Collaborative Spectrum Sensing for Cognitive Radio Networks

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1. Introduction

The fast user growth in wireless communications has created significant demands for new wireless services in both the licensed and unlicensed frequency spectra[1]. Recent studies show that a fixed spectrum assignment policy cannot achieve good spectrum utilization (FCC, 2005) . To address this problem, cognitive radio (CR) has been developed as a technology to facilitate the utilization of temporally idle frequency bands (commonly known as white space or spectrum holes) to increase the spectral efficiency.

A key component of cognitive radio is spectrum sensing. The basic tasks of spectrum sensing are to detect the PUs and to identify available spectrum bands. Spectrum sensing is responsible for a CR system to satisfy two fundamental requirements. First, a CR system should be able to identify white spaces or spectrum holes to satisfy the throughput and quality of service requests of SUs. Second, the CR system needs to ensure that any SU will not cause harmful interference to the other users' frequency bands.

Currently, shadowing, multi-path fading, and receiver uncertainty problems (Cabric et al., 2004; Ghasemi & Sousa, 2005) at receivers decreased significantly the performance of spectrum sensing. However, partial diversity of CR locations can potentially improve the accuracy of spectrum sensing. SUs at different locations can observe different portions of the wireless spectrum, if SUs can cooperate and share the sensing results, the collaborative decision from the collected observations can be better than the local decision at each SU. This is why cooperative spectrum sensing is an attractive and effective approach to overcome different fading, shadowing, and receiver uncertainty problems (Mishra et al., 2006).

The primary idea of cooperative spectrum sensing is to improve the sensing performance by using observations from diversely located SUs. Not only that SUs can improve their decisions through collaboration, the sensing time can also be reduced by cooperation among SUs and this allows each SU to have more time for data transmission over white spaces. Furthermore, with cooperative spectrum sensing, the hardware requirement to maintain the same accurate sensing can be reduced.

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[1] In the literature, the users of licensed and unlicensed frequency spectra are known as Primary User (PU) and Secondary User (SU) respectively.

The cooperative sensing for finding the spectrum holes starts with individual or local sensing performed by each SU, which needs to determine the presence ($\mathcal{H}_1$) and absence ($\mathcal{H}_0$) of PU in one frequency band. According to different hypothesis, the received signal at SU $x(t)$ can be modeled by (Akyildiz et al., 2009)

$$x(t) = \begin{cases} n(t) & , \mathcal{H}_0 \\ h(t) \times s(t) + n(t) & , \mathcal{H}_1 \end{cases} \tag{1}$$

where $h(t)$ denotes the channel gain of sensing channel, $s(t)$ is the transmitted signal of PU, and $n(t)$ is zero mean additive white Gaussian noise. In addition, we denote the probability of presence ($\mathcal{H}_1$) and absence ($\mathcal{H}_0$) of PU as $P(\mathcal{H}_0)$ and $P(\mathcal{H}_1)$ respectively. We will use three common metrics to measure the performance of a spectrum sensing algorithm: the probability of detection P_d, the probability of false alarm P_f, and the probability of missed detection P_f, which are defined by

$$\begin{aligned} P_d &= Pr\{decision = \mathcal{H}_1 | \mathcal{H}_1\} = Pr\{Y > \lambda | \mathcal{H}_1\}, \\ P_f &= Pr\{decision = \mathcal{H}_1 | \mathcal{H}_0\} = Pr\{Y > \lambda | \mathcal{H}_0\}, \\ P_m &= Pr\{decision = \mathcal{H}_0 | \mathcal{H}_1\} = 1 - P_d, \end{aligned} \tag{2}$$

where Y is the decision statistic and λ is the decision threshold.

One important concern for the cooperative spectrum sensing design is the overhead for exchange sensing results. This overhead directly depends on the structure of the SUs' cooperation which can be divided into three categories: "centralized" (Unnikrishnan & Veeravalli, 2008), "distributed" (Li et al., 2010) and "relay-assisted" (Zhang & Letaief, 2008). In the centralized structure, the fusion center (FC) or base station (BS), which is an identified SU to manage the communication and decision making, selects one of the channels and asks the other SUs to send their local sensing results through the selected channel (known as the common control channel). Then, the FC receives the SUs' sensing results via a reporting channel. Lastly, the FC combines the SUs' information[2] and determine the existence of a PU.

Unlike centralized approach, we do not have a FC in the distributed spectrum sensing. All SUs communicate among themselves and make decisions by a distributed algorithm. The distributed algorithm is applied iteratively until all SUs converge to a decision. For example, one particular SU senses and sends its information to others. Then, the SU combines its data with received data of others and makes a decision. If its decision does not satisfy the local criterion, the SU must perform the following three steps iteratively until converge to a decision that satisfies the criterion. The first step is to send combined data through the report channel. The second step is to combine the received data with the local sensing data. And the last step is to make a decision and validate it with the local criterion. Also, in a distributed structure, for evaluation and comparison of the spectrum sensing algorithms, the rate and speed of convergence and convergence guarantee are the essential metrics.

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[2] Based on received data of SUs, the FC can combine the information in three ways such as "soft combining", "quantized soft combining" and "hard combining". If SU sends complete local sensing data, the fusion process is classified as soft combining. If SU quantizes the local sensing information, before sending to the FC, the fusion process is classified as quantized soft combining. For hard combining fusion, a SU makes decision after sensing and sends one bit as its decision to the FC.

The third type of cooperative spectrum sensing is relay-assisted. As we mentioned before, the channels are not perfect, especially the report channel and the sensing channel. The relay-assisted schema can improve the performance. For example, a SU can find out that its report channel is weak and its sensing channel is strong; yet another SU can have a strong report channel and a weak sensing channel. These two SU can complement and cooperate with each other in a relay-assisted schema. This structure can be used in distributed or centralized schema. Here, a SU with a strong reporting channels will help carry the sensing information of a SU that has a weak reporting channel. In the literature, the centralized and distributed schema are considered as one-hop cooperative sensing and relay-assisted approach is considered as multi-hop cooperative sensing.

