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Collaborative Spectrum Sensing Mechanism Based on User Incentive in Cognitive Radio Networks

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Abstract

Cognitive radio networks have been expected to improve the spectrum utilization by allowing unlicensed users, called secondary users (SUs), to use the idle spectrum of licensed users, called primary users (PUs). Since the interference in PU's communications should be minimized, collaborative spectrum sensing (CSS) by multiple SUs has been proposed to improve the detection performance of SUs to the signal of PU. After SUs conduct CSS, each SU individually aims to use the idle spectrum, which is a kind of competitive situations. In this thesis, we propose a CSS mechanism based on user incentive for multi-PU cognitive radio networks. In the proposed mechanism, communication opportunities are allocated to SUs according to their detection performance. We first formulate the group formation as an optimization problem where each SU aims to maximize its own communication opportunities under a constraint on the upper limit of miss detection probability, by selecting an appropriate PU and forming a group with appropriate SUs. We also propose a selfish group reformation scheme where each SU aims to improve its own communication opportunities by reforming the group. Through several simulation experiments, we show that the proposed mechanism can increase the ratio of winning SUs, which meet the constraint on miss detection probability and acquire the communication opportunities, compared to the existing scheme. We also demonstrate that introducing the user incentive contributes to not only allocating the communication opportunities to SUs according

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to their detection performance but also improving the ratio of winning SUs with low detection performance. Finally, we also show that the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

Keywords:

Cognitive radio, collaborative spectrum sensing, group formation, detection probability

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1. Introduction

The radio resources are essential for wireless communication systems but most frequency bands have already been allocated to various existing systems. It is an important issue to solve the spectrum exhaustion problem and to improve the spectrum utilization, due to the rapid increase in demand on wireless communication. To tackle this problem, cognitive radio has been studied, in which unlicensed users, i.e., secondary users (SUs), utilize the spectrum of a licensed user, i.e., primary user (PU), while avoiding interference in PU's communications [1]. Each SU tries to detect the use status of the PU's spectrum by spectrum sensing, and attempts to utilize the spectrum only when he/she judges that the spectrum is idle. Therefore, the accuracy of the SU's spectrum sensing is important to avoid interference in PU's communication and to improve the spectrum utilization.

There are several factors which affect SU's spectrum sensing results, e.g., propagation loss of the PU signal, fading and noise. Spectrum sensing errors are classified into two types: miss detection and false alarm. The miss detection is a sensing error that an SU recognizes the spectrum of the PU is idle even though it is actually used by the PU. Therefore, it is important for the PU to suppress the probability of miss detection. The false alarm is a sensing error that an SU judges the spectrum of the PU is busy even though it is actually unused by the PU. Thus, it is important for the SU to suppress the probability of false alarm, in order to acquire communication opportunities.

Collaborative spectrum sensing (CSS) has been proposed to improve the accuracy of spectrum sensing [2]. In CSS, multiple SUs share the sensing results and derive a collaborative sensing result from them. It has been pointed out that the collaborative sensing result based on OR-rule can reduce the probability of miss detection. CSS requires group formation for collaboration among SUs. Saad et al. have proposed a distributed group formation scheme using a game theoretic approach for single-PU cognitive radio networks, called *coalition formation with detection probability (CF-PD) algorithm* [3]. In [3], each SU forms a group based on the utility function that exhibits the trade-off between decrease of the group miss detection probability and increase of the group false alarm probability. Since this scheme focuses on the spectrum sensing itself, it assumes that all SUs in a group has the same utility as the group utility, which indicates that they behave cooperatively each other. After CSS, each SU individually aims to use the idle spectrum, which is a kind of competitive situations.

In this thesis, we propose a CSS mechanism that takes account of user incentive for joining cognitive radio networks. We also assume that there are one or more PUs in the target area where the spectrum utilization of PUs may differ. In the proposed mechanism, communication opportunities are allocated to each SU according to its detection performance. The objective of SUs is to increase its own communication opportunities but there also exists a constraint that the SUs should not interfere with the PUs' communication. We assume that the each PU imposes an upper limit of the probability of miss detection on SUs. Each SU aims to meet the constraint on probability of miss detection by performing single spectrum sensing or CSS with other SUs. Each SU select a PU and forms a group such that the group can maximize their own communication opportunities while meeting the constraint. We evaluate the effectiveness of the proposed scheme through several simulation experiments.

