SECONDARY USERS COOPERATION IN COGNITIVE RADIO NETWORKS: BALANCING SENSING ACCURACY AND EFFICIENCY

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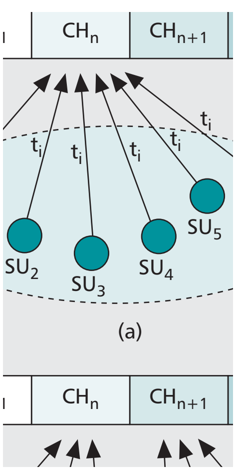

The authors identify the fundamental trade-off between sensing accuracy and efficiency in spectrum sensing in cognitive radio networks, and they present several cooperation mechanisms.

ABSTRACT

Cooperative spectrum sensing is a promising technique in cognitive radio networks by exploiting multi-user diversity to mitigate channel fading. Cooperative sensing is traditionally employed to improve the sensing accuracy while the sensing efficiency has been largely ignored. However, both sensing accuracy and efficiency have very significant impacts on the overall system performance. In this article, we first identify the fundamental trade-off between sensing accuracy and efficiency in spectrum sensing in cognitive radio networks. Then, we present several different cooperation mechanisms, including sequential, full-parallel, semi-parallel, synchronous, and asynchronous cooperative sensing schemes. The proposed cooperation mechanisms and the sensing accuracy-efficiency trade-off in these schemes are elaborated and analyzed with respect to a new performance metric achievable throughput, which simultaneously considers both transmission gain and sensing overhead. Illustrative results indicate that parallel and asynchronous cooperation strategies are able to achieve much higher performance, compared to existing and traditional cooperative spectrum sensing in cognitive radio networks.

INTRODUCTION

Current spectrum usage in wireless networks is based on a fixed assignment policy. The Federal Communications Commission (FCC) [1] spectrum usage measurement report has revealed that, although the demand for radio spectrum is explosively increasing, a large segment of the assigned spectrum band is severely under-utilized. The increasingly developing cognitive radio technology [2] is known as a promising approach to effectively address the spectrum scarcity and inefficiency, and hence a potential communications paradigm for complex information systems, e.g., the Smart Grid [3]. In a cognitive radio network, the unlicensed secondary users (SUs) are allowed to opportunistically access the vacant portions of the spectrum assigned to the licensed primary users (PUs). Designing a cognitive radio network is considerably challenging. The secondary system should be able to discover the spectrum opportunities as many as possible, and meanwhile, strictly avoid interference to the primary transmissions.

Spectrum sensing is a crucial technology in cognitive radio networks to efficiently and accurately detect PUs for avoiding interference to PUs. However, many unpredictable problems, e.g. channel instability and noise uncertainty, may significantly degrade the performance of spectrum sensing. The performance of spectrum sensing is characterized by both sensing accuracy and sensing efficiency.

- Sensing accuracy: Sensing accuracy refers to the precision in detecting PU signals such that the primary transmissions are not interfered. Sensing accuracy is represented by the false alarm probability and the detection probability
- Sensing efficiency: Sensing efficiency refers to the number of discovered spectrum opportunities by consuming a unit of sensing cost in terms of sensing overhead and throughput.

Sensing accuracy and efficiency are two opposite aspects that reflect the performance of spectrum sensing. Let us consider a simple example where multiple SUs sense an identical wireless channel. It is observed that more sensing SUs will lead to higher sensing accuracy but more sensing overhead (i.e., less sensing efficiency). There is a fundamental trade-off between the sensing accuracy and efficiency. Since the overall system performance of cognitive radio networks potentially depends on both the sensing accuracy and efficiency, the trade-off between them should be optimally addressed.

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Recently, cooperative networking technologies, which inherently exploit the broadcasting nature of wireless channels and the spatial diversity of cooperative users, are introduced as a powerful means to facilitate the design of cognitive radio networks. Two types of cooperation paradigms in cognitive radio networks have been studied up to date: cooperation between PUs and SUs (called *PU-SU cooperation*), and cooperation only among SUs (called *inter-SU cooperation*). For the PU-SU cooperation, PUs are aware of the existence of SUs. The primary system regulates the spectrum leasing policy for the secondary system. The SUs utilize a small segment of the licensed spectrum, and in return, cooperate with PUs to improve the quality of primary transmissions. For the inter-SU cooperation, there is no interaction between primary and secondary systems. Typical cooperative networking technologies for SUs include cooperative spectrum sensing, cooperative relaying, cooperative network coding, and cooperative routing.