In this chapter, we review the recent studies about cooperative spectrum sensing in cognitive radio. In addition, the open research challenges will be identified. The chapter goes through the theoretical studies of the performance bounds and limits of cooperative spectrum sensing in Section (2). In this section, we will review and compare the research for optimizing the parameters which affect the throughput of cooperative spectrum sensing such as frame size, sensing time, fusion rules and etc. Also, a brief review of the sensing scheduling techniques is included in Section (2). Section (3) addresses the game theoretical approaches in cooperative cognitive radio. In this section, two main categories of game theory applications are described. The first category is coalitional games for formation of cooperative sets, which are used to reduce the overhead of communication in distributed cooperative spectrum sensing. The second category of game theoretical approach is evolutionary games which are useful for analyzing and managing the behavior of SUs. Also, the strategy selection for large networks will be described. Section (4) reviews the compressed sensing studies for cooperative cognitive radio. This section contains a brief introduction about basic concepts in the area of compressed sensing, then the usage of compressed sensing in cognitive radio will be described. Section (5) explores the evaluation studies of cooperative sensing performance in various types of wireless environments such as Radar, UAV, VANET, WiFi Networks. Finally, the chapter is concluded in section (6).

2. Theoretical bounds and limits

In cognitive radio networks, the opportunities for transmission are limited. All SUs would like to increase their chances for data transmission and save more power without causing harmful interference. Theoretical studies for optimizing the cooperation spectrum sensing parameters, which affect the data transmission opportunities, will help SU to improve their throughput and decrease the energy consumption. Also, to efficiently find spectrum holes, one needs to model the PU behavior, carefully distribute sensing tasks among SUs, and optimize the sensing time for each SU. In following Section (2.1), the trade-off between sensing time and throughput of system will be described. Then, in Section (2.2), dynamic spectrum sensing will be reviewed.

2.1 Sensing vs throughput Trade-off

In the literature, a frame-based structure (or periodic) spectrum sensing is broadly studied for cognitive radios (Fan & Jiang, 2009; Jiang et al., 2009; Liang et al., 2008; Lifeng et al., 2011). We refer to a frame as the duration of time composed of *spectrum sensing slot* and *data*

transmission slot. During the spectrum sensing slot, SUs sense the spectrum to check for the peresence of any PU using the spectrum or not. Then, during the following transmission slot, they will initiate communication if no PU is detected. In general, the duration of sensing slot affects the accuracy of spectrum sensing. A longer sensing slot leads to a higher probability of detection P_d and lower probability of false alarm P_f. However, it reduces the time available for data transmission and thus decrease the throughput of SUs. The optimal trade-off between sensing time and the other parameters such as resource allocation[3] (Fan et al., 2011), fusion center properties (Peh et al., 2009) and cooperation time (Zhang et al., 2010) is still under investigation.

The optimal trade-off between sensing and throughput is formulated by (Liang et al., 2008) to maximize a SU's throughput without affecting the quality of service (QoS) of PU. (Liang et al., 2008) considered two scenarios. The first scenario is when SU detects an idle slot and indeed there is no PU using the channel. In this case, the SU throughput is $C_0 = \log_2(1 + \frac{P_s}{P_n})$, where P_s and P_n are the received SU power and the noise power, respectively. The second scenario happens when there is a detection error that a SU thinks that the slot is idle but is actually occupied by an undetected active PU. The throughput in this case will be $C_1 = \log_2(1 + \frac{P_s}{P_p + P_n})$, where P_p is the interference power due to the undetected PU. Then, they combined the throughput of each scenario and obtained the average throughput of the SU as

$$
\begin{aligned}
R(\tau, \varepsilon) &= C_0 \frac{T - \tau}{T} \big(1 - P_f(\tau, \varepsilon)\big) P(\mathcal{H}_0) + C_1 \frac{T - \tau}{T} \big(1 - P_d(\tau, \varepsilon)\big) P(\mathcal{H}_1) \\
&\triangleq R_0(\tau, \varepsilon) + R_1(\tau, \varepsilon),
\end{aligned}
\tag{3}
$$

where T, τ and ε are the frame duration and the sensing slot duration and threshold for energy detectors, respectively. The goal of (Liang et al., 2008) is then to maximize the expected throughput without sacrificing the QoS of PUs through varying the sensing slot duration τ. That is,

$$
\max_\tau R(\tau, \varepsilon) = R_0(\tau, \varepsilon) + R_1(\tau, \varepsilon) \quad s.t. \quad P_d(\tau, \varepsilon) \geq \bar{P}_d
\tag{4}
$$

where $\bar{P}_d$ is the target probability of detection for sufficient protection of PUs. With assumption $C_0 > C_1$, the value of $R_0(\tau, \varepsilon)$ would dominate the value of $R_1(\tau, \varepsilon)$ and the problem (4) is solved in simplified form where

$$
\max_\tau \tilde{R}(\tau, \varepsilon) = R_0(\tau, \varepsilon) \quad s.t. \quad P_d(\tau, \varepsilon) \geq \bar{P}_d.
\tag{5}
$$

The simulation result confirmed the accuracy of formulation and estimated solution. The work of (Liang et al., 2008) was the foundation of later research on sensing throughput trade-off.

Beside the studies about the effect of sensing time on the throughput of cognitive radio networks, the *k* value of "*k out of N*" fusion rule (Peh et al., 2009) and the frame size (Zhang et al., 2008) are other important parameters in cognitive radio networks that can affect the throughput. In (Peh et al., 2009), they extended equations (3) and (4) for general case with *N*

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[3] In resource allocation, each secondary user is assigned one channel or a portion of channel at a certain transmission power.

nodes[4] and formulated the sensing-throughput trade-off problem to determine the optimal k and sensing time subject to sufficient protection of PU. They achieve this by rewriting (3) as

$$R(\tau, k, \varepsilon) = R_0(\tau, k, \varepsilon) + R_1(\tau, k, \varepsilon) \tag{6}$$

$$= C_0 \frac{T - \tau}{T} \left(1 - \mathbb{P}_f(\tau, \varepsilon)\right) P(\mathcal{H}_0) + C_1 \frac{T - \tau}{T} \left(1 - \mathbb{P}_d(\tau, \varepsilon)\right) P(\mathcal{H}_1) \tag{7}$$

where

$$\mathbb{P}_d(\tau, k, \varepsilon) = \sum_{i=k}^{N} \binom{N}{i} P_d(\tau, \varepsilon)^i \left(1 - P_d(\tau, \varepsilon)\right)^{N-1} \tag{8}$$

and

$$\mathbb{P}_f(\tau, k, \varepsilon) = \sum_{i=k}^{N} \binom{N}{i} P_f(\tau, \varepsilon)^i \left(1 - P_f(\tau, \varepsilon)\right)^{N-1} \tag{9}$$

are the corresponding detection and false alarm probabilities given τ and ϵ. Here, a slot is considered idle only when k or more SUs cannot detect any activities during the sensing slot.