The rest of the thesis is organized as follows: Chapter 2 presents related work. In Chapter 3, we propose a CSS mechanism based on user incentive and we show simulation results in Chapter 4. Finally, conclusions and future work are given in Chapter 5.

2. Related Work

2.1 Collaborative Spectrum Sensing

CSS in cognitive radio networks is an effective method to reduce the probability of miss detection of PU's signal by exploiting spatial diversity [4]. There are several fusion rules, e.g., AND, OR, K-out-of-N and majority rules, to derive a cooperative decision from individual decisions of SUs in CSS [4]. In [2], Ghasemi and Sousa have shown that an OR-based fusion method can suppress the probability of group miss detection with the sacrifice of the probability of group false alarm when the number of SUs increases. Liang et al. have studied the trade-off between sensing time and throughput. A long sensing time can reduce the false alarm probability but also results in shortening the data transmission time. They have formulated the optimization problem for optimal sensing time that takes account of the trade-off. They have analyzed how various types of decision functions affect the optimal sensing time and throughput with increase in the number SUs. Zhang and Letaief have proposed CSS based on transmission diversity to suppress the channel errors, which are caused by fading, during information sharing about sensing results [5]. In [6], Gupta et al. have proposed a two-level decision fusion scheme with collaboration among multiple fusion centers (FCs). In the first-level decision fusion, an FC collects the local decisions from SUs whose decision accuracy is greater than a predefined threshold, and then combines them using the OR-based fusion rule. In the second level decision fusion, all the FCs communicate with each other and combine the decisions using OR rule in order to take a global decision. Finally, they propagate the global decision to all SUs through respective FCs.

2.2 Group Formation

Since CSS requires the collection of individual sensing results from SUs and the distribution of the cooperative decision to SUs, the communication overhead will increase with the number of SUs. To tackle this problem, group formation of SUs for CSS is effective [3, 7–10]. Such group formation schemes are classified into a centralized approach and a decentralized approach. In the centralized approach, a server that manages SUs derives an optimal group formation by calculating all possible group patterns among all SUs. In [7], a server calculates all possible group patterns among all SUs and forms the group with the highest utility. In the succeeding process, the server continues the same approach until the group formation is completed. In [3], it has been reported that the exhaustive search of optimal group formation becomes intractable when the number of SUs is over eight.

In the distributed approach, each SU tries to form a group with neighboring SUs based on its own incentive for CSS. Saad et al. have proposed a distributed scheme to form groups among SUs based on the utility function that exhibits the trade-off between decrease of the group miss detection probability and increase of the group false alarm probability [3]. They have modeled the problem of group formation among SUs as a coalition formation (CF) game with a nontransferable utility (NTU) in game theory. A CF game is a type of cooperative games in which each player participating in the game forms a coalition with other players based on the utility of the coalition [11]. The utility of a coalition cannot be apportioned between the coalition's players in CF-game with NTU [11,12]. In [13], Balaji and Hota have proposed a CSS scheme in which the cost function has been redesigned from [3] to consider the battery power and mobility of SUs. Gupta et al. have also proposed a distributed CSS scheme where each group merges with other groups based on the utility function that takes account of throughput and energy/time consumption [6]. In [8], Wang et al. have proposed a group formation scheme that considers the limited transmission power and bandwidth of SUs. The group formation among SUs is formulated as an overlapping CF (OCF) game in which it allows each SU to belong to multiple coalitions. Although these distributed group formation schemes are designed for single-PU cognitive radio networks, there may be more than one PU in actual systems.

Some group formation schemes in cognitive radio networks with multiple PUs have been studied [7,9,10]. Jing et al. have proposed a group formation scheme for cooperative spectrum prediction in multi-PU cognitive radio networks [7]. Each SU predicts the spectrum status of each PU, and selects a PU with the highest spectrum prediction accuracy. For each PU, a group is formed by some SUs in a centralized manner. In [9], a group formation scheme based on sensing accuracy and energy efficiency in multi-PU cognitive radio networks has been proposed. The groups are formed by using the utility function that takes into account both sensing accuracy and energy required to communication and sensing. Wang et al. have studied a distributed cooperative multi-channel spectrum sensing scheme for multi-PU cognitive radio networks [10]. Each SU selects the channel with the highest Signal-to-Noise Ratio (SNR) of PU signals and forms a group with other SUs selecting the same channel.

