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Cooperative spectrum sensing in cognitive radio networks: A survey

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ABSTRACT

Spectrum sensing is a key function of cognitive radio to prevent the harmful interference with licensed users and identify the available spectrum for improving the spectrum's utilization. However, detection performance in practice is often compromised with multipath fading, shadowing and receiver uncertainty issues. To mitigate the impact of these issues, cooperative spectrum sensing has been shown to be an effective method to improve the detection performance by exploiting spatial diversity. While cooperative gain such as improved detection performance and relaxed sensitivity requirement can be obtained, cooperative sensing can incur cooperation overhead. The overhead refers to any extra sensing time, delay, energy, and operations devoted to cooperative sensing and any performance degradation caused by cooperative sensing. In this paper, the state-of-the-art survey of cooperative sensing is provided to address the issues of cooperation method, cooperative gain, and cooperation overhead. Specifically, the cooperation method is analyzed by the fundamental components called the elements of cooperative sensing, including cooperation models, sensing techniques, hypothesis testing, data fusion, control channel and reporting, user selection, and knowledge base. Moreover, the impacting factors of achievable cooperative gain and incurred cooperation overhead are presented. The factors under consideration include sensing time and delay, channel impairments, energy efficiency, cooperation efficiency, mobility, security, and wideband sensing issues. The open research challenges related to each issue in cooperative sensing are also discussed.

1. Introduction

The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization. To address this problem, cognitive radio (CR) [1,2] has emerged as a promising technology to enable the access of the intermittent periods of unoccupied frequency bands, called *white space* or *spectrum holes*, and thereby increase the spectral efficiency. The fundamental task of each CR user in CR networks, in the most primitive sense, is to detect the licensed users, also known as primary users (PUs), if they are present and identify the available spectrum if they are absent. This is usually achieved by sensing the RF environment, a process called spectrum sensing [1–4]. The objectives of spectrum sensing are twofold: first, CR users should not cause harmful interference to PUs by either switching to an available band or limiting its interference with PUs at an acceptable level and, second, CR users should efficiently identify and exploit the spectrum holes for required throughput and quality-of-service (QoS). Thus, the detection performance in spectrum sensing is crucial to the performance of both primary and CR networks.

The detection performance can be primarily determined on the basis of two metrics: *probability of false alarm*, which denotes the probability of a CR user declaring that a PU is present when the spectrum is actually free, and *probability of detection*, which denotes the probability of a CR user declaring that a PU is present when the spectrum is indeed occupied by the PU. Since a miss in the detection

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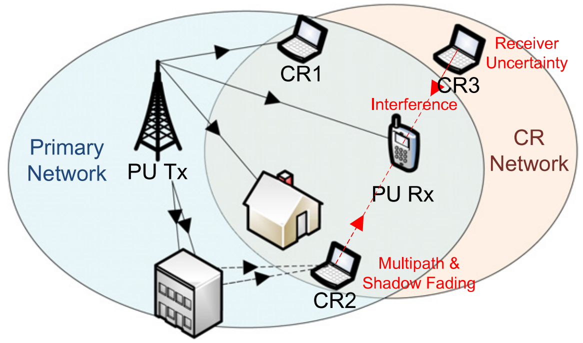

Fig. 1. Receiver uncertainty and multipath/shadow fading.

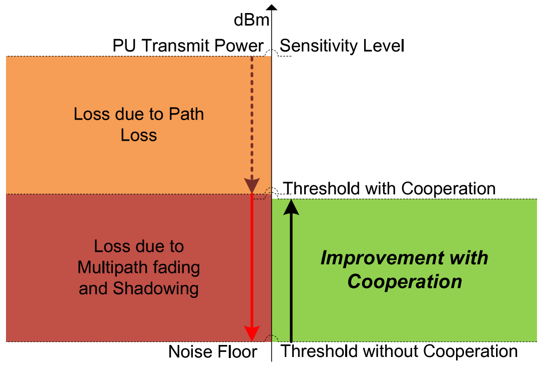

Fig. 2. Improvement of sensitivity with cooperative sensing [7].

will cause the interference with the PU and a false alarm will reduce the spectral efficiency, it is usually required for optimal detection performance that the probability of detection is maximized subject to the constraint of the probability of false alarm.

Many factors in practice such as multipath fading, shadowing, and the receiver uncertainty problem [1] may significantly compromise the detection performance in spectrum sensing. In Fig. 1, multipath fading, shadowing and receiver uncertainty are illustrated. As shown in the figure, *CR*1 and *CR*2 are located inside the transmission range of primary transmitter (PU TX) while *CR*3 is outside the range. Due to multiple attenuated copies of the PU signal and the blocking of a house, *CR*2 experiences multipath and shadow fading such that the PU's signal may not be correctly detected. Moreover, *CR*3 suffers from the receiver uncertainty problem because it is unaware of the PU's transmission and the existence of primary receiver (PU RX). As a result, the transmission from *CR*3 may interfere with the reception at PU RX. However, due to spatial diversity, it is unlikely for all spatially distributed CR users in a CR network to concurrently experience the fading or receiver uncertainty problem. If CR users, most of which observe a strong PU signal like *CR*1 in the figure, can cooperate and share the sensing results with other users, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observations at each CR user. Thus, the overall detection performance can be greatly improved. This is why cooperative[1] spectrum sensing (simply called *cooperative sensing* thereafter) [5–7] is an attractive and effective approach to combat multipath fading and shadowing and mitigate the receiver uncertainty problem.

The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. By cooperation, CR users can share their sensing information for making a combined decision more accurate than the individual decisions [5]. The performance improvement due to spatial diversity is called *cooperative gain*. The cooperative gain can be also viewed from the perspective of sensing hardware. Owing to multipath fading and shadowing, the signal-to-noise ratio (SNR) of the received primary signal can be extremely small and the detection of which becomes a difficult task. Since receiver sensitivity indicates the capability of detecting weak signals, the receiver will be imposed on a strict sensitivity requirement greatly increasing the implementation complexity and the associated hardware cost. More importantly, the detection performance cannot be improved by increasing the sensitivity, when the SNR of PU signals is below a certain level known as a SNR wall [8]. Fortunately, the sensitivity requirement and the hardware limitation issues can be considerably relieved by cooperative sensing. As shown in Fig. 2, the performance degradation due to multipath fading and shadowing can be overcome by cooperative sensing such that the receiver's sensitivity can be approximately set to the same level of nominal path loss without increasing the implementation cost of CR devices [7]. However, cooperative gain is not limited to improved detection performance and relaxed sensitivity requirement. For example, if the sensing time can be reduced due to cooperation, CR users will have more time for data transmission so as to improve their throughput. In this case, the improved throughput is also a part of cooperative gain. Thus, a well-designed cooperation mechanism for cooperative sensing can significantly contribute to a variety of achievable cooperative gain.

Although cooperative gain can be achieved in cooperative sensing as previously discussed, the achievable cooperative gain can be limited by many factors. For example, when CR users blocked by the same obstacle are in spatially correlated shadowing, their observations are correlated. More spatially correlated CR users participating in cooperation can be detrimental to the detection performance [6,7]. This raises the issue of user selection for cooperation in cooperative sensing. In addition to gain-limiting factors, cooperative sensing can incur *cooperation overhead*. The overhead refers to any extra sensing time, delay, energy, and operations devoted to cooperative sensing compared to the individual (non-cooperative) spectrum sensing case. Moreover, any performance degradation in correlated shadowing or the vulnerability to security attacks is also a part of the cooperation overhead. Thus, we are motivated to explore the idea of cooperation in spectrum sensing and provide an insight on how cooperative

[1] Cooperation and collaboration are interchangeable in this paper.

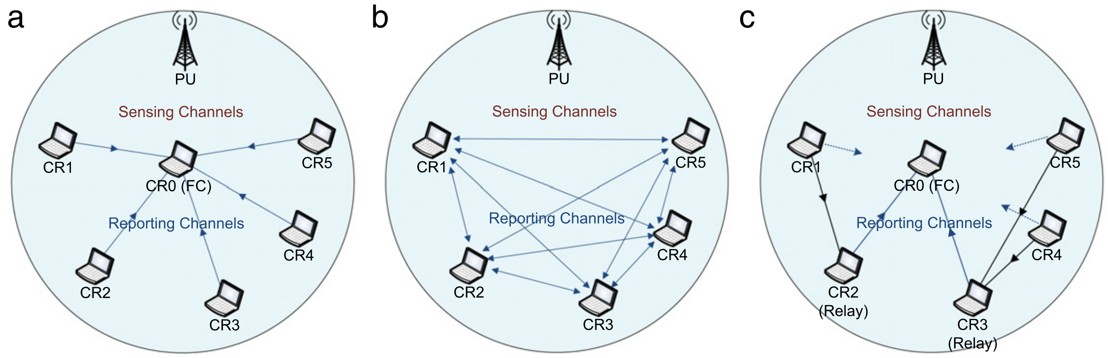

Fig. 3. Classification of cooperative sensing: (a) centralized, (b) distributed, and (c) relay-assisted.

sensing can be effectively leveraged to achieve the optimal cooperative gain without being compromised by the incurred cooperation overhead.

In [5], Cabric et al. identified the "three main questions regarding cooperative sensing" as follows [5]

- *How can cognitive radios cooperate?*
- *How much can be gained from cooperation?*
- *What is the overhead associated with cooperation?*

These three questions surrounding the issues of *Cooperation Method*, *Cooperative Gain*, and *Cooperation Overhead*, respectively, should be addressed in every cooperative sensing scheme. In this paper, we aim to survey the state-of-the-art research in cooperative sensing centering these three issues by first analyzing the cooperation method with the fundamental components of cooperative sensing and then presenting the impacting factors of achievable cooperative gain and incurred cooperation overhead. In addition, we identify open research challenges related to each issue in cooperative sensing along with the discussion.

The remainder of this paper is organized as follows. In Section 2, cooperative sensing schemes are classified by how CR users share their sensing data. In addition, the framework of cooperative sensing is presented. In Section 3, the process of cooperative sensing is analyzed in detail by its components. In Section 4, an insight into cooperative sensing tradeoff between cooperative gain and cooperation overhead is provided. Finally, the paper is concluded in Section 5.

2. Classification and framework of cooperative sensing

In this section, we present the problem of the primary signal detection in cooperative sensing and introduce the classification and the framework of cooperative sensing.

2.1. Primary signal detection

The process of cooperative sensing starts with spectrum sensing performed individually at each CR user called local sensing. Typically, local sensing for primary signal detection can be formulated as a binary hypothesis problem as follows [2]:

$$x(t) = \begin{cases} n(t), & H_0 \\ h(t) \cdot s(t) + n(t), & H_1 \end{cases} \tag{1}$$

where $x(t)$ denotes the received signal at the CR user, $s(t)$ is the transmitted PU signal, $h(t)$ is the channel gain of the sensing channel, $n(t)$ is the zero-mean additive white Gaussian noise (AWGN), H_0 and H_1 denote the hypothesis of the absence and the presence, respectively, of the PU signal in the frequency band of interest. For the evaluation of the detection performance, the probabilities of detection P_d and false alarm P_f are defined as [9]

$$P_d = P\{decision = H_1|H_1\} = P\{Y > \lambda \mid H_1\} \tag{2}$$

$$P_f = P\{decision = H_1|H_0\} = P\{Y > \lambda \mid H_0\} \tag{3}$$

where Y is the decision statistic and λ is the decision threshold. The value of λ is set depending on the requirements of detection performance. Based on these definitions, the probability of a miss or miss detection is defined as $P_m = 1 - P_d = P\{decision = H_0|H_1\}$. The plot that demonstrates P_d versus P_f is called the receiver operating characteristic (ROC) curve, which is the metric for the performance evaluation of sensing techniques. In cooperative sensing, the probabilities of detection and false alarms for evaluating the performance of cooperative decisions are denoted by Q_d and Q_f, respectively, which will be discussed in Section 3.5.

2.2. Classification of cooperative sensing

To facilitate the analysis of cooperative sensing, we classify cooperative spectrum sensing into three categories based on how cooperating CR users share the sensing data in the network: centralized [10,6,11], distributed [12], and relay-assisted [13–15]. These three types of cooperative sensing are illustrated in Fig. 3.

