent, if both of the two independent components have low nongaussianity property whereas the primary network signal is present if one of the two independent components has high nongaussianity property. In the second scenario, we suppose that the cognitive network transmitter is in operation. In this scenario, one of the two independent components is an estimation of the cognitive transmitted signal and is strongly correlated with it. Therefore, we measure the nongaussianity property of the other independent component. In this case, the primary network signal is absent, if this independent component has low nongaussianity property whereas the primary network signal is present if this independent component has high nongaussianity property.

In the following, we propose to apply the Kurtosis metric in order to measure the nongaussianity property of the two independent components, i.e., the primary network and the cognitive network signals. The definition of the Kurtosis metric is as follows:

$$Kurtosis(y_i) = \frac{E\{(\mathbf{y_i} - \mu_i)^4\}}{\sigma^4} \tag{18}$$

where $\mathbf{y_i}$ for $i = 1,2$ is the i-th independent component of the BSS algorithm output with

$$\mathbf{y_i} = \sum_{j=1}^{N} w_{i,j}\mathbf{x_j}. \tag{19}$$

For the case in which both of the primary signal and the cognitive signal are present, the vector $\mathbf{y_i}$ can be rewritten as:

$$\mathbf{y_i} = \sum_{j=1}^{N} w_{i,j}\left(\sum_{k=1}^{2} h_{k,j}\mathbf{s_k} + \mathbf{z_j}\right) \tag{20}$$

and aslo for the vector $\mathbf{y_i}$ we have:

$$\mu_i = E\{\mathbf{y_i}\} \tag{21}$$

and

$$\sigma_i^2 = Var(\mathbf{y_i}). \tag{22}$$

The output signals of the Fast ICA algorithm, y_1 and y_2, are zero mean with unit variances. Therefore, the Kurtosis metric in (18) can be simplified as:

$$Kurtosis(\mathbf{y_i}) = E\{\mathbf{y_i}^4\}. \tag{23}$$

Considering (15) and using

$$\mathbf{y_i} = \sum_{i=1}^{2} a_i\mathbf{s_i} + \mathbf{z}'. \tag{24}$$

it is straightforward to calculate (24) as:

$$Kurtosis(\mathbf{y_i}) = E\{(\mathbf{s_i} + \mathbf{z}')^4\}. \tag{25}$$

In the above equations, a_i for $(i = 1,2)$ are constant coefficients and

$$\mathbf{z}' = \sum_{j=1}^{N} w_{i,j}\mathbf{z_j}. \tag{26}$$

since z' is a linear combination of the gaussian variables, it has a gaussian distribution.

The Kurtosis metric indicates the gaussian property of each source. In Section III, by using the fast ICA metric, we obtain the estimation of the two mixed source signals ($\mathbf{y_1}$ and $\mathbf{y_2}$) in order to satisfy the following equation:

$$\mathbf{WH} \simeq \mathbf{I}. \tag{27}$$

In this section, by applying the Kurtosis metric on the separated sources, we can conclude that the estimated signals have gaussian property or not. Therefore, the BSS spectrum sensing algorithm based on the Kurtosis metric can be summarized as follows:

A. The cognitive transmitter is OFF:

$$\theta_1^{BSS} = \begin{cases} H_1 & \text{if } \min(Kurtosis(\mathbf{y_i})) \le T_1, \\ H_0 & \text{if } \min(Kurtosis(\mathbf{y_i})) > T_1. \end{cases} \tag{28}$$

B. The cognitive transmitter is ON:

$$\theta_2^{BSS} = \begin{cases} H_1 & \text{if } \max(Kurtosis(\mathbf{y_i})) \le T_2, \\ H_0 & \text{if } \max(Kurtosis(\mathbf{y_i})) > T_2, \end{cases} \tag{29}$$

where T_1 and T_2 are the Kurtosis based BSS spectrum sensing method threshold and are chosen to satisfy the desired false-alarm probability.

Comparing the BSS based spectrum sensing and the conventional spectrum sensing such as RMT that is mentioned above, although the performance of BSS based spectrum sensing is less than the performance of RMT spectrum sensing method, there are some advantages by using BSS based spectrum sensing that we can not have in conventional spectrum sensing methods. The main advantage is that we can sense the spectrum even if the CR transmitter is in operation.

More precisely, synchronization is required in techniques like energy detection where spectrum sensing should be done absolutely when the CR is OFF, i.e., in within the beginning part of each primary data frame

In contrast, with BSS, since the CR is allowed to transmit during sensing, the spectrum sensing can be done any time during the primary frame and this feature relaxes synchronization between the primary frame and the CR sensing frames.

