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ON THE LOCATION-AWARE COOPERATIVE SPECTRUM SENSING IN URBAN ENVIRONMENT

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ABSTRACT

Spectrum sensing is a key enabling technology for cognitive radio networks (CRNs). The main objective of spectrum sensing is to provide more spectrum access opportunities to cognitive radio users without interfering with the operations of the licensed network. Spectrum sensing decisions can lead to erroneous sensing with low performance due to fading, shadowing and other interferences caused by either terrain inconsistency or dense urban structure. In order to improve spectrum sensing decisions, in this paper a cooperative spectrum sensing scheme is proposed. The propagation conditions such as the variance and intensity of terrain and urban structure between two points with respect to signal propagation are taken into consideration. We have also derived the optimum fusion rule which accounts for location reliability of secondary users (SUs). The analytical results show that the proposed scheme slightly outperforms the conventional cooperative spectrum sensing approaches.

KEYWORDS

Cooperative spectrum sensing, Location-aware, Cognitive radio, Signal propagation, Urban environment.

1. INTRODUCTION

Today's wireless networks are characterized by a fixed spectrum assignment policy. As a result of increasing demands for wireless applications, there is a lack of frequency resources. In recent years, we have seen a significant interest in quantitative measurements of licensed and unlicensed spectrum utilization. Several research groups, companies and regulatory bodies have conducted studies of varying times and locations with the aim to capture the overall utilization rate of spectrum. These studies have given a significant amount of insight into spectrum use [1], [2]. Most of these studies have shown that a large amount of allocated spectrum are under-utilized and create what is called *spectrum holes*, resulting in a waste of valuable frequency resources [3]–[5]. *Spectrum holes* represent the potential opportunities for non-interfering use of spectrum and are considered as multi-dimensional regions within frequency, time and space. Consequently, high blockage probabilities are unavoidable for many users due to shortages of frequency resources caused by inefficient utilization. Cognitive radio (CR) technology is introduced in the literature to solve these ongoing spectrum inefficiency problems. The term cognitive radio was first introduced by Mitola in the 1990s to take advantage of the under-utilized scarce wireless spectrum [6]. CR is a key enabling technology for dynamic spectrum

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access, which provides higher bandwidth to mobile users via heterogeneous wireless architectures [7].

There are three main CR paradigms for sharing the spectrum: interweave, overlay and underlay. In interweave paradigm, cognitive users opportunistically exploit the primary radio spectrum only when the primary signal is detected to be idle. In overlay paradigm, cognitive users help maintain and/or improve primary users' (incumbent users) communication while utilizing some spectrum resources for their own communication needs. The underlay paradigm allows cognitive users to share the frequency bandwidth of the primary network only if the resultant interference power level at the primary receiver is below a given threshold.

CR is performed by a cycle which consists of three main stages: spectrum sensing, dynamic spectrum allocation and transmit power control, see Figure 1. Spectrum sensing is considered as one of the most challenging tasks in CR technology [8]-[9]. In dynamic spectrum allocation, channels are allocated to users based on spectrum availability. This allocation also depends on internal and/or external policies between cooperative networks. Transmit power control enables CR transmission to be controlled at the beginning of and during the transmission. This enables CRNs to serve more users and to lower the interference to the spectrum owners [10]. In spectrum sensing, the performance is usually measured by two key factors: probability of detection and probability of false alarm. The former is a probability that the detector correctly detects the signal when it is present in a given band. On the contrary, probability of false alarm is a probability that the detector incorrectly detects the presence of a signal though it is actually in temporal/permanent idle state. Probabilities are usually represented in a plot of the probability of detection versus the probability of false alarm, which is commonly referred to as radio operating characteristics (ROC). In this paper, these two factors will be the basis for determining the reliability of the proposed scheme and the results will be compared with the performance of the conventional hard combining scheme. The main contributions of this paper are as follows:

- We analyze the effect of the SUs' locations on spectrum sensing.
- We derive the fusion rule with consideration of SUs' locations within cooperative cognitive spectrum sensing.
- We propose a location-aware cooperative sensing scheme that combines the sensing results from multiple SUs. The sensing results are considered according to the reliability measured by the location information.

The remainder of the paper is organized as follows. Back- ground and motivation are presented in the next section. In Section 3, we define the system model and assumptions of the cooperative CR network that is used in our analysis. Section 4 gives a review of our proposed sensing method. Analytical results are discussed in Section 5. Finally, we make our concluding remarks in Section 6.

2. BACKGROUND AND MOTIVATION

2.1 Spectrum Sensing

Spectrum sensing is considered as one of the most challenging tasks in CR technology [8]-[9]. In the literature, various spectrum sensing methods and algorithms have been investigated, each having different operational requirements, advantages and disadvantages. The most common sensing methods are: feature detector, matched filtering and energy detection. Feature detector is performed using cyclic spectrum density function of the received signal or by matching general features of the received signal to the already known primary signal characteristics. If the structure of the signal source is known, optimal detection in stationary Gaussian noise is achieved by matched filtering method and coherent detection. This type of coherent detection may be a viable approach for early CR deployment, where the secondary system is limited to

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operate within a few systems such as Television (TV) and Digital Video Broadcasting (DVB). However, if more bands are being opened for opportunistic access, the implementation cost and complexity associated with this approach will increase [11]. A simpler alternative for the detection of a signal in Gaussian noise is to employ energy detection, which has drawn more attention in recent years, mainly due to its low complexity [12]. Energy detection determines the existence or absence of PUs by comparing the received energy at a CR to a pre-defined threshold. The performance of the energy detection increases monotonically with the quality of the received signal [13]. In [9], energy detection technique has been tested in an environment of low signal to noise ratio (SNR), while in [14] sequential energy detection was proposed to reduce sensing time. The authors in [15]-[16] studied the performance of energy detection under different channel constraints, such as additive white Gaussian noise (AWGN) and fading channels. Measuring the power of the received signal is the only requirement for energy detection, which then can be compared with a pre-defined threshold [17].