This article presents key challenges and solutions in cooperative spectrum sensing to address sensing accuracy-efficiency trade-off in cognitive radio networks, including different cooperation mechanisms, cooperative protocols, theoretical analysis, and performance comparison. We illustrate the design challenges in cooperative spectrum sensing and proposes various cooperation mechanisms. We also present a new performance metric achievable throughput to simultaneously take into account both sensing accuracy and sensing efficiency. We then elaborate sequential and parallel cooperative sensing schemes; and synchronous and asynchronous cooperative sensing schemes. Illustrative results indicate that parallel and asynchronous cooperation strategies are able to achieve much higher achievable throughput, compared to existing and traditional cooperative spectrum sensing. The conclusion of the article is presented.

Cooperative Spectrum Sensing

In cooperative spectrum sensing, multiple users of the secondary system cooperate to combat the unpredictable dynamics in wireless environments and improve the sensing accuracy and efficiency. In the cooperation mechanism, several terminologies in the secondary system are defined.
- Source SU: the SU that has data packets to transmit.
- Destination SU: the SU that is going to receive data packets from the source SU.
- Cooperative SUs: the SUs that are appointed to perform cooperative spectrum sensing.
- Fusion Center: the component that is responsible for receiving and combining the sensing results to make a final decision.

Figure 1 shows the procedure of cooperative spectrum sensing. The source SU that intends to transmit packets will send a request to the fusion center, claiming for the cooperative spectrum sensing. The fusion center selectively assigns several cooperative SUs for cooperation. The sensing results are sent back to the fusion center for collaborative decision. Once the spectrum opportunities are discovered, the packets could be

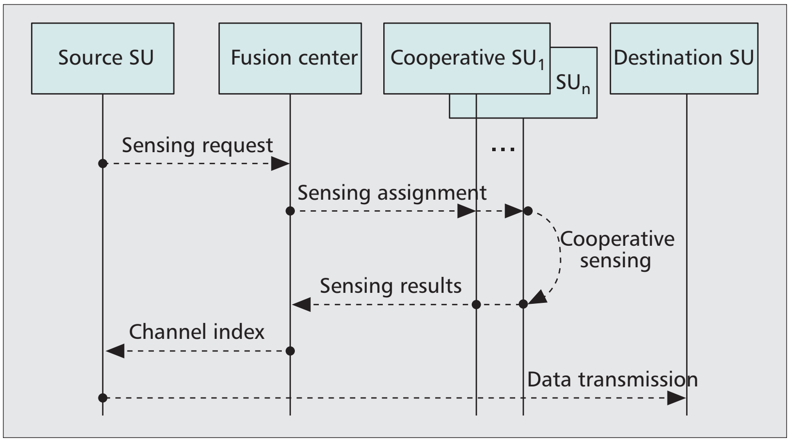

Figure 1. *Procedure of cooperative spectrum sensing.*

transmitted from the source SU to the destination SU on the detected channel specified by the fusion center.

Design Challenges

Compared with non-cooperative spectrum sensing, cooperative spectrum sensing has the inherent advantage of exploiting the spatial multi-user diversity. However, the inter-SU cooperation mechanism also poses a number of unique challenges.
- Common control channel (CCC): As the basis of inter-SU cooperation, a reliable common control channel should be built up to transmit control information among the cooperative SUs.
- Spatial diversity modeling: The channel conditions are uncorrelated for different cooperative SUs. The effect of this spatial difference should be quantitatively characterized when combining sensing results in the fusion center.
- Temporal diversity modeling: Since a cooperative SU needs a time interval to send back the sensing result, there is an essential delay from the moment when the channel is sensed to the time when the sensing result reaches the fusion center. The impact of this time difference should be modeled in the fusion center.
- Clock synchronization: The scheduling of the cooperative SUs and the sensed data fusion are all dependent on a synchronized clock. Setting up a precise synchronization mechanism is crucial for cooperative sensing, especially in a decentralized network architecture without an infrastructure.
- Security: In most existing cooperative spectrum sensing schemes, the cooperative SUs are all supposed to be friendly. However, the hostile or selfish SUs could make the cooperation mechanism vulnerable, and then return with false sensing results.

