A Blind Source Separation-Based Positioning Algorithm for Cognitive Radio Systems

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Abstract: In Cognitive Radio (CR) networks, estimating the location of primary users can be used to avoid interfering primary users and exploit spatial resources by using some relaying or beamforming schemes. In this paper, we propose an algorithm to find the position of the primary users by exploiting blind source separation techniques. While conventional positioning algorithms proposed for CR networks need to use antenna arrays to estimate the position of more than one primary user, the main advantage of the proposed method is that it can estimate the position of more than one primary user at once, by using only a single antenna. Simulation results confirm the adequacy of the proposed method with an acceptable accuracy compared to conventional positioning techniques.

Key words: Blind source separation, cognitive radio, kurtosis, positioning and localization

INTRODUCTION

Cognitive Radio (CR) (Haykin, 2005) is referred to as an intelligent wireless communication system that is aware of its surrounding environment by adapting its parameters accordingly (parameters such as carrier frequency, power, etc.). The main advantage of a CR system is to utilize the unused part of the spectrum in both time and frequency. Two different type of users are present in each CR network:

- Primary or licensed users (PU) and
- Secondary or unlicensed users (SU)

The SU aims at finding spatial or temporal spectrum holes to access them opportunistically. To this end, each CR network should have a spectrum sensing part to determine whether a specific spectral resource is empty or occupied.

In order to identify spatial resources, the CR network should dispose of a localization unit to find the position of the primary user. Then, beamforming techniques can be exploited in order to prevent harmful interference to PUs. This makes the coexistence of PUs and SUs possible even when the PUs are in operation. This approach is commonly referred to as overlay spectrum sharing (Zander, 2009., (Peha, 2005).

Several algorithms are proposed in the literature for estimating the position of PUs in a CR network. These algorithms can be classified into two main families:)

- Range-based algorithms and
- Range-free algorithms (Arslan, 2007)

In range-based algorithms, the Time of Arrival (TOA), the Received Signal Strength Indicator (RSSI) or the angle (or direction) of arrival (AOA) statistics of the received signal is used to estimate the location of different sources that are in operation in the network. In the range-free method, there are three approaches referred to as hop-count-based, centroid, and area-based schemes (Arslan, 2007).

Let us describe some conventional positioning methods, such as Time of Arrival (TOA) and Time Difference of Arrival (TDOA) belonging to the family of range-free methods. In TOA, each user calculates the time of arrival of the signal based on which the distance is estimated. In TDOA, the time difference of arrival between users where one of them is the reference is first calculated. Thus, each pair of users can estimate the position of the source signal on a hyperbola and finally the position is determined by the intersection of such hyperbolas. Although the RSS approach is similar to the TOA method, where the position of the source signal is determined by the intersection of circles, however in RSS, the radius of circles is estimated by the received power at each user in contrast to TOA where the delay of the received signal determines the radios of circles.
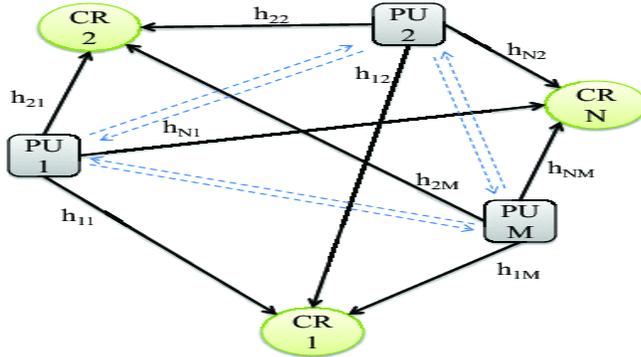
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Fig. 1: Considered network model composed of M primary transceivers and N cognitive radio users. The channel between the i-th PU and the j-th CR user is denoted as $h_{j,i}$

In Celebi and Arslan (2007), an adaptive positioning system for CRs has been proposed that combines the TOA and the RSS information. In addition, some other references such as Kazemi *et al.*(2010b) and Kazemi *et al.* (2010a) have also proposed positioning algorithms by combining RSS and AOA. An iterative localization algorithm is introduced in (Ma *et al.*, 2010) that is based on a weighted least-squares method. AOA techniques are usually implemented by means of antenna arrays (Arslan, 2007). However, one of the practical limitations in each CR network is that the cost and complexity of CR terminals must be as low as possible. Therefore, reducing the number of antennas used at a SU is of practical importance.

