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A Blind Source Separation Technique for Spectrum Sensing in Cognitive Radio Networks Based on Kurtosis Metric

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***Abstract*—Cognitive radio is proposed as a key solution to overcome the inefficient spectrum usage and spectrum sensing is an important part of cognitive radio networks. In classical methods of spectrum sensing, when the secondary user analyzes the channel to find out if primary users are in operation or not, secondary users are not allowed to transmit. In this paper, we propose a spectrum sensing method based on blind source separation technique by using Kurtosis metrics that can sense the spectrum while secondary transmitters are in operation. We compare our proposed channel sensing method with classical ones. Simulation results provided in terms of receiver operating characteristic (ROC) curves indicate that the proposed method outperforms the conventional spectrum sensing techniques, considerably.**

Keywords-cognitive radio; spectrum sensing; blind source separation; Kurtosis.

I. INTRODUCTION

In cognitive radio (CR) systems [1], spectrum sensing is a necessary part; it indicates the absence or presence of primary user (PU). If the spectrum sensor indicates the absence of PU, the secondary user (SU) starts using the unused spectrum band and transmit its data opportunistically. There are different proposed methods for spectrum sensing in literature such as energy detection (ED), cyclostationary detection and matched filter detection. In ED method, the level of received (sensed) energy of signal indicates the presence or absence of PU. Cyclostationary method uses the statistical properties of signal and noise to detect if the PU is in operation or not. Matched filter method maximizes SNR in received signal in presence of Gaussian noise and then detects the signals.

Making the correct decision in spectrum sensing is very important in CR networks. In one hand, if the channel is busy by PU but this is not detected by channel sensor (missed detection), then the SU uses that channel and this causes a severe interference to PU, consequently. On the other hand, if the channel is not busy by PU but channel sensor detects it busy by mistake (false alarm), then that channel becomes useless and this decreases the spectral efficiency of the cognitive network. There are some challenges in spectrum sensing such as the impact of fading channels and hidden terminal problem [2] [3]. Also, cooperative spectrum sensing has improved the performance of spectrum sensing and particularly helps to solve the hidden terminal problem [4].

One of the main limitations in spectrum sensing methods such as ED is that the SU transceiver should not transmit during spectrum sensing, because the spectrum sensing unit cannot differentiate between the SU and PU signals. This limitation forces the SU to be synchronized with the PU in order to sense the spectrum at the beginning of PU data frame. If spectrum sensing indicates the absence of PU, then the SU can transmit its data in the rest of the data frame, and this limitation reduces the SUs' throughput.

Blind source separation (BSS) has been proposed to be applied in CR networks [5], particularly in spectrum sensing. For instance, in [6] a BSS based spectrum sensing is proposed that can sense in multi frequency bands. It separates different signals in different frequencies by BSS approach and detects if some of them are free. In [7], BSS is used to separate sensed signals and the correlation between separated received signals at SU is measured to make decision about channel status; if PU is in operation or not. In [8] fast ICA is used to separate receiving signals and then Kurtosis metric is utilized to demonstrate the properties of separated signals and then to make decision about the presence or absence of PU. In [11], a novel framework for spectrum sensing is proposed that combines blind source separation spectrum sensing and covariance based spectrum sensing. In this paper, we use Kurtosis metric both for separating between received signals and indicating the properties of the separated signals. In fact, Kurtosis metric measures the non-Gaussian property of a signal and then signals will be separated in order to maximize non-Gaussian property of separated signals. Then, the maximum of non-Gaussian property leads us to decide about the separated signal. If the signal is severely non-Gaussian, it is concluded that the signal should not be noise and an independent signal has been sensed.

The rest of this paper is organized as follows. The spectrum sensing formulation and the assumed system model are presented in Section II. In Section III we explain our proposed method for spectrum sensing. Section IV provides

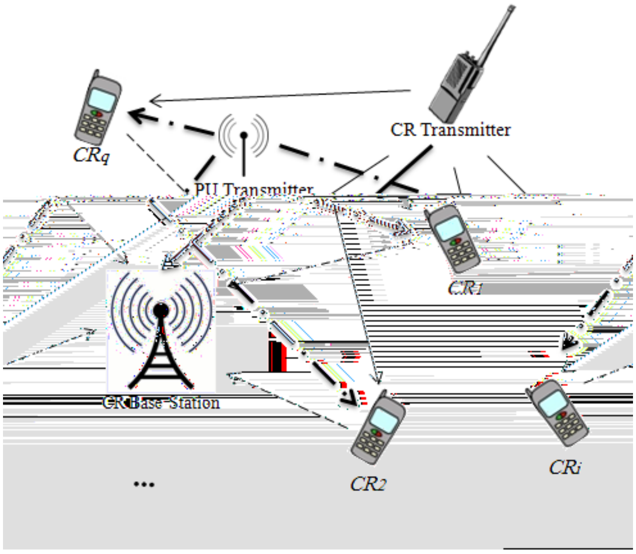

Figure 1. Architecture of the considered cognitive radio network. In this architecture, both the primary and the cognitive networks can transmit their signals on the same bandwidth. The solid arrows show the channels between CR transmitter and the other CR users. The dashed arrows are reporting channels and dash-dot arrows are sensing channels.

simulation results and discussions, and finally Section V draws our conclusions.