They proposed an iterative algorithm to find the maximum $R(\tau, k, \varepsilon)$ with two steps. In the first step, it finds the optimum k^* value for an initial given τ by exhaustively trying all possible values in $[1, N]$. The second step of the algorithm uses the k^* value of the first step and solves equation (10) to find the optimum length of sensing slot τ^*.

$$\max_{\tau} R(\tau, k, \varepsilon) \quad s.t. \quad \mathbb{P}_d(\tau, \varepsilon) \geq \bar{\mathbb{P}}_d \quad and \quad 0 \leq \tau \leq T \quad and \quad 1 \leq k \leq N \tag{10}$$

τ^* obtained in step two is used in step one again for the next iteration of the algorithm τ. These two steps repeat alternatively until k^* and τ^* converge. Their results showed that values for k and τ are very sensitive to the level of noise. In addition, the throughput of their iterative algorithm consistently performs better than the OR-fusion-rule and the AND-fusion-rule.

Prior research works for finding optimum sensing duration usually assumed that the transmission power and rate are fixed and dynamic resource allocation was not considered (Fan & Jiang, 2009; 2010; Kang et al., 2009; Liang et al., 2008). In addition, there are some research works on wide-band spectrum sensing (Quan et al., 2008; 2009) which detect the PU over multiple band of frequency rather than over one band at a time. These studies have motivated the investigation on techniques of optimizing spectrum sensing and resource allocation jointly. As an example for dynamic resource allocation application, in (Fan et al., 2011), the authors considered a network with M frequency bands and three slots for each frame to be responsible for sensing, reporting, and transmission. They used wide-band spectrum sensing technique (Bletsas et al., 2010) for sensing the M channels and estimated the average throughput for secondary user n as

$$R_n = \left(1 - \frac{\tau}{T}\right) \sum_{m=1}^{M} \left[\left(1 - P_m^f(\tau, \varepsilon_m)\right) P(H_m^0).r_{m,n}^0 + \left(1 - P_m^d(\tau, \varepsilon_m)\right) P(H_m^1).r_{m,n}^1\right] \tag{11}$$

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[4] N nodes include one secondary base station and $N - 1$ SUs, where the secondary base station acts as a sensor node to cooperatively detect the presence of a PU.

where $r_{m,n}^0$ and $r_{m,n}^1$ are the achievable transmission rates of SU when the channel is free and when the channel is busy (missed detection was happened), respectively. Also, the subscript m under parameters shows those are belong to the mth channel. They found the maximum of R_n for all channels by changing the polyblock algorithm[5]. The numerical simulations show that the result of modified polyblock algorithm is close to global maximum of R_n.

2.2 Sensing schedule

According to Section (2.1), the increase in sensing cooperation for a specific channel will increase the probability of detection P_d and reduce the probability of false alarm P_f. Also, as mentioned in Section (2.1), there have been some investigations for finding optimum sensing time to reach the maximum throughput. On the other hand, long sensing duration could decrease the overall performance. For example, some SUs can sense cooperatively to reach higher sensing accuracy, but they will lose opportunity to exploit the other channels. Therefore, there is a trade-off between sensing accuracy on one channel and exploring all channels to seek opportunities for data transmission. Research works such as (Chen et al., 2009; Fan & Jiang, 2010; Wu & Tsang, 2009) show that the dynamic spectrum sensing could be an efficient way to seize the opportunities of transmission without sacrificing sensing accuracy. The dynamic spectrum sensing is used where the SUs can not sense multiple frequency bands and there is more than one PU. In this situation, if there is a schedule for sensing different bands by one particular SU, it can give more opportunities to SUs to find hole of spectrum and improve their average throughput.

In addition, as PUs start and stop their communications, the dynamic spectral activities can only be partially observed by SUs because of imperfect spectrum sensing techniques. Thus, the dynamic spectrum sensing methods used for time-varying environments need to be able to model system with partially observed variables. Markov modeling is one of the well-known and widely studied techniques for modeling the behavior of PUs. For example, (Zhao, Tong, Swami & Chen, 2007) considered the optimal distribution MAC protocols for opportunistic spectrum access in the partially observable Markov decision process (POMDP) framework. Also, Zhao et al. investigated the structure of myopic policy in their POMDP problem and compare it with the optimal policy (Zhao, Krishnamachari & Liu, 2007). (Zhao & Krishnamachari, 2007) worked on similar problem and considered the imperfect sensing performance. (Chen et al., 2009) studied the threshold structure of optimal sensing and access policies for reducing the complexity of optimal policy searching.

Recently, (Zhang et al., 2010) worked on dynamic scheduling for cooperative sensing under time-varying spectrum environments. They formulate the sensing schedule problem with POMDP. They derived an optimal policy that determined which SUs must sense which channels with what sensing accuracy. Also, they studied the solution structure for the myopic and optimal policy under a simplified model with only two SUs analytically.

The time-domain combining spectrum sensing (TDC–SS) based on the Bayesian method and the Neyman–Pearson theorem was proposed in (Lee & Kim, 2011). (Lee & Kim, 2011) assumed that the state of the PU evolves according to the Markov ON–OFF process (Sung et al.,

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[5] The polyblock algorithm is a monotonic programming method which can solve monotonic optimization problems. The solution of polyblock algorithm is ϵ-optimal. For more information, see (Floudas & Pardalos, 2009)

2006). By using Bayesian method and considering rate of the ON–OFF, the TDC–SS algorithm sequentially updated the likelihood ratio of PU state and decided the current PU state from Neyman–Pearson criterion. Also, the TDC–SS algorithm can adapt itself with transition rate of PU state.