Blind Source Separation (BSS) is a signal processing technique that can separate for instance, non Gaussian and independent source signals from their linear (or convolutive) combination without any *prior* knowledge about the sources and the channel (Choi *et al.*, 2005). Recently in Tafaghodi Khajavi *et al.*(2010), the authors have used BSS for spectrum sensing in CR systems. In Fiori and Burrascano(2002) a localization method based on BSS has been proposed that uses BSS to estimate the channel matrix. To overcome the scaling ambiguity, the latter work assumes one of the sensors used for location estimation as the reference sensor and then normalizes all estimated channel coefficients by the estimation madded by the reference sensor.

In this study we don't have a reference sensor, in fact we use all possible combination of separation matrix in order to localize PU in CR network. We also assume shadowing effect in our channel model and cancel this effect by averaging. We compare our method with the method that proposed in Fiori and Burrascano (2002).

In this study we propose a BSS-based positioning algorithm for PU localization in CR networks. The proposed algorithm does not need any *prior* information about the channel and the source signals. Another advantage of our proposed method is that the processing is performed at the cognitive fusion center, leading to a reduction of the hardware complexity at CR terminals. In addition, our proposed method can localize more than one source at once as suitable in each CR network. Moreover, in contrast to (Fiori and Burrascano, 2002) that considers only one sensor as reference, we propose an averaging scheme among the observations made by sensors for improving the accuracy of the PU's location estimation.

SYSTEM MODEL

In this section, we first propose the network model and then we describe our main assumptions about the considered system and channel models. The assumed system model is illustrated in Fig. 1. In the considered model, the primary network consists of M primary transceivers. The secondary network coexists with the primary network and consists of N SUs that are uniformly distributed in the network. These SUs aim at determining the position of the PUs. Also we assume that N > M. When the SUs are not in operation, the received signal at the j-th SU can be written as:

$$x_j = h_{j,1}S^{PU_1} + h_{j,2}S^{PU_2}+...$$
$$+ h_{j,M}S^{PU_M} + z_j \tag{1}$$

where the vector $x_j = [x_{i,1}...,x_{j,L}]$ denotes the sensed symbols at the j-th SU and L denotes the number of symbols used for spectrum sensing that is our frame length. $s^{PU_i} = [s_1^{PU_i},..., s_1^{PU_i}]$ denotes the i-th transmitted PU signal. The noise vector $z_i = [z_{i,1},..., z_{i,L}]$ is assumed to be Zero-Mean Circularly Symmetric Complex Gaussian (ZMCSCG) with distribution $z_j \sim CN(0, \sigma^2_{zj}I_L)$, and $h_{i,j}$ is the channel frequency gain between the i-th SU and the j-th PU. Moreover, channel coefficients are assumed to be constant during a frame. We thus assume a quasi-static channel model.

For convenience, we also introduce the following more compact system model which is equivalent to (1):

$$X = HS + Z \qquad (2)$$

where,

$$\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,L} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,L} \\ \vdots & \vdots & & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,L} \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \qquad (3)$$

$$\begin{bmatrix} S_1^{PU_1} & S_2^{PU_1} & \cdots & S_L^{PU_1} \\ S_1^{PU_2} & S_2^{PU_2} & \cdots & S_L^{PU_2} \\ \vdots & \vdots & \cdots & \vdots \\ S_1^{PU_M} & S_2^{PU_M} & \cdots & S_L^{PU_M} \end{bmatrix} = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_M \end{bmatrix} \qquad (4)$$

$$H = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,M} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,M} \\ \vdots & \vdots & & \vdots \\ h_{N,1} & h_{N,2} & \cdots & h_{N,M} \end{bmatrix} \qquad (5)$$

and

$$Z = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \cdots & Z_{1,L} \\ Z_{2,1} & Z_{2,2} & \cdots & Z_{2,L} \\ \vdots & \vdots & & \vdots \\ Z_{N,1} & Z_{N,2} & \cdots & Z_{N,L} \end{bmatrix} = \begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_N \end{bmatrix} \qquad (6)$$