Classification of Cooperation Mechanisms

Cooperation mechanisms in cooperative spectrum sensing are different in the way that:
- The cooperative SUs are selected and scheduled for cooperation
- The sensing results are transmitted to fusion center
- The sensing results are combined

Since multiple channels are detected in one sensing period, the period in finding all available channels is much shorter than that in sequential cooperative sensing. The sensing efficiency is then significantly enhanced.

Cooperative scheme	Sensing overhead	Sensing delay	Network throughput	Interference to PUs	Operation mode
Sequential	Moderate	Large	Low	Light	Centralized
Parallel	Moderate	Small	High	Moderate	Centralized
Synchronous	Moderate	Large	Low	Light	Centralized
Asynchronous	Small	Small	High	Moderate	Centralized or decentralized

Table 1. *Comparison among cooperative sensing schemes.*

According to the number of sensed channels in one sensing period, cooperative spectrum sensing could be broadly categorized into *sequential* and *parallel* cooperative sensing.

- Sequential cooperative sensing: All the cooperative SUs are scheduled to sense an identical channel in each sensing period. Channels are sensed one by one sequentially.
- Parallel cooperative sensing: More than one channels are sensed in each sensing period. The cooperative SUs are divided into multiple groups while each group senses one channel.

SUs cooperation can also be categorized into synchronous and asynchronous mechanisms based on the moments when sensing operations are carried out.

- Synchronous cooperative sensing: All cooperative SUs have the same sensing period, and perform spectrum sensing at the same time. All sensing results have the identical time tag indicating the moment that a sensing operation takes place.
- Asynchronous cooperative sensing: Each cooperative SU performs spectrum sensing according to its own sensing period. Hence, the moments when SUs perform sensing may be different. Accordingly, the sensing results have different time tags.

Table 1 shows the comparison among the aforementioned four classes of cooperative sensing schemes. In addition, Fig. 2 shows the cooperation mechanisms in the spectrum sensing schemes, which are further clarified later .

Sequential and Parallel Cooperative Sensing

Sequential Cooperative Sensing

Figure 2a shows the sequential cooperative sensing, where the cooperative SUs (SU_1–SU_6) are scheduled to sense a single channel at the same time t_i. Channels are sensed one by one in a sequential manner. Due to the unpredictable wireless environments, (e.g., fading, shadowing, and hidden/exposed terminal), non-cooperative sensing may be error-prone. The sequential cooperative sensing is the so-called traditional cooperative spectrum sensing scheme for the sake of improving the sensing accuracy by inherently exploiting the spatial diversity of the cooperative SUs.

In the literature, some sequential cooperative sensing have been proposed. The recent work in [4] proposes an optimal sensing framework to multiuser cooperation environment. The spatial-correlated sensing results provided by the cooperative SUs are combined to increase sensing accuracy. In the pioneering study [5], a two-user cooperative spectrum sensing scheme is proposed, in which one of the user acts as a relay and forwards the sensing result to the other. This relay-based cooperation mechanism is able to decrease the detection time and increase the overall agility. The study in [6] presents a novel wideband cooperative spectrum sensing scheme that exploits the spatial diversity among multiple SUs to improve the sensing reliability. The work in [7] investigates the sensing-throughput tradeoff in cognitive radio networks. Each sensing slot is split into multiple mini-slot to exploit the time diversity. In a multi-user environment, decision fusion rules (AND, OR, or MAJORITY) are applied to combine sensing results of different SUs and in different mini-slots.

A common feature of the aforementioned studies is to significantly improve the sensing accuracy by scheduling all cooperative SUs to sense an identical channel in a single sensing period. The multi-user spatial diversity is exploited, and therefore the sensing accuracy is high in these schemes. In these schemes, only a single channel is detected in one sensing period.

Full-Parallel Cooperative Sensing

The motivation of parallel cooperative sensing is to enhance the sensing efficiency by allowing the cooperative SUs to sense distinct channels in one sensing period. Since multiple channels are detected in one sensing period, the period in finding all available channels is much shorter than that in sequential cooperative sensing. The sensing efficiency is then significantly enhanced.