2.2 Cooperative Spectrum Sensing

The main challenge faced today by CR researchers is the ability to detect and utilize spectrum opportunities on a non-interference basis. Constructive and/or destructive interference can occur when signals travel along different paths to reach receivers, which causes attenuation and delay to the signal.

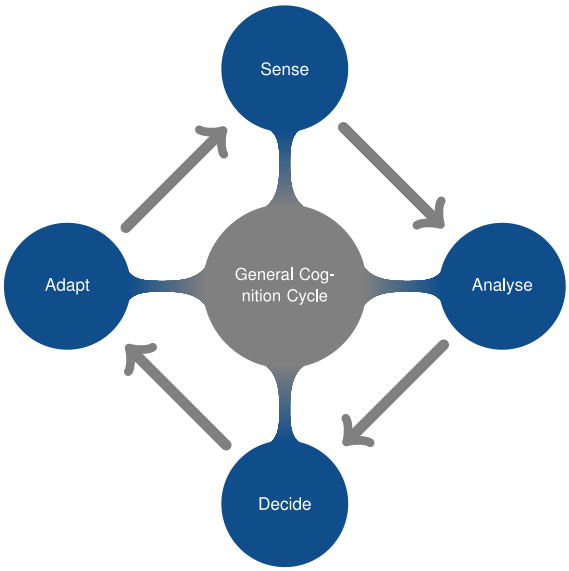

Figure 1. Cognitive cycle.

The received signal consists of several multi-path components, each of which is the result of the interaction of the transmitted waves with the surrounding environment. This issue has prompted researchers to turn to cooperative cognitive radio (CCR) networks, where all CRs collaborate in the spectrum sensing process. The advantage gained by using CCR networks lies at the achievable space diversity due to using multiple CRs [18]-[19]. In this context, cooperation indicates that a number of CRs are responsible to sense one particular channel at defined time and location. Cooperative sensing has gained interest in recent research papers, such as the work in [20]–[23]. Different cooperative sensing strategies have been studied to achieve better reliability of detecting primary signals. Sensing performance of a multiple primary user detector is discussed in [11]. Analytical formulae have been found for its false alarm probability and decision threshold. Numerical examples show significant performance gain over several detection algorithms in scenarios with realistic parameters. In [24], a weighted cooperative

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spectrum sensing scheme based on energy detection for minimizing the total error probability in CCR networks is investigated and analyzed, with resorting to allocation of optimal weight coefficients to individual cooperative secondary users.

Cooperative sensing is proposed in the literature as a solution to the problems that arise in spectrum sensing due to noise uncertainty, fading and shadowing [20]. However, the performance of cooperative spectrum sensing can be deceptive, because it highly depends on the reliability of the global decision. To address this challenge, various potential solutions were presented, as in [24] and [11]. In these studies, it is assumed that all secondary users are capable of estimating the received power with equal accuracy. However, such an assumption may not be always realistic, especially in high terrain and urban areas, where the structure of signal paths can vary dramatically. In this paper, we specifically address this issue and propose a new scheme to optimize spectrum sensing by considering location awareness. We show that the accuracy of spectrum sensing can be improved by avoiding secondary users' incorrect decisions caused by refraction and diffraction of primary signals. Furthermore, the proposed scheme takes advantage of spatial diversity raised due to the random distribution of secondary users within the coverage area.

Table 1. Notations used.

Notations	Descriptions
$P_{f,i}$	Probability of false alarm at the ith user
$P_{d,i}$	Probability of detection at the ith user
H_0	Null hypothesis
H_1	Alternative hypothesis
λ	Threshold
σ_w^2	Noise power
$Q(.)$	Q function
γ	Average signal to noise ratio
Y	Received energy for binary hypothesis
$r(t)$	Received energy
h	Channel gain
$s(t)$	Transmitted signal
$w(t)$	AWGN with zero mean and unit power
N	Sample Number
M	Number of SUs
u_0	Global binary decision at the SBS
u_i	Binary decision at the ith SU
Q_d	Overall detection probability
Q_f	Overall false alarm probability
S_j	Set of all decisions at the SBS which are equal to j where $j \in (0, 1)$

3. SYSTEM MODEL AND ASSUMPTIONS

In this paper, we consider an infrastructure-based CCR network which consists of one primary and one secondary network. A secondary base station (SBS) which also functions as a fusion center is also part of the secondary network. The network includes *M* number of secondary users (SUs), which are scattered in a given geographical area at the periphery of the coverage of the SBS.

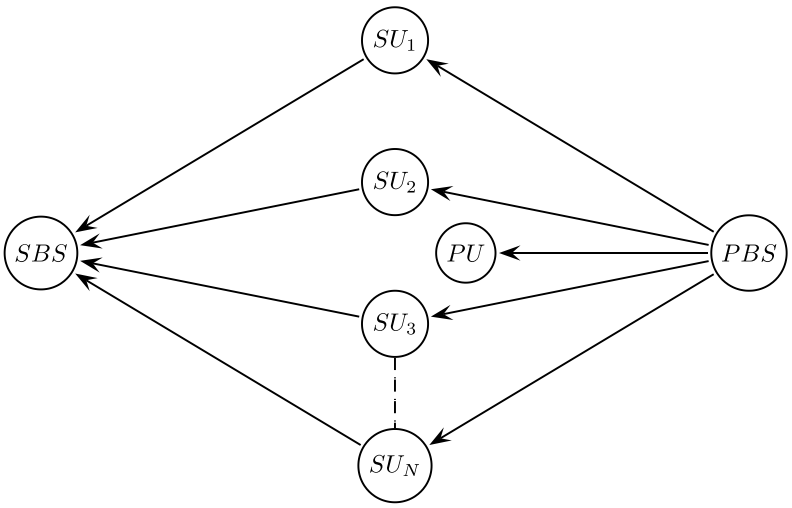

Figure 2. System model.