2.3 Challenges

In Section (2.1), the studies of optimal trade-off between sensing time and transmission time are reviewed. In these studies, the report channel is assumed to be an error-free channel, but it may not be true in practice. Optimizing the cooperative spectrum sensing parameters with noisy reports channel is one of the research challenges in cognitive radio. It seems that applying coding techniques on the report channel and studying its effects can be one way to mitigate the problem of noisy report channels (Cheng et al., 2009). Also, in most prior works, finding the theoretical bound of spectrum sensing parameters is limited to the centralized structure. The distributed cooperative spectrum sensing needs more theoretical investigations to optimize its key parameters such as sensing time. Comparing to one-hop structure, the multi-hop structured systems is more difficult to analyze because of their complex structures in contrast to one-hop systems.

3. Game theoretical approaches

In cognitive radio networks, SUs are able to sense, learn and act to optimize their throughput. They can also cooperate with each other to improve their performance with the same or less power consumption. In addition, the wireless environments change continuously due to the movement of SU and/or PU, the change of background noise and the variation of users' traffics. In traditional spectrum sensing, each change will force the network controller to re-allocate the spectrum resources. The re-allocation of the spectrum resource through all SUs will create a lot of communication overhead and more time for convergence.

Some studies such as (Saad et al., 2011; 2009b; Wang, Liu & Clancy, 2010; Wang, Wu & Liu, 2010) tried to use the the game theoretical techniques to tackle these challenges. By using game theory framework in cognitive radio, the SUs and PUs behaviors can be studied and analyzed as a game where each user can choose a strategy to maximize its own utility function. Also, as we briefly described in Sections (2.1) and (2.2), the optimization of spectrum usage is a multi-objective optimization problem.

There are two major approaches based on game theory to model cognitive radio systems, there are "Evolutionary games" (bargaining games) and "Coalitional games". The example of evolutionary game can be seen in the work of (Wang, Liu & Clancy, 2010) who studied the behavior of selfish SUs in cooperative and non-cooperative spectrum sensing games. The other type of cooperative spectrum sensing, called coalitional game, was studied in (Saad et al., 2011), where SUs self-organize into coalition groups and select coalition heads[6] by a distributed algorithm. Then, they only share their sensing information through the coalition group. In Sections (3.1) and (3.2), the details of coalitional and evolutionary spectrum sensing games will be described.

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[6] In a coalition set S, the SU with the lowest non-cooperative probability of missed detection will be chosen as a coalition head.

3.1 Coalition game for spectrum sensing

In the literature, the centralized approach for cooperation has been most widely studied for cooperative spectrum sensing. In this approach, the SUs send their sensnig data, or decisions, to a fusion center and then the fusion center will make a decision about the presence or absence of PU and will inform the SUs. Also, it is possible to have some SUs, which are working for different service providers, collaborate with each other without a unique centralized fusion center. The solution using a centralized fusion center will significantly increase the complexity and overhead when the number of SUs increases.

To tackle the problem of complexity and communication overhead, in some papers such as (Kim & Shin, 2008; Sun et al., 2007), the idea of making clusters for cooperative spectrum sensing was used to improve the spectrum utilization of SUs. For example, in (Sun et al., 2007), the centralized fusion center employed clustering to reduce the error over a reporting channel. However, it did not propose any specific algorithm for creating clusters. Further, (Kim & Shin, 2008) focused on analyzing the performance of cooperative spectrum sensing based on different detection algorithms with respect to geographical restriction on clustering of the users. The research shows composing clusters and making decisions for the SUs belonging to the same cluster will reduce the complexity of decision making and overhead of communication.

Followed the aforementioned cluster-based cognitive spectrum sensing, (Saad et al., 2011) recently employed game theoretical techniques for forming optimal clusters and conducting distributed decision making. The major contribution of (Saad et al., 2011) is the derived distributed strategy for cooperative spectrum sensing between the SUs. Also, they studied the effect of network topology on the probability of detection $Q_{m,S}$ and false alarm $Q_{f,S}$ for each coalition group S, which are given by

$$Q_{m,S} = \prod_{i \in S} [P_{m,i}(1 - P_{e,i}) + (1 - P_{m,i})P_{e,i}], \tag{12}$$

$$Q_{f,S} = 1 - \prod_{i \in S} [(1 - P_{f,i})(1 - P_{e,i}) + P_{f,i}P_{e,i}], \tag{13}$$

where $P_{m,i}$ and $P_{f,i}$ are the probability of missed detection and false alarm for each SU i in the coalition set S, respectively. Also, $P_{e,i}$ is the probability of error on the report channel[7]. In (Saad et al., 2009b), based on importance of false alarm, the logarithmic barrier function (Boyd & Vandenberghe, 2004) was used for penalizing the false alarm in the cost function. (Saad et al., 2009b) defined the cost function $C(Q_{f,S}, \alpha)$ and the utility function $v(S)$ by

$$C(Q_{f,S}, \alpha) = \begin{cases} -\alpha^2 . log\left(1 - \left(\frac{Q_{f,s}}{\alpha}\right)^2\right) & , if\ Q_{f,S} < \alpha \\ +\infty & , if\ Q_{f,S} \geq \alpha \end{cases} \tag{14}$$

$$v(S) = Q_{d,S} - C(Q_{d,S}, \alpha_S) = (1 - Q_{m,S}) - C(Q_{d,S}, \alpha_S) \tag{15}$$

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[7] According to distributed structure for the fusion center, the report channels are defined between the SUs and the coalition head of same coalition set S.

They modeled the problem as a non-transferable[8] coalition game (Saad et al., 2009a), and they applied a distributed algorithm to collaborative sensing. This distributed algorithm has three phases: "neighborhood discovery", "coalition group formation", and "coalition sensing" respectively.

In the first phase, the distributed algorithm needs to acquire the distances between neighbors, i.e., the distance between the SU and the PU or the distances between the SUs. In addition, the probability of missed detection and false alarm of each SU in the neighbors and the existence of other coalitions are necessary for the coalition group formation. This type of information can be obtained:

- directly via control channel such as Cognitive Pilot Channel (CPC) (Filo et al., 2009; Sallent et al., 2009);
- estimated via signal processing techniques (Cardoso et al., 2008; Damljanovic, 2008; Hossain et al., 2009);
- estimated via ad-hoc routing neighborhood discovery (Arachchige et al., 2008; Damljanovic, 2008; Krishnamurthy et al., 2009);
- estimated via geo-location techniques (Shellhammer et al., 2009).