In centralized cooperative sensing, a central identity called fusion center (FC)[2] controls the three-step process of cooperative sensing. First, the FC selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to

[2] The fusion center [16,11,17,18] is also known as base station [19,20], common receiver [21,22,13,14], combining node [23,24], master node [10], designated controller [7], and others.

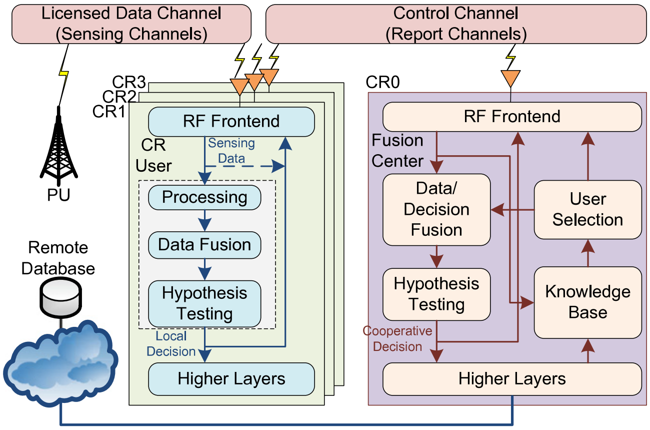

Fig. 4. Framework of centralized cooperative sensing.

cooperating CR users. As shown in Fig. 3(a), CR0 is the FC and CR1–CR5 are cooperating CR users performing local sensing and reporting the results back to CR0. For local sensing, all CR users are tuned to the selected licensed channel or frequency band where a physical point-to-point link between the PU transmitter and each cooperating CR user for observing the primary signal is called a *sensing channel*. For data reporting, all CR users are tuned to a *control channel* where a physical point-to-point link between each cooperating CR user and the FC for sending the sensing results is called a *reporting channel*. Note that centralized cooperative sensing can occur in either centralized or distributed CR networks. In centralized CR networks, a CR base station (BS) is naturally the FC. Alternatively, in CR ad hoc networks (CRAHNs) where a CR BS is not present, any CR user can act as a FC to coordinate cooperative sensing and combine the sensing information from the cooperating neighbors.

Unlike centralized cooperative sensing, distributed cooperative sensing does not rely on a FC for making the cooperative decision. In this case, CR users communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. Fig. 3(b) illustrates the cooperation in the distributed manner. After local sensing, CR1–CR5 share the local sensing results with other users within their transmission range. Based on a distributed algorithm, each CR user sends its own sensing data to other users, combines its data with the received sensing data, and decides whether or not the PU is present by using a local criterion. If the criterion is not satisfied, CR users send their combined results to other users again and repeat this process until the algorithm is converged and a decision is reached. In this manner, this distributed scheme may take several iterations to reach the unanimous cooperative decision.

In addition to centralized and distributed cooperative sensing, the third scheme is relay-assisted cooperative sensing. Since both sensing channel and report channel are not perfect, a CR user observing a weak sensing channel and a strong report channel and a CR user with a strong sensing channel and a weak report channel, for example, can complement and cooperate with each other to improve the performance of cooperative sensing. In Fig. 3(c), CR1, CR4, and CR5, who observe strong PU signals, may suffer from a weak report channel. CR2 and CR3, who have a strong report channel, can serve as relays to assist in forwarding the sensing results from CR1, CR4, and CR5 to the FC. In this case, the report channels from CR2 and CR3 to the FC can also be called *relay channels*. Note that although Fig. 3(c) shows a centralized structure, the relay-assisted cooperative sensing can exist in distributed scheme. In fact, when the sensing results need to be forwarded by multiple hops to reach the intended receive node, all the intermediate hops are relays. Thus, if both centralized and distributed structures are one-hop cooperative sensing, the relay-assisted structure can be considered as multi-hop cooperative sensing. In addition, the relay for cooperative sensing here serves a different purpose from the relays in cooperative communications [25], where the CR relays are used for forwarding the PU traffic.

2.3. *Framework of cooperative sensing*

The framework of cooperative sensing consists of the PUs, cooperating CR users including a FC, all the elements of cooperative sensing, which will be introduced in Section 3, the RF environment including licensed channels and control channels, and an optional remote database. Fig. 4 illustrates the framework of centralized cooperative sensing from the perspective of the physical layer. In this framework, a group of cooperating CR users performs local sensing with an RF frontend and a local processing unit. The RF frontend can be configured for data transmission or spectrum sensing. In addition, the RF frontend includes the down-conversion of RF signals and the sampling at Nyquist rate by an analog-to-digital converter (ADC). The raw sensing data from the RF frontend can be directly sent to the FC or be locally processed for local decision. To minimize the bandwidth requirement of the control channel, certain local processing is usually required. The processing includes the calculation of test statistics, and a threshold device for local decision. Once the raw sensing data or the local decisions are ready, a medium access control (MAC) scheme is required to access the control channel for reporting the sensing results. The sensing results may also be used by higher network protocol layers

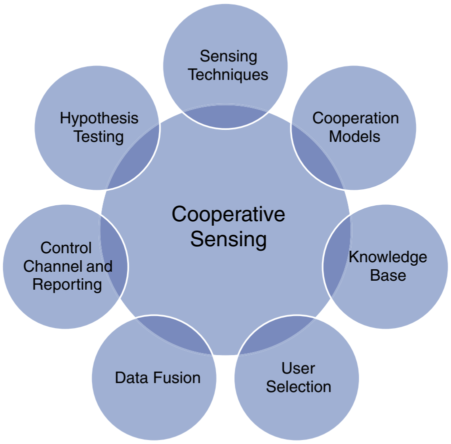

Fig. 5. Elements of cooperative spectrum sensing.

for spectrum-aware routing selection [26] for example. The FC in the framework is a powerful CR user, which includes all the capabilities of a regular CR user and the additional user selection capability with the assistance of a embedded knowledge base. If the FC is as powerful as a base station, it may have the connection to the remote database for PU activity and white space information. For the framework of distributed cooperative sensing, all CR users are essentially the same and similar to the FC in the framework of centralized cooperative sensing with an optional and smaller knowledge base for local use.

In the next section, we analyze the process of cooperative sensing by its elements.

3. Elements of cooperative spectrum sensing

As described in Section 2.2, conventional cooperative sensing is generally considered as a three-step process: local sensing, reporting, and data fusion. In addition to these steps, there are other fundamental components that are crucial to cooperative sensing. We call these fundamental and yet essential components as the *elements of cooperative sensing*. In this section, we analyze and present the process of cooperative sensing by seven key elements: (i) cooperation models, (ii) sensing techniques, (iii) control channel and reporting, (iv) data fusion, (v) hypothesis testing, (vi) user selection, and (vii) knowledge base. As shown in Fig. 5, these elements are briefly introduced as follows:

- *Cooperation models* consider the modeling of how CR users cooperate to perform sensing. We consider the most popular parallel fusion network models and recently developed game theoretical models.
- *Sensing techniques* are used to sense the RF environment, taking observation samples, and employing signal processing techniques for detecting the PU signal or the available spectrum. The choice of the sensing technique has the effect on how CR users cooperate with each other.
- *Hypothesis testing* is a statistical test to determine the presence or absence of a PU. This test can be performed individually by each cooperating user for local decisions or performed by the fusion center for cooperative decision.
- *Control channel and reporting* concerns about how the sensing results obtained by cooperating CR users can be efficiently and reliably reported to the fusion center or shared with other CR users via the bandwidth-limited and fading-susceptible control channel.
- *Data fusion* is the process of combining the reported or shared sensing results for making the cooperative decision. Based on their data type, the sensing results can be combined by signal combining techniques or decision fusion rules.
- *User selection* deals with how to optimally select the cooperating CR users and determine the proper cooperation footprint/range to maximize the cooperative gain and minimize the cooperation overhead.
- *Knowledge base* stores the information and facilitates the cooperative sensing process to improve the detection performance. The information in the knowledge base is either a priori knowledge or the knowledge accumulated through the experience. The knowledge may include PU and CR user locations, PU activity models, and received signal strength (RSS) profiles.

Next, we discuss each element of cooperative sensing in detail.

3.1. Cooperation models

The cooperation of CR users for spectrum sensing can be modeled by different approaches. The modeling in cooperative sensing is primarily concerned with how CR users cooperate to perform spectrum sensing and achieve the optimal detection performance. The most popular and dominating approach originated from the parallel fusion (PF) model in distributed detection and data fusion [27]. Nevertheless, recent studies [28,29] model the behaviors of cooperating CR users in cooperative sensing by using game theory [30]. The PF models aim to achieve the detection performance by using the distributed signal processing techniques to determine how the observations are combined and tested and how the decisions are made. Unlike the PF models, game theoretical models focus on improving the sensing-parametric utility function by analyzing the interactions and the cooperative or non-cooperative behaviors of CR users. It can be informally stated that the parallel cooperation model emphasizes the "sensing" part while the game model focuses on the "cooperative" part in cooperative sensing. In this paper, we discuss these two approaches to the modeling of CR user cooperation.

3.1.1. Parallel fusion model

In the study of distributed detection and data fusion [27], a group of spatially distributed sensors observes a physical phenomenon H through the observations y_i and report their observations u_i to a central processor known as a FC [16]. The FC combines the reported data by data fusion and makes the global decision u by using binary hypothesis testing. This PF model in the context of cooperative sensing is illustrated in Fig. 6.

Due to the similarity to the process of distributed detection, a large number of proposed schemes [6,17,11]

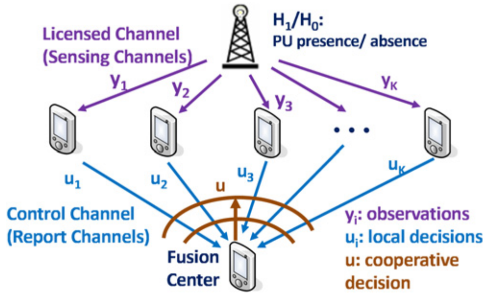

Fig. 6. Cooperation model: parallel fusion model.

adopted the PF model or variations of this model for cooperative sensing. In these schemes, cooperative sensing follows the same three-step process: local sensing, data reporting, and data fusion. All CR users are assumed to be synchronized by the FC for sensing the channel or the frequency band of interest and reporting the sensing results. The FC combines the reported local sensing data and makes a cooperative decision. This decision is broadcast to all cooperating CR users. We can see the similarity by comparing Fig. 6 to Fig. 3(a). In addition, each cooperating CR user shares, collects, and combines the sensing data in distributed cooperative sensing is similar to the FC in the PF model. Thus, distributed cooperative sensing can also be represented by this model.

3.1.2. Game theoretical model

In game theoretical models, cooperative sensing is modeled as a game with a set of players, which are the cooperating CR users. Depending on the nature of the game, the behaviors of cooperating CR users are modeled differently. For example, in a coalitional game [28], CR users cooperate in the form of groups, called coalitions while in an evolutionary game [29], CR users are selfish users who may choose to cooperate or not cooperate depending on their own benefits.

In [28], cooperative sensing is modeled as a non-transferable (N, v) coalitional game, where N is the set of cooperating CR users and v is the utility function. The coalitional game is said to have non-transferable utility because each CR user has its own utility within the coalition. The utility of a coalition S is defined as [28]

$$v(S) = Q_{d,S} - C(Q_{f,S}) \tag{4}$$

where $Q_{d,S}$ and $Q_{f,S}$ are the detection and false alarm probabilities, respectively, of coalition S, and $C(Q_{f,S})$ is the cost function of $Q_{f,S}$ defined by a logarithmic barrier penalty function [31]. In this model, CR users can autonomously collaborate and self-organize into disjoint independent coalitions while taking into account the tradeoff between achieving maximum Q_d and cost incurred in reducing Q_f.

The cooperative sensing is performed in each coalition. To improve the detection performance and respond to PU activity and topology change, CR users merge or split the coalitions if the utility of the merged or split coalitions is larger than the original coalition partitions. An example of coalitions in the model is illustrated in Fig. 7. The

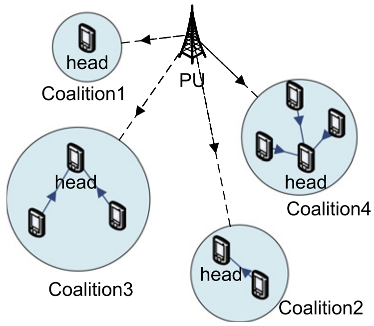

Fig. 7. Cooperation model: coalitional game.

cooperative game model is then realized by a distributed algorithm containing three phases: (1) *Local Sensing:* each individual CR user performs spectrum sensing locally and makes binary decisions. (2) *Adaptive Coalition Formation*: CR users interact in order to assess whether to share their sensing results with nearby coalitions. An iteration of sequential merge-and-split rules occur in the network whereby each coalition decides to merge or split if the merging or splitting results in the utility improvement. (3) *Coalition Sensing*: after the merge-and split process, the CR users in the same coalition report their local decisions to the coalition head, which can use a fusion rule to make a final cooperative decision.