In the following, we briefly introduce a new framework for spectrum sensing which is the combination of RMT and BSS methods. The RMT method is not able to detect the presence or the absence of the primary signal while sending the information data on the desired subchannel and so is used when the cognitive transmitter is not in operation. Besides, the BSS method is able to separate the mixed signals and so can detect the presence of the primary signal in the desired frequency band while the cognitive transmitter signal is present in this frequency band and so is used when the cognitive transmitter is in operation.

This spectrum sensing framework can be modeled by a finite-state Markov chains [25]. The Markov chains theory says, there is always at least a stationary distribution for a finite markov chain. By using the the Markov chain modeling and after some calculus, the equivalent false-alarm and miss-detection probabilities for the combination of the two methods in our framework can be obtained as:

$$P_f = \frac{P_f^{m2}}{P_f^{m2} + 1 - P_f^{m1}}, \tag{30}$$

and

$$P_m = \frac{P_m^{m1}}{1 - P_m^{m2} + P_m^{m1}}, \tag{31}$$

where P_f^{mi} and P_m^{mi} (for $i = 1,2$) are the false-alarm and miss-detection probabilities corresponding to the RMT method and the BSS method, respectively.

V. NUMERICAL RESULTS AND DISCUSSION

In this section, numerical results are presented for evaluating the performance provided by the proposed spectrum sensing method in comparison with conventional techniques presented in [12, 13, 7]. Throughout the simulations, the transmitted power for both primary and cognitive transmitters is normalized to one. We provide simulations for different number of cognitive users and different values of signal-to-noise ratio (SNR). The number of sensing sensors in each sensing window is set to 100 (i.e., $L = 100$).We first focus on the BSS method which based on the Kurtosis metric. Then, we will discuss about the proposed improved spectrum sensing method introduced in Section IV.

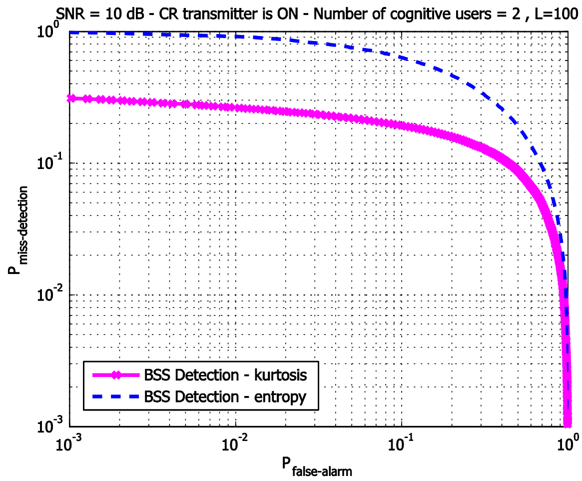

Figure. 2. The miss-detection probability versus the false-alarm probability. For different BSS based spectrum sensing methods while the cognitive transmitter is in operation.

The receiver operating characteristic (ROC) curve achieved by the BSS spectrum sensing method in comparison to that obtained by using the entropy-based spectrum sensing method [21] is plotted in Fig. 2. The figure is plotted for two cognitive users while the cognitive transmitter is in operation. Furthermore, the sensing channel SNR is set to 10 dB. As shown, using the Kurtosis metric improves the spectrum sensing ROC which results in better detection of the primary network signal.

Figure 3 plots the miss-detection probability versus the false-alarm probability for different thresholds values. In this figure, the RMT method and the Kurtosis-based BSS method are plotted for the following two conditions: i) the cognitive transmitter signal is present and ii) the cognitive transmitter signal is absent. It is shown that the Kurtosis based BSS spectrum sensing method outperforms the RMT method when the cognitive network and the primary network signals are both present. Furthermore, as shown, the RMT method also outperforms the Kurtosis based BSS spectrum sensing method when the cognitive transmitter signal is absent.

Figure 4 plots the miss-detection probability versus the false-alarm probability for different thresholds values when the cognitive network transmitter is ON. In this figure, the entropy based fast ICA spectrum sensing method is plotted in comparison with the STFD based BSS (TFBSS) spectrum sensing method and the TALS based BSS spectrum sensing method. As obvious from this figure, when the cognitive transmitter signal is present, the entropy based fast ICA spectrum sensing method has better performance compared to the methods in an SNR equal to 5 dB when 2 cognitive users are in cooperation.