The second phase is the coalition group formation. This phase is a distributed iterative algorithm based on information about the neighborhood discovery performed in the first phase. The main operations of the second phase are merge, split, and adjust operations that find the suitable topology of the network. The merge operation tries to group some SUs to increase the utility function $v(S)$. The split operation tries to separate some SUs for the coalition group S if the splitting will increase the $v(S)$. The coalitions decide to merge or split if at least one of the SUs can improve its utility function without decreasing the others' utility function. The adjust operation excludes some SUs from coalition group S that do not affect the $v(S)$. All operations in the coalition group formation must repeat every period θ to adapt the topology of the network with the dynamic changes of PUs and SUs.

The complexity of the second phase of algorithm depends on the number of merge and split operations in each iteration. The worst case scenario for N number of SUs before finding the suitable topology needs to $\sum_{i=1}^{N-1} i = \frac{N(N-1)}{2}$ merge operation attempts. In practice, the number of attempts is much less than the worst case. Also, for the split operations, the number of possible partitions is proportional to the *Bell number*[9], which grows exponentially with the number of the SUs in each coalition set. However, a coalition does not need to search all possible cases. It can find a way of splitting in the middle of a search. In addition, the number of SUs in the coalition sets is very small; therefore, the possible splitting options are restricted.

In the last phase, coalition sensing, each SU reports its sensing bit to the coalition head about the presence or absence of the PU through the wireless channel, and the coalition head makes

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[8] A coalition game is non-transferable if the value of the utility function of a coalition can not be arbitrarily apportioned between coalition's players (for more information see (Ray, 2007; Saad et al., 2009a))

[9] The number of ways a set of n elements can be partitioned into nonempty subsets is called a Bell number and is denoted as B_n. For example, there are five ways the numbers $\{1, 2, 3\}$ can be partitioned: $\{\{1\}, \{2\}, \{3\}\}$, $\{\{1, 2\}, \{3\}\}$, $\{\{1, 3\}, \{2\}\}$, $\{\{1\}, \{2, 3\}\}$ and $\{\{1, 2, 3\}\}$, so $B_3 = 5$ and similarly $B_4 = 15$.

the final decision by using the decision fusion OR-rule. Clearly, the required bandwidth for communication in each coalition set to reach the final decision is significantly less than the common fusion center, because it needs to send a bit to each PU only through its group. Also, this strategy has an advantage in reducing the probability of missed detection and power consumption by sending the sensing bit of each SU to its coalition head only.

3.2 Evolutionary game for spectrum sensing

In most of the studies about cooperative spectrum sensing, a fully cooperative spectrum sensing is considered. It means in all frames, all SUs take part in sensing and send their own sensing results to the other SUs for fusion and make final decision about presence or absence of PUs. According to discussions in Sections (2.1) and (2.2), sensing the PU band consumes energy and needs certain amount of time. Depend on QoS, performance and throughput of cognitive radio systems, a SU needs to optimize the length of sensing time in each sensing slot. Furthermore, with the emergence of new wireless applications and networks, there may be some SUs which are selfish and attend to take advantage of other sensing result, save their energy and time and have more time for data transmission. Therefore, the study of dynamic cooperative behavior of the selfish SUs in the competitive environments is essential to improve the performance of system and fairness between the SUs.

Modeling the behaviors of SUs as an evolutionary game, where the payoff is defined as SU's throughput, has attracted lots of attention in the research community recently. In (Wang, Liu & Clancy, 2010), an evolutionary game model is studied where selfish SUs tend to overhear the others' sensing results and contribute less to the common task. For example, the SUs like to spent less time in sensing and more time for data transmission. (Wang, Liu & Clancy, 2010) incorporated practical multi-user effect and constraints into the spectrum sensing game. They analyzed the strategy of updating SU's profile using the replicator dynamics equations (Fudenberg & Levine, 1998). They derived the evolutionary stable strategy (ESS) of game and proved its convergence by analyzing the dynamic of SU's behavior. Also, they proposed a distributed learning algorithm that SUs update their strategies by exploring different actions at each time, adaptively learning during the strategic interaction, and approaching the best response strategy.

Similar to equation (3), they defined the average throughput function by

$$R(N) = R_{\mathcal{H}_0}(N)P(\mathcal{H}_0) + R_{\mathcal{H}_1}(N)P(\mathcal{H}_1) \tag{16}$$

$$= \frac{T - \delta(N)}{T}(1 - P_f)C_{\mathcal{H}_0}P(\mathcal{H}_0) + \frac{T - \delta(N)}{T}(1 - P_d)C_{\mathcal{H}_1}P(\mathcal{H}_1)$$

where N is the number of collected samples and $C_{\mathcal{H}_0}$ and $C_{\mathcal{H}_1}$ are the data rate of SU under $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively. Also, $\delta(N) = N/f_s$ where f_s is the frequency of sampling. They assumed that there was only one PU and its licensed band was divided into K sub-bands. When the PU was idle, each SU operated exclusively in one of K sub-bands. They defined a narrow-band signaling channel for exchanging the sensing results. By this setup, some of SUs can contribute in the sensing part, called, "C" (Contributer) and some of them can refuse to contribute in the sensing part, in the hope that other will do it for them, called, "D" (Denier). If no SU contributes in the sensing part, the average throughput or utility of SUs will be zero.

(Wang, Liu & Clancy, 2010) defined payoff functions for homogeneous[10] and heterogeneous[11] players separately. For Homogeneous players, the payoff function was defined as

$$U_C(J) = U_0(1 - \frac{\tau}{J}), \; if \; J \in [1, K] \tag{17}$$

and

$$U_D(J) = \begin{cases} U_0 \; , \; if \; J \in [1, K-1] \\ 0 \; , \; if \quad\quad J = 0 \end{cases} \tag{18}$$

where J is the number of contributer SUs and U_C and U_D are the payoff for contributers and deniers respectively. U_0 denotes the throughput of a denier and $\tau = \delta(N)/T$. Here, the denier can use all of the its time to transmit the data, but the contributer will spend τ/J of its time for the spectrum sensing and the rest of time for the data transmission. Also, equations (17) and (18) show that the payoff of players, who do not contribute in the sensing part, will be more than the payoff of contributer players except no one perform the spectrum sensing.