In [29], distributed cooperative sensing is modeled as an evolutionary game to study the cooperative and non-cooperative behaviors of selfish CR users to maximize their own throughput. In this non-cooperative spectrum sensing game, a CR user can select an action from the action set $\{C, D\}$, where C represents that the CR user *contributes* to cooperative sensing and D represents that the CR user *denies* the participation in cooperation. On one hand, CR users can achieve a stable throughput by contributing to cooperative sensing at the expense of reduced throughput due to less time for its own transmissions. On the other hand, CR users may choose not to participate in cooperative sensing to enhance their own throughput at the risk of obtaining zero throughput when no one contributes to cooperative sensing. Thus, by using replicator dynamics in evolutionary game theory, CR users interact with each other and learn the best strategy of whether or not to cooperate in cooperative sensing.

For each CR user s_j with throughput C_{s_j} and the received primary signal SNR γ_j in distributed cooperative sensing, the utility of each action C or D can be defined as the function of the sensing time, the number of cooperating CR users, the probabilities of detection and false alarm, and the chosen fusion rule, in addition to C_j and γ_j. The evolution dynamics of the probability of CR user s_j choosing strategy $h \in \{C, D\}$ at time t is denoted by $x_{h,s_j}(t)$ and given by [29]

$$\dot{x}_{h,s_j} = [\bar{U}_{s_j}(h, x_{-s_j}) - \bar{U}_{s_j}(x)]x_{h,s_j} \tag{5}$$

where $\bar{U}_{s_j}(h, x_{-s_j})$ is the average utility of s_j choosing h, x_{-s_j} is the set of strategies chosen by other CR users (excluding s_j), and $\bar{U}_{s_j}(x)$ is the average utility of s_j choosing mixed strategy x_{s_j}. From (5), the growth rate $\dot{x}_{h,s_j}/x_{h,s_j}$ is proportional to the average utility difference of choosing pure strategy h over mixed strategy x_{s_j}. Thus, CR user s_j will choose h with higher probability if a higher utility can be achieved by selecting h.

By the approximation of $\bar{U}_{s_j}(h, x_{-s_j})$ and $\bar{U}_{s_j}(x)$, a distributed learning algorithm is also proposed to iteratively update the probability of choosing actions in distributed cooperative sensing and converge to the stable equilibrium. As a result, the general cooperation strategy for distributed cooperative sensing is obtained as follows. Without compromising its throughput, s_j may gradually increase (decrease) the probability of contributing to cooperative sensing x_{C,s_j} if the initial x_{C,s_j} is low (high). In addition, s_j can take advantage of other CR users with better detection performance by reducing x_{C,s_j} and cooperate with other CR users to improve detection performance by increasing x_{C,s_j}.

3.1.3. Research challenges

The dominance of PFN models in the literature results in the needs of proposing novel models in cooperative sensing for new applications. Thus, the open challenges regarding cooperation models include the following:

- *Modeling of cooperation overhead:* Most existing models for cooperative sensing are centered at the detection performance, that is cooperative gain. Only a few cooperation overhead issues have been discussed in proposed schemes. For example, in [29], only the number of cooperating CR users and the sensing time-throughput tradeoff are considered in forming utility functions. While cooperative gain is important in the model, proper modeling of cooperation overhead can reveal realistic achievable cooperative gain. Thus, the modeling of cooperation overhead is still an open challenge in the modeling for cooperative sensing.
- *Modeling of primary user cooperation:* Most existing models for cooperative sensing focus on the detection of a single large-scale PU such as a TV base station and assume that the PUs do not cooperate with CR users. However, in certain applications such as military CR networks, these assumptions may not be true, since the PUs may be motivated to cooperate with CR users and the PUs may be connected in an ad hoc manner. As a result, new models that model the cooperation between PUs and CR users for cooperative sensing and cooperative communications such as the one in [32] are desired. In addition, the detection of small-scale mobile PUs such as wireless microphones is a known open challenging research problem, which will need a new model for cooperative sensing.

3.2. Sensing techniques

Regardless of the cooperation models, the process of cooperative sensing starts with local spectrum sensing at each cooperating CR user. Similar to traditional spectrum sensing without cooperation, the objective of the local spectrum sensing is primary signal detection. Sensing techniques are crucial in cooperative sensing in the sense that how primary signals are sensed, sampled, and processed is strongly related to how CR users cooperate with each other. Thus, sensing techniques are one of the fundamental elements in cooperative sensing.

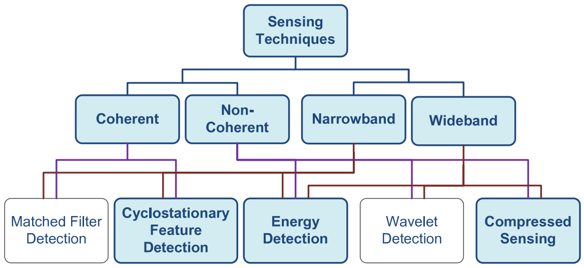

Fig. 8. Classification of sensing techniques.

From the perspective of signal detection, sensing techniques can be classified into two broad categories: coherent and non-coherent detection. In coherent detection, the primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with a priori knowledge of primary signals. In non-coherent detection, no a priori knowledge is required for detection. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest for sensing: narrowband and wideband. The classification of sensing techniques is shown in Fig. 8. Note that our discussion here focus on the most popular sensing techniques in cooperative sensing rather than an exhaustive search for all primary detection methods. Thus, we discussed three most popular sensing techniques in cooperative sensing: energy detection, cyclostationary feature detection, and compressed sensing. The former two techniques are mainly for narrowband sensing while the latter is primarily used for wideband sensing. The detailed discussion of other sensing techniques such as matched filter detection and wavelet detection can be found in [3,4,25]. The hypothesis testing of the detection problem is discussed in Section 3.3.

3.2.1. Energy detection

Energy detection [33,9] is a non-coherent detection method that detects the primary signal based on the sensed energy. Due to its simplicity and no requirement on a priori knowledge of PU signals, energy detection is the most popular sensing technique in cooperative sensing. However, energy detection is often accompanied by a number of disadvantages. (i) The sensing time taken to achieve a given probability of detection may be high. (ii) The detection performance is subject to the uncertainty of noise power. (iii) Energy detection cannot be used to distinguish primary signals from CR user signals. As a result, CR users need to be tightly synchronized and refrained from transmissions during an interval called *Quiet Period* in cooperative sensing. (iv) Energy detection cannot be used to detect spread spectrum signals. In spite of these problems, the energy detector remains the most common detection mechanism in cooperative sensing. This is because some of the issues such as the performance degradation due to noise uncertainty can be mitigated by the diversity gain resulting from cooperation.

For the signal detection by using energy detection, it can be found in [9] that the test statistic is central chi-square distributed under H_0 and non-central chi-square distributed with N degree of freedom under H_1, where

$N/2$ is the number of samples from either in-phase (I) or quadrature (Q) components. Given the number of samples N, received SNR γ, noise power σ^2, and detection threshold λ, the closed-form expressions of the probabilities of detection P_d and false alarm P_f over AWGN channels and fading channels including Rayleigh and more general Nakagami fading are given in [9]. From these expressions, we know that, with other parameters fixed, P_d and P_f are related through λ. In general, The detection threshold λ can be derived in terms of the required P_f if P_f is specified as the constraint of the detection problem. By plugging λ into the expression of P_d, we obtain the corresponding P_d. Thus, by varying the value of P_f from 0 to 1, we obtain the ROC curve that shows the corresponding detection performance of the energy detector.

In addition to narrowband sensing, energy detection has been used for multiband joint detection (MJD) in wideband sensing by employing an array of energy detectors, each of which detects one frequency band [34]. The MJD method enables CR users to simultaneously detect PU signals across multiple frequency bands for efficient management of wideband spectrum resource at the cost of detection hardware.

3.2.2. Cyclostationary feature detection

Cyclostationary feature detection [35] exploits the periodicity in the received primary signal to identify the presence of PUs. The periodicity is commonly embedded in sinusoidal carriers, pulse trains, spreading code, hopping sequences, or cyclic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation, which is not found in stationary noise and interference. Thus, cyclostationary feature detection is robust to noise uncertainties and performs better than energy detection in low SNR regions. Although it requires a priori knowledge of the signal characteristics, cyclostationary feature detection is capable of distinguishing the CR transmissions from various types of PU signals [5,36]. This eliminates the synchronization requirement of energy detection in cooperative sensing. Moreover, CR users may not be required to keep silent during cooperative sensing and thus improving the overall CR throughput. This method has its own shortcomings owing to its high computational complexity and long sensing time. Due to these issues, this detection method is less common than energy detection in cooperative sensing.

In [37], a cooperative sensing scheme with cyclostationary feature detection is proposed. By utilizing the generalized likelihood ratio test (GLRT) (Section 3.3), the proposed method enables the detection of cyclostationary signals over multiple cyclic frequencies. The test statistic for data fusion at the FC is also developed for cooperative sensing. Moreover, to improve energy efficiency, this method employs a censoring technique for each cooperating CR user to send the local sensing results to the FC subject to a communication rate constraint (Section 4.3).

3.2.3. Compressed sensing

Energy or cyclostationary detection is based on a set of observations sampled by ADC at Nyquist rate in the band of interest. Due to hardware limitations on the sampling speed, these sensing techniques are primarily used to sense one band at a time. To sense multiple frequency bands, CR users may need to scan the spectrum or use multiple RF frontends for sensing multiple bands. However, using these approaches for wideband sensing either causes long sensing delay or incurs higher computational complexity and hardware cost. Recent advances in compressed sensing[3] [38–40] enables the sampling of the wideband signals at sub-Nyquist rate to relax the ADC requirements. Based on the assumption that the spectrum is underutilized (e.g. suburban or rural area), compressed sensing can be utilized to approximate and recover the sensed spectrum, which facilitates the detection of sparse primary signals in wideband spectrum. Thus, the techniques of compressed sensing provide promising solutions to promptly recover wideband signals and facilitate wideband sensing at the reasonable computational complexity.

In compressed sensing, a sparse signal can be recovered by random sampling at a sub-Nyquist rate as long as the sampling matrix satisfies the restricted isometry property [41,42]. In the conventional compressed sensing scheme [40], the first step is to generate measurements $\mathbf{x}_t$ of size $K \times 1$ by sub-Nyquist-rate random sampling. If $\mathbf{r}_t$ of size $M \times 1$ is the discrete-time vector of the received wideband signal $r(t)$, the compressed sensing process can be represented by $\mathbf{x}_t = \mathbf{S}^T\mathbf{r}_t$, where $\mathbf{S}^T$ is the $M \times K$ projection matrix, $K < M$. The second step is to reconstruct wideband spectrum $\mathbf{r}_f = \mathbf{F}_M\mathbf{r}_t$ from $\mathbf{x}_t$, where $\mathbf{F}_M$ is M-point discrete Fourier transform. To achieve this, efficient reconstruction methods such as basis pursuit (BP) [43] can be used to solve the following convex optimization problem with the sparseness constraint in $\mathbf{r}_f$ [44]:

$$\hat{\mathbf{r}}_f = \arg\min_{\mathbf{r}_f} \| \mathbf{r}_f \|_1, \quad \text{s.t. } \mathbf{x}_t = (\mathbf{S}^T\mathbf{F}_M^{-1})\mathbf{r}_f. \tag{6}$$

In addition to the conventional scheme, an alternative approach for random sampling and spectrum reconstruction is fast Fourier sampling [45,46] based on the reconstruction method named orthogonal matching pursuit (OMP) [47]. Once the spectrum is reconstructed, the locations of PU-occupied bands in a wideband spectrum can be identified.

