A Received Signal Strength-based Primary User Localization Scheme for Cognitive Radio Sensor Networks Using Underlay Model-based Spectrum Access

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Abstract

For cognitive radio sensor networks (CRSNs) that use underlay-based spectrum access, the location of the primary user (PU) plays an important role in the power control of the secondary users (SUs), because the SUs must keep the minimum interference level required by the PU. Received signal strength (RSS)-based localization schemes provide low-cost implementation and low complexity, thus it is suitable for the PU localization in CRSNs. However, the RSS-based localization schemes have a high localization error because they use an inexact path loss exponent (PLE). Thus, applying a RSS-based localization scheme into the PU localization would cause a high interference to the PU. In order to reduce the localization error and improve the channel reuse rate, we propose a RSS-based PU localization scheme that uses distance calibration for CRSNs using underlay model-based spectrum access. Through the simulation results, it is shown that the proposed scheme can provide less localization error as well as more spectrum utilization than the RSS-based PU localization using the mean and the maximum likelihood calibration.

Keywords: cognitive radio sensor network, received signal strength, primary user localization, distance calibration, underlay model

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1. Introduction

Due to the spectrum scarcity and the needs for more intelligent communication systems in wireless environments, cognitive radio (CR) technology has recently received considerable attention because it can improve spectrum utilization and support high adaptability to dynamic wireless environments [1-3]. In many cases, the licensed bands used by the primary user (PU) that has the license are underutilized from 15% to 85% with regard to time and space. CR technology can enable a secondary user (SU) to opportunistically access an unused portion of the licensed bands. In regard to the methods for opportunistic spectrum access that improve spectrum utilization, CR technology can be categorized into the following two approaches [4-6]: i) the *overlay approach*, in which the SUs identify an unused portion of the licensed bands through the spectrum sensing process and opportunistically access the available spectrums for data transmission; ii) the *underlay approach*, in which the communication of the SUs coexists with that of the PUs on the same channel, and the SUs avoid interfering with the communication of the PUs by using power control such as the interference temperature limit (ITL) [7-9].

CR sensor networks (CRSNs) have a PU detection problem similar to the hidden terminal problem that commonly occurs in the wireless sensor networks (WSNs); this is one of the critical issues in spectrum sensing and spectrum decision of CR technology, and it is referred to as the *hidden receiver problem* [10,11]. Since PU receivers have no duty to announce their reception to SU transmitters, CRSNs cannot combat this problem without sharing local and global information on the detection of the PUs. Hence, CRSNs need to be a network based on either fusion centers or clusters. Such an approach has been studied in cooperative spectrum sensing (CSS) research [12-15].

To use the underlay approach in CSS-based CRSNs, a fusion center (FC) may need location information on the PUs. Unlike the overlay approach, the location of the PUs plays an important role for power control in the underlay approach because the core of the underlay approach involves keeping the minimum interference level required by the PUs. Hence, the location information on the PUs can help the SUs use more much portions of the licensed bands without interference with the communication of the PUs, in which the SUs have to be able to adjust their transmission power.

In the context of implementing a localization scheme in CRSNs, the use of received signal strength (RSS)-based localization schemes can be a good choice for estimating the PU location because it can provide the implementations with low-cost of size, deployment, power consumption, communication range, computation, and etc., which are required as the characteristics of CRSNs. However, the RSS-based localization schemes have a high localization error because they use an inexact path loss exponent (PLE). In general, the PLE in the RSS-based localization schemes is considered a fixed value, but in reality, the PLE varies over the network. Thus, the RSS-based localization schemes that use a fixed PLE are not suitable for PU localization.

In this study, we propose a RSS-based PU localization scheme that uses distance calibration to reduce the localization error and to improve the channel reuse rate for an underlay model-based spectrum access in CRSNs. The rest of this paper is organized as follows. In Section 2, the related works are briefly reviewed. In Section 3, the network model is described. In Section 4, the proposed RSS-based PU localization scheme is presented. The simulation results are shown in Section 5. Finally, the conclusions are given in Section 6.