II. Spectrum Sensing System Model

Sensing the presence of PU in a specific frequency band usually is viewed as a binary hypothesis. We define these two hypotheses as:

$$\begin{cases} H_0: & \textit{primary user is not in operation} \\ H_1: & \textit{primary user is in operation} \end{cases} \qquad (1)$$

In the above definition, there is a difference between the real state of primary network and the sensed state. We define H_i^{PN} for the real state of primary network. ($i=0$ means that the PU is not in operation and $i=1$ means that the PU is in operation). We also define H_i^{CN} as the decision in cognitive network. ($i=0$ means that the PU is not in operation and $i=1$ means that the PU is in operation). There are two different errors that we define and the simulation results are based on them:

$$P_m = P(H_0^{CN} \mid H_1^{PN}) \qquad (2)$$
$$P_f = P(H_1^{CN} \mid H_0^{PN}) \qquad (3)$$

The equation (2) is miss detection probability. In this probability the PU is in operation and the result of spectrum sensing states that PU is not in operation. The equation (3) is false alarm probability. In this probability the PU is not in operation and the CR network considers that PU is in operation. A good spectrum sensing algorithm has a low miss detection probability and false alarm probability at the same time.

The architecture of network is illustrated in Fig.1. In this model, when the PU is detected absent, one of the SUs can transmit its data on sensed frequency band to destination SU. The received signal at the j^{th} SU can be written as:

$$\mathbf{y}_j = h_{j,1}\mathbf{a}^{PN} + h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j \qquad (4)$$

and

$$\mathbf{a}^{PN} = [a_1^{PN} \quad a_2^{PN} \quad \cdots \quad a_L^{PN}], \qquad (5)$$
$$\mathbf{a}^{CN} = [a_1^{CN} \quad a_2^{CN} \quad \cdots \quad a_L^{CN}], \qquad (6)$$
$$\mathbf{n}_j = [n_{j,1} \quad n_{j,2} \quad \cdots \quad n_{j,L}] \qquad (7)$$

where $\mathbf{a}^{PN}$ is the transmitted PU symbols, $\mathbf{a}^{CN}$ is the transmitted SU symbols, and L is the frame length. We assume that only one of the SUs can send its data on sensed frequency band. Also $\mathbf{n}_j$ is ZMCSCG noise with distribution $\mathbf{n}_j \sim CN(\mathbf{0}, \sigma_{n,j}^2 \mathbf{I}_L)$ and $h_{j,i}$ is channel coefficient with Rayleigh distribution, and frame length is assumed to be constant. When the primary network is not in operation, all the symbols in vector $\mathbf{a}^{PN}$ will be zero. Therefore, if the SU is in operation we have:

$$\mathbf{y}_j = \begin{cases} h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j & H_0^{PN}, \\ h_{j,1}\mathbf{a}^{PN} + h_{j,2}\mathbf{a}^{CN} + \mathbf{n}_j & H_1^{PN}, \end{cases} \qquad (8)$$

and if the SU is not in operation, we have:

$$\mathbf{y}_j = \begin{cases} \mathbf{n}_j & H_0^{PN}, \\ h_{j,1}\mathbf{a}^{PN} + \mathbf{n}_j & H_1^{PN}, \end{cases} \qquad (9)$$

We show the number of SUs by q. We can write the matrix form of these equations as follows:

$$\mathbf{Y}(k) = \mathbf{H}.\mathbf{A}(k) + \mathbf{N}(k) \qquad (10)$$

where:

$$\mathbf{Y}(k) = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,L} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,L} \\ \vdots & \vdots & \ddots & \vdots \\ y_{q,1} & y_{q,2} & \cdots & y_{q,L} \end{bmatrix} = \begin{bmatrix} \mathbf{y_1} \\ \mathbf{y_2} \\ \vdots \\ \mathbf{y_q} \end{bmatrix} \qquad (11)$$