In Figure 2, SUs observe the same hypotheses independently and transmit their measurements to the SBS through a dedicated control channel which is assumed to maintain communication between SUs and their associated SBS. Here, the control channel is considered to be perfect. Similarly, the primary network consists of a primary base station (PBS) and primary users (PUs). Since we are interested in the downlink frequency channels of the primary network, SUs only perform spectrum sensing to target downlink channels (from the base station to the user), which are transmitted by the PBS. SBS decides whether a primary signal exists or not, which is a normal random process that depends on both the PBS activities and the spectrum sensing accuracy of SUs. Spectrum sensing at the SUs is performed using energy detection, which is commonly formulated as a Neyman-Pearson (NP) type binary hypothesis test problem. In such sensing technique, the received signal at each SU and at time *t* is given by [16].

$$r_i(t) = \begin{cases} w_i(t) & \text{if channel is free } H_0 \\ h s_i(t) + w_i(t) & \text{if channel is busy } H_1 \end{cases} \quad (1)$$

where h is the channel given,is the AWGN with zero $w_i(t)$ and is the transmitted signal $s_i(t)$ mean and unit power $\mathcal{N}(0,1)$. The hypothesis models H_0 and H_1 as presented in Equation (1) denote the absence and the presence of the primary signal, respectively. The performance measurement of any CR system is determined by its probability of detection $(P_{d,i})$ and probability of false alarm $(P_{f,i})$. High $(P_{d,i})$guarantees minimal interference with primary network, and low $(P_{f,i})$ guarantees throughput improvement for the secondary network. Both measurements are used as the basis to determine the performance of CR systems in this paper. $P_{d,i}$ and $P_{f,i}$ can be estimated by:

$$P_{d,i} = \Pr\{Y > \lambda | H_1\} \quad (2)$$

and

$$P_{f,i} = \Pr\{Y > \lambda | H_0\}, \quad (3)$$

where *Y* is the received energy. The probability of detection in Equation (2) refers to the probability of accepting H_1 when H_1 is true. The probability of false alarm in Equation (3) refers to the probability of accepting H_1 when H_0 is true [9]. With direct computation of (2) and

(3), we have:

$$P_{d,i} = Q\left(\left(\frac{\lambda}{N\sigma_w{}^2} - 1 - \gamma\right)\frac{\sqrt{N}}{1+2\gamma}\right) \tag{4}$$

and

$$P_{f,i} = Q\left(\left(\frac{\lambda}{N\sigma_w{}^2} - 1\right)\sqrt{N}\right), \tag{5}$$

where λ is the threshold, $\sigma_w{}^2$ is the noise power, $Q(.)$ is the Q function, γ is the average signal to noise ratio and N is the sample number [16]. According to the information collected from SUs, the SBS makes its final decision about the spectrum availability. A specified decision method is adopted in order for the SBS to reach its final conclusion. Decision methods are generally divided into hard combination decision and soft combination decision. In hard combination decision, each SU reports its local decision to the SBS and the decision is made from a specific rule, such as logic "AND" and logic "OR". Hard combining is simple to implement and requires lower overhead (e.g., one-bit) [25]. For soft combination decision, the original observed data at the SUs, such as received power, is reported to the SBS and the decision is obtained by using one of the available techniques, such as equal gain combining (EGC) and log likelihood ratio (LLR) [25]–[27]. Soft combining method outperforms hard combining method in terms of the probability of missed opportunity. However, hard combining decisions are found to perform as good as soft decisions when the number of SUs is high [25]. In this paper, we consider hard combination decision as the core of our cooperative spectrum sensing decision method. In order to improve the accuracy of the chosen sensing method, we assume that the system is aware of the SU's location. SUs can be located in high dense built areas, where power measurements are less reliable due to various phenomena such as diffraction and reflection. It is important that the sensing decision method considers the SUs' locations to determine the environmental conditions of SUs, because the sensing accuracy is a function of location in respect to the source signal. Inaccurate sensing measurements, which are sent to the SBS, can potentially degrade the sensing accuracy. In a typical cellular network, the locations are stored in the HLR (Home Location Register). The HLR is the central user database in the mobile radio network. It stores the user and subscriber information. The location of both PBS and SUs can be described by longitude and latitude, which are a random collection of points on a coverage area [7]. The locations of PBSs can be obtained based on publicly available data, such as Consolidated Database System (CDBS). The locations of mobile SUs can be determined by various location estimation techniques, such as time-of-arrival (TOA), angle-of-arrival (AOA), received signal strength (RSS), pattern recognition and Bayesian filters [28].

4. LOCATION-AWARE COOPERATIVE SPECTRUM SENSING

4.1 Urban Propagation

Since spectrum is a very limited commodity in mobile communication systems, particularly in urban areas, we focus our study on urban environment [29]. Propagation of electromagnetic waves in urban areas in cellular frequencies is influenced by the geographical and structural area. Therefore, a detailed vector database of the buildings is required in order to establish a propagation map. Typically, the multi-path propagation is very important in urban environments. Urban propagation models already play an important role in the development, planning and deployment of mobile radio systems where coverage is the primary goal. Urban propagation models could also be used for signal detection reassessment, as we show in this

paper. The attenuation of the signal strength in cellular frequencies is caused by three factors: path loss, multi- path fading and shadowing [30]. Here, we define the three attenuation factors:

- Path loss factor characterizes the rate at which the signal strength decays with the increase of the distance from a transmitter. Path loss factor increase is observed when signal propagation is subject to reflection and deflection from surrounding objects, such as floors, walls and trees.
- Multi-path fading, also called fast fading, is the propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths. This is caused by reception of multiple copies of a transmitted signal through multi-path propagation. An amplitude distribution is often described by a Rician or Rayleigh distribution, depending on whether a dominant component among the multiple copies exists or not. Usually, fast fading effect can be removed by averaging the received power over a time interval.
- Shadowing, often referred to as slow fading, represents a slow variation in a received signal strength due to obstacles in propagation paths. This factor increases the signal detection uncertainty.