Figure 2b shows the full-parallel cooperative scheme, where each cooperative SU senses a distinct channel in a centralized and synchronized mode. Upon receiving the request of parallel cooperative sensing from the source SU, the fusion center will deliberately select a subset of cooperative SUs to perform sensing. Each of these selected SUs is assigned to sense a different channel at the same time during the sensing period. Thereby, these SUs perform spectrum sensing in a parallel manner. After each round of sensing, the cooperative SUs will send back the sensing results to the fusion center, indicating the channel availability (busy or idle). When

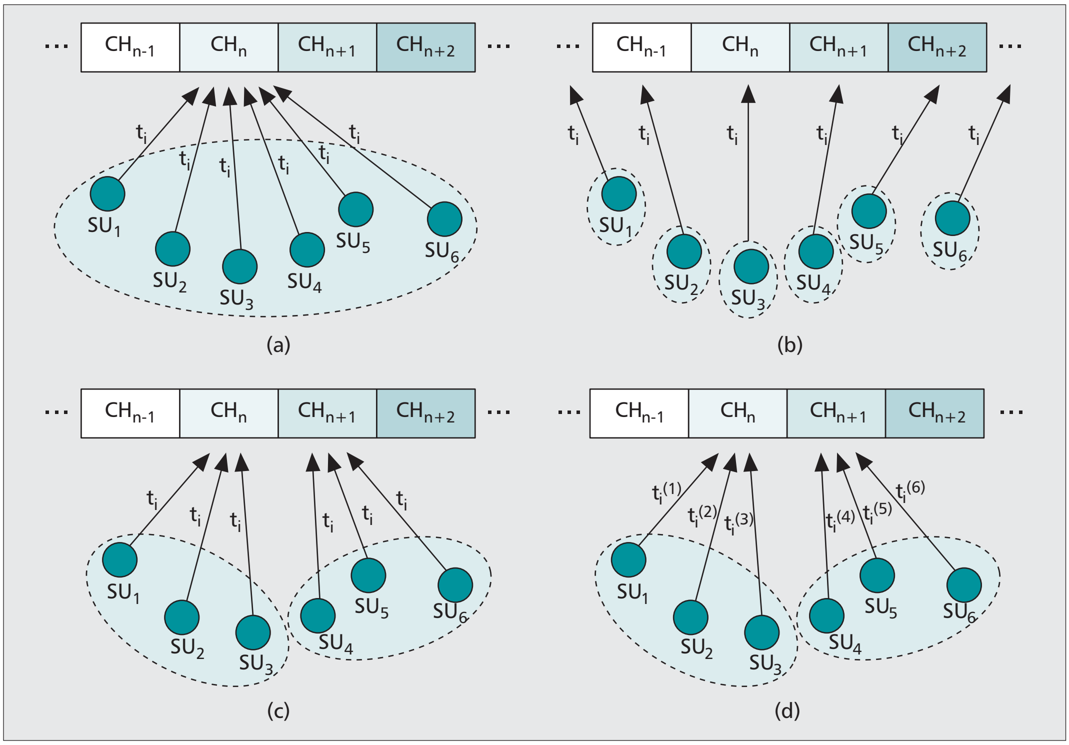

Figure 2. *Illustration of cooperation mechanisms: a) sequential cooperative sensing; b) full-parallel cooperative sensing; c) semi-parallel cooperative sensing; d) asynchronous cooperative sensing.*

the sequential cooperative sensing mainly aims to improve the sensing accuracy in cognitive radio networks. On the contrary, the full-parallel cooperative sensing is designed for the enhancement of sensing efficiency. The sensing accuracy remains the same as that in non-cooperative sensing.

the available channel with satisfying data rate has been found, the fusion center will broadcast the stopping command to terminate the parallel cooperative sensing. The fusion center selects the discovered available channel with the highest achievable rate for the source SU. The fusion center then delivers the channel index to the source SU, which will transmit over this allocated channel.

In the full-parallel cooperative sensing, there are two key parameters: the number of cooperative SUs and the channel rate threshold for stopping the sensing operation. It is noteworthy that the cooperative SUs have to temporarily pause their own data transmission to help the source SU sense the spectrums. As a consequence, more cooperative SUs are able to sense more channels in one sensing period but more transmission opportunities will be lost. In addition, higher channel rate threshold will lead to longer searching time but higher quality of the discovered channels. In order to take into account both accuracy and efficiency as well as determine key parameters, we introduce a new performance metric *achievable throughput*. Let n and x denote the number of the cooperative SUs and the channel rate threshold, respectively. The achievable throughput of the full-parallel cooperative sensing is defined as

$$T^*_{\text{FPCS}} = \max_{n,x}\{\mathcal{G}(n,x) - \mathcal{O}(n,x)\} \quad (1)$$