In wideband cooperative sensing based on compressed sensing [44,48,42], CR users individually perform compressed sensing, cooperatively estimate the wideband spectrum by exchanging spectrum estimates, and iteratively reach a cooperative decision by exchanging local decisions. The wideband cooperative sensing schemes are discussed in Section 4.7.

3.2.4. Research challenges

Compressed sensing is a promising wideband sensing technique in cooperative sensing. However, it also gives rise to many open research challenges:

- *Near far problem:* Due to the sub-Nyquist-rate sampling and insufficient number of samples, a weak PU signal with a nearby strong signal may not be properly reconstructed for detection in a wideband spectrum. Thus, it is a challenge to achieve the detection sensitivity by compressed sensing in a wideband spectrum.

[3] Compressed sensing is also known as compressive sensing or compressive sampling.

- *Implementation issues:* Compressed sensing is achieved by the random sampling of wideband signals. To realize random sampling, new ADC architecture with non-uniform timing and the pseudo-random clock generator such as the one in [49,50] is needed. Since the complex clocking system will be the key factor of random sampling performance, how these implementation issues in compressed sensing affect cooperative sensing needs further investigation.

3.3. Hypothesis testing

In spectrum sensing, statistical hypothesis testing is typically performed to test the sensing results for the binary decision on the presence of PUs. In this subsection, we first introduce two binary hypothesis testing schemes commonly used in spectrum sensing. Then we discuss composite hypothesis testing methods such as the generalized likelihood ratio test (GLRT) and sequential testing methods such as the sequential probability ratio test (SPRT).

3.3.1. Binary hypothesis testing

There are two basic hypothesis testing methods in spectrum sensing: the Neyman–Pearson (NP) test and the Bayes test. In an NP test, the objective is to maximize the detection probability P_d given the constraint of $P_f \leq \alpha$, where α is the maximum false alarm probability. Based on the signal detection problem in (1), it can be shown that the NP test is equivalent to the following likelihood ratio test (LRT) given by

$$\Lambda(\mathbf{y}) = \frac{f(\mathbf{y}|H_1)}{f(\mathbf{y}|H_0)} = \prod_{k=1}^{N} \frac{f(y_k|H_1)}{f(y_k|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{7}$$

where $\Lambda(\mathbf{y})$ is the likelihood ratio, $f(\mathbf{y}|H_j)$ is the distribution of observations $\mathbf{y} = \{y_i\}_1^N$ under hypothesis H_j, $j \in \{0, 1\}$, λ is the detection threshold, and N is the number of samples. Notice that, in (7), the second equality holds only if the observations $\{y_i\}_1^N$ are independent and identically distributed (i.i.d.) under H_j. As a result, the optimal test at FC in cooperative sensing is the NP-based LRT if the conditional independence is assumed [16]. Thus, the detector (local sensing) or the FC (cooperative sensing) declares H_1 if $\Lambda(\mathbf{y}) > \lambda$ and declares H_0 otherwise.

In a Bayes test, the objective is to minimize the expected cost called the *Bayes Risk* given by $R = \sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij}P(H_i \mid H_j)P(H_j)$, where C_{ij} and $P(H_i \mid H_j)$ are the cost and the probability, respectively, of declaring H_i when H_j is true, and $P(H_i)$ is the prior probability of hypothesis H_i, $i, j \in \{0, 1\}$. In this case, $P_d = P(H_1 \mid H_1)$, $P_m = P(H_0 \mid H_1)$, and $P_f = P(H_1 \mid H_0)$. In other words, the Bayes risk to be minimized is the sum of all possible costs weighted by the probabilities of two incorrect detection cases (false alarm and miss detection) and two correct detection cases. With the knowledge of a priori probabilities $P(H_i)$, the LRT of a Bayes test can be represented as

$$\Lambda(\mathbf{y}) = \frac{f(\mathbf{y}|H_1)}{f(\mathbf{y}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)(C_{10} - C_{00})}{P(H_1)(C_{01} - C_{11})} = \lambda. \tag{8}$$

Thus, the detector or the FC can minimize the Bayes Risk by declaring H_1 if $\Lambda(\mathbf{y}) > \lambda$ and declaring H_0 otherwise.

3.3.2. Composite hypothesis testing

In binary hypothesis testing, the distributions under both hypotheses $f(\mathbf{y}|H_i)$ are completely known. When there are unknown parameters in the PDFs, the test is called composite hypothesis testing. One of the approaches to composite hypothesis testing that does not require prior knowledge of unknown parameters is the generalized likelihood ratio test (GLRT). In GLRT, the unknown parameters are determined by the maximum likelihood estimates (MLE). Although GLRT is not an optimal test, it is robust and easy to implement.

In [37], GLRT statistics are derived for cyclostationary detection over multiple cyclic frequencies in cooperative sensing. In [51], the Rao test and the locally most powerful (LMP) test are proposed for detecting weak PU signals at the FC with soft decisions from cooperating CR users in cooperative sensing. The Rao test is asymptotically equivalent to GLRT and does not require the MLE of unknown parameters. Thus, it does not rely on the second and fourth order PU statistics required by the NP-based LRT. In addition, in [52], a linear composite hypothesis testing approach is proposed for cooperative sensing. The linear test statistics are derived for unknown PU and channels statistics scenarios. When channel statistics are known, the test statistics of the LMP detector are also derived. This method provides the robustness to the uncertainties in PU signals and channel gains, and its performance is comparable to the optimal NP-based LRT.

3.3.3. Sequential testing

In the previously discussed hypothesis testing methods such as the NP-based LRT, the number of required samples for testing is fixed, which corresponds to the fixed sensing time. To reduce the sensing time, sequential testing that requires a variable number of samples can be used. The sequential probability ratio test (SPRT) developed by Wald [53] is the sequential testing scheme that can minimize the sensing time subject to the detection performance constraints.

In SPRT, samples are taken sequentially and the test statistics are compared with two thresholds λ_0 and λ_1, $\lambda_0 < \lambda_1$, which are determined by detection requirements. If the likelihood ratio is greater than λ_1, the detector decides on H_1 while if it is smaller than λ_0, it decides on H_0. When the ratio falls between the two thresholds, it waits for the next observation, as the currently available information is not sufficient to achieve the final decision that satisfies the target constraints. In this case, the process is repeated until the decision can be determined. In cooperative sensing, the SPRT can also be applied to the detection at the FC.

The main advantage of the SPRT is that it requires fewer samples on the average than those fixed-sample testing methods to achieve the same detection performance. It is proven that the SPRT is optimal in minimizing the average number of independent samples and the corresponding average sensing time. The disadvantage of the SPRT includes the cost for obtaining samples and the possibly large number samples needed to reach the decision resulting in long sensing time [54].

In [55,56], a sequential detection scheme with the SPRT is proposed for cooperative sensing. In this method, the FC sequentially accumulates the log-likelihood statistics from cooperating CR users and determines when to stop taking more sequential observations and make a cooperative decision. This method is further applied to the cases of unknown parameters in signal statistical models by exploiting the GLRT and replacing the unknowns with the MLEs during sequential detection.

3.4. Control channel and reporting

In cooperative sensing, a common control channel (CCC) [1,57] is commonly used by CR users to report local sensing data to the FC or share the sensing results with neighboring nodes. As a result, a control channel is the element of cooperative sensing. The control channel can be implemented as a dedicated channel in licensed or unlicensed bands, or an underlay ultra-wideband (UWB) channel [5]. A MAC scheme for multiple access is generally used by all cooperating CR users to access the control channel. From the perspective of the physical layer, a physical point-to-point link from a cooperating CR user to the FC is called a reporting channel.

For reporting sensing data, three major control channel requirements must be satisfied in cooperative sensing: bandwidth, reliability, and security. Thus, we discuss bandwidth and reliability requirements in this subsection, and will discusses the primary control channel security issue: control channel jamming in Section 4.6.

3.4.1. Bandwidth requirement

The bandwidth of the control channel is identified in [7] as one the factors of determining the level of cooperation. This is because the amount of local sensing data that can be transmitted to the FC or shared with the neighbors is limited by the control channel bandwidth.

In [22], the problem of cooperative sensing under control channel bandwidth constraints is addressed by censoring and quantizing local sensing data. Each cooperating CR user performs the censoring by reporting the result only if the local decision is determined by the SPRT test. Thus, censoring reduces the unnecessary reporting and the usage of control channel bandwidth. In [23], a bandwidth-efficient combination scheme is proposed to enable the simultaneous reporting to the FC with the fixed required control channel bandwidth in cooperative sensing, regardless of the number of cooperating CR users. The test statistics for testing the superposition of all received local sensing data are devised for Gaussian and Rayleigh fading reporting channels.

3.4.2. Reliability requirement

In addition to the bandwidth requirement, the reliability of the control channel has the great impact on cooperative sensing performance. Like data channels, the control channel is susceptible to multipath fading and shadowing. Hence, the channel impairments must be considered in the reliability issue of the control channel. While early studies [6,10] assume a perfect error-free control channel in cooperative sensing, recent studies investigate the effect of Gaussian noise [58], multipath fading [15], and correlated shadowing [59] on the control channel and the sensing performance.

In [15], a transmit diversity-based cooperative sensing method is proposed to address the performance degradation caused by reporting channels under fading. Due to the reporting errors, the results show that the probability of false alarm Q_f is lower bounded and linearly increases with the probability of reporting errors. In addition, a censor-and-relay method is proposed for the FC to censor the received results from unreliable reporting channels. The CR users who do not have good reporting channels are instructed to forward their sensing results to those neighbors in good reporting channel conditions. These neighbors then report its own results and relay others' forwarded results through orthogonal control channels to avoid the mutual interference. In [60,59], the issue of correlated log-normal shadowing on the reporting channel is investigated. The results show that the performance degradation caused by the shadowing correlation on the reporting channel is similar to that on the sensing channel.

3.4.3. Research challenges

- *Reliability:* Apart from the unrealistic assumption of using a perfect control channel in cooperative sensing, recent studies have focused on the cooperative sensing performance with the consideration of imperfect control channels. However, how to design a control channel resilient to channel impairments, robust to PU activity, and bandwidth-efficient for delivering sensing data is a nontrivial task.
- *Dynamic allocation:* Most existing cooperative sensing schemes assume a dedicated control channel for data reporting. In certain applications where the control channel needs to be dynamic allocated according to PU activity, channel availability, and network topology, the dynamic control channel allocation significantly increases the difficulty for CR user cooperation and data reporting in cooperative sensing.

3.5. Data fusion

In cooperative sensing, data fusion is a process of combining local sensing data for hypothesis testing, which is also an element of cooperative sensing. Depending on the control channel bandwidth requirement, reported sensing results may be of different forms, types, and sizes. In general, the sensing results reported to the FC or shared with neighboring users can be combined in three different ways in descending order of demanding control channel bandwidth: (i) *Soft Combining:* CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision. (ii) *Quantized Soft Combining:* CR users can quantize the local sensing results and send only the quantized data for soft combining to alleviate control channel communication overhead. (iii) *Hard Combining:* CR users make a local decision and transmit the one-bit decision for hard combining. Obviously, using soft combining at the FC can achieve the best detection performance among all three at the cost of control channel overhead while the quantized soft combining and hard combining require much less control channel bandwidth with possibly degraded performance due to the loss of information from quantization. In this subsection, we first discuss soft combining and quantized soft combining techniques, and then focus on the fusion rules for decision fusion when the hard combining is used.

3.5.1. Soft combining and quantized soft combining

Existing receiver diversity techniques such as equal gain combining (EGC) and maximal ratio combining (MRC) can be utilized for soft combining of local observations or test statistics. In [61], an optimal soft combination scheme based on NP criterion is proposed to combine the weighted local observations. The proposed scheme reduces to EGC at high SNR and reduces to MRC at low SNR. Since such a soft combining scheme results in large overhead, a softened two-bit hard combining scheme is also proposed in [61] for energy detection. In this method, there are three decision thresholds dividing the whole range of test statistics into four regions. Each CR user reports the quantized two-bit information of its local test statistics. This method shows the comparable performance with the EGC scheme with less complexity and overhead.