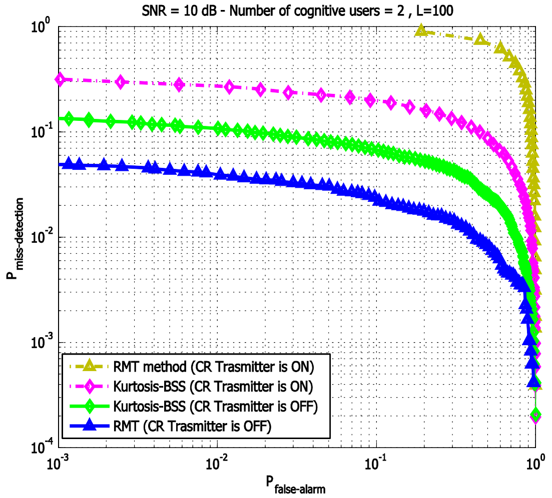

Figure. 3. The miss-detection probability versus the false-alarm probability for the comparison between the proposed improved spectrum sensing method and the BSS and RMT method when they are employed separately.

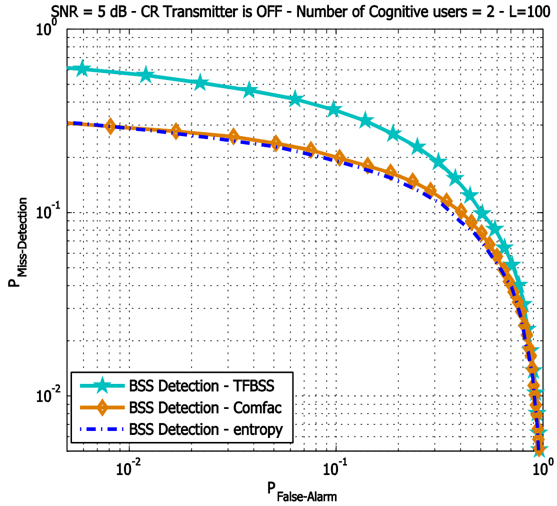

Figure. 5. The miss-detection probability versus the false-alarm probability for the proposed improved spectrum sensing methods TFBSS, Comfac (Improved TALS) and entropy based Fast ICA.

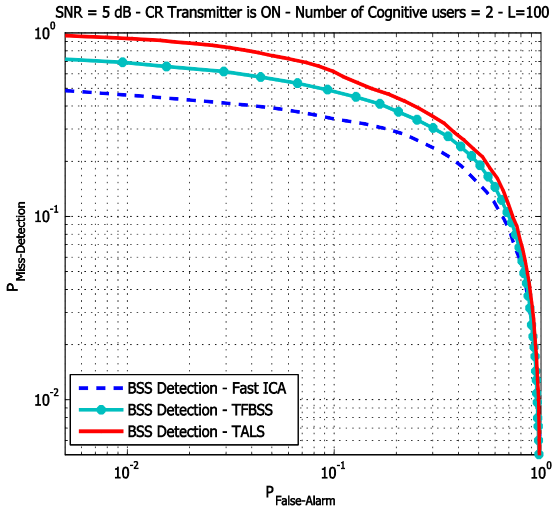

Figure. 4. The miss-detection probability versus the false-alarm probability for the comparison between the proposed improved spectrum sensing methods TALS, TFBSS and Fast ICA.

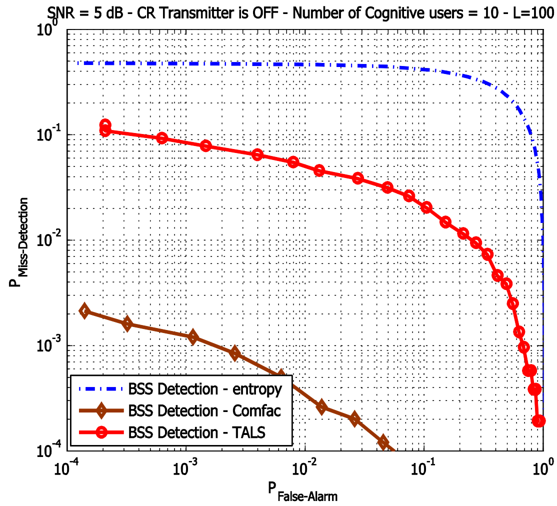

Figure. 6. The miss-detection probability versus the false-alarm probability for the proposed improved spectrum sensing methods TFBSS, Comfac (Improved TALS) and entropy based Fast ICA.

Figure 5 plots the miss-detection probability versus the false-alarm probability for different threshold values when the cognitive network transmitter is OFF. In this figure, the entropy based Fast ICA spectrum sensing method is compared to the TFBSS spectrum sensing method and to the Comfac (improved TALS) based BSS spectrum sensing method. As clear from this figure, when the cognitive transmitter signal is absent, the entropy based fast ICA and the Comfac based BSS algorithm spectrum sensing methods have better performance compared to the TFBSS method in an SNR equal to 5 dB when 2 cognitive users are in cooperation.