In this thesis, we also consider CSS in cognitive radio networks but the main difference from these existing works is taking account of each SU's individual motivation to join CSS. In the existing works, SUs in the same group are cooperative with each other and have the same utility function to succeed CSS itself. After CSS, they, however, will be placed in a competitive situation where each of them aims to acquire its own communication opportunities. In this thesis, we focus on this users' selfishness and propose a CSS mechanism that takes account of the user incentive.

3. Proposed Scheme

In cognitive radio networks with multiple PUs, SU's miss detection probability and PU's utilization of its own spectrum may be different among PUs. Moreover, after SUs conduct CSS, they individually aim to use the idle spectrum, which is a kind of competitive situations. Therefore, it is required for each SU to appropriately select a PU and form a group with other SUs such that it can maximize its own communication opportunities without interfering with the corresponding PU's communication. In this thesis, we propose a user incentive based CSS mechanism for multi-PU cognitive radio networks, in which communication opportunities are allocated to SUs according to their detection performance. In addition, we also propose a group reformation scheme where SUs try to select better groups based on their own utility.

In what follows, we first present the system model. Next, we propose a CSS mechanism based on user incentive for joining cognitive radio networks. Finally, a selfish group reformation is proposed.

3.1 System Model

We consider a cognitive radio network consisting of L PUs, labeled from 1 to L, and N SUs, labeled from 1 to N. Let $\mathcal{L} = \{1, \ldots, L\}$ and $\mathcal{N} = \{1, \ldots, N\}$ denote the set of all PUs and that of all SUs, respectively. Each SU recognizes the busy state of PU's spectrum when it detects the PU's signal. Each PU imposes the upper limit of miss detection probability, χ $(0 \leq \chi \leq 1)$, on SUs [14]. SUs that satisfy this requirement can obtain the communication opportunities. As in [15], we assume a Rayleigh fading environment where SU i's miss detection probability to PU l, $P_{i,l}^{\text{miss}}$, and SU i's false alarm probability, P_i^{false}, are given by

$$\begin{aligned} P_{i,l}^{\text{miss}} &= 1 - e^{-\frac{\lambda}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n - \left(\frac{1+\bar{\gamma}_{i,l}}{\bar{\gamma}_{i,l}}\right)^{m-1} \cdot \\ &\quad \left[e^{-\frac{\lambda}{2(1+\bar{\gamma}_{i,l})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\lambda \bar{\gamma}_{i,l}}{2(1+\bar{\gamma}_{i,l})}\right)^n \right], \qquad (1) \end{aligned}$$

$$P_i^{\text{false}} = P^{\text{false}} = \frac{\Gamma(m, \frac{\lambda}{2})}{\Gamma(m)},$$

where m is the time-bandwidth product and λ is the energy detection threshold. Moreover, $\overline{\gamma}_{i,l}$ represents the average SNR of received signal from PU l to SU i, which is given by $\overline{\gamma}_{i,l} = P_l h_{l,i}/\sigma^2$, where P_l is the transmit power of PU l, σ^2 is the Gaussian noise variance, and $h_{l,i}$ is the path loss between SU i and PU l. $h_{i,l}$ is given by $h_{l,i} = \kappa/d_{l,i}^{\mu}$, where κ is the path loss constant, μ is the path loss exponent, and $d_{l,i}$ is the distance between PU l and SU i. $\Gamma()$ is the gamma function and $\Gamma(,)$ is the incomplete gamma function. As a result, $P_{i,l}^{\text{miss}}$ becomes small when the distance between PU l and SU i, called PU-SU distance, is short. On the contrary, P_i^{false} is independent of PU-SU distance.

When SU i's miss detection probability to PU l, $P_{i,l}^{\text{miss}}$, exceeds upper limit χ, SU i should form a group with other SUs and perform CSS to reduce the group miss detection probability. To form a group, each SU i first requires to discover the candidates of SUs for the group formation. As in [8], we assume that the set of SU i's candidate SUs, $\mathcal{N}_i$, consists of SUs within SU i's transmission range $\tilde{d}$,

$$\tilde{d} = \sqrt[\mu]{\kappa P_{\text{SU}}/\gamma_0\sigma^2},$$

where P_{SU} is the SU's transmit power to report its sensing result and γ_0 is the minimum average SNR set to be 0 [dB] as in [8]. As in [3, 4, 8], we assume that this communication is conducted through a control channel. The details of group formation will be described in Section 3.2.