where $\mathcal{G}(n, x)$ and $\mathcal{O}(n, x)$ are the transmission gain and the sensing overhead under parameters n and x, respectively. Let N denote the total channel number, r_m the m-th channel rate level (m = 1, 2, …, M), $p_j^m(m, x)$ the probability that the channel with rate r_m is discovered in the j-th round of full-parallel cooperative sensing, and $\overline{T}_a$ the average duration of channel available/idle time. The transmission gain is given by

$$\mathcal{G}(n,x) = \sum_{j=1}^{\left\lceil \frac{N}{n} \right\rceil} \left[\sum\nolimits_{m=x}^{M} p_j^m(n,x) r_m \overline{T}_a\right]$$

Let t_s denote the sensing time of each cooperative SUs, and r_{sum} the sum of channel rate of all the n cooperative SUs. The sensing overhead is represented by

$$\mathcal{O}(n,x) = \sum_{j=1}^{\left\lceil \frac{N}{n} \right\rceil} \left[\sum\nolimits_{m=x}^{M} p_j^m(n,x) r_{\text{sum}} j t_s\right].$$

Note that, to reduce the sensing overhead, the fusion center will sort the all the SUs by their instant channel rate from the lowest to the highest, and then select the first n SUs as the cooperative SUs.

Semi-Parallel Cooperative Sensing

As aforementioned, the sequential cooperative sensing mainly aims to improve the sensing accuracy in cognitive radio networks. On the contrary, the full-parallel cooperative sensing is designed for the enhancement of sensing efficiency. The sensing accuracy remains the same as that in non-cooperative sensing. Both mechanisms merely deal with one aspect of the sensing accuracy and efficiency while neglecting the other one.

To trade-off the sensing accuracy and efficiency, the *semi-parallel cooperative sensing* is proposed and described in Fig. 2c. The cooperative SUs is scheduled by the fusion center in a centralized manner. Upon receiving the sensing request from the source SU, the fusion center sends a beacon to a number of SUs to invite the participation in the sensing operation. The fusion center then divides the cooperative SUs into multiple groups. The cooperative SUs in a same group are notified to sense an identical channel, while each group is assigned with a different channel. All the cooperative SUs sense channels synchronously. After a sensing period, all the sensing results are sent back to the fusion center, which will determine the availability of all the sensed channels. Once an available channel is discovered, the fusion center should stop the sensing procedure and declare the success of cooperative sensing. The source SU will be informed with the index of an available channel.

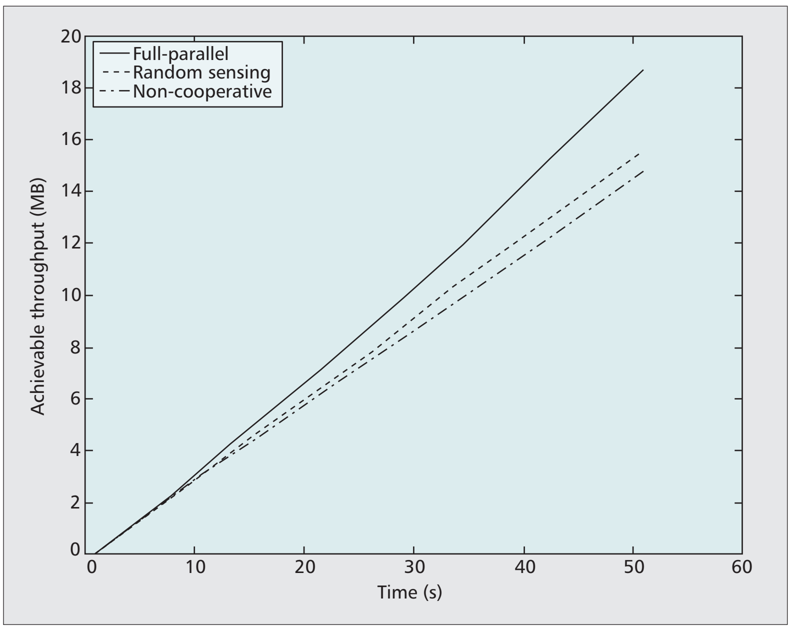

Figure 3. *Comparison among the full-parallel cooperative sensing, the random sensing, and the non-cooperative sensing schemes.*