Due to the computational complexity of the LRT-based fusion methods that involves quadratic forms, an efficient linear combination of local test statistics is proposed in [58]. In this method, the local test statistics are weighted by weighting coefficients, which are optimized based on the target P_f and P_d requirements of the CR network. Since the combining weights affect the PDF of the global statistic, a modified deflection coefficient (MDC) is introduced to measure the effect of the PDF on the detector performance. Simulation results show that maximizing the MDC can result in better detection probability. This heuristic algorithm can significantly reduce the computationally complexity of obtaining the global decision with a slight degradation in the detection performance. Overall, the optimal linear combination strategy is subject to performance degradation when the channel noise level increases.

3.5.2. Hard combining and decision fusions

When binary local decisions are reported to the FC, it is convenient to apply linear fusion rules to obtain the cooperative decision. The commonly used fusion rules are *AND*, *OR*, and majority rules. Let u_i be the local decision of CR user i and u be the cooperative decision made by the FC, $u_i, u \in \{0, 1\}$, and a "1" and a "0" indicate a PU's presence (H_1) and absence (H_0), respectively. The *AND* rule refers to the FC determines $u = 1$ if $u_i = 1, \forall i$. Similarly, the *OR* rule refers to $u = 1$ if $u_i = 1$, for any i. The majority rule requires at least a half of the CR users to report "1". These simple fusion rules can be generalized to the k out of the N rule. Under this rule, the FC declares H_1 ($\mathcal{H}_1$) if k out of N CR users report "1". The false alarm and detection probabilities for cooperative sensing under this rule for data fusion are given by [62]

$$Q_f = Prob\{\mathcal{H}_1|H_0\} = \sum_{l=k}^{N} \binom{N}{l} P_f^l (1 - P_f)^{N-l} \tag{9}$$

$$Q_d = Prob\{\mathcal{H}_1|H_1\} = \sum_{l=k}^{N} \binom{N}{l} P_d^l (1 - P_d)^{N-l}. \tag{10}$$

It can be observed in (9) and (10) that when the value of k is taken as 1 and N, the k out of N rule becomes the *OR* and *AND* rules, respectively. The *OR* rule works best when the number of cooperating CR users is large. Similarly, the *AND* rule works well when the number of cooperating users is small. The majority rule can be obtained from the k out of N rule under the condition when $k \geq N/2$. Thus, it is important to determine the optimal value of k for which the detection errors are minimized. It can be shown that the optimal value of k depends on the detection threshold. For a small fixed threshold, the optimal rule is the *AND* rule, i.e., $k = N$. Similarly, for a fixed very large threshold, the *OR* rule ($k = 1$) is said to be optimal. The k out of N rule is also equivalent to *Counting Rule* or *Voting Rule* when the threshold for determining H_1 equals k. In [63], the proposed cooperative sensing scheme uses the k out of N rule for data fusion at the FC. The optimal value of k and the optimal sensing time are obtained by optimizing the average achievable throughput subject to the detection performance.

If the simple fusion rule is not used, advanced fusion techniques can be devised to utilize the statistical knowledge for decision fusion. In [11], a linear-quadratic (LQ) fusion method is proposed to consider the correlation between CR users in cooperative sensing. With the binary local decisions reported by cooperating CR users, this method provides a suboptimal solution to the decision fusion problem by using the partial statistical knowledge: the second-order statistics of the local decisions under H_1 and the fourth-order statistics under H_0. Based on the deflection criterion, the LQ detector compares a LQ function of the local decisions with a predetermined threshold and achieves better error probability with a higher value of deflection. The results show that the proposed scheme outperforms the Counting Rule in correlated shadowing.

3.6. User selection

The selection of CR users for cooperative sensing plays a key role in determining the performance of cooperative sensing because it can be utilized to improve cooperative gain and address the overhead issues. For example, when cooperating CR users experience correlated shadowing, it is shown in [7] that selecting independent CR users for cooperation can improve the robustness of sensing results. Moreover, removing malicious users from cooperation ensures the security and the reliability of the network. In Section 4, we will discuss how user selection can be used to address overhead issues such as correlated shadowing, cooperation efficiency, security, energy, and mobility. In this subsection, we present the centralized and cluster-based user selection schemes in cooperative sensing.

3.6.1. Centralized selection

The centralized user selection schemes is usually performed at the FC to take advantage of the available information collected from all cooperating CR users. For example, the FC is able to select independent users for cooperation to counter the effect of correlated shadowing based on the location estimates of CR users.

In [19], three user selection algorithms with different degrees of the knowledge of CR user positions are proposed for cooperative sensing to address the shadow correlation problem in a cellular system. The first algorithm aims to select a set of cooperating users with the minimum correlation measure among them by a greedy approach. Specifically, users with the largest summed correlation with respect to the remaining users are successively removed one at a time from the set until the desired number of CR users for cooperation is reached. Based on the knowledge of CR user locations, the correlation can be evaluated from the distance between two CR users. Starting with the BS only in the set of cooperating users, the second algorithm selects users by successively adding uncorrelated users to the set if the selected users are located at a distance greater than the decorrelation distance d_0 from all existing members of the set. The third algorithm finds K cooperating users within the radius r of the BS that satisfy the desired probability of uncorrelated K users with only the radius information from the BS to users. This method makes use of the probability of correlated shadowing between two users to compute the number of users that can be accommodated in circular cells of different sizes. The complexity in partitioning the users into two groups: uncorrelated users and correlated users can be evaluated by two bounds: *sphere packing upper bound* and *random selection lower bound*. As in sphere packing on a hexagonal lattice, the upper bound indicates the maximum number of users that experience uncorrelated shadowing in a cellular area. The lower bound is obtained by the expected number of randomly placed CR users in a cell. All aforementioned user selection algorithms perform better than the lower bound.

3.6.2. Cluster-based selection

Centralized user selection may incur high overhead such as control channel bandwidth, energy efficiency, and reporting delay when a large number of CR users need to cooperate in sensing and report the results to the FC. To alleviate this problem, grouping the cooperating users into clusters [64,21,65,66] or coalitions [28] for cooperative sensing is an effective approach to reduce the cooperation range and the incurred overhead.

In [64], four clustering methods are considered for user selection depending on the availability of location information. First, *random clustering* is adopted where the CR users are randomly divided into clusters of equal size when the positions of both CR users and PUs are not available. Second, *reference-based clustering* is based on CR user positions with respect to a given reference. In *statistical clustering*, clusters are formed by using the statistical information and the proximities of CR users when only the positions of CR users are known. Lastly, in *distance-based clustering*, only k out of K CR users closer to the PU in a cluster participate in cooperative sensing when the positions of both CR users and PUs are known.

In [21], clustering is utilized to exploit user selection diversity to improve the detection performance through reporting channels under Rayleigh fading. In each cluster, the CR user with the largest reporting channel gain is selected as the clusterhead (CH) to reduce the reporting errors. The CH collects local sensing data from the members of the cluster and forward the results to the FC. The results show that this clustering method outperforms the conventional cooperative sensing scheme. In [65], a cluster-based cooperative sensing scheme is proposed to address control channel bandwidth and sensing delay problems. The CHs are selected by the BS according to the distance from the BS and the received PU signal power. Since the overhead is reduced as the number of clusters is decreased, the method minimizes the number of clusters subject to the required sensing performance. The results show that the proposed clustering method outperforms the K-mean clustering scheme. In [66], a cluster-and-forward scheme is proposed to address the energy efficiency issue. To balance the energy consumption of users, CR users dynamically form clusters with the CH selected from the user with the largest channel gain at each time step. Moreover, to further improve the energy efficiency, the CHs take turn to act as the FC. The results show that, for each cluster size, there is an optimal number of clusters that can save the largest amount of energy.

3.6.3. Research challenges

User selection is critical for cooperation performance. However, devising user selection scheme is nontrivial, especially when the geolocation information is unavailable. The challenges are summarized as follows.

- *Cooperation footprint:* Cooperation footprint [7] is the area where CR users cooperate with each other. Since cooperative gain is obtained from spatial diversity, cooperation footprint is an important parameter to evaluate the performance and the overhead in cooperative sensing. Thus, user selection schemes should consider the distribution of CR users and the the area covered by their cooperation, not just the distance between the CR users. However, deriving the exact footprint of cooperation from the user selection is a challenge.
- *User selection and overhead:* It is obvious that user selection is strongly related to every type of cooperative sensing overhead, among others, from control channel bandwidth, energy efficiency, to security issues. There exists a tradeoff between the detection performance and one type of overhead. Most user selection schemes target at addressing one or two of these issues. Thus, it is a challenge to address all the overhead issues with the user selection scheme.

3.7. Knowledge base

The performance of cooperative sensing schemes largely depends on the knowledge of PU characteristics such as traffic patterns, location, and transmit power. The PU information, if available in a database, can facilitate the PU detection. The database that stores all the knowledge of the RF environments is called a *knowledge base*. Knowledge base is an indispensable element of cooperative sensing because it can be utilized to assist, complement, or even replace cooperative sensing for detecting PU signals and identifying the available spectrum.

Knowledge base serves as two roles in cooperative sensing: (i) to enhance the detection performance by

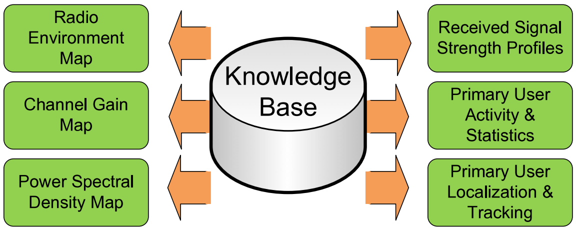

Fig. 9. Knowledge base in cooperative sensing.

utilizing the accumulated knowledge and the learned experience such as statistical models in the database and (ii) to alleviate the burden of cooperative sensing by retrieving the spectrum information such as a list of PU-occupied channels from the database. As shown in Fig. 9, the knowledge base can provide PU information such as locations, tracking, transmit power, and activity in the forms of spatial–temporal–spectral maps for cooperative sensing. In this subsection, we discuss the following knowledge base approaches: radio environment map (REM) [67], received signal strength (RSS) profiles [68], channel gain map [69,70], and power spectral density (PSD) map [71].

3.7.1. Radio environmental maps

Radio environment map (REM) [67] is a central database that can, among other things, be used as the infrastructure in CR networks to provide radio environment information for spectrum access, such as the locations of CR users, available spectrum, spectrum regulation and policies, shadowing areas, and PU signal types. In cooperative sensing, all the environment information, if available, can be accessed and utilized by each CR user to improve the detection performance in local sensing and in cooperative sensing. However, REMs may lead to large communication overhead due to a large amount of information transferred among CR users.

3.7.2. Spatial received signal strength profiles

In [68], a mechanism to establish spatial received signal strength (RSS) profiles is proposed for cooperative sensing. In this scheme, each cooperating CR user accumulates the RSS samples to establish the distribution of test statistics at each CR user's location. When all these temporal profiles from different CR user locations are combined at the FC, the spatial RSS profile is constructed and can be used as the detection criterion at the FC. In cooperative sensing, the FC can determine the presence of PU signals if the observed RSS values are similar to those in the profile. When PU signals are not present, each CR user estimates the noise power distribution for RSS profiles. The training period of performing RSS profiling should be long enough to accurately estimate the RSS distributions. The frequency of updating the RSS profile can be determined based on the time variation of the RSS profiles.

3.7.3. Power spatial density maps

In [71], a distributed cooperative sensing scheme based on power spectral density (PSD) maps is proposed for CRAHNs. In this scheme, CR users locally collect PSD samples and cooperatively estimate the basis expansion coefficients of the PSD map by exchanging messages with one-hop neighbors. The consensus on the estimates is reached by using the distributed least-absolute shrinkage and selection operator (D-Lasso) algorithm. In addition, the exponentially weighted moving average (EWMA) method is utilized to track the slowly varying PSDs. Due to the narrowband PSDs of PU signals in the wideband spectrum and the sparsely located PUs with active signals in a given area, the sparsity in both frequency and space are also exploited to formulate the non-negative Lasso criterion for ℓ_1-norm minimization of the unknowns. With the constructed PSD maps, this method is able to adapt to the environment change and track the locations and the power of PU transmitters.

3.7.4. Channel gain maps

In [69,70], a cooperative sensing scheme by using channel gain maps is proposed to track the PU locations and their transmit power. In this scheme, each CR user maintains a map of channel gain that consists of path loss, shadowing, and fading components. By extending the Kalman filter with the linear spatial interpolator, the Kriged Kalman filtering is used for tracking shadow fading at any point in an area. Similar to [71], cooperative sensing is formulated as a sparse regression problem with time-weighted non-negative Lasso to exploit the sparsity of PU locations. Based on the established channel gain maps, a centralized algorithm and a distributed algorithm using alternating direction method of multipliers (ADMoM) are used for tracking PU locations.