Consider a simple heterogeneous environment with only two players "1" and "2" with different false alams probabilities $P_{f,1}$ and $P_{f,2}$. We also assume that a contributing player will spend τ of its time for spectrum sensing and $1 - \tau$ of time for the data transmission and a user will transmit at the data rate C_i when no PU is observed. Similar to a homogeneous environment, at least one of the heterogeneous players has to be a contributer to avoid zero payoff. The payoff function for the players can be easily found and is shown in Table (1).

player 1 \ player 2	Contributing	Denying
Contributing	$C_1 P(\mathcal{H}_0)(1 - P_f)(1 - \frac{\tau}{2})$, $C_2 P(\mathcal{H}_0)(1 - P_f)(1 - \frac{\tau}{2})$	$C_1 P(\mathcal{H}_0)(1 - P_{f,1})(1 - \tau)$, $C_2 P(\mathcal{H}_0)(1 - P_{f,1})$
Denying	$C_1 P(\mathcal{H}_0)(1 - P_{f,2})$, $C_2 P(\mathcal{H}_0)(1 - P_{f,2})(1 - \tau)$	0,0

Table 1. Payoff table for heterogeneous players

(Wang, Liu & Clancy, 2010) derived the replicator dynamic equations (Fudenberg & Levine, 1998) and found an ESS for this problem. In addition, they proposed a distributed learning algorithm for ESS and showed its convergence by computer simulations.

3.3 Challenges

As we discussed in Section (3.1), the rate of changes in the environment can affect the performance of coalition group formation. To avoid performance reduction, the operations in coalition group formation should not be repeated periodically to adapt the dynamic changes of networks. How to tune the length of period and how to learn it based on the changes of environment are some of meaningful research challenges. A potential direction is to use modeling techniques to analyze environmental changes so as to reduce the overhead of periodic coalition group formation.

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[10] The individual players with identical data rate and received primary SNR and the same set of pure strategies will be called homogeneous players.

[11] Two players are heterogeneous if they do not have the identical set of parameters (data rates, received primary, the set of strategies, etc.).

4. Compressed sensing

Wide-band spectrum sensing is essential for efficient dynamic spectrum sharing in cognitive radio networks. The wider the range of shared spectral resources the higher the cognitive network capacity. However, this gain comes at the cost of increasing the complexity of network spectral resource management at several levels. In particular, the cost of spectrum sensing is proportional to the range of the sensible spectrum.

While cooperative techniques are used to relax the complexity constraints of wide-band spectrum sensing, this relaxation is not sufficient or effective in large-scale cognitive radio networks. In such networks, the range of shared spectrum and/or the number of cooperative nodes can be too large rendering high cost of sensing data acquisition unit and wide bandwidth for control channel to exchange sensing information among cooperative nodes.

Compressed sampling is one solution used to address scalability problems in signal processing by reducing the cost of acquisition at the sensor (Donoho, 2006; Polo et al., 2009; Romberg, n.d.). Using compressive sensing framework, it is possible to recover the sampled signals on a probabilistic basis from a few number of measurements, which are less than the number imposed by the Nyquist rate for band-limited signals. However, successful signal recovery is conditioned by two factors: signal sparsity and incoherency (Candès & Wakin, 2008; Donoho, 2006). Signal sparsity means that the rate of information to be captured from the acquired signal is small relatively compared to the signal dimension. In spectrum sensing applications, this condition implies that the occupancy of the spectrum should be relatively small compared to the complete range of the spectrum, i.e., the sensed spectrum is sparse. The incoherency condition means that representation domain of the signal should be incoherent with the sampling domain. This condition is satisfied in spectrum sensing applications since the representation domain of the signal is the frequency domain while the sampling domain is the time domain. The time domain is incoherent with the frequency domain as sudden changes in one of these domains spreads out in the other one.

Motivated by the fact that the wireless spectrum in rural areas is highly underutilized, i.e., sparse (Rysavy, 2009), recent studies have examined the application of these compressive techniques in spectrum sensing (Bazerque & Giannakis, 2010; Candès et al., 2006; Laska et al., 2011; Liang et al., 2010; Tian, 2008; Tian & Giannakis, 2007; Zeng et al., 2010). The research efforts attempt to exploit the efficiency of compressive sensing technique to reduce the cooperation overhead or sampling complexity in cooperative spectrum sensing.

The compressive sensing framework is comprised of two stages: signal sampling and signal recovery. The compressive sensing requires a random access to the sensed signal samples or a linear combination of them. There are several signal sampling systems that have been proposed in literature for that purpose such as the *Random Demodulator* (Tropp et al., 2010), the *Modulated Wide-band Converter* (Mishali & Eldar, 2010) and the *Analog to Information Converter* (Kirolos et al., 2006). Also, a frequency selective filter has been recently suggested as means of obtaining linear combinations of multiple channel information at the sensing circuit (Meng et al., 2011).

In addition to the signal sampling systems, several signal recovery technique based on compressive samples have been proposed in literature. They can be grouped into two main categories: based on solving linear convex optimization problem such as *Basis Pursuit*

technique (BP) (Chen et al., 1999) and greedy algorithms such as *Matching Pursuit* (MP) (Mallat & Zhang, 1993) and Orthogonal Matching Pursuit (OMP) (Tropp & Gilbert, 2007).

Orthogonal matching pursuit technique is proposed in a distributive spectrum sensing framework when the received signals among cooperative nodes are highly correlated (Liang et al., 2010). In (Tian, 2008; Zeng et al., 2010), a distributive compressive sensing technique based on BP signal recovery technique is presented. The dissemination of sensing information in this distributive technique enforces consensus among local spectral estimates and shown to converge with reasonable computational cost and power overhead. The lowest SNR at which the collaborative compressed sensing in (Zeng et al., 2010) can perform with is probability of detection around 90% and compression ratio of 50% is approximately 5 dB. However, this sensing technique assumes identical spectral observations among cooperative nodes. This can be a limiting factor for deploying it in large scale networks where the observed spectrum might vary among widely scattered cooperative nodes.

Using similar signal recovery technique, (Bazerque & Giannakis, 2010) has proposed a cooperative compressive sensing technique that exploits two forms of signal sparsity, i.e. in the frequency domain and spatial domain. The sparsity in the frequency domain is a result of the narrow-band nature of transmitted signal compared to the overall range of shared spectrum. The second form of sparsity emerges from scattered active primary users' radios that co-exist with the cooperative cognitive radio. The join spectral-spatial analysis featured in this technique allows it to be used in large-scale networks since it takes into consideration the variation of spectral observation due to spatial diversity among cooperative nodes.