4.2 Proposed Scheme

We propose a scheme, which is capable of improving the sensing accuracy of a CCR system. In this scheme, SUs determine their locations to realize the signal path quality in reference to the PBS (source signal). The location data of SUs are sent to the SBS for further investigation, see Figure 3. Knowledge of SUs' locations at the SBS can determine whether a line-of-sight (LOS) between transmitter and receiver exists and whether the path is obstructed by large building developments and structures such as wind turbines (e.g., Non- line-of-sight (NLOS) propagation), …etc., which can potentially cause the received signal to be less detectable at the SUs. Such consequential impact can degrade the sensing quality when considering a global decision.

4.3 Trust Value

In the proposed scheme, the sensing results from SUs are returned to the SBS along with location coordinates. We note that when SBS is in possession of the locations of SUs and PBS and PBS's networking information, including channel, height, transmit power antenna directionality …etc., the SBS will have the ability to approximate a trust value. There are a number of propagation models, which are well designed and give good accuracy of signal propagation, such as Okumura-Hata model, which is one of the most widely used empirical propagation prediction models. It was developed through works of Y. Okumura and M. Hata and is based on the results of extensive measurements in certain urban and sub-urban areas of Japan. Such propagation model is used to predict the signal power of any point on a map, which could be used to assign trust values for SUs. The pattern shown in Figure 4 is typical for a power law based empirical model used in an urban environment. The sector antenna patterns are clearly seen from the shape of the results. The lobes in the vertical pattern of each antenna explain the alternating colours along a radius away from each antenna [31].

The trust value accounts for the density of the surrounding structure of a given SU and the propagation environment in reference to the PBS (source signal) and can be written as:

$$T_{i(t)} = f(d_{i,PBS}(t), h_{i(t)}, h_B, f_0, L, C), \quad (6)$$

where $T_{i(t)} \in \leq T_{i(t)} \leq 1$, $d_{i,PBS}(t)$ denotes the distance between the ith SU and the PBS at time t, $h_i(t)$ denotes the SU height at time t, h_B denotes the PBS height, L denotes the propagation loss, f_0 denotes the central frequency of the signal and C is any physical constant.

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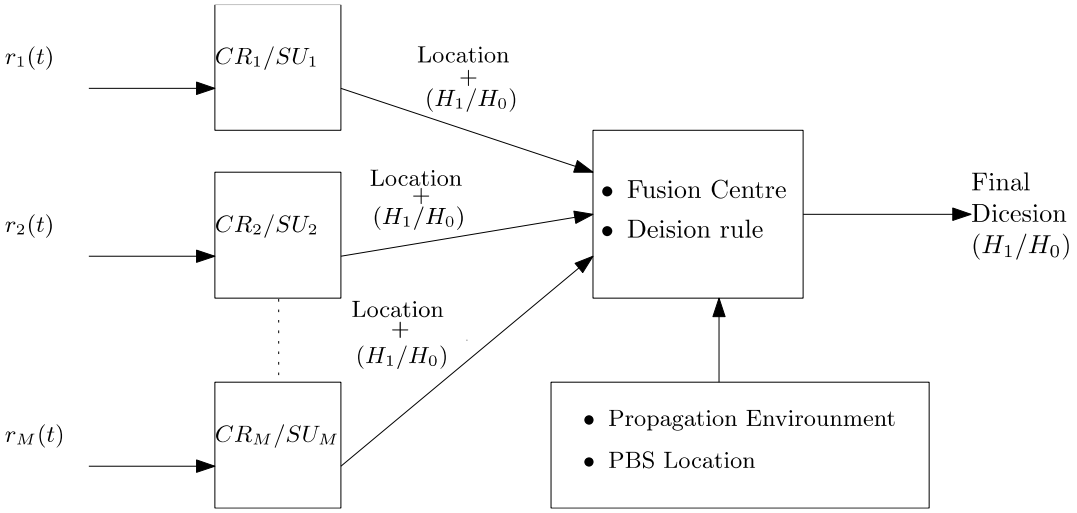

Figure 3. Proposed scheme.

The coverage area of the SBS can be divided into smaller sectors and a trust value is assigned for each sector to represent the environmental propagation in respect to the relevant PBS. The trust value reassesses the sensing data before the fusion process to obtain the global decision. The motivation is to make a comparison between the real sensed signal power, which is received at the SUs, and the expected signal power at each corresponding sector in the coverage area. Trust value contributes to enhance the accuracy of the SBS when the global decision of a particular channel status is calculated.

4.4 Elimination

An SU can be assigned either a low or high trust value. A low trust value indicates that an SU is located in a shadowed area (e.g., highly dense urban area); whereas a high trust value indicates that an SU is located in a less structured region (e.g., LOS propagation is predicted). If an SU is assigned a low trust value, it will be eliminated from subsequent procedures. This step ensures that such an SU does not make any significance when considering a global decision at the SBS. SUs submit the locations and the sensing results simultaneously; therefore, assigning trust values to SUs is time and space dependent. When an SU moves to a new location, a new trust value is assigned which reflects the current location of the SU.

In this paper, we assume that all SUs in the coverage area of the SBS follow the same process. Further steps are taken to SUs, which are assigned a high trust value. SUs measure the received power using energy detection technique, which we briefly discussed in section 3.

SUs submit their local decision to the SBS in a form of hard decision $(\mathrm{H}_0, \mathrm{H}_1)$. These measurements are further processed at the SBS. Based on the results obtained from the SUs, the SBS determines whether the corresponding channel is free of any primary transmission. We list the detailed procedure in Algorithm 1.