Suppose that each group $\mathcal{S} \in 2^{\mathcal{N}}$ elects an SU called *head* from all SUs of the group. The head collects individual sensing results from other SUs in the group, which are called *members*, and makes a group decision by combining the obtained results. We apply the OR-based fusion rule to the group decision, which is effective to reduce the group miss detection probability.

As in [3], group $\mathcal{S}$'s miss detection probability to PU l, $Q_{\mathcal{S},l}^{\text{miss}}$, and group $\mathcal{S}$'s false alarm probability to PU l, $Q_{\mathcal{S}}^{\text{false}}$, are given by

$$Q_{\mathcal{S},l}^{\text{miss}} = \prod_{i\in\mathcal{S}}[P_{i,l}^{\text{miss}}(1 - P_{e,i,k}) + (1 - P_{i,l}^{\text{miss}})P_{e,i,k}], \tag{2}$$

$$Q_{\mathcal{S}}^{\text{false}} = 1 - \prod_{i\in\mathcal{S}}[(1 - P^{\text{false}})(1 - P_{e,i,k}) + P^{\text{false}}P_{e,i,k}], \tag{3}$$

where $P_{e,i,k}$ is the error probability on the reporting channel between member i and head k, which is given as the error probability of BPSK (Binary Phase Shift

Keying) modulation in Rayleigh fading environments [16].

$$P_{e,i,k} = \frac{1}{2}\left(1 - \sqrt{\frac{\overline{\gamma}_{i,k}}{1+\overline{\gamma}_{i,k}}}\right),$$

where $\overline{\gamma}_{i,k}$ represents the average SNR between member i and head k. As in [3], we select the most reliable SU, which has the minimum miss detection probability to the corresponding PU, as the head, in order to avoid the risk that the sensing result of that SU is wrongly reported during the information sharing.

In terms of $P_{e,i,k}$, grouping near SUs can decrease both $Q^{\text{miss}}_{\mathcal{S},l}$ and $Q^{\text{false}}_{\mathcal{S}}$. However, there is a trade-off between $Q^{\text{miss}}_{\mathcal{S},l}$ and $Q^{\text{false}}_{\mathcal{S}}$: Increasing group size $|\mathcal{S}|$ improves $Q^{\text{miss}}_{\mathcal{S},l}$ but degrades $Q^{\text{false}}_{\mathcal{S}}$.

3.2 Collaborative Spectrum Sensing Mechanism Based on User Incentive

Recall that each SU can use the PU's spectrum only when it satisfies the PU's requirement for miss detection probability. As in [3], we call SUs (resp. groups) that satisfy the PU's requirement with CSS *winning* and the remaining SUs (resp. groups) *losing*. In particular, we call a winning SU that does not require to form a group with other SUs *single SU*.

Since each group individually conducts the CSS, we assume that communication opportunities are equally allocated to the winning groups. On the other hand, in each group, communication opportunities are allocated to each SU corresponding to its own detection performance by taking account of the user incentive. SU i must first meet the constraint on the miss detection probability. Next, SU i meeting the constraint selects a PU and forms a group such that it can maximize its own communication opportunities. These can be represented by the following objective function and constraint:

$$\max_{\mathcal{S}_i \in \mathbf{S}_i,\ l \in \mathcal{L}_{\mathcal{S}_i,\chi}} \left(1 - R^{\text{use,PU}}_l\right)\left(1 - Q^{\text{false}}_{\mathcal{S}_i}\right)\frac{1}{N^{\text{group}}_l}\frac{P^{\text{detect}}_{i,l}}{\sum_{j\in\mathcal{S}_i} P^{\text{detect}}_{j,l}}, \tag{4}$$
$$\text{s.t.}\ \ \mathcal{L}_{\mathcal{S}_i,\chi} = \{l \in \mathcal{L} \mid Q^{\text{miss}}_{\mathcal{S}_i,l} \le \chi\},$$

where $\mathbf{S}_i$ is the set of all possible $|\mathcal{N}_i|$ groups for SU i and $\mathcal{L}_{\mathcal{S}_i,\chi}$ is the set of PUs to which SU i's group $\mathcal{S}_i \in \mathbf{S}_i$ can meet the constraint on the miss detection probability. Moreover, $R_l^{\text{use,PU}}$ is the probability that PU l uses its own spectrum, N_l^{group} is the number of winning groups selecting PU l and $P_{j,l}^{\text{detect}}$ is SU j's detection probability to PU l, i.e., $P_{j,l}^{\text{detect}} = 1 - P_{j,l}^{\text{miss}}$. We assume that each SU can obtain or estimate $R_l^{\text{use,PU}}$ and N_l^{group} with the help of existing approaches. For example, an reinforcement learning approach is proposed, which can estimate the PU's spectrum utilization from historical sensing results [17]. On the other hand, the number of winning groups can be directly shared among SUs through the control channel in a multi-hop manner.