2. Related Work

The recent literatures of the RSS-based localization can be largely classified into two trends: i) the RSS-based localization scheme with PLE knowledge of wireless environment, which means an exact PLE is given or the PLE is locally identical; ii) the RSS-based localization with PLE estimation, which considers a PLE calibration approach. Specifically, in the cases of the former, Yi et al. [16] dealt with the PLE as a fixed parameter in WSNs because they assumed the physical environment is in stationary. Similarly, Nazar et al. [17] used the least square method to obtain the PU location in CRNs, where they considered the identical PLE between the PU and all the SUs that detect the PU on the channel. Praful et al. [18] regarded the PLE as locally the same in CRNs where consists of some areas with different PLE. These schemes above have two main problems: i) the schemes cannot cover the localization errors when the structure of the physical environment changes; ii) since the PLE between the PU and the SU in practice has variations according to time and space, and the localization error is very sensitive to the PLE fluctuations, the schemes may output high localization errors. In the cases of the latter, Cong et al. [19] and Hoang et al. [20] considered the linearity of the PLEs between the unknown node and the anchor nodes in WSNs and CRNs, respectively. However, the assumption of the linearity has the problem that can be ensured only in the particular environment. Junho et al. [21] used an iterative PLE estimation method targeting a fixed PLE. Thus, if the fixed PLE has variations, the convergence time of the iterative method may largely increase. In addition to [21], the authors also considered the linearity of the PLEs similar to [19,20]. Hence, the localization scheme in [21] will encounter the same problem. Qun et al. [22] exploited the curve fitting method for estimating the PLE, based on the big data of the RSS indicators (RSSI) from the actual environment. Thus, this approach may not be able to reflect the actual PLE state as the structure of the actual environment quickly changes.

3. Network Model

In this section, we describe the network model considered in this paper. The following assumptions are made on the PU and the SU networks: the licensed band for the PUs is divided into N channels; consequently, the number of the PUs is a maximum of N; the SU network is considered as a CRSN based on CSS, thus there is a fusion center (FC) that schedules spectrum sensing, collects the local sensing data, and determines whether the channels are available for the SUs or not; each SU has the ability to know its own location.

Fig. 1 illustrates the network model considered in the paper. All the SUs periodically perform spectrum sensing according to a sensing schedule given by the FC, and report their local sensing data to the FC on a pre-determined control channel. The FC sorts N channels into available and unavailable channels, based on the reports. Then, for available channels, the FC conducts channel assignments for the SUs in the overlay approach, while unavailable channels are dealt with in the underlay approach where they can be reused through power control only if there is no harmful interference to the PUs that use the same channel. The FC utilizes a RSS-based PU localization scheme using distance calibration to estimate the location of the PUs for unavailable channels, and then checks whether there are the SUs that can reuse the unavailable channels according to a given rule.

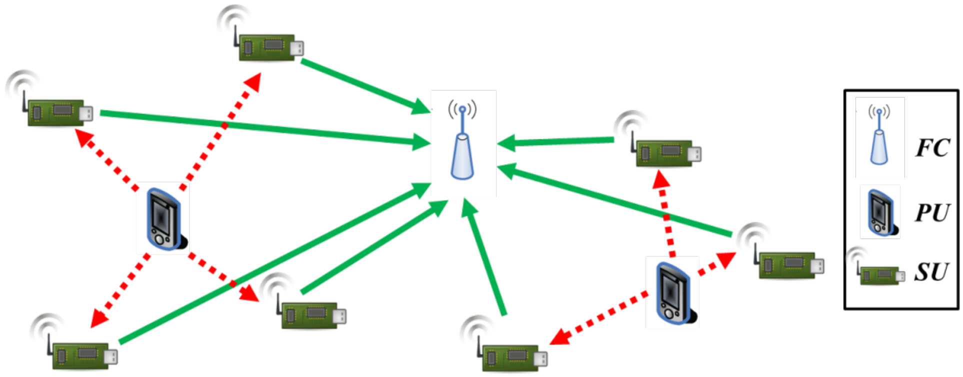

Fig. 1. Network model

The signal propagation model for the RSS-based PU localization is built up as follows: for efficient localization performance analysis of the signal propagation, we consider a stochastic model of an average RSS value, as expressed in [23]:

$$P_{rx}(d) = P_{tx} \cdot \left(\frac{\lambda}{4\pi}\right)^2 \cdot \frac{1}{d^\tau} \tag{1}$$

where d is the distance between a transmitter and a receiver; $P_{rx}(d)$ is the received power; P_{tx} is the transmission power; λ is the wavelength; and τ is the path loss exponent.