3.7.5. Research challenges

- *Knowledge base for security:* Most existing knowledge base methods are used to identify PU characteristics such as locations, power, and activity. To address security issues in cooperative sensing, the database should include other knowledge such as the behavior model of CR users and the model for jammer identification. Although it is a challenge to cooperatively establish accurate statistical models for security purposes, the knowledge derived from these models can significantly improve the security in cooperative sensing.
- *Remote knowledge base access:* As a recent FCC ruling [72] removes the spectrum sensing requirement in TV white space, CR devices are enabled to access PU activity and spectrum information from a remote spectrum database. This ruling raises new challenges in using the on-demand service and web-based processing techniques such as cloud computing [73,74] to provide CR users with a fast, secure, scalable, and energy-efficient access to remote knowledge base.

4. Gain and overhead in cooperative sensing

The exploitation of spatial diversity in cooperative sensing results in a significant improvement in detection performance. The performance improvement as the result of cooperation is termed diversity gain or *cooperative gain* [7]. Regardless of the improvement of detection performance,

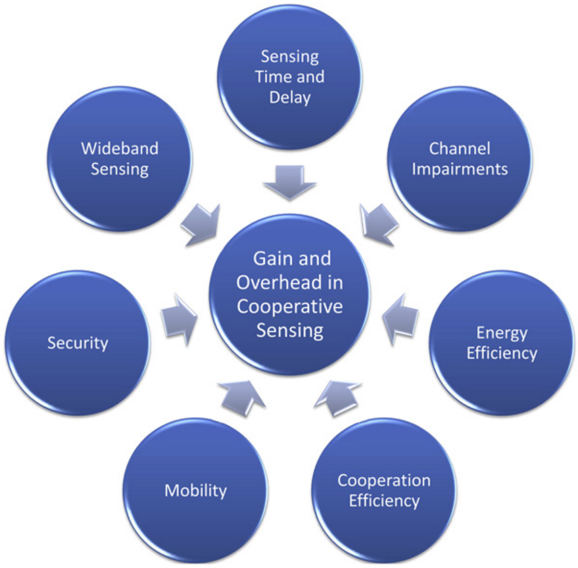

Fig. 10. Dominating factors of cooperative gain and cooperation overhead.

cooperation among CR users may also introduce a variety of overheads that limits or even compromises the achievable cooperative gain. The overhead associated with all elements of cooperative sensing are called *cooperation overhead*. In this section, we consider the issues of achievable cooperative gain and incurred cooperation overhead in cooperative sensing. These issues, called *dominating factors* of the cooperative gain and cooperation overhead, include (i) sensing time and delay, (ii) channel impairments, (iii) energy efficiency, (iv) cooperation efficiency, (v) mobility, (vi) security, and (vii) wideband sensing, which are shown in Fig. 10 and extensively discussed as follows.

4.1. Sensing time and delay

In conventional cooperative sensing [6], all cooperating CR users are assumed to be perfectly synchronized and their sensing results are also assumed to be available instantly and concurrently at the fusion center. As a result, the sensing delay such as sensing time, reporting delay, and synchronization issue are seldom addressed in cooperative sensing. Recent studies [63,24,75] have taken into account some, if not all, of these practical sensing delay issues. In this subsection, we address the issues of sensing time, reporting delay, synchronization issue, and asynchronous reporting as the cooperative sensing delay overhead in cooperative sensing.

4.1.1. Sensing time

Sensing delay mainly depends on the sensing technique being used. The sensing time is proportional to the number of samples taken by the signal detector. General speaking, the longer the sensing time is, the better the detection will be. However, due to the hardware limitation that a single RF transceiver equipped in each CR user cannot simultaneously perform sensing and transmissions, the more time is devoted to sensing, the less time is available for transmissions and thus reducing the CR user throughput. This is known as the sensing efficiency problem [76] or the sensing-throughput tradeoff [77] in spectrum sensing.

In [63], the sensing-throughput tradeoff is formulated as an optimization problem in cooperative sensing aiming to maximize the average CR throughput under the presence and the absence of PUs, subject to the constraint of detection probability for PU protection. With the energy detection for local sensing and the "K-out-of-N rule" for data fusion at the FC, the improvement in the throughput performance can be achieved when the optimal sensing time and the number of CR users determining the PU's presence (K) are jointly optimized.

4.1.2. Reporting delay

In cooperative sensing, sharing local sensing data with the FC or other CR users incurs reporting delay. This is cooperation overhead because it does not exist in spectrum sensing with no cooperation. In addition to transmission delay from the cooperating CR users to the FC, there are many reasons that can result in reporting delay. First, if cooperating CR users transmit on the control channel by a random access scheme, it is possible that the control messages sent from different CR users collide and then retransmission is required. Moreover, delivering the sensing data by multiple hops such as the case in the relay-assisted cooperative sensing incurs extra reporting delay. Thus, reporting delay is the overhead that should be considered in cooperative sensing schemes.

In [78], the authors address the issue of cooperation-processing tradeoff in cooperative sensing. The tradeoff is formulated as an optimization problem to minimize the total sensing time subject to constraints of false alarm and detection probabilities. The total sensing time to be minimized includes the integration time of the energy detector for local processing and the reporting time, proportional to the number of cooperating CR users, for cooperation. The results show that, for higher detection sensitivity, the longer integration time is generally required. However, with cooperation, the increasing number of cooperating CR users reduces the required sensing time to achieve the same level of detection sensitivity, even the reporting delay is longer in this case. In [75], a reinforcement learning-based cooperative sensing scheme is proposed to minimize the cooperative sensing delay and improve the detection probability in spatially correlated shadowing. By considering the reporting delay and spatial correlation among CR users in calculating the reward functions, the learning algorithm effectively finds the optimal solution to obtain the optimal sensing/report sequence and minimize the total reporting delay from all cooperating CR users while the detection performance is improved in correlated shadowing.

4.1.3. Synchronization issue

In addition to delays, many cooperative sensing schemes [10] require the synchronization of all the cooperating users and rely on simultaneous reporting of the CR users to perform the likelihood ratio testing. For example, due to the lack of the capability for distinguishing the PU signal from CR signals, spectrum sensing with energy detectors requires a scheduled quiet period for simultaneous local sensing operations. However, the synchronization may not be easily achieved for a large amount of CR users in CRAHNs. Thus, many asynchronous cooperative sensing methods [79,80,24] are proposed to deal with this issue.

In [79], a sliding window algorithm is proposed to resolve the synchronization issue by detecting the change point sequentially in the sensing reports received within an observation window. Similar to SPRT, the window is advanced if more sensing reports are required to make a decision. Compared to the WSPRT method [81], this method is able to achieve higher detection accuracy and reduce the detection time with and without misbehaving users. In [80,24], a probability-based combination scheme is proposed to combine asynchronous reports at the FC. Based on the knowledge of PU ON/OFF period distribution and the Bayesian decision rule, the conditional probability of the sensing reports received at different times and their combined likelihood ratio can be calculated to make the final decision.

4.1.4. Research challenges

The challenges to improve cooperative sensing delay are as follows:

- *Multiple tradeoffs in cooperative sensing delay:* The sensing-throughput tradeoff analysis in cooperative sensing should consider not only the sensing time and CR throughput, but also the report delay and the delay for synchronization or asynchronous reporting. Thus, the challenge is to balance the tradeoff between the CR throughput and cooperative sensing delay, which consists of multiple delay components depending on the cooperative sensing schemes.
- *Delay analysis in distributed schemes:* Distributed cooperative sensing schemes usually require an iterative process to reach the cooperative decision. The cooperative sensing delay is dominated by the report delays if the number of iterations for convergence is large. As a result, the delay analysis and the convergence of the distributed cooperative algorithm should be jointly considered.

4.2. Channel impairments

Channel impairments refer to the phenomena that cause the attenuation and variations of signals propagated through the wireless channels. These phenomena, including path loss, multipath fading, shadowing, and interference, can inevitably compromise the accuracy of PU detection in spectrum sensing. While cooperative gain can be achieved by using cooperative sensing to combat multipath fading and independent shadowing, spatially correlated shadowing can limit the achievable cooperative gain and incur overhead. In this subsection, we discuss the gain and overhead in cooperative sensing as the result of channel impairments.

4.2.1. Multipath fading and shadowing

Signal power attenuates as the signal travels through the space. The attenuation is exponentially proportional to the distance the signal travels. Such a energy loss along the path from the transmitter to the receiver is the path loss. In some cooperative sensing schemes, the effect of path loss is assumed to be same for all CR users. This assumption is reasonable only when the distance from any CR user to the PU transmitter is much greater than the distance between any two CR users. When the PU transmission range is small, the receive power at each CR user can vary significantly due to path loss. Although cooperative sensing cannot be used to directly address the path loss issue, CR users receiving weak PU signals due to path loss can benefit from cooperative sensing to correctly detect the PU's presence.

Unlike path loss, multipath fading and log-normal shadowing are primary channel impairments that can be countered by cooperative sensing schemes. This is because only a subset of CR users may experience multipath fading and shadowing at a given time. It is shown in [6] that cooperative sensing can effectively combat multipath fading and independent shadowing. As a result, a large cooperative gain can be achieved in these cases.

4.2.2. Spatially correlated shadowing

In log-normal shadowing, the observations of two closely located CR users may be correlated due to their proximity. In this case, CR users experience similar shadowing effects called spatially correlated shadowing. In [6], it is shown that spatial correlation in shadowing can degrade the detection performance and compromise the achievable cooperative gain. In [82], it is further shown that having a small number of CR users over a large distance may be more effective than a large number of closely located users in correlated shadowing scenarios. Hence, it is important to select uncorrelated CR users for cooperation to minimize the effect of correlated shadowing. It is obvious that spatially correlated shadowing incurs overhead.

Due to its importance, spatially correlated shadowing needs to be considered during the user selection for cooperation. The selection of uncorrelated users requires the evaluation of the correlation between users. To achieve this, a correlation model [83,6] derived from empirical data with decaying exponential function is commonly used to determine the spatial correlation in urban and suburban environments. In general, the spatial correlation between two CR users exponentially decreases as the distance between these two increases. These two CR users can be considered uncorrelated if the distance is larger than a value, called decorrelation distance.

In addition to the simple correlation model, advanced models are also needed. It is essential to accurately model the correlated log-normal shadowing in order to properly analyze its impact on cooperative sensing. However, this is a challenging task. For example, in a cooperative sensing scheme based on energy detection and square-law combining (SLC) at the FC, the average detection probability requires the probability density function (PDF) of the power-sum of correlated log-normal random variables (RVs) [84]. However, the lack of the closed-form PDF has resulted in the inaccuracy in modeling correlated shadowing.

In [60,59], a two-step approximation method is proposed to approximate the power-sum of log-normal RVs and model the correlated shadowing in sensing and reporting channels. This method offers good approximation accuracy while keeping the computational complexity at a moderate level. In the first step, the log-normal power-sum RVs are approximated by a log-normal RV. The PDF of the log-normal RVs is obtained by log-normal approximation of the power-sum of generically correlated log-normal RVs when the number of summands (cooperating CR users) is small. In the second step, a non-log-normal approximation method is used to obtain the PDF of correlated Log-Normal RVs when the number of summands is large. The latter gives a more accurate approximation of the log-normal shadowing effects on the reporting channel.

4.3. Energy efficiency

In cooperative sensing, CR users involve in activity such as local sensing and data reporting that consumes additional energy. The energy consumption overhead can be significant if the number of cooperating CR users or the amount of sensing results for report is large. Thus, energy efficiency should be considered in cooperative sensing schemes. To address this issue, existing solutions reduce energy consumption by two main approaches: reducing the amount of reporting data by censoring [21,37] and improving energy efficiency by optimization [85,86].

4.3.1. Censoring

Censoring was introduced in sensor networks as an energy-efficient technique for distributed detection [87,88]. In cooperative sensing, it is used to limit the amount of reported sensing data according to certain criteria or constraints. Since the censoring criteria are chosen to refrain cooperating CR users from transmitting unnecessary or uninformative data, the energy efficiency can be improved in cooperative sensing. In addition, censoring can lower the control channel bandwidth requirement (Section 3.4) due to the reduced number of control messages.