we now introduce the path loss model into the channel coefficient that we have defined in (5). Considering the shadowing effect in a log-normal path-loss model, we have:

$$P^{rx} = K \frac{p^{tx}}{d^\alpha S} \qquad (7)$$

where, P^{rx} is received power and P^{tx} is transmitted power, $S = 10^{0.1X}$ is a Log-Normal random variable and X is a Gaussian random variable with zero mean and variance σ^2. Parameter d is the distance between the transmitter and the receiver, and K is the channel constant (Munoz *et al.*, 2009). Using this model, the received power at the j-th SU can be written as:

$$P_j^{rx} = K \frac{p_1^{tx}}{d_{j,1}^\alpha S_{1,j}} + K \frac{p_2^{tx}}{d_{j,2}^\alpha S_{2,j}} +$$
$$\ldots + K \frac{p_M^{tx}}{d_{j,M}^\alpha S_{M,j}} \qquad (8)$$

where, K is the channel constant, P^{tx}_i is the transmitted power of the i-th PU, P^{rx}_j is the received power at the j-th SU, $d_{j,i}$ is the distance between the i-th PU and the j-th SU. Note that an advantage of our proposed algorithm is that unlike existing methods, we assume that the parameter K in (8) is unknown.

Proposed positioning algorithm based on blind source separation:
Blind source separation: The aim of (BSS) is to recover original signals from a mixture of signals (Choi *et al.*, 2005). Considering the observation model (2), matrix S is the source signal, H is the mixing matrix and X represents the received linearly mixed signals. BSS aims at recovering S from X. The estimated signal Ŝ can be written as:

$$\hat{S} = \hat{W}X = \hat{W}(HS + Z) =$$
$$(\hat{W}H)S + \hat{W}Z = GS + \hat{W}Z \qquad (9)$$

where, Ŵ is the estimated un-mixing matrix. There are several methods to find Ŵ based on optimizing a cost function such as maximizing the Kurtosis of the estimated source signals, for instance. We assume that the number of observations is greater than the number of independent source signals so that the optimization algorithm converges. In this paper, we employ the maximization of the Kurtosis of the source signals (Papadias, 2000) as the criteria for signal separation. We have:

$$\begin{cases} \arg_G \min \sum_{j=1}^{M} \left| K(\hat{S}_j) \right| \\ Subject\ to: GG^H = I_M \end{cases} \qquad (10)$$

where, $\hat{s}_j$ is the j-th row of Ŝ and I stands for identity matrix and:

$$K(x) = E(|x|^4) - 2E^2(|x|^2) - |E(x^2)|^2 \qquad (11)$$

The output of this optimization problem is Ŵ. We can multiply this estimated un-mixing matrix by observation X and the result is the estimated source signals. The inverse of estimated un-mixing matrix is the estimated mixing matrix (Ĥ) that we assumed to be unknown.

After estimating S by BSS, there remains two main ambiguities. In fact BSS will only give the separated matrix S up to a column permutation and a scaling factor (Choi *et al.*, 2005). Permutation means that the first signal in the BSS output is not guaranteed to be the first input source. In this regard, we can exchange the columns in the estimated $\hat{H}$ matrix. The scaling ambiguity means that each column of $\hat{H}$ may be multiplied by an unknown constant term related to the transmission power. Interested readers are urged to read (Choi *et al.*, 2005) and (Papadias, 2000) for a complete survey of BSS method, if necessary.

BSS based positioning algorithm in CR networks: The proposed positioning method in this paper is based on the channel gains that are estimated from the BSS algorithm, i.e., $\hat{H}$ that has N rows and M columns. Obviously, each column of $\hat{H}$ corresponds to a specific PU. The initial model (2) can be rewritten in an equivalent form as:

$$\begin{cases} x_1 = \hat{h}_{11}s_1 + \hat{h}_{12}s_2 + \dots + \hat{h}_{1M}S_M + Z_1 \\ x_2 = \hat{h}_{21}s_1 + \hat{h}_{22}s_2 + \dots + \hat{h}_{2M}S_M + Z_2 \\ \\ x_N = \hat{h}_{N1}s_1 + \hat{h}_{N2}s_2 + \dots + \hat{h}_{NM}S_M + Z_N \end{cases} \quad (12)$$

where, $\hat{h}_{i,j}$ are the elements of the estimated channel matrix $\hat{H}$. Now, we have to estimate the i-th primary user's position from $\hat{h}_{i,j}$'s; $j = 1,2,\dots,N$. Notice that all of these elements may be multiplied by a constant number.