4.5 Proposed Fusion Rule

In cooperative spectrum sensing and in hard combining scheme, SUs send their final one-bit decisions to the SBS. $u_i \in \{0,1\}$ is the binary decision made by the ith SU, which in essence is a logical decision metric. In this context, 0 and 1 indicate the absence and the presence of the primary signal, respectively. There can be a number of fusion rules which are represented by

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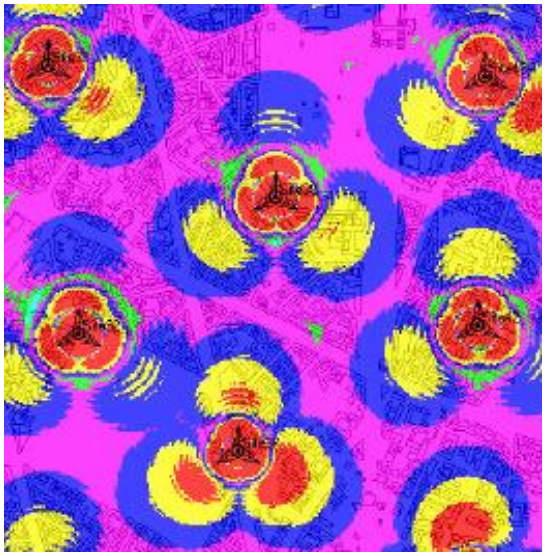

Figure 4. Signal strength from empirical propagation predictions [31].

Algorithm 1 Proposed Spectrum Sensing

Initialisation
Number of SUs in the network = M
$\mathbf{R} \leftarrow Empty$
for $i = 1:1:M$ **do**
  Obtain SU's Location
  if ith SU is assigned low trust value **then**
    Eliminate ith SU from further analysis
  else
    $\mathbf{R} \leftarrow i$th SU
    where $\mathbf{R}$ is a vector containing all SUs with high trust value
  end if
end for
Collect sensing results from SUs in $\mathbf{R}$
Run log likelihood ration test for all SUs in $\mathbf{R}$
Calculate detection and false alarm probability probability
return

k-out-of-K rule and for such rule, the overall detection and false alarm probabilities are, respectively:

$$Q_d = \sum_{q=k}^{K} \binom{K}{q} \left\{ \prod_{i=1}^{q} P_{d,i} \times \prod_{j=1}^{K-q} \left(1 - P_{d,i}\right) \right\} \tag{7}$$

and

$$Q_f = \sum_{q=k}^{K} \binom{K}{q} \left\{ \prod_{i=1}^{q} P_{f,i} \times \prod_{j=1}^{K-q} \left(1 - P_{f,i}\right) \right\}; \tag{8}$$

where

$$\binom{K}{q} = \frac{K!/(K-q)!}{q!}. \tag{9}$$

SBS receives decisions from M SUs, decide H_1 if any of the total M individual decisions is H_1 and decides H_0 otherwise. This fusion rule is known as the OR-rule or 1-out-of-M rule, while AND rule corresponds to the case where $k = K.$ SBS receives decisions from *M* SUs and decides H_1 if all of the total M individual decisions are H_1 and decides H_0 otherwise. The global probabilities of false alarm and detection for the two fusion rules can be obtained as:

OR fusion rule:

$$Q_{d,or} = 1 - (1 - P_d)^M \tag{10}$$

and

$$Q_{f,or} = 1 - (1 - P_f)^M \tag{11}$$

AND fusion rule:

$$Q_{d,and} = (P_d)^M \tag{12}$$

and

$$Q_{f,and} = (P_f)^M. \tag{13}$$

Fusion of incoming local decisions and decisions that are made at the SBS are considered in this paper. In the scenario discussed here, SUs could make only hard decisions, such that u_i could take only two values 0 or 1 based on its local observation $u_i \in \{0,1\}$. All the local detector SUs observe the same channel at the same time. Each SU makes a local binary decision u_i, where $\{i = 1,...,M\}$ based on the local observation. The SBS produces the global decision $u_o \in \{0,1\}$. This problem is known as the binary hypothesis test, since the system chooses, between two hypotheses, where H_0 and H_1 are the noise only hypothesis and the signal plus noise hypothesis, respectively. The optimum fusion rule for this problem is given by the likelihood ratio test (LRT) as:

$$\frac{\Pr(u_1, u_2, ..., u_M | H_1)}{\Pr(u_1, u_2, ..., u_M | H_0)} \underset{u_o=0}{\overset{u_o=1}{\gtrless}} \eta, \tag{14}$$

where η is a threshold which is determined by the specified values of $P_{d,i}$ and $P_{f,i}$. Next, we assume that $P_{d,i} \geq P_{f,i}$, where $\{i = 1,...,M\}$. This assumption is common in CCR network sensing scenarios. We also make the following definitions:

$$P_{f,i} = \Pr(u_i = 1 | H_0) \tag{15}$$

and

$$P_{d,i} = \Pr(u_i = 1 | H_1), \tag{16}$$

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where u_o is the global decision at the SBS. Given this assumption, the optimum fusion rule can be written as:

$$\frac{\Pr(u_1,u_2,...,u_M|H_1)}{\Pr(u_1,u_2,...,u_M|H_0)}=\prod_{i=1}^{M}\frac{\Pr(u_i=j|H_1)}{\Pr(u_i=j|H_0)}=\prod_{S_1}\frac{\Pr(u_i=1|H_1)}{\Pr(u_i=1|H_0)}\times\prod_{S_0}\frac{\Pr(u_i=0|H_1)}{\Pr(u_i=0|H_0)}$$

$$=\prod_{S_1}\frac{P_{d,i}}{P_{f,i}}\times\prod_{S_0}\frac{1-P_{d,i}}{1-P_{f,i}}, \tag{17}$$

where S_j is the set of all decisions made at the SBS that are equal to $j, j=0,1$. The fusion rule that minimizes the probability of false alarm and maximizes the probability of detection is given by:

$$\prod_{S_1}\frac{P_{d,i}}{P_{f,i}}\times\prod_{S_0}\frac{1-P_{d,i}}{1-P_{f,i}}\underset{u_o=0}{\overset{u_o=1}{\gtrless}}\eta. \tag{18}$$