In [21], a simple censoring method is proposed to decrease the average number of sensing bits reported to the FC. Similar to the SPRT, the energy detector output O_i of CR user i is compared to two thresholds λ_1 and λ_2, $\lambda_1 < \lambda_2$. If O_i is smaller than λ_1 or larger than λ_2, decision 0 or 1 is determined, respectively, and sent to the FC. Otherwise, no decision is made and this sensing output is censored from reporting. The results show that even though the Q_f may degrade due to the possibility that the sensing outputs of all CR users are censored, the amount of reported local decisions can be dramatically reduced. Thus, the energy efficiency can be traded off with Q_f.

In [89,37], a censoring scheme with communication rate constraints is proposed to reduce energy consumption in cyclostationarity-based cooperative sensing. In this scheme, CR users send the test statistic from the cyclostationary detector $\mathcal{T}^{(i)}$ to the FC if the following constraint is satisfied:

$$p(\mathcal{T}^{(i)} > t_i \mid H_0) \leq \kappa_i, \quad i = 1, \ldots, L \tag{11}$$

where κ_i is the communication rate constraint of user i for reporting sensing data, t_i is the threshold such that the probability of CR user i sending the test statistic under the null hypothesis H_0 is κ_i, and L is the number of cooperating CR users. As a result, energy efficiency is improved by independently selecting κ_i for each user i based on the required detection performance. It is proven in [88] that, for $t_i = 0$, the probability of miss detection is minimized if the communication rate constraints κ_i in (11) are chosen such that the probability of false alarm is less or equal to $1 - \prod_{i=1}^{L}(1 - \kappa_i)$.

4.3.2. Energy minimization

Another approach to improving energy efficiency is to optimize the CR performance with energy constraints [90] or minimize energy consumption with detection performance constraints [85,86].

In [85], the energy efficiency problem is addressed by energy minimization under detection performance constraints. Specifically, this method investigates the tradeoff between the two aspects of sensing time. On one hand, longer sensing time consumes more energy of each CR user. On the other hand, longer sensing time can improve detection performance at each CR user and reduce the number of cooperating users and the associated energy consumption overhead. Thus, this method finds the optimal sensing time and the optimal number of cooperating users to balance the energy consumption in local sensing and the energy overhead due to cooperation for required detection performance.

In [86], a sleeping and censoring combined scheme is proposed to jointly optimize the energy consumption cost under the detection constraints. Specifically, to find the optimal sleeping rate μ and the censoring thresholds λ_1, λ_2, the optimization problem is formulated as

$$\min_{\mu,\lambda_1,\lambda_2} (1-\mu) \sum_{i=1}^{N} (C_{s_i} + C_{t_i}(1-\rho))$$
$$\text{s.t. } Q_f \leq \alpha, Q_d \geq \beta \tag{12}$$

where C_{s_i} and C_{t_i} are the energy cost of CR user i in sensing and transmission, respectively, $\rho = Pr(\lambda_1 < E_i < \lambda_2)$ is probability of CR user i's energy detector output E_i being censored, and N is the number of cooperating CR users. The results show that this method significantly reduces energy consumption with or without a priori knowledge of PU activity. Moreover, for $\alpha = 0.1$ and $\beta = 0.9$, as the number of cooperating users increases, the optimal sleeping rate increases dramatically to minimize the overall energy consumption in cooperative sensing.

4.3.3. Research challenges

As the advent of the green communications era, efficient energy conservation techniques in cooperative sensing are indispensable. The open research challenges are the following:

- *Energy efficient user selection:* Censoring techniques only reduce the energy consumption on reporting sensing data. However, the energy is still consumed by sensing even if the result is censored. Thus, it is a challenge to properly select the CR users for cooperation such that all the sensing results are informative and the energy spent on unnecessary sensing operations is saved.

- *Modeling of energy consumption:* Existing methods simply model the energy consumption in sensing, sleeping, and transmission/reporting as fixed values. However, many factors will affect the degree of energy efficiency in these operations. For example, different sensing techniques and sensing interval will consume different amounts of energy. In addition, energy consumption in reporting may depend on the transmit power level adapted to channel conditions. Thus, a more accurate energy model for cooperative sensing is needed.

4.4. Sensing efficiency

Cooperative sensing efficiency indicates how often cooperative sensing should be scheduled to sense an appropriate number of channels/bands within a time constraint [91] or how fast a decision can be reached in each round of cooperative sensing. The former primarily refers to the sensing scheduling performed at the FC in centralized cooperative sensing and the latter refers to the convergence rate of distributed cooperative sensing schemes. Thus, these efficiency issues have great impact on the gain and overhead in cooperative sensing.

4.4.1. Sensing scheduling

Conventional centralized cooperative sensing schemes focus on the detection performance resulted from one cooperation. However, the efficiency of centralized cooperative sensing is determined by sensing scheduling, which determines how often CR users cooperate with each other (sensing period) and what type of sensing CR users should perform (fast sensing or fine sensing).

In [68], an online sensing scheduling algorithm is proposed to minimize the sensing period and address the interactions between sensing scheduling and cooperative sensing in IEEE 802.22 scenarios. The algorithm regularly schedules quiet periods for fast sensing. In each round, the FC collects sensing results from cooperating users and compares the test statistic Δ with thresholds A and B, $A < B$, derived from the required detection performance, by using the SPRT. The FC will instruct cooperating users to vacate the channel if a PU is detected ($\Delta > B$), schedule fine sensing if no cooperative decision can be determined after a certain number of times of fast sensing are performed ($A < \Delta < B$), or declare if the PU is not present ($\Delta < A$). The sensing algorithm enables the fast decision at FC to both meet the IEEE 802.22 timing requirement and reduce the cost incurred by fine sensing.

In [92,93], an in-band sensing scheduling algorithm is proposed to find the optimal sensing period and minimize sensing overhead in cluster-based CR networks. Specifically, for each value of sensing time T_I, the algorithm finds the optimal sensing period T_P by repeatedly reducing the number of periodic sensings within the sensing time requirement and checking the probability of miss detection until the detection performance is satisfied. After exploring a range of T_I values, the optimal pair (T_I, T_P) that minimizes the sensing overhead T_I/T_P is chosen. This algorithm can be used to schedule either fast sensing or fine sensing.

4.4.2. Speed of convergence

In distributed cooperative sensing, the concern with efficiency focuses on how fast CR users can reach a unanimous cooperative decision, i.e. the convergence rate of the distributed algorithm for making a decision. One of the distributed algorithms that is proven for convergence and commonly used in cooperative sensing is the consensus scheme.

In [12,94], a consensus-based cooperative sensing scheme is presented. In this method, cooperating CR users exchange local sensing information and iteratively update the test statistic to reach the consensus on the presence of PUs. Each CR user maintains a consensus variable x_i, which is used as the estimate of local sensing statistics. To reach the consensus, the individual variable x_i at CR user i asymptotically converges to a common value x^*, i.e., $x_i(k) \to x^*$ as $k \to \infty$, where k is the discrete time index. Finally, CR users compare the average consensus x^* with a predefined threshold λ and reach a cooperative decision locally. In this scheme, $x_i(k)$ is updated based on the previous state of CR user i and its neighbors as follows.

$$x_i(k+1) \leftarrow x_i(k) + \epsilon \sum_{j \in \mathcal{N}_i} (x_j(k) - x_i(k)) \tag{13}$$

where ϵ is the step size and $\mathcal{N}_i$ is the set of CR user i's neighbors. The selection of step size ϵ has a great effect on the convergence of the consensus scheme.

The average consensus scheme is also incorporated into the distributed cooperative sensing algorithm in [44,42]. The update equation in their algorithms is given by

$$c_j(t+1) \leftarrow c_j(t) + \sum_{k \in \mathcal{N}_j} w_{jk}(c_k(t) - c_j(t)) \tag{14}$$

where w_{jk} is the set of the weights that guarantee the asymptotic average consensus [95].

4.4.3. Research challenges

The efficiency issues have not been well-studied in cooperative sensing. The research challenges are

- *Sensing scheduling:* MAC sensing usually studies the optimization of sensing and channel access of one CR user [92,91]. The sensing scheduling schemes can consider how CR users can cooperate to efficiently sense multiple channels. It is also a challenge to consider the scheduling of narrowband and wideband sensing in addition to fast and fine sensing to further improve the cooperation efficiency.
- *Analysis of convergence rate:* All distributed cooperative sensing schemes are required to converge to a cooperative decision. However, how fast the distributed scheme can converge is usually not well-analyzed. Since a PU's behavior may be highly dynamic, it is a challenge to devise an efficient distributed scheme that can converge in a timely fashion to match the PU's activity change.

4.5. Mobility

Most existing cooperative sensing techniques do not consider the movement of PUs and CR users during cooperative sensing. However, the mobility of PUs and CR

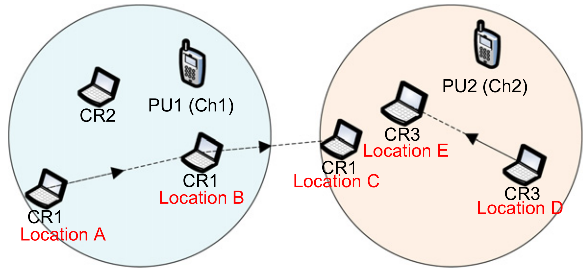

Fig. 11. CR user mobility and cooperative sensing.

users may have the impact on the detection performance and how CR users cooperate in cooperative sensing. For example, as shown in Fig. 11, when *CR*1 moves from location *A* to *B*, *CR*1 creates the spatial diversity in the observations of *PU*1 by mobility. The cooperation between *CR*1 and other CR user like *CR*2 can be reduced to minimize the cooperation overhead. On the other hand, if *CR*1 continues to move to location *C* and *CR*3 moves from location *D* to *E* toward *CR*1, *CR*1 and *CR*3 may be correlated due to their proximity. As a result, mobility can induce the correlated shadowing and the incurred overhead. Moreover, as *CR*1 moves, it may need to cooperate with different CR users depending on the moving direction and speed, and sense different channels from *Ch*1 to *Ch*2 in this case. The scenario could be further complicated if both *PU*1 and *PU*2 are mobile. Thus, mobility may improve or compromise the achievable cooperative gain. The cooperation overhead can also occur due to mobility. Here we focus on the issues of PU mobility and CR mobility separately as follows.

4.5.1. Primary user mobility

For large-scale PUs such as TV powers or cellular base station s, it is a reasonable assumption that the PUs are stationary. On the other hand, for small-scale PUs, such as wireless microphones in IEEE 802.22 or radios in emergency and military networks, the PUs can be mobile. The detection of small-scale PUs by an individual CR user is a challenge owing to their small transmit power and mobility. Thus, cooperative sensing with the assistance of PU tracking methods and the spectrum knowledge base could be the solution to this problem. To the best of our knowledge, no solution has yet been proposed to consider the impact of PU mobility on cooperative sensing.

4.5.2. CR user mobility

Intuitively, the movement of a CR user creates the spatial diversity in the observations taken on the move. As a result, a mobile CR user can improve the detection performance with its local samples and require less cooperation from others to reduce the cooperation overhead, depending on the speed and the direction of the movement and the location of the cooperating CR users. However, it is also likely that the mobility creates the correlation among CR users if the distance between CR users may be reduced by CR user movement. In addition, the network topology changes as CR users move. In this case, CR users may need to join or leave the group of cooperating CR users similar to the merge and split of coalitions in [28]. Thus, all the cooperation overhead due to mobility must be considered in cooperative sensing of mobile CR users.

In [20], the impact of mobility on spectrum sensing is investigated. For a single mobile CR user with energy detection, it is shown that the mobility increases the spatial–temporal diversity in the received PU signals. Without the cooperation from other users, the CR user mobility can improve the detection performance with increasing moving speed. This is because the observations are less correlated as the speed is increased. The simulation results also show that higher mobility speed can reduce the frequency of scheduled sensing for a given detection performance. This reduces the frequency of periodic sensing and the overall sensing time. It is also implied that it is more efficient to cooperate with other users than scheduling multiple times of sensing when CR users are slowly moving. On the other hand, when CR users are moving at high speed, it is more efficient to sense individually multiple times than cooperate with other users. In addition, the number of cooperating CR users can be decreased if the number of times to perform sensing is increased. This results in a tradeoff between cooperation and scheduling. Moreover, the mobility speed can reduce the average received signal strength. Thus, the degradation in sensitivity of energy detection must be compensated by the spatial–temporal diversity. These results imply that CR users can reduce the cooperation overhead with the speed of mobility if the independent observations with the spatial–temporal diversity can be obtained.