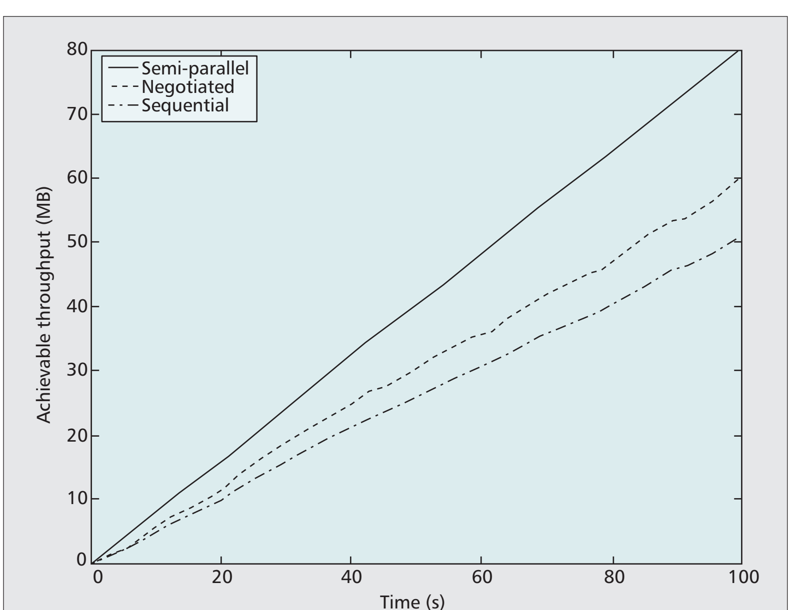

Figure 4. *Comparison among the semi-parallel, the negotiation-based, and the sequential cooperative sensing schemes.*

In the semi-parallel cooperative sensing, the grouping strategy will determine the levels of sensing accuracy and efficiency. For a given total number of the cooperative SUs, more SUs in a group will lead to higher accuracy. In this case, there are less groups and hence lower sensing efficiency. If all the cooperative SUs are allocated in a same group, the scheme becomes the sequential cooperative sensing. If each cooperative SU is individually set as a group, the scheme reduces to the full-parallel cooperative sensing. By varying the number of groups and the number of cooperative SUs in each group, the tradeoff between sensing accuracy and efficiency could be adjusted to a different extent. Let u and v denote the number of groups and the number of cooperative SUs in each group, respectively. These parameters are determined by maximizing the achievable throughput

$$T^*_{\mathrm{SPCS}} = \max_{u,v}\left\{\mathcal{G}(u,v) - \mathcal{O}(u,v)\right\} \tag{2}$$

where $\mathcal{G}(u, v)$ and $\mathcal{O}(u, v)$ are the transmission gain and the sensing overhead under parameters u and v, respectively. Let $p_j(u, v)$ denote the probability that the available channel is discovered in the j-th round of semi-parallel cooperative sensing, and $\bar{r}$ the average channel rate for SUs. The transmission gain and the sensing overhead are given by

$$\mathcal{G}(u,v) = \sum_{j=1}^{\left\lceil \frac{N}{u} \right\rceil} p_j(u,v)\bar{r}\bar{T}_a$$

and

$$\mathcal{O}(u,v) = \sum_{j=1}^{\left\lceil \frac{N}{u} \right\rceil} p_j(u,v)v\bar{r}jt_s,$$

respectively.

Performance Comparison

From Eq. 1. and Eq. 2, we know that the achievable throughput in the full-parallel and semi-parallel cooperative sensing schemes are achieved by varying the parameters (n, x) and (u, v), respectively. These two cooperation mechanisms are equivalent under the conditions $x = 1$ and $v = 1$. Let us consider the case when $x = 1$. Then, we have $\sum_{m=1}^{M} p_j^m(n, 1)r_m = p_j(n, 1)\bar{r}$, which reveals the inherent connection between the key probabilities $p_j^m(n, x)$ and $p_j(u, v)$ in these two mechanisms. Let $P_f(v)$ denote the false alarm probability in the semi-parallel cooperative sensing, and q the channel available probability. The probability to successfully discover an available channel is represented by $P_s(v) = q[1 - P_f(v)]$. Then, we have $p_1(u, v) = \sum_{k=1}^{u} \binom{u}{k}[1 - P_s(v)]^{u-k} P_s(v)^k$, and $p_j(u, v) = [1 - p_1(u, v)]^{j-1} p_1(u, v)$. We observe that, in the semi-parallel cooperative sensing, different combinations of parameters u and v have different sensing accuracy, consequently leading to different achievable throughput. In the full-parallel cooperative sensing, the sensing accuracy are not tunable, e.g., the false alarm probability Pf is fixed. The achievable throughput is related to the number of cooperative SUs n. By introducing selective grouping policy, the cooperation mechanism in the semi-parallel cooperative sensing is more resilient than that in the full-parallel cooperative sensing. In other words, semi-parallel cooperative sensing exploits the inter-SU cooperation in a more efficient way than full-parallel cooperative sensing.