The work of (Meng et al., 2011) has addressed the sensing problem in small and large scale networks jointly using compressive sensing techniques. As a result, two spectrum recovery approaches were proposed. The first one is based on matrix completion and the second spectrum recovery approach is based on joint sparsity recovery. The matrix completion approach is appropriate for small scale cooperative networks as it recovers the channel occupancy information from a small number of cooperative sensing. The joint sparsity approach, on the other hand, scales better to large networks because it skips recovering the reports and directly reconstructs channel occupancy information by exploiting the fact that each occupied channel is observable by multiple cooperative sensing nodes.

4.1 Challenges

A number of challenges arise from using compressive sensing techniques for spectrum sensing in general, and in cooperative sensing in particular. One challenge resulted from sensing densely occupied spectrum where spectrum sparsity condition does not hold. Furthermore, cognitive radio networks attempt to utilize the available spectral resources in sparse spectrum through dynamic spectrum access. This can negatively impact the efficiency of compressive sensing techniques as it increases the occupancy (reduces sparsity) of the sensed spectrum (Laska et al., 2011). Sensing dense spectrum using compressive sensing technique is still an open problem. However, (Zhang et al., 2011) have addressed this problem by proposing a detection mechanism of compressive sensing failure due to sparsity reduction. This is achieved by modeling the compressed spectrum reconstruction as a Gaussian process so that the correlation of model parameters can be exploited to detect the failure of compressed reconstruction due to non-sparse spectrum.

Sensing heterogeneous sets of active radios poses another challenge because the detection thresholds for each one might be different. Hence, the ability to classify signals using compressive samples can be useful in this context and there are a number of recent studies that have addressed this matter (Davenport et al., 2010). Also, certain signal features can be exploited to distinguish between legitimate signals and spurious interference from adjacent cognitive radios. In (Zeng et al., 2010), the orthogonality between the spectrum of primary users and that of cognitive radio users was utilized as a constraint for consensus optimization during distributed collaborative sensing.

Another intriguing direction for future research is shadowing effects in cooperative compressive sensing techniques. (Tian & Giannakis, 2007) suggested complementing the distance-only dependent propagation functions used in the compressive sensing design with non-parametric models that can be learned from the data (Mateos et al., 2009).

5. Applications

The characteristics of the wireless environment have considerable impacts on the design and development of cooperative sensing. Among these characteristics are the mobility of sensing nodes, the spatial density, power and bandwidth of the co-existing wireless networks. The literature has reported several performance evaluation studies of cooperative sensing in various types of wireless environments such as Radar (Wang et al., 2008), UAV (Gu et al., 2006), VANET (Wang & Ho, 2010), WiFi Networks (You et al., 2011), Relaying-based network (Roshid et al., 2010), Positioning Services in ad-hoc Networks (Gellersen et al., 2010), Small scale wireless devices (Min et al., 2011).

5.1 Radar

Cooperative sensing is used to enable sharing different parts of the spectrum with various types of primary user networks. S-band radar spectrum features great spectral opportunities for band sharing compared with those at the TV spectrum frequencies (Research, 2005; SYSTEM, 2006). Studies have examined the feasibility of using cooperative sensing for managing the coexistence between radar and other communication systems. One study has concluded that sharing the radar band with another communication system is feasible on the basis of causing "*acceptable interference*" to the radar. Acceptable interference is determined by calculating the safe regions where radar and communication systems can coexist without causing unacceptable interference to the radar systems. Priori knowledge about the radar systems, such as swept radar rotation rate and main beam to side-lobe ratio, and the radar system maximum interference-to-noise ratio (INR) threshold, can assist in determining the borders of the safe region. It turns out that the number of cooperative nodes, their channel correlation levels, channel conditions and the detection probability threshold have considerable impact on the cooperation gain obtained in such wireless environments (Wang et al., 2008). Therefore sensing node grouping strategies are needed in order to maximize the cooperative gain with minimum number of sensors.

5.2 UAV

High mobility in wireless environments imposes considerable challenges for cooperative sensing. Unmanned Air Vehicle networks and Vehicular ad-hoc Network are examples of

such wireless environments. Cooperative sensing using unmanned aerial vehicles (UAVs) is a fundamental element in combat intelligence, surveillance, and reconnaissance (ISR) to estimate the position and velocity of the ground moving target (GMT). In (Gu et al., 2006), the performance of cooperation sensing among a set of pulse Doppler radar sensors mounted on a group of UAVs is studied. Specifically, the number and geometry of sensor distributions impact on the quality of the position and velocity estimates is analyzed. The quality of the estimation is characterized by its statistical variance and the theoretical minimum variance is derived based on Cramer-Rao bounds. However, the complexity of such analysis increases as more types of sensor measurements are involved. In such application and wireless environment, various type of measurements are obtained; namely: azimuth, range and range rate measurements. One common assumption to maintain the tractability of the mathematical analysis is the variance is identical for each measurement type at each UAV. In case that this assumption is not held, numerical methods are used instead for estimation error minimizations (Gu et al., 2006). Also, it was found that optimizing the configuration of the UAV team is essential for efficient "*ground moving target identification*" (GMTI) and "*moving surface target engagement*" (MSTE) operations in ISR systems. One possible representation of the optimal geometrical set up can be defined by the bearing angle formed by each UAV and the GMT (Gu et al., 2006).

5.3 VANET

Another type of highly mobile wireless environment is VANET networks. The accuracy and efficiency of spectrum sensing is essential to maintain reliable information exchange and data transmission between nearby On-Board Units (OBUs) and Roadside Units (RSUs) for applications such as route planning, traffic management, as well as other wireless Internet service in the unlicensed spectrum resources (Wang & Ho, 2010). One fundamental challenge of cooperative sensing in such networks is the sparsity and variability of spatial density of vehicles equipped with CR technologies. Another challenge is the heterogeneity of primary user signals. Nevertheless, cooperative sensing is used in such environments to resolve some problems that can-not be mitigated by individual sensing such as coordination and fairness among nodes for efficient resource utilization. In this context, a sensing coordination node is introduced to establish an adaptive sensing coordination framework (Wang & Ho, 2010) that combines the advantages of both stand alone and cooperative sensing between CR-VANETs. Rather than having complete control of spectrum sensing and access, the coordinating nodes assist and coordinate the VANETs for efficient spectral utilization and minimal communication interruptions. This framework relies on some priori knowledge such as feature carriers, channel spacing of frequency bands, proactive fast sensing information, as well as user-based class information, to perform intelligent channel selection of spectrum.