Now, we would like to use the relation between channel coefficients, $h_{i,j}$, and the distance between PU transmitters to the SU receivers, to estimate the location of the PU transmitters, from the estimated channel matrix $\hat{H}$. After BSS, we can have the model $P^{rx} = h^2 P^{tx}$ where h is the channel gain (the matrix elements), and comparing to (7) we find:

$$h^2 = \frac{K}{d^\alpha S} \quad (13)$$

Let us consider the ratio of two different channel coefficients in the same environment:

$$\frac{h_{m,j}}{h_{n,j}} = \frac{d_{n,j}^{a/2} S_1^{1/2}}{d_{m,j}^{a/2} S_2^{1/2}} \quad (14)$$

In order to explain the proposed method for PU localization, we consider two SUs and one PU scenario for the sake of simplicity. In this sc4enario, the received signal at each SU can be written as:

$$\begin{cases} x_1 = \hat{h}_{11}S_1 \\ x_2 = \hat{h}_{21}S_1 \end{cases} \quad (15)$$

where $\hat{h}_{11}$ and $\hat{h}_{21}$ are the channel coefficients between PU and SU1 and SU2 respectively, and $\hat{h}_{11}$ and $\hat{h}_{21}$ are the corresponding estimated values as a result of applying the BSS method. Remember that in the demixing process, the columns of the estimated matrix $\hat{H}$, can be multiplied by a constant, say k. In the assumed simple scenario here, this means that:

$$\begin{cases} \hat{h}_{11} = kh_{11} \\ \hat{h}_{21} = kh_{21} \end{cases} \quad (16)$$

Then, from (14) we have:

$$\frac{d_{21}}{d_{11}} = \left(\frac{\hat{h}_{11}}{\hat{h}_{21}}\right)^{\frac{2}{a}} \left(\frac{S_2}{S_1}\right)^{\frac{1}{a}} = \left(\frac{\hat{h}_{11}}{\hat{h}_{21}}\right)^{\frac{2}{a}} (10\frac{0,1(x_2 - x_1)}{a}) \quad (17)$$

where, d_{11} and d_{21} are the distances between PU and the first and second SU, respectively, and x_is are normal random variables. The random term in (17) makes inaccuracy in estimating the location, and we can overcome to this inaccuracy by averaging the estimated position. It means that the primary user is located on a point that the ratio of distance from this point to each SU is a constant number. These points are on circles with known center and radius. Therefore, each pair of the SUs can estimate the position of each PU on a circle with known center and radius, and then we can find the position of the PU as the intersection of all these possible circles (Fig. 2).
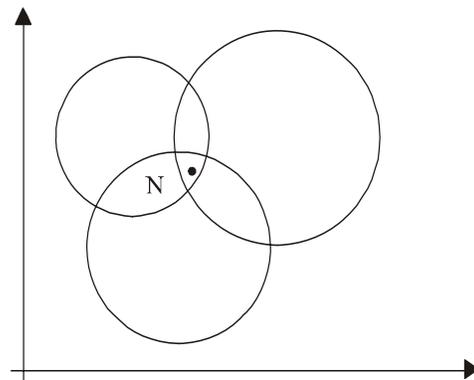

Fig. 2: Intersection of 3 circles corresponding to the unknown location; each circle is related to two SUs. As illustrated, we have to find the point *N* that has a minimum distance from all these possible circles

These circles have not intersection in the same point because of noise. In this problem each pair of two SUs gives us a known circle and we have to find the N point in this problem.

We do this procedure for each column of matrix Ĥ to stimate the location of each PU. In fact there are M(M-1)/2M possible circles for SUs for determination of each PU's location.