As shown in Fig. 3, a simulation is conducted to compare the achievable throughput among the full-parallel cooperative sensing, the random sensing policy, and the non-cooperative sensing scheme. In the random sensing policy, each cooperative SU randomly selects a channel to sense. In the simulation, there are 30 SUs and 30 wireless channels with rate randomly ranging from 0.1 to 1 Mbyte/s. The channel busy and idle activities are described by the two-state ON-OFF model. The result in Fig. 3 indicates that the full-parallel cooperative sensing outperforms the other two mechanisms by approximately 20 percent enhancement in achievable throughput.

In Fig. 4, the achievable throughput in the semi-parallel cooperative sensing, the negotiation-based sensing, and the sequential cooperative sensing scheme are compared. The negotiation-based sensing scheme was proposed in [9] with an attempt to sense distinct channels via a local negotiation. In this simulation, the system has 10 SUs and 10 wireless channels with rate fixed by 1 MB/s. The two-state ON-OFF model is also used to characterize the channel busy and idle activities. It is observed from Fig. 4 that, the semi-parallel cooperative sensing scheme achieves about 30 percent and 60 percent higher performance than the negotiation-based sensing policy and the sequential cooperative sensing, respectively.

Synchronous and Asynchronous Cooperative Sensing

Synchronous Cooperative Sensing

In the synchronous cooperative sensing, all the cooperative SUs sense channels at the same time. Synchronization among the cooperative SUs is usually achieved in an infrastructure-based architecture. For instance, the infrastructure access point (AP) manages the network and serves as a fusion center. Upon the request from the source SU for spectrum sensing, an AP will send out the scheduling instruction to the cooperative SUs. The aforementioned sequential and parallel cooperation mechanisms can be directly applied here. In other words, the cooperative SUs could synchronously scheduled to cooperatively sense the spectrum either mode (e.g., Fig. 2a) or a parallel manner Fig. 2c). It is noteworthy that, in the parallel manner, the sensing moments of different groups are also synchronized. When some cooperative SUs are transmitting packets, they have to temporally pause and help the source SU to search the available spectrums. This interruption of data transmissions has two disadvantages. Firstly, the cooperative SUs may lose their own spectrum opportunities since there is no guarantee that the channels are still available when the cooperative SUs return for re-transmissions after the cooperative sensing phase. Secondly, additional packet delay will be induced for the cooperative SUs, which degrades the Quality-of-Service (QoS) of the cooperative SUs' transmissions. To overcome these shortages, we propose an asynchronous cooperative sensing.

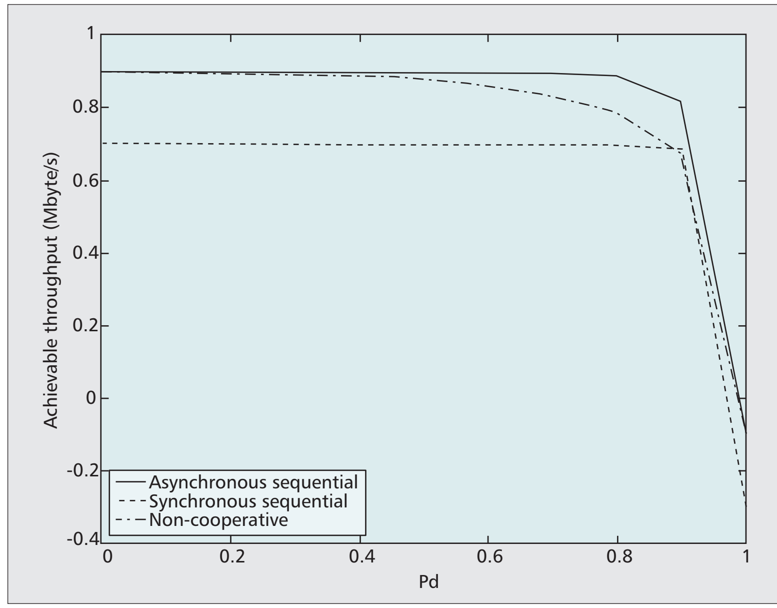

Figure 5. *Comparison among the asynchronous sequential, the synchronous sequential cooperative sensing and the non-cooperative sensing schemes. The achievable throughput is time-averaged. The negative achievable throughput is due to the difference between gain and overhead.*