So far, we have discussed the fusion rules for the binary hypothesis problem. Next, we include the case in which the SU is assigned a trust value which represents the signal strength in its respective region. Trust values are modeled as the probability of an SU to be located in a region of acceptable reception, e.g., $T_i = j$, and $j \in 0 \le j \le 1$, where T_i is spatially independent and $j=0$ represents the respective SU location being in a high shadowed area, while $j=1$ indicates that a user is located within a line of sight in respect to the sensed signal (source signal). These trust values are transmitted to the fusion center for further processing to reach the global decision. The fusion rule in this case is given by the LRT in (19), since it indicates for each value of *Ti* the likelihood of H_1 versus the likelihood of H_0 and can be expressed as:

$$\frac{\Pr(T_1,T_2,...,T_M|H_1)}{\Pr(T_1,T_2,...,T_M|H_0)}\times\frac{\Pr(u_1,u_2,...,u_M|H_1)}{\Pr(u_1,u_2,...,u_M|H_0)}\underset{u_o=0}{\overset{u_o=1}{\gtrless}}\eta. \tag{19}$$

Now, let us define the following probabilities:

$$\alpha_{i,j} = Pr\{T_i = j\,|H_0\} \tag{20}$$

$$\beta_{i,j} = Pr\{T_i = j\,|H_1\}. \tag{21}$$

The ratio $\frac{\Pr(T_1,T_2,...,T_M|H_1)}{\Pr(T_1,T_2,...,T_M|H_0)}$ in Equation (19) can be expressed as:

$$\frac{\Pr(T_1,T_2,...,T_M|H_1)}{\Pr(T_1,T_2,...,T_M|H_0)}=\prod_{i=1}^{M}\frac{\Pr(T_i|H_1)}{\Pr(T_i|H_0)}=\prod_{i=1}^{M}\prod_{S_j}\frac{\Pr(T_i=j|H_1)}{\Pr(T_i=j|H_0)}. \tag{22}$$

Substituting (20) and (21) in (22), we obtain the following expression:

$$\frac{\Pr(T_1,T_2,...,T_M|H_1)}{\Pr(T_1,T_2,...,T_M|H_0)}=\prod_{j=o}^{j-1}\prod_{S_j}\left(\frac{\beta_{ji}}{\alpha_{ji}}\right). \tag{23}$$

Subsequently, by substituting (23) and (18) in (19), we obtain the following fusion rule:

$$\prod_{j=o}^{j-1}\prod_{S_j}\left(\frac{\beta_{ji}}{\alpha_{ji}}\right)\times\prod_{S_1}\frac{P_{d,i}}{P_{f,i}}\times\prod_{S_0}\frac{1-P_{d,i}}{1-P_{f,i}}\begin{matrix}u_o=1\\ >\\ <\\ u_o=0\end{matrix}\eta, \tag{24}$$

and by taking the logarithm of both sides, we obtain the optimum fusion rule that minimizes the false alarm and maximize the probability of detection as:

$$\sum_{j=o}^{j-1}\sum_{S_j}\log\left(\frac{\beta_{ji}}{\alpha_{ji}}\right)+\sum_{S_1}\log\frac{P_{d,i}}{P_{f,i}}+\sum_{S_0}\log\frac{1-P_{d,i}}{1-P_{f,i}}\begin{matrix}u_o=1\\ >\\ <\\ u_o=0\end{matrix}\log\eta. \tag{25}$$

5. ANALYSIS AND RESULTS

In order to evaluate the performance of our scheme, analytical results are given in this section. In our analysis, it is assumed that the SBS is aware of the relevant primary network parameters, as well as the locations of SUs and PBS and the trust value can be calculated. In the analysis, we set the number of cooperative SUs to be 30. For the analytical results, it is reasonable that we compare our proposed scheme with the conventional cooperative spectrum sensing schemes. The comparison is presented in Figure 5. We varied the signal to noise ratio (SNR) form (-2dB) to (2dB). We consider two false alarm probability P_f values which are set to be 0.1 and 0.2, while the SUs which are located in high trust value are set at 0.75. Figure 5 shows the improved performance of our proposed scheme when eliminating the SUs which are considered to be located in high shadowed areas, with a percentage of 25% of all participating SUs. Because these SUs are eliminated from further processing, they have no impact on the final global decisions. It is clear for both values of false alarm probabilities that the probability of detection P_d increased when we apply our proposed scheme. Results also indicate a slight improvement in terms of required average SNR for detection.

The results in Figure 6 show the ROC performance comparison of the proposed location-aware and conventional (or the case where location and propagation models are not considered) cooperative spectrum sensing schemes when T = 0.78 and T = 0.6. T = 0.78 indicate that 22% of the SU are located in a highly shadowed areas. These SUs are eliminated from further processing at the SBS. The location-aware scheme slightly outperforms the conventional scheme when most of the SUs are located in the same environment. However, Figure 6 shows that the performance has improved further when T = 0.6, which indicates that 40% of the SUs are located in unreliable locations.

Table 2. Sensing procedure comparison.