In this equation $y_{q,l}$ is the l^{th} sensed symbol in the q^{th} SU. We also have:

$$\mathbf{A}(k)=\begin{bmatrix}\mathbf{a}^{PU}\\ \mathbf{a}^{CR}\end{bmatrix}=\begin{bmatrix}\mathbf{a_1}\\ \mathbf{a_2}\end{bmatrix} \tag{12}$$

$$\mathbf{H}=\begin{bmatrix}h_{11} & h_{12}\\ \vdots & \vdots\\ h_{q1} & h_{q2}\end{bmatrix} \tag{13}$$

where $\mathbf{H}$ includes the channel coefficients that assumed to be constant during the spectrum sensing. Also we can write:

$$\mathbf{N}(k)=\begin{bmatrix}n_{1,1} & n_{1,2} & \cdots & n_{1,L}\\ n_{2,1} & n_{2,2} & \cdots & n_{2,L}\\ \vdots & \vdots & \ddots & \vdots\\ n_{q,1} & n_{q,2} & \cdots & n_{q,L}\end{bmatrix}=\begin{bmatrix}\mathbf{n_1}\\ \mathbf{n_2}\\ \vdots\\ \mathbf{n_q}\end{bmatrix} \tag{14}$$

III. SPECTRUM SENSING BASED ON BLIND SOURCE SEPARATION

A. Blind Source Separation

Blind source separation is one of the signal processing methods that can recover some independent signals from their linear combination. As we mentioned in system model, we can show the system equations by this matrix:

$$\mathbf{Y}=\mathbf{H}.\mathbf{A}+\mathbf{N} \tag{15}$$

In this matrix equation, $\mathbf{Y}$ is our observation and each row of $\mathbf{Y}$ is related to one SU that contains L symbols. In BSS problem, only the matrix $\mathbf{Y}$ (as our observation) is known and we estimate $\mathbf{H}$ from the observation $\mathbf{Y}$. Then we multiply the observation by the inverse of estimated $\mathbf{H}$ and calculate the estimation of matrix $\mathbf{A}$ as independent sources. There are several methods for estimating $\mathbf{H}$ such as FAST ICA, MUK, TALS, COMFAC [9] [10].

The spectrum sensing method introduced in [8] uses fast ICA algorithm to recover the original signals and then uses the Kurtosis metric to find the properties of separated signals. In this paper, we use Kurtosis both for separating and finding the properties of separated signals, and we call our proposed technique as MUK (multiuser Kurtosis algorithm) [10].

Let's start with our matrix system model in (15). In BSS problem, Y is our observation matrix, $\mathbf{H}$ is the mixing matrix, matrix A is independent components and n is Gaussian noise. Therefore, we have:

$$\begin{aligned}z(k)&=W^T(k)Y(k)=W^T(k).H.A(k)+n'(k)\\ &=G^T(k)A(k)+n'(k)\end{aligned} \tag{16}$$

In this algorithm we find a value for $\mathbf{W}$ that maximizes the non-Gaussian property. This algorithm uses the Kurtosis metric to estimate the non-Gaussian property of separated signals. Thus we have:

$$\begin{bmatrix}z_1(k)\\ z_2(k)\end{bmatrix}=\begin{bmatrix}w_{11} & \cdots & w_{q1}\\ w_{12} & \cdots & w_{q2}\end{bmatrix}.\begin{bmatrix}\mathbf{y_1}\\ \mathbf{y_2}\\ \vdots\\ \mathbf{y_q}\end{bmatrix}=\begin{bmatrix}g_{11} & g_{12}\\ g_{21} & g_{22}\end{bmatrix}.\begin{bmatrix}\mathbf{a_1}\\ \mathbf{a_2}\end{bmatrix} \tag{17}$$

Finally, the blind source separation problem formulation can be written as the following optimization problem:

$$\begin{cases}\max\limits_{G}\{F(G)=\sum\limits_{j=1}^{2}\left|K(z_j)\right|\}\\ Subject\,to: G^H G=I_2\end{cases} \tag{18}$$

where I_2 is identity matrix, and:

$$K(x)=E(|x^4|)-2E^2(|x|^2)-|E(x^2)|^2 \tag{19}$$

B. BSS Based Spectrum Sensing

After solving the optimization problem and finding the best value for $\mathbf{W}$ that maximizes the cost function, we have two separated signals. Notice that we measure the non-Gaussian property by Kurtosis metric. Surly the Kurtosis of Gaussian noise is equal to zero. The cost function that we maximize is:

$$F(G)=\sum_{j=1}^{2}\left|K(z_j)\right|=|K(z_1)|+|K(z_2)| \tag{20}$$

After maximizing of the $F(G)$, each absolute term will be maximized, and if each absolute value is greater than a threshold, it means that there is an independent signal. Therefore, we obtain the following rule:

If CR transmitter is in operation:

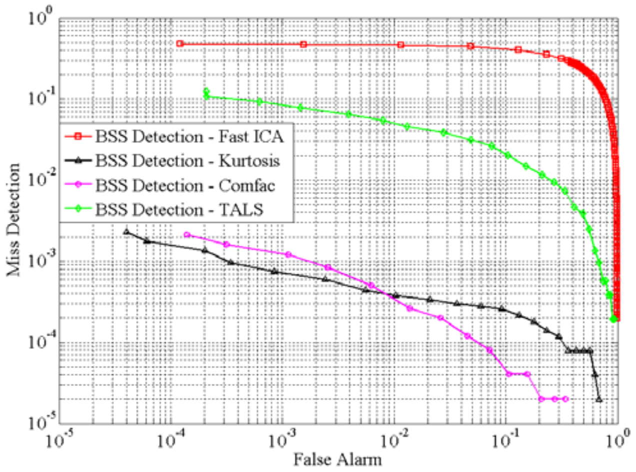

Figure 2. The miss-detection probability versus the false-alarm probability for the comparison between the proposed Kurtosis based spectrum sensing method and the other BSS methods. SNR=5dB, SUs number = 10 , CR transmitter is NOT in operation.

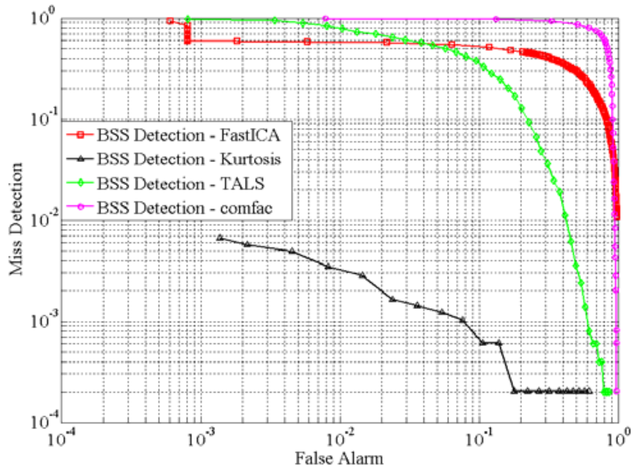

Figure 3. The miss-detection probability versus the false-alarm probability for the comparison between the proposed Kurtosis based spectrum sensing method and the other BSS methods. SNR=5dB, SUs number = 10 , CR transmitter is in operation.

- If we have two independent component (both of absolute values are greater than a threshold), it means that PU transmitter is in operation.
- If we have one independent component (just one of the absolutes has a great value and the other one is small), it means that PU transmitter is not in operation.

If CR transmitter is not in operation:

- If we have one independent component (just one of the absolutes has a great value and the other one is small), it means that PU transmitter is in operation.
- If we don't have any independent component (both absolute values are small), it means that PU transmitter is not in operation.

This rule can be used to sense the channel

IV. Simulation Results And Discussion

In this section, simulation results are presented and compared with other classic methods. We show the results as ROC curves. The ROC curve shows the probability of miss detection versus the probability of false alarm for each threshold. The method with better performance has lower miss detection probability in fixed false alarm probability. Through the simulations, the transmitted power in both primary and secondary transmitter is normalized to one. The simulation is provided for different number of users. The SNR is set to 5 dB and we compare different methods including the method that used in [8]. We have used MATLAB to simulate the proposed sensing method and compare it with other methods.

In Fig.2 the CR transmitter is not in operation. The SNR is set to 5 dB and the cognitive users' number is set to 10. We compare different methods for BSS in spectrum sensing. Fast ICA was proposed in [8] and Kurtosis based is proposed in this paper. The Comfac and TALS method in BSS are proposed in [9] to separate CDMA signals. It can be seen from the curve that in low miss detection probabilities, Comfac method has a better performance than our proposed method.

In Fig.3, the cognitive transmitter is in operation, the SNR is set to 5 dB and cognitive users' number is 10. Different methods for BSS are applied and compared. This simulation shows that our proposed method outperforms the other methods. The Comfac method performance changes extremely if the cognitive user is in operation.

V. Conclusion

CR is intended to use spectral resources opportunistically and spectrum sensing is one of the main parts in each CR system. The performance of the employed spectrum sensing method is very important. Performing spectrum sensing and transmitting data simultaneously can help us to improve the performance of CR systems.

In this paper, we introduced a new method to separate signals for blind source separation based spectrum sensing, that improves the ROC curve of spectrum sensing. BSS based spectrum sensing can sense the PU even if the SU transmitter is in operation. Simulation results illustrated that in both situations whether the SU transmitter is in operation or not, our proposed Kurtosis based method outperforms other classical methods considerably.

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