Asynchronous Cooperative Sensing

Figure 2d presents the asynchronous semi-parallel cooperative sensing. All the cooperative SUs are allowed to have different sensing moments. Although the cooperative SUs of a same group cooperate to sense the identical channel, their sensing moments are different. The procedure of asynchronous cooperative sensing is triggered by the fusion center upon the request from the source SU. The fusion center then schedules the cooperative SUs to sense the spectrum. Upon receiving a command, a cooperative SU is allowed to firstly complete its own current transmission (if having one), and then participate the cooperative sensing in its spare time. In this new paradigm, the moments for the cooperative SUs to perform sensing are not necessary to be synchronized. As a consequence, each cooperative SU may have its own sensing period. If energy detector is employed, each SU will integrate the received signal energy and output the energy information (EI). The cooperative SU will attach the EI with a time tag indicating the sensing moment, and send back to the fusion center. The fusion center collects the EIs and the corresponding time tags from the cooperative SUs. Next, the EIs of the same channel are linearly combined into a single EI for decision making. Once an available channel is discovered, the fusion center stops the cooperation procedure and informs the source SU with the channel index.

Spatial and Temporal Diversities — The asynchronous cooperative sensing exploits both spatial and temporal diversities. The combination of EIs in the fusion center plays an important role in the

The asynchronous cooperative sensing exploits both spatial and temporal diversities. The combination of EIs in the fusion center plays an important role in the asynchronous cooperative sensing.

asynchronous cooperative sensing. The study [8] found that the probability of channel availability varies as time goes on. Based on this observation, we introduce the weight to show the importance of an EI. If a time tag has a smaller value, the associated EI has higher importance and hence larger weight. The collected EIs of an identical channel reflect the channel state in different sensing moments. Therefore, the unique feature of asynchronous cooperative sensing is to further exploit the temporal diversity of channel availability. The multi-user spatial diversity is indicated by the essential cooperation among multiple SUs.

Distributed Implementation — The synchronous cooperative sensing could only operate in a centralized manner while the asynchronous cooperative sensing could operate in a centralized or decentralized manner. The basic mechanism of decentralized asynchronous cooperative sensing operates as follows. An SU will invite some of its neighboring SUs to organize a local cooperation team. Each team member will serve as a volunteer to help the others upon the request from the source SU. A cooperative SU only help the others in its idle time and hence the overhead during the sensing cooperation is low.

Performance Comparison

The trade-off between sensing accuracy and efficiency in the asynchronous cooperative sensing is different from that in the synchronous cooperative sensing. Due to the non-synchronization of sensing moments, there are induced sensing delay in the asynchronous cooperative sensing since the fusion center has to collect EIs from all cooperative SUs. The delay is the new consideration that should be taken into account when dealing with trade-off between sensing accuracy and efficiency.

Figure 5 shows the comparison of achievable throughput among the asynchronous sequential, synchronous sequential cooperative sensing, and non-cooperative sensing in terms of the probability of detection P_d. In this case, the number of cooperative SUs in the asynchronous sequential and synchronous sequential cooperative sensing are both set to be 3. It is known from Fig. 5 that, the asynchronous scheme has the highest performance. In particular, when $P_d = 0.8$, the achievable throughput in the asynchronous sequential cooperative sensing is nearly 30 percent higher than that in the synchronous sequential cooperative sensing, and about 15 percent higher than that in the non-cooperative sensing.

Conclusion

In this article, we first identified the fundamental trade-off between sensing accuracy and efficiency in user cooperation for spectrum sensing in cognitive radio networks. Then, we presented two new cooperation mechanisms, including the parallel and the asynchronous cooperative sensing. The proposed cooperation mechanisms and the sensing accuracy-efficiency trade-off were elaborated, analyzed, and evaluated with respect to the difference between transmission gain and sensing overhead. Illustrative results indicated a significant improvement in our proposed cooperation strategies.

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