$P_{l,i}^{\text{detect}} / \sum_{j \in \mathcal{S}_i} P_{l,j}^{\text{detect}}$ is SU i's contribution to the detection performance of group $\mathcal{S}_i$ selecting PU l. $(1/N_l^{\text{group}}) \cdot (P_{l,i}^{\text{detect}} / \sum_{j \in \mathcal{S}_i} P_{l,j}^{\text{detect}})$ represents the allocated transmission rate of SU i in a winning group selecting PU l. Each SU can maximize its own communication opportunities if it can become a single SU. If the SU cannot meet the constraint on the miss detection probability by itself, it attempts to form a group with other SUs for CSS to meet the constraint. When each SU forms a group with other SUs, the SU with high detection performance can acquire more communication opportunities by forming a group with an SU with low detection performance. On the other hand, there is also user incentive for the SU with low detection performance because it can become a winning SU by forming a group. Recall that the miss detection probability increases with the distance between PU and SU, as shown in (1). As a result, the proposed scheme encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa.

Algorithm 1 shows SU i's control procedure for PU selection and group formation. First, each SU $i \in \mathcal{N}$ forms a group by itself and discovers SUs in its transmission range $\tilde{d}$ as the set of neighboring SUs, $\mathcal{N}_i$ (line 2). Next, each SU i checks whether it meets the constraint on miss detection probability under single spectrum sensing (lines 3–7). If SU i can become winning, it selects a PU to maximize the expected value of its own communication opportunities according to (4) (line 5). Otherwise, it becomes losing and selects a PU with the minimum miss detection probability (line 7).

Each SU $i \in \mathcal{N}$ attempts to update its group $\mathcal{S}_i$ for maximizing its own communication opportunities (lines 10–23). Note that the acting order among SUs in lines 10–23 will be random because each SU acts in a distributed manner.

Algorithm 1 PU selection and group formation.

1: $\forall i \in \mathcal{N}$, $\mathcal{S}_i = \{i\}$ ▷ Initialization

2: $\forall i \in \mathcal{N}$ discovers their neighboring SUs $\mathcal{N}_i$ ▷ Discovery

3: **for all** $i \in \mathcal{N}$ **do** ▷ Trying non-cooperative sensing

4:     **if** $\mathcal{L}_{\mathcal{S}_i,\chi} \neq \emptyset$ **then** ▷ Winning case

5:         i selects PU according to (4)

6:     **else** ▷ Losing case

7:         i selects PU according to $\arg\min_{l \in \mathcal{L}} P_{i,l}^{\text{miss}}$

8: **repeat** ▷ Group update

9:     $\mathcal{T}^{\text{winning}} = \{\mathcal{S}_i \mid i \in \mathcal{N}, \mathcal{L}_{\mathcal{S}_i,\chi} \neq \emptyset\}$

10:     **for all** $i \in \mathcal{N}$ **do** ▷ Trying group update

11:         **if** $\mathcal{L}_{\mathcal{S}_i,\chi} == \emptyset$ **then** ▷ Trying cooperative sensing

12:             $\mathcal{W}_i = \emptyset$ ▷ Calculating candidates of cooperation

13:             **for all** $j \in \{m \in \mathcal{N}_i \mid \mathcal{L}_{\mathcal{S}_m,\chi} == \emptyset\}$ **do**

14:                 **if** $\mathcal{L}_{\mathcal{S}_i \cup \mathcal{S}_j,\chi} \neq \emptyset$ **then**

15:                     i adds $\{\mathcal{S}_i \cup \mathcal{S}_j\}$ to $\mathcal{W}_i$

16:             **if** $\mathcal{W}_i \neq \emptyset$ **then** ▷ Winning case

17:                 i replaces $\mathcal{S}_i$ with $\mathcal{S} \in \mathcal{W}_i$ such that (4) is maximized

18:                 $\mathcal{S}_i$