Due to the noise and shadowing effect, the intersections of these circles are not a single point. Therefore, we find the best coordinate for the PU that has a minimum distance from all these circles, by using the following equation:

$$X_K^{PU} \ Y_K^{PU} \sum_{J=1}^{M-1} \sum_{i=j+1}^{M}$$

$$\left| \sqrt{\frac{(x_k^{PU} - x_i^{SU})^2 (y_k^{PU} - y_i^{SU})^2}{(x_k^{PU} - x_j^{SU})^2 (y_k^{PU} - y_j^{SU})^2}} - \frac{d_{ik}}{d_{jk}} \right| \quad (18)$$

where, (x_k^{PU}, y_k^{PU}) is the k-th primary user's coordinate and (x_k^{SU}, y_k^{SU}) is the i-th SU's known coordinate. The solution of this equation which is a multilateration problem (Munoz *et al.*, 2009).

Equation (18) is a surface in the (x, y, z) plane and we want to find the minimum of this surface. One of the widely used method to solve Eq. (18) is Newton's method.

Note that in the aforementioned proposed method, we assume that the PU locations can only change every L symbols. Therefore, depending on the speed of the PU, we can extend L or we can repeat this approach for several times and average the results to reach a better performance.

RESULTS AND DISCUSSION

Throughout simulations, we consider a scenario with four SUs and two PUs. An AWGN noise with a fixed variance is assumed for all users. The PU's power is fixed
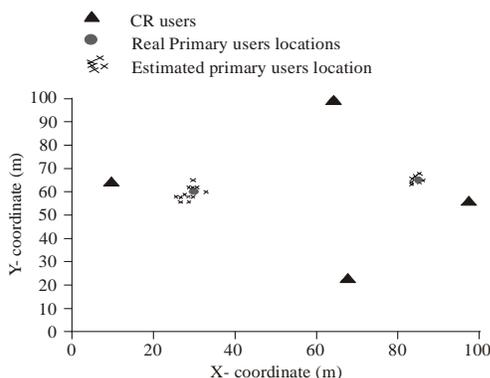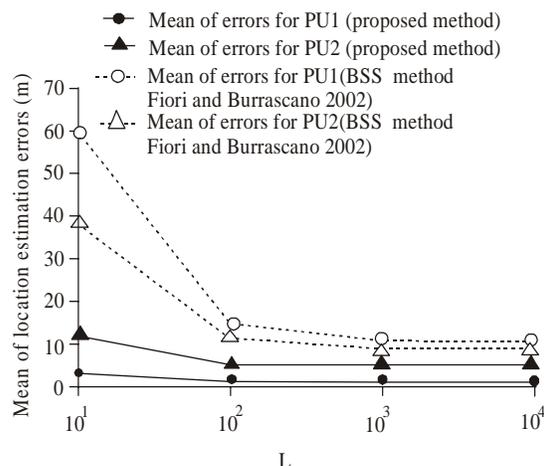

Fig. 3: Estimated PU locations
SNR = 10dB and =2

Fig. 4: Mean of location estimation errors versus frame length parameter L. The SNR is fixed to 10 dB, and the channel attenuation factor a in (7) is set to 3, we have not considered the shadowing effect and we use only one frame of length L to estimate the unknown location

so as to provide a desired SNR in the other PU. Other users may receive greater or less than this normalized

SNR value. However, the employed localization algorithm in blind and does not need to know this SNR value.

To analyze the performance of the proposed method, we use the mean of the error which is defined as the difference between the estimated location of PUs and its exact value.

In Fig. 3, we have illustrated the general behavior of the proposed method where the SNR at each PU is equal to 10 dB, and the channel attenuation factor a in (7) is set to 2. We observe that the location estimated by the proposed positioning algorithm is very close to the exact unknown Pus'location.

We have illustrated in Fig. 4 the mean location estimation error of the proposed algorithm. We observe that the proposed algorithm outperforms the conventional positioning technique for both PU1 and PU2.

In Fig. 5 we show the location estimation error at a fixed SNR for different values of a. In fact the attenuation factor a depends on the propagation channel. The SNR is set to 10 dB at each PU and we use one frame of PU to estimate the location, and the frame length L is equal to 100. Again we observe the superiority of the proposed algorithm compared to the conventional technique.