	Proposed Scheme	Conventional Schemes
SUs Make Local Decisions	✓	✓
SUs Send Decision to SBS	✓	✓
SUs Send Geo-Location to SBS	✓	
SBS Calculate Distance from PBS to SUs	✓	
SBS Calculate Channel Condition	✓	
SBS Calculates Trust value for each SU	✓	
SBS Calculates Global Decision	✓	✓

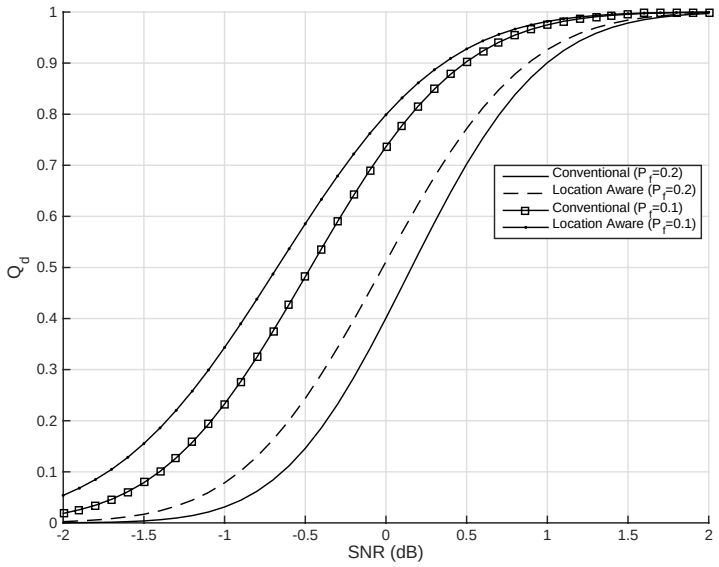

Figure 5. Probability of detection comparison of proposed location-aware scheme and conventional hard combining scheme for different SNR when false alarm probability constraint is 0.1 and 0.2.

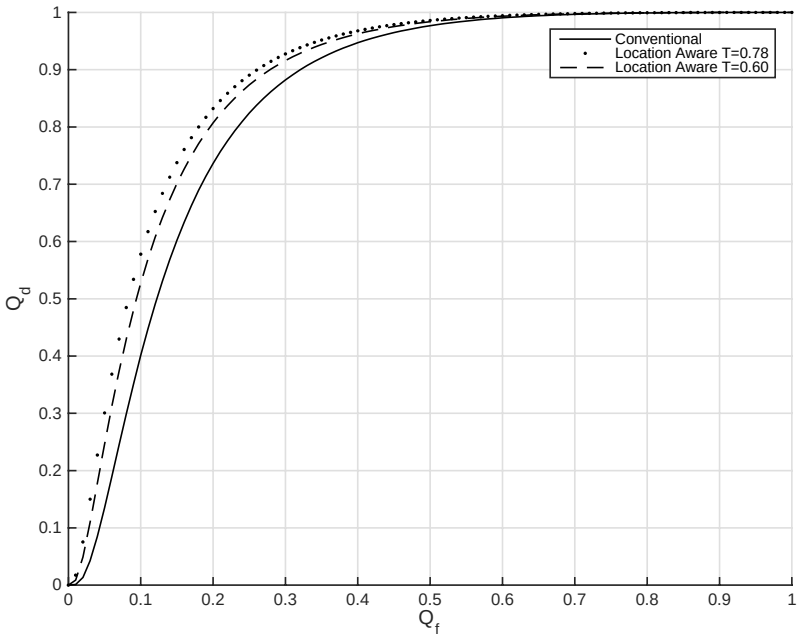

Figure 6. ROC comparison of proposed location-aware scheme and conventional hard combining scheme under Gaussian channel when the number of cooperative users = 30 for different trust values.

Figure 7 depicts the ROC analytical curves using the proposed scheme when the number of cooperative users is 30 and 35% of the SUs are located in highly shadowed areas. The high value of sensing results means that most of the participating CRs are located nearby the source signal. On the other hand, since 35% of the CRs are located too far from the source signal and/or NLOS is predicted, because they are located in highly shadowed areas, those CRs can not be considered as valuable sources of information. Therefore, they are eliminated from further action. It is evident from Figure 7 that the proposed cooperative sensing scheme provides better performance than the conventional hard combination scheme. When T=0.65, for the detection probability of 0.9, the false alarm probability of the proposed scheme is 0.25, while for the conventional scheme it is 0.32.

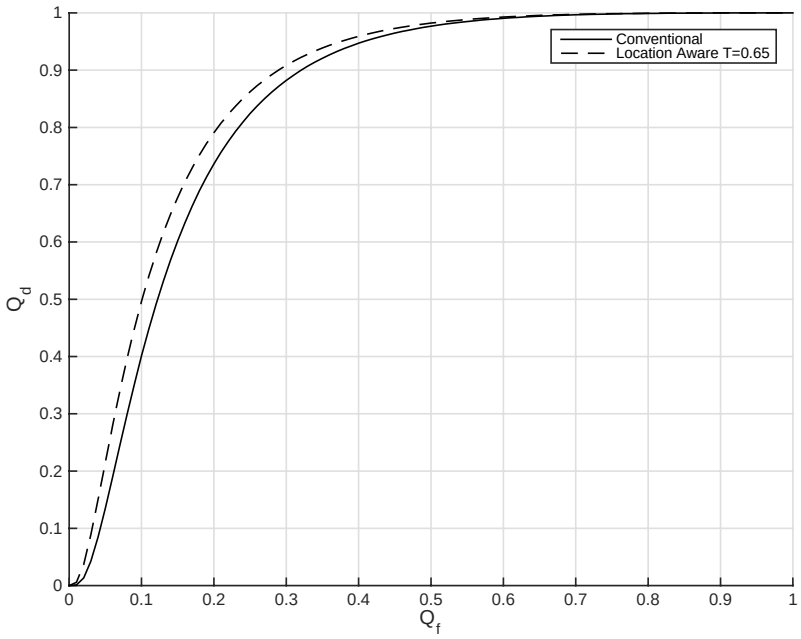

Figure 7. ROC comparison of proposed location-aware scheme and conventional hard combining scheme under Gaussian channel when the number of cooperative users = 30 and 35% of the SUs are located in highly shadowed areas.

In Figure 8, we plot the probability of detection against the SNR. The figure presents the probabilities of detection for different numbers of cooperative cognitive radios in the network.

It is evident that the detection improves with increased number of CRs, since more accurate results mean better performance for the network. The number of CRs is typically large in the case of urban networks. However, the proposed scheme can eliminate the CRs with low trust value from participating in the cooperative sensing. The proposed scheme does not only improve performance of detection, but also reduces sensing time.