4.5.3. Research challenges

Despite some preliminary studies, there are still many unanswered questions regarding the impact of mobility on cooperative sensing. For example, what is the optimal way to perform cooperative sensing if CR users are moving? If CR users can be stationary or mobile, how to select the cooperating CR users? How to perform cooperative sensing in a stable and reliable manner at mobile or vehicular speed? We find that the research challenges on mobility issue in cooperative sensing are

- *PU mobility and tracking:* Due to the mobility of PUs, the tracking of PU movement becomes an important problem in cooperative sensing. The accurate tracking of PUs relies on an efficient localization method with location estimation. The development of an effective location estimation method based on the received signal strength values of PU signals remains a challenge.
- *Impact of mobility parameters:* It is a challenge to identify the mobility parameters that affect the detection performance, and their relations with cooperative gain and cooperation overhead. For example, mobility may increase or decrease the correlation among CR users and thus improving or degrading the detection performance in cooperative sensing. The possible parameters may include the mobility speed, the direction of movement, the doppler frequency, the density of CR users, or a profile that contains the moving trajectory and locations of CR users.

4.6. Security

The cooperation among CR users raises new concerns for the reliability and the security in cooperative sensing. This is because, when multiple CR users cooperate in sensing, a few CR users who report unreliable or falsified sensing data can easily influence the cooperative decision. During cooperation, malfunctioning CR users may unintentionally send unreliable data to the FC. For example, the report from a malfunctioning user could deviate from the real value. Moreover, CR users, called malicious users or Byzantine adversaries in this case, can intentionally manipulate the sensing data and report the falsified data for their own benefits. For instance, malicious users may obtain spectrum access by falsely reporting the presence of PUs. It is reported in [7] that the cooperative gain can be severely affected by malfunctioning or malicious CR users in cooperative sensing.

To address the security and reliability issues, additional mechanisms are required to identify malicious CR users and manipulated sensing data, and remove them from cooperation. Although these countermeasures may incur overhead in cooperative sensing, they are required to ensure secure operations of cooperative sensing and obtain reliable sensing results in hostile environments. Next, we consider reliability and security issues by mainly focusing on two areas: *data falsification*, where the detection performance is affected by the falsified sensing data, and *security attack*, where cooperative sensing is compromised or even disrupted by adversary attacks such as PU emulation, control channel jamming, node capture, and center of failure.

4.6.1. Data falsification

To address the data falsification problem, existing cooperative sensing schemes aim to detect the anomaly in the reported sensing data and establish a mechanism to distinguish the malicious users from the authentic ones such that malicious users can be excluded from the cooperation to ensure the integrity of the sensing decisions.

In [81], the weighted SPRT with a reputation-based mechanism is proposed as the robust cooperative sensing scheme to address the data falsification problem. As a first step, the reputation ratings for cooperating CR users are calculated depending upon their sensing accuracy. Whenever the local sensing result matches the final decision, the reputation is increased. Otherwise, it is decreased. The reputation values are converted to the weights to be used in the modified likelihood ratio of a SPRT for data fusion. In this manner, the impact of the unreliable CR users can be reduced by putting weights on the genuine sensing data over the falsified ones.

In [96], a simple outlier detection is proposed for the pre-filtering of the extreme values in sensing data. The trust factor that measures the CR user's reliability is then evaluated as the weights in calculating the mean value of received sensing data. In that way, cooperative sensing can be more reliable by building trust toward CR users that report a sensing value close to the mean of all collected results at the FC. The method is extended in [97] to detect malicious users by the outlier factors, which are calculated based on the weighted sample mean and the standard deviation of the energy detector outputs. The outlier factors can be adjusted according to the dynamic PU activity and the observations from closest neighbors in a neighborhood to further improve the detection of malicious users.

In [98], a consensus-based cooperative sensing scheme is proposed to address the data falsification problem in CRAHNs. As discussed in Section 3.6, each CR user iteratively selects neighbors for cooperation and sensing data exchange such that the consensus (cooperative decision) is gradually reached in a distributed manner. When selecting cooperating neighbors, each authentic CR user checks the received sensing data by comparing it with the local mean value. The neighbor reporting the result with maximum deviation from the local mean will be rejected for cooperation. With this scheme, the reliability of cooperative sensing can be improved by isolating malicious users in the neighborhood.

4.6.2. Security attacks

In addition to data falsification problem, cooperative sensing is vulnerable to a variety of security attacks in hostile environments such as PU emulation attack, control channel jamming attack, and node capture attack.

In PU emulation attack, malicious users transmit signals similar to those of the PUs. Since these malicious users are mistaken as PUs, legitimate CR users will vacate the frequency band and the attackers will have the wrongful privilege to access the spectrum. To address this problem, a transmitter verification scheme based on localization is proposed in [99] to counter the attack. In this method, an RSS-based localization is utilized by collecting the RSS values from cooperating CR users to estimate the PU's transmitter location. The PU's identity can be verified by comparing the estimates with known PU's characteristics.

In a control channel jamming attack, a strong interference signal injected to the control channel disables the reception of valid control messages at CR users. In this case, CR users are unable to exchange control messages on control channels for cooperative sensing and higher-layer network functions. This resulting in the denial-of-service (DoS). In general, the spread spectrum techniques can mitigate the jamming attack by introducing the pseudo random channel access unknown to malicious users.

In [100], a dynamic control channel allocation scheme based on hopping sequences is proposed to mitigate the control channel jamming attacks in cluster-based ad hoc networks. In this method, the clusterhead of each cluster determines the hopping sequence and the operating control channel within the cluster. During the jamming attack, the affected area is reduced due to the clustering of the network. Based on the defined hopping sequence, cooperating CR users can resume the communications on the new control channel after the old one is jammed. Moreover, the hopping sequences are encrypted by the public key of each cooperating CR user to provide the protection from the intruders. Thus, this method can provide a scheme to temporarily restore the control channel until the jammer is removed.

When the hopping sequences are known to malicious users (compromised users) through node capture attack, the anti-jamming techniques such as [100] may be ineffective. In [101], a control channel access scheme with random key assignment is proposed to address the jamming problem under node capture attacks. By increasing the diversity of keys (control channel identifier) assigned to users, authorized users increase the probability of holding keys unknown to compromised users. Thus, this control channel access scheme is more robust to jamming by compromised users. However, this method also increases the communication and storage overhead due to the increase of the number of keys.

4.6.3. Research challenges

The security in cooperative sensing cannot be assured by only detecting falsified data because the security attacks come in various forms aiming at attacking different network components and functions. The open research challenges on security in cooperative sensing include the following:

- *Physical layer security:* The techniques of physical layer security can be applied to cooperative sensing to improve the cooperative sensing security without the implementation complexity of cryptographic functions. For example, the cooperative scheme in [102] utilizes relays to cooperatively nullify the interfering and jamming signals of eavesdroppers. However, it is a challenge to analyze the tradeoff between the gain from physical layer security and the overhead.
- *Large-scale node capture attacks:* Existing cooperative sensing solutions to data falsification problem may be effective in detecting a few malfunctioning or malicious users. When a large number of CR users are captured and reporting false data, the detection of a malicious user cannot be guaranteed solely by data analysis. A novel scheme is required to counter the large-scale node capture attacks.
- *Security of fusion center:* An absolutely secure FC is usually assumed in centralized cooperative sensing schemes. However, the FC may be susceptible to attacks even if it is relatively more secure than cooperating users. If the security of the FC cannot be guaranteed, it is a challenge for cooperating CR users to identify the vulnerability and the failure of the FC.

4.7. Wideband sensing

Conventional cooperative sensing exploits the spatial diversity of cooperating CR users and focuses on the sensing of one frequency band during each round of cooperation. To determine the availability of the spectrum in multiple channels or bands, CR users need to be synchronized to switch to another band and perform cooperative sensing separately in each band. This process can incur significant switching delay and synchronization overhead. Alternatively, CR users can cooperatively sense multiple channels or frequency bands to reduce the total sensing time for all users. In this subsection, we discuss multi-band cooperative sensing [34,103] and wideband cooperative sensing [44,42].

4.7.1. Multi-band cooperative sensing

In multi-band cooperative sensing, CR users cooperate to sense multiple narrow bands instead of focusing on one band at a time. In [34], a spatio-spectral joint detection (SSJD) scheme is proposed for combining the statistics of sensing K bands from M spatially distributed CR users. The FC calculates the test statistic and make a cooperative decision in each band. The weight coefficients and detection thresholds of all bands are obtained by jointly maximizing the aggregate CR throughput in each band subject to miss detection and false alarm probability constraints. To enable the multi-band sensing at each CR user, an energy detector is required for each band of interest. As a result, the method may incur higher hardware cost when the number of bands for cooperative sensing is large.

In [103], a parallel cooperative sensing scheme is proposed to enable the multi-channel sensing by optimally selected cooperating CR users. Unlike the multi-band sensing scheme in [34], each of cooperating CR users senses a different channel. By this method, multiple channels can be cooperatively sensed in each sensing period. The objective is to maximize the CR throughput while minimizing the sensing overhead such as the sensing time and the number of required CR users for cooperation.

4.7.2. Wideband cooperative sensing

As discussed in Section 3.2, compressed sensing techniques facilitate wideband sensing with the sampling at sub-Nyquist rate. Based on the assumption that the wideband spectrum is sparsely occupied by PUs, the spectrum of the wideband signal can be reconstructed for PU detection. Thus, we focus on the wideband cooperative sensing schemes utilizing compressed sensing [44,48,42].

In [44], a distributed cooperative sensing scheme is proposed for wideband sensing in CRAHNs. In this scheme, each CR user performs compressed sensing locally, determines the local spectral estimates, and sends the spectrum state vectors to one-hop neighbors. By using the distributed average consensus method, each CR user iteratively updates its spectrum state vectors with the weighted sum of the difference values between the CR user and its neighbors. As a result, the spectrum state vectors converge to the average statistic at each CR user for PU detection. Similarly, the spectral estimates can be obtained cooperatively by the consensus averaging.

In [48], the work in [44] is extended to consider the spectrum occupied by CR users, called spectral innovation, in addition to PUs in wideband sensing. The accuracy of spectrum estimation is improved by utilizing the spectral orthogonality between PUs and CR users. Based on the work in [44,48], a distributed consensus optimization scheme is proposed in [42] for wideband sensing in CRAHNs. After compressed sensing, each CR user finds spectrum estimates by performing the consensus optimization for global optimality and broadcasts it to one-hop neighbors. This process is repeated until the convergence is reached. The average consensus technique incorporated in the constraints ensures a fast convergence. In addition, this method is also considered in the presence of spectral innovation.

4.7.3. Research challenges

Wideband cooperative sensing has recently gained much attention in the literature. However, it raises many open research problems in cooperative sensing. Two major challenges are given as follows.

- *Narrowband–wideband tradeoff:* Using multi-band and wideband sensing can reduce the sensing time and channel switching overhead of narrowband sensing. However, additional hardware cost or overhead is required to facilitate simultaneous detection in multiple bands. The tradeoff between narrowband sensing and wideband sensing needs to be investigated for detection performance, sensing delay, complexity, and throughput.
- *Signal classification in wideband sensing:* The sparsity of the spectrum utilization is the main assumption in the compressed sensing approach. However, this assumption may not hold if many CR users share the wideband spectrum with PUs. Moreover, the assumption of the orthogonality of PU and CR user bands in [42] may not be realistic. Thus, signal classification techniques must be combined with compressed sensing to distinguish PUs from CR users and address the coexistence issue in wideband sensing.

5. Conclusions

Cooperative sensing is an effective technique to improve detection performance by exploring spatial diversity at the expense of cooperation overhead. In this paper, we dissect the cooperative sensing problem into its fundamental elements and investigate in detail how each element plays an important role in cooperative sensing. Moreover, we define a myriad of cooperation overheads that can limit the achievable cooperative gain. We further identify the research challenges and unresolved issues in cooperative sensing that may be used as the starting point for future research.

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