Similar plots are shown in Fig. 6 when the cognitive transmitter is OFF. In this figure, the entropy based Fast ICA spectrum sensing method is plotted in comparison with the TALS based BSS spectrum sensing method and the Comfac based BSS spectrum sensing method. We observe that when the cognitive transmitter signal is absent, the Comfac based BSS algorithm spectrum sensing method has better performance compared to the TALS and the entropy based BSS specrtrum sensing methods in a SNR equal to 5 dB when 10 cognitive users are in cooperation. Comparing the Comfac method in Fig. 5 which is for 2 cognitive users with this method in this figure, we conclude that increasing the number of cognitive users will improve the performance of the Comfac method more than other methods.

Fig. 7 plots the miss-detection probability versus the false-alarm probability when the cognitive network transmitter is ON. As observed, when the cognitive transmitter signal is present, the Comfac based BSS algorithm spectrum sensing method has very poor performance compared to other methods. This figure also shows that the TFBSS BSS algorithm spectrum sensing method in an SNR equal to 5 dB when 10 cognitive users are in cooperation has the best sensing performance.

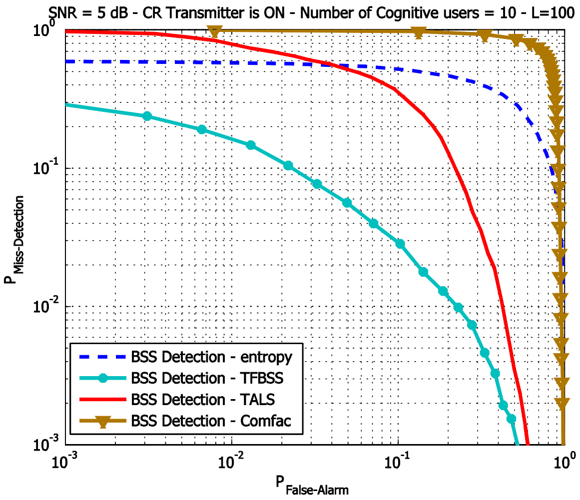

Figure. 7. The miss-detection probability versus the false-alarm probability for the comparison between the proposed improved spectrum sensing method TALS, TFBSS, Comfac (Improved TALS) and entropy based Fast ICA.

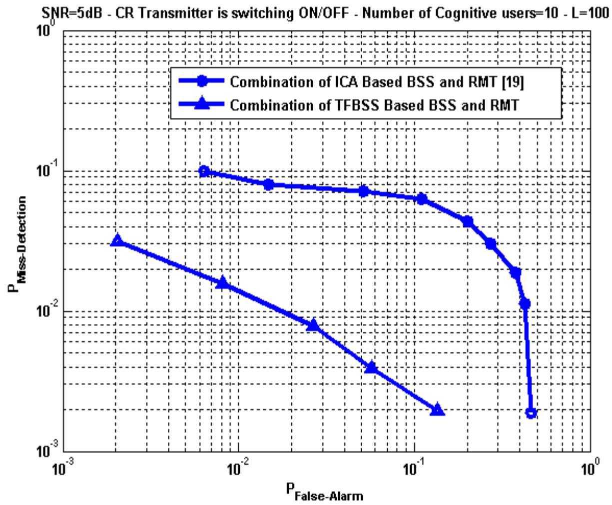

Figure. 8. The miss-detection probability versus the false-alarm probability for the combined spectrum sensing technique of [19] in which the BSS spectrum sensing method is based on TFBSS (used this paper) and fast ICA (used in [19]). Other simulation parameters are similar to those used in Fig. 7.

Fig. 8 depicts the performanace of the spectrum sensing approach presented in [19] for the case where the BSS algorithm is the one developed in this paper compared to a conventional BSS technique used in [19]. More precisely, this results shows the advantage achieved by using the proposed BSS technique. We observe that by using the proposed BSS techniques (the TFBSS technique used here) in the context of the spectrum sensing [19], a considerable accuracy is provided for the sensing algorithm.

VI. Conclusion

Spectrum sensing is one of the most important parts in the implementation of each cognitive system. In this paper, a new blind spectrum sensing method based on the BSS metric is proposed. More precisely, we proposed a new spectrum sensing framework that uses the Kurtosis metric inside the blind source separation algorithms. This framework improves the spectrum sensing detection performance specially when the cognitive radio and the primary network are in operation simultaneously. Moreover, we proposed to apply STFD BSS and TALS BSS algorithms for spectrum procedure at the cognitive network. We also proposed to perform spectrum sensing by combining blind source separation with conventional random matrix theory based spectrum sensing. Simulation results provided in terms of receiver operating characteristic curves show that the proposed spectrum sensing outperforms the detection performance achieved with the conventional BSS spectrum sensing based on the entropy metric.

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