Based on the lognormal shadowing model, which is a more practical model because it considers the presence of obstacles [24-26], the path loss is defined in decibel (dB) as:

$$PL^{dB}(d) = PL^{dB}(d_0) + \tau \cdot 10\log(d / d_0) + X_\sigma^{dB} \tag{2}$$

where d_0 is the reference distance; $PL^{dB}(d)$ and $PL^{dB}(d_0)$ are the path loss in dB at the distance d and d_0, respectively; X_σ^{dB} is the Gaussian random variable with mean zero and variance σ^2 called the shadowing variance.

To ensure that a SU does not interfere with the communication of the PU, the SU must satisfy the minimum signal-to-interference-plus-noise-ratio (SINR) required by the PU, denoted as $\gamma_{\min}$. Thus, when the *i*-th SU and a PU coexist on a channel, the SINR of the PU should satisfy the inequality:

$$\frac{\dfrac{Q_{PU}}{PL^{real}\left(d_{\max}^{PU}\right)}}{Q_n + \dfrac{Q_i}{PL^{real}\left(d_{ij}\right)}} \geq \gamma_{\min} \tag{3}$$

where Q_{PU} and Q_i are the transmission power of the PU and the *i*-th SU, respectively; Q_n is the noise power; $PL^{real}\left(d_{\max}^{PU}\right)$ is the path loss in real scale at the PU maximum transmission distance $d_{\max}^{PU}$; and $PL^{real}\left(d_{ij}\right)$ is the path loss at the distance d_{ij} between the *i*-th SU and *j*-th

SU, which is a neighbor to the *i*-th SU. Hence, the non-interfering maximum transmission power for the *i*-th SU can be obtained from:

$$Q_i\left(d_{ij}\right)=\frac{PL^{real}\left(d_{ij}\right)\left(Q_{PU}-\gamma_{\min}Q_nPL^{real}\left(d_{\max}^{PU}\right)\right)}{\gamma_{\min}PL^{real}\left(d_{\max}^{PU}\right)} \tag{4}$$

To apply the underlay model into CRSNs, the SU needs the PU knowledge at least on Q_{PU}, $d_{\max}^{PU}$, and $\gamma_{\min}$, which are usually available in the network.

4. Proposed RSS-based PU Localization Scheme

In this section, we propose a RSS-based PU localization scheme using distance calibration in order to reduce the localization error and improve the channel reuse rate. As mentioned in Section 3, the FC sorts N channels into available and unavailable channels after collecting local sensing data reported by the SUs. This sorting operation can be easily performed through a pre-defined decision rule such as AND rule, OR rule, or Half Voting rule. Therefore, we focus only on applying the underlay approach into the SU network considered in this paper.

In the subsections below, we will explain how to localize a PU, based on RSS values measured from the PU signal. The proposed scheme is summarized as follows: first, all the SUs carry out local sensing to detect PU channel occupations according to a sensing schedule given by the FC, and send a reporting message to the FC. At this time, the SUs can estimate PLEs amongst themselves and their neighbors through the reporting process. The estimated PLEs are included in the reporting message. Using the information given in the reporting messages, the FC sorts the channels into available and unavailable channels, calculates an average PLE and the distances between a PU and the SUs detecting the PU for each unavailable channel. Next, the FC performs distance calibration by comparing the calculated distance to the PU maximum transmission distance, and calculates the PU locations. Finally, the FC searches for the SUs that would not interfere with the communication of the PUs by using an adjusted transmission power.

4.1 Path Loss Exponent Estimation among Neighbors

While periodically performing local sensing, each SU sends a reporting message (R-MSG), which includes information on the local sensing data and its own location, to the FC. If a SU detects a PU signal on a sensing channel, the SU adds the RSS value measured from the signal into the R-MSG. Since the *i*-th SU can listen to the R-MSG from the *j*-th neighbor, the SU can estimate the PLE between itself and its neighbors by using:

$$\tilde{\tau}_{ij}=\frac{PL^{dB}\left(d_{ij}\right)-\left(PL^{dB}\left(d_0\right)+X_\sigma^{dB}\right)}{10\log\left(d_{ij}/d_0\right)} \tag{5}$$

4.2 Distance Calibration

In order to calculate the distances between a PU and the SUs detecting the PU, the FC should choose a temporal PLE (TPLE). Normally, TPLE is chosen as a fixed value in accordance with wireless environments, such as outdoors and indoors. Here, we use an average PLE of the SUs detecting a PU occupation on channel n, which is defined by:

$$\tau_{in}^{T} = \frac{1}{M_n} \sum_{j \in m_n, j \notin i} \tilde{\tau}_{ij} \tag{6}$$

where m_n is a set of the SUs detecting a PU occupation on channel n; and M_n is the number of the elements of the set m_n. With TPLE τ_{in}^{T}, the FC can calculate the distance d_{in} between the i-th SU and the n-th PU by:

$$d_{in} = \left(Q_{PU} \cdot \frac{\lambda}{4\pi} \cdot \frac{1}{RSS_{in}} \right)^{\frac{1}{\tau_{in}^{T}}} \tag{7}$$

where RSS_{in} is a RSS value of the i-th SU for channel n.