Cooperative spectrum sensing may become impractical in CRNs with a large number of SUs, because in a time slot only one SU sends its local decision to the SBS in order for the decisions to be separated easily. Hence, it may make the whole sensing time intolerably long. The scheme proposed here does not take into account the users that are located in low trust value regions, therefore it minimizes the number of participating SUs in a selective manner. Consequently, the processing time for the global decision at the SBS will be minimized while not compromising spatial diversity. This implies that SBSs have the incentive to adapt the proposed sensing decision method, since it can lead to achieve higher reliability and lower sensing time. The

fundamental differences between our proposed scheme and the conventional methods are shown in Table 2.

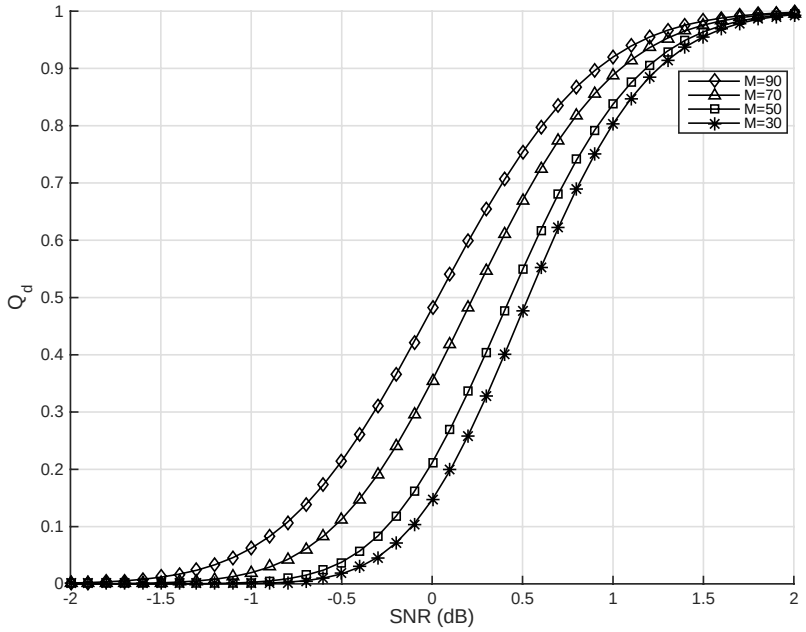

Figure 8. ROC of proposed location-aware scheme with different numbers of cognitive radio users under Gaussian channel and 35% of the SUs are located in highly shadowed areas.

6. CONCLUSIONS

We have studied the performance of cooperative cognitive spectrum sensing with energy detection in CR networks. Location-aware cooperative spectrum sensing has been investigated. We have derived the optimum fusion rule, as well as the probability of detection, taking location reliability into consideration. The proposed scheme has proved to exhibit better ROC, especially in highly shadowed regions (e.g., under NLOS propagation conditions). Analytical results of the proposed location-aware scheme show an improved performance over the conventional hard combining schemes (e.g., [32]), highlighting the requirements of location knowledge in CRNs, especially in urban environments. Since this sensing accuracy is mainly related to the signal propagation environments, the more accurate the propagation models are, the better the expected performance will be from our proposed scheme. Moreover, for a cognitive radio network, high probability of detection results in less interference to the primary network, which means more capacity and more offered service at high quality. A major issue concerning the practical implementation of the proposed scheme is the availability of complete statistical information corresponding to source signal parameters, particularly their variation with distance. However, lack of spectrum resources encourages the adoption of new ways of sharing, including sharing of specific data related to the incumbent operators.

There are several natural directions suggested by our paper. The most obvious one is to utilize the eliminated CRs from the first step of the cooperative sensing. For example, it would be interesting to develop some more complex schemes of spectrum sensing, e.g., assign the eliminated CRs to sense different channels which are in LOS and/or in close proximity to

different source signals. This could improve the efficiency of sensing, not only by sensing more channels simultaneously but also with high accuracy. Moreover, to gain further understating of our proposed scheme, the sensing time performance could be evaluated.

In the case of Universal Mobile Telecommunications System (UMTS), the transmitting power is adapted to the propagation conditions. The transmitting power is always selected to be only as high as necessary for adequate connection quality. Moreover, each service supported by UMTS networks requires specific threshold values and the network behavior and size change with traffic. Data transmission adds yet another dimension of complexity. This makes detecting UMTS signals much more difficult than in the case of other technology; e.g., Global System for Mobile Communications (GMS). Therefore, it would be very useful to conduct a study that specifically addresses UMTS networks.

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ملخص البحث:

يُعدّ استشعار الطيف من تقنيات التمكين الأساسية لشبكات الراديو الإدراكية (*CRNs*). والهدف الرئيسي من استشعار الطّيف هو توفير المزيد من فرص الوصول إلى الطيف لمستخدمي الراديو الإدراكيّ دون التداخل مع عمليات الشبكة المرخّصة. ويمكن للقرارات المتعلقة باستشعار الطيف أن تقود إلى استشعار غير صحيح ذي أداء متدنٍّ بسبب الاضمحلال أو التظليل أو التداخلات الأخرى الناجمة إمّا عن عدم تجانس التضاريس أو البنية الحضرية الكثيفة.

ومن أجل تحسين قرارات استشعار الطيف، نقترح في هذه الورقة نظاماً تعاونياً لاستشعار الطيف. ويأخذ النظام المقترح بعين الاعتبار ظروف الانتشار، مثل: تفاوت التضاريس وشدّتها والبنية الحضرية بين نقطتين بالنسبة لانتشار الموجات. كذلك، تمّ اشتقاق قاعدة الاندماج الأمثل التي تفسّر موثوقية الموقع للمستخدمين الثانويّين. وتبين النتائج التحليلية أن النظام المقترح يتفوق بعض الشيء على الطّرق التقليدية المستخدمة في الاستشعار التعاوني للطّيف.