5.4 WiFi

Recent explosive data increase (mostly due to smart phones) for wireless internet access results in a spectrum shortage and increasing demand for additional spectrum to support the dramatic increase in data traffic on WiFi networks. One good solution for the spectrum shortage is to use the underutilized TV spectrum based on Cognitive radio techniques. Cooperative sensing is proposed in WiFi networks coordinate the coexistence between WiFi and wireless devices in TV spectrum (You et al., 2011). The study has analyzed the

performance "$k\ out\ of\ N$" rule for cooperative sensing in WiFi networks (You et al., 2011). The performance of sensing is controlled by sensing time and number of sensors. Both factors are optimized to maximize data transmission throughput and minimize detection error respectively.

5.5 Integration of cooperative communication and cooperative sensing

Cooperation strategies are not limited to spectrum sensing application. Other form of cooperation appears in wireless communication such as relaying. An interesting extension of cooperative strategies is to integrate cooperative sensing and cooperative communication in wireless networks with relaying support. This integration was suggested in (Roshid et al., 2010). Cooperative communication is performed through relaying with different resource allocation strategies (power allocation for relaying PU traffic and bandwidth allocation for relaying CR traffic). Such integration of cooperation strategies necessitates an efficient spectrum management system e.g., spectrum broker in centralized systems and multi-agent and cognitive pilot channels (CPC) in distributed systems (Roshid et al., 2010). However, there is no clear description to this date on how the integration can be done. Also, another open problem is the signaling that enables a joint cooperation of communication and sensing that can impact the architecture of current networks leading to higher transmission capacity and transparent coexistence among heterogeneous set of wireless networks.

5.6 Positioning

Cooperative sensing technique is also applied for positioning application in ad-hoc wireless networks. Unlike most infrastructure based positioning systems that are based on heterogeneous architecture (fixed/reference and mobile nodes), cooperative-relative-positioning systems relies on a homogeneous set of nodes that can measure the relative distance between each pair of nodes. Performing cooperative positioning in such network setup pertains the following challenges: additional measurements such as angle measurements may be required, scalable coordination and synchronization system that can operate in ad-hoc environment, and increasing computational load on sensing node due to the absence of a centralized entity at which most computational load can be outsourced. The communication among cooperative nodes is performed in time division multiple access basis. Each node broadcasts to the rest of nodes its measurements along with the received measurements from other nodes. Synchronous distributed jam signaling (SDJS) for data fusion on the physical layer is used to manage a systematic measurement error removal by estimating statistical measurement parameters from a coordinated transmission of jamming signals.

5.7 Small scale primary user

As more wireless standards continues to evolve to fulfill the requirements of the new wireless services, the coexistence among heterogeneous set of wireless networks becomes a critical challenge. This is particularly true when heterogeneity is not only a result of difference in the waveform but also in the coverage range. For example, the WiFi network coverage is around 20-30m in 2.4 GHz while Bluetooth coverage in that portion of the spectrum is around 5 m (for Bluetooth class 3). Another example is the digital TV signal (DTV) signal

and wireless microphone signals. Most of the cooperative sensing research has focused on detecting large scale networks. However, detecting small scale networks bears additional challenges due to the unpredictability of their transmission schedule and high mobility profile i.e., highly dynamic temporal and spatial transmission pattern. In such cases, the knowledge of the transmitter location is more critical than in the case for detecting large scale networks. Recent studies have examined the problems of detecting small-scale networks. One solution is to use a disabling beacon additional information such as the signature/authentication and geo-location of the small scale transmitter as is the case for wireless microphones in the 802.22 Task Group 1 (TG 1) proposal (Lei & Chin, 2008). More recently, a solution proposed in (Min et al., 2011) identifies the optimal range of sensing fusion in cooperative sensing strategies so that the average detection delay is minimized for a given sensing performance requirements. This solution, however, is sensitive to power and location estimation errors. Hence, a join power-location estimation technique (DeLOC) is proposed (Min et al., 2011) to minimize the estimation errors and improve the overall detection performance with optimal fusion range.

Limited work has been done in this area, further improvements can be made in the performance of detection by incorporating further communication layers in addition to the MAC layer (Min et al., 2011). Also, the fusion of different sensing measurements such as time, location, orientation and wireless signal power using different types of sensors can further improve the detection performance.

6. Conclusion

In this chapter, we reviewed the recent studies about cooperative spectrum sensing in cognitive radio and identified the research challenges and unsolved issues. The chapter introduced some basic concepts of cooperative spectrum sensing and reviewed theoretical studies of known bounds and limits. Then, we surveyed the game theoretical approaches in cooperative cognitive radio briefly. The chapter followed by reviewing compressed sensing studies for cooperative cognitive radio. In the end, we explored the application of cooperative spectrum sensing in various types of wireless environments such as Radar, UAV, VANET, WiFi Networks and etc.

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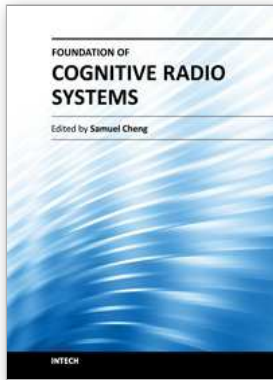
Foundation of Cognitive Radio Systems

Edited by Prof. Samuel Cheng

The fast user growth in wireless communications has created significant demands for new wireless services in both the licensed and unlicensed frequency spectra. Since many spectra are not fully utilized most of the time, cognitive radio, as a form of spectrum reuse, can be an effective means to significantly boost communications resources. Since its introduction in late last century, cognitive radio has attracted wide attention from academics to industry. Despite the efforts from the research community, there are still many issues of applying it in practice. This books is an attempt to cover some of the open issues across the area and introduce some insight to many of the problems. It contains thirteen chapters written by experts across the globe covering topics including spectrum sensing fundamental, cooperative sensing, spectrum management, and interaction among users.

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