Due to the difference between the actual PLE and TPLE, d_{in} can exceed the PU maximum transmission distance $d_{\max}^{PU}$, which becomes a major cause that increases the localization error. To solve this problem, the *distance calibration* is used as follows:

***Step* 1.** Check for all of the unavailable channels

$$\text{For each unavailable channel, go to } \textit{Step } 2 \text{ if } d_{in} > d_{\max}^{PU}\text{. Otherwise skip.} \tag{8}$$

***Step* 2.** Update τ_{in}^{T} according to the rule below, and calculate d_{in} again by using Equation (7). After that, go to *Step* 1.

$$\tau_{in}^{T} = \min\left[\left(\max_{j \in m_n, j \notin i} \left(\tilde{\tau}_{ij} \right) \right), \left(\tau_{in}^{T} + \alpha \left(\max_{j \in m_n, j \notin i} \left(\tilde{\tau}_{ij} \right) - \tau_{in} \right) \right) \right] \tag{9}$$

where α is a constant from 0 to 1. If all the unavailable channels are skipped in *Step* 1, the distance calibration is completed.

4.3 PU Localization

Next, the FC calculates the location of the PUs for the unavailable channels using the least square (LS) method as follows: let (x_n, y_n) be the location of the n-th PU and (x_i, y_i) be the location of the i-th SU; then the distance $d_{i,n}$ between the i-th SU and the n-th PU can be obtained by:

$$d_{i,n} = \sqrt{\left(x_n - x_i\right)^2 + \left(y_n - y_i\right)^2} \tag{10}$$

Through manipulation of $d_{m_n(1),n}$ and $d_{m_n(2),n}$, we can obtain:

$$\begin{aligned} &2x_n\left(x_{m_n(1)}-x_{m_n(2)}\right)+2y_n\left(y_{m_n(1)}-y_{m_n(2)}\right) \\ &=x_{m_n(1)}^2+y_{m_n(1)}^2-x_{m_n(2)}^2-y_{m_n(2)}^2-d_{m_n(1),n}^2+d_{m_n(2),n}^2 \end{aligned} \tag{11}$$

where $m_n(k)$ for $k=1,...,M_n$ is the *k*-th element of the set m_n.
For M_n SUs, Equation (11) is extended as:

$$A\cdot\upsilon_n=B,\ \upsilon_n=\begin{bmatrix} x_n \\ y_n \end{bmatrix} \tag{12}$$

$$A=2\begin{bmatrix} \left(x_{m_n(1)}-x_{m_n(2)}\right) & \left(y_{m_n(1)}-y_{m_n(2)}\right) \\ \left(x_{m_n(1)}-x_{m_n(3)}\right) & \left(y_{m_n(1)}-y_{m_n(3)}\right) \\ \dots & \dots \\ \left(x_{m_n(1)}-x_{m_n(M_n)}\right) & \left(y_{m_n(1)}-y_{m_n(M_n)}\right) \end{bmatrix}$$

$$B=\begin{bmatrix} x_{m_n(1)}^2+y_{m_n(1)}^2-x_{m_n(2)}^2-y_{m_n(2)}^2-d_{m_n(1),n}^2+d_{m_n(2),n}^2 \\ x_{m_n(1)}^2+y_{m_n(1)}^2-x_{m_n(3)}^2-y_{m_n(3)}^2-d_{m_n(1),n}^2+d_{m_n(3),n}^2 \\ \dots \\ x_{m_n(1)}^2+y_{m_n(1)}^2-x_{m_n(M_n)}^2-y_{m_n(M_n)}^2-d_{m_n(1),n}^2+d_{m_n(M_n),n}^2 \end{bmatrix}$$