In Fig. 6 we have shown the mean location estimation error for different values of SNRs at each PU. Again, from this figure, we observe that the proposed method is more accurate than the competitive conventional method.

To analyze the behavior of the proposed method versus the shadowing effect, we have depicted in Fig. 7,
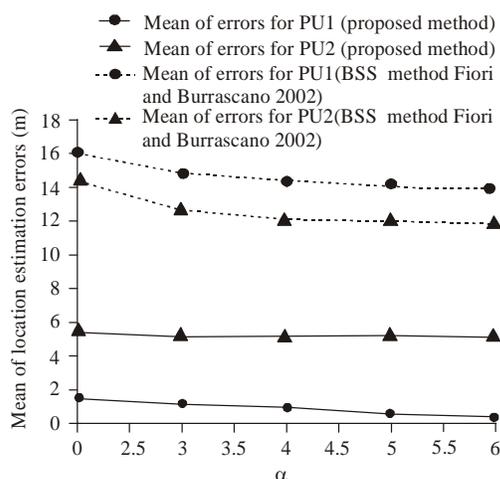
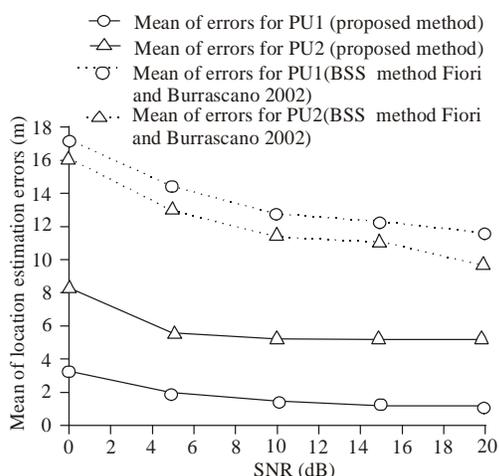Fig. 5: Mean of location estimation errors versus the channel attenuation factora

Fig. 6: Mean of location estimation errors versus SNR at each PU. The channel attenuation factor σ in (7) is set to 2, we have not considered the shadowing effect and we use only one frame of length L to estimate the location

the average location estimation errors versus the shadowing parameter σ. Although we observe that the accuracy of both considered algorithms decreases when σ increases, however we observe that the proposed algorithm outperforms the conventional technique even for large values of parameter σ.

CONCLUSION

A new positioning method for CR systems has been proposed in this paper. The proposed method was based on a BSS technique and has the advantage of estimating more than one source at once compared to conventional
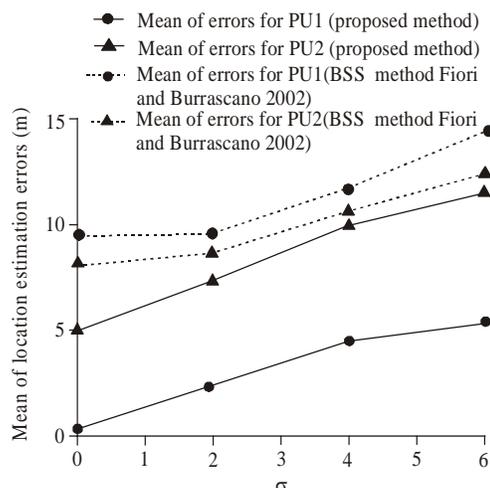

Fig. 7: Mean of location estimation errors versus the shadowing parameter σ. The SNR at each PU is equal to 10 dB and the channel attenuation factor σ in (7) is set to 3 and the frame length L is equal to 100 , we have averaged over 10 frames to reduce the shadowing effect.

techniques that inherently can not detect more than one source. Moreover, the proposed method works in a blind manner i.e., without requiring any *a priori* information about primary sources. Moreover, we proposed an averaging scheme among the observations made by cognitive users for improving the accuracy of the PU's location estimation. Simulation results indicated that the accuracy of the proposed method outperforms that of conventional BSS-based positioning techniques. By applying the proposed method and finding the location of the PUs, we can exploit beamforming techniques and operate in an overlay manner in the CR network.

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