Using the LS method, the *n*-th PU's estimated location can be obtained as:

$$\tilde{\upsilon}_n=\left(A^TA\right)^{-1}A^TB \tag{13}$$

4.4 Channel Assignment for Reusable Channels

For the unavailable channels, the FC checks whether there are the SUs that satisfy Equation (14). If there exist certain SUs that satisfy the condition of Equation (14), the unavailable channels can be reused only for those SUs in the underlay approach.

$$\begin{gathered} R_n=\arg\max_{i=1,...,U}\left(d_{in}-\min_{j=1,...,U,\,j\neq i}\left(d_{\max}^{PU}+d_{ij}\right)\right) \\ \text{subject to}\left(d_{in}-\min_{j=1,...,U,\,j\neq i}\left(d_{\max}^{PU}+d_{ij}\right)\right)>0,\ \text{ and }\ Q_i\left(d_{ij}\right)\leq TP_{\max}^{SU} \end{gathered} \tag{14}$$

where U is the number of all the SUs in the CRSN; $TP_{\max}^{SU}$ is the maximum transmission power of the SU; and $Q_i(\cdot)$ can be obtained from Equation (4).

5. Simulation Results

Some assumptions and settings of the simulation environment are as follows: the whole number of the channels allowed for the licensed band is 25; the licensed band is underutilized by 25 PUs; the number of the SUs uniformly distributed in a 200 x 200 meter square is 50; there is a FC located at point (0,0); and the PLE is randomly changed in a uniform distribution pattern with a mean value of 3.85 and a variance of 0.4408. For performance comparisons, we consider two RSS-based PU localization schemes. One scheme utilizes the mean (MEAN) calibration, which is called *MEAN scheme* in this paper. In this scheme, a fixed PLE is utilized for the RSS-based PU localization, which can be obtained from pre-survey or empirical RSS data analysis before localization [17-18]. In the simulation, we consider a mean value of 3.85 for MEAN scheme. The other scheme utilizes the maximum likelihood (ML) calibration, which is called *ML scheme*. In this scheme, an appropriate PLE will be chosen based on the maximum likelihood approach for the RSS-based PU localization by considering the PLEs of the SUs that detect the PU [21,27-28]. For the implementation of ML scheme, we adopt the averaging way of the PLEs between the SU and its neighbors in which they all are the SUs that detect the PU, as in [21].

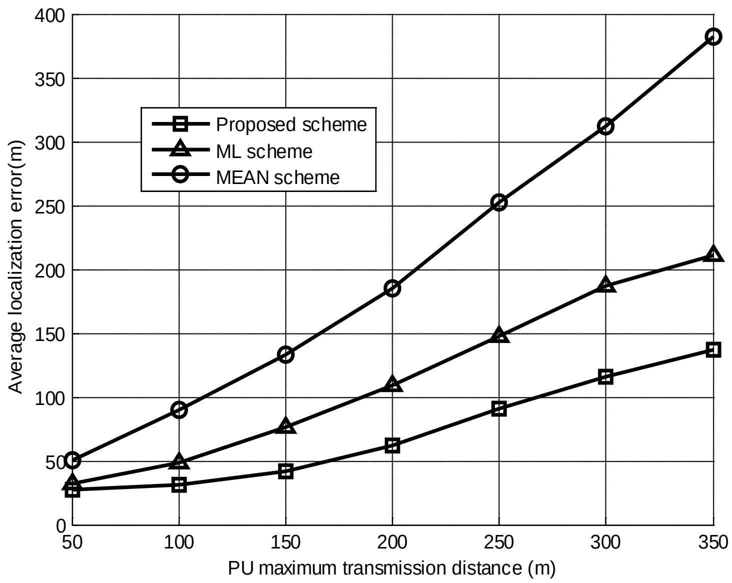

Fig. 2. Average localization error according to the maximum transmission distance of the PUs.

Fig. 2 shows the average localization error when the maximum transmission distance of the PUs increases and the shadowing variance of X_σ^{dB} is given as 1. Here, the localization error is defined as the Euclidean distance between the actual PU location and the estimated PU location. It is observed that the proposed scheme outperforms the other schemes in all the cases and has the lowest variation when the maximum transmission distance of the PUs increases.

Fig. 3 shows the average localization error when the standard deviation of X_σ^{dB} increases from 1 to 10 and the maximum transmission distance of the PUs is fixed at 200 meters (m). We can find that the performance of the proposed scheme is bounded at about 60 m. This result shows that the distance calibration works well under deep noise and can provide a boundary to the localization error.

Fig. 4 shows the channel reuse rate when the maximum transmission distance of the PUs increases and the shadowing variance of X_{σ}^{dB} is given as 1. Here, the channel reuse rate is defined as the ratio between the total number of reusable channels determined by a localization scheme and the number of actually reusable channels. All schemes have good performance between 50 m and 100 m, although the localization error exceeds one half of the PU maximum transmission distance. It is mainly due to the fact that the interference range from the localization error is relatively smaller than the entire size of the SU network. It is observed that the proposed scheme provides more radio resources than the other schemes for all the cases of the PU maximum transmission distance.

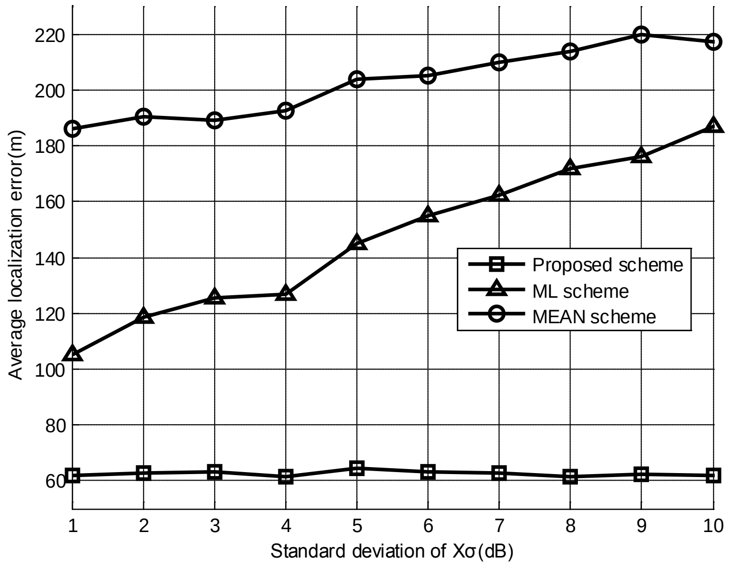

Fig. 3. Average localization error according to the standard deviation of X_{σ}^{dB}

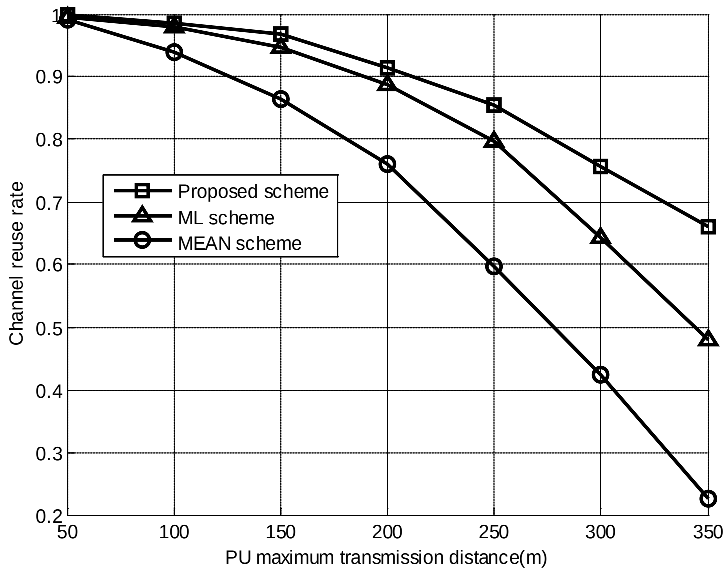

Fig. 4. Channel reuse rate according to the maximum transmission distance of the PUs

6. Conclusions

In this study, we have considered a mixture of the overlay and underlay approach for CRSNs, especially on an underlay model-based spectrum access. Since the CSS scheme is applied to the network model, a FC that is in charge of scheduling spectrum sensing and accessing for the SUs determines whether a channel should be used in the overlay approach or the underlay approach. In order to apply the underlay approach into CRSNs requiring low complexity, we have proposed a RSS-based PU localization scheme that uses the distance calibration, which reduces the localization error and improves the channel reuse rate. The simulation results have shown that the proposed scheme outperforms the RSS-based PU localization schemes with the MEAN and the ML calibrations, respectively, in terms of the average localization error and the channel reuse rate when the PU maximum transmission distance and the standard deviation of the shadowing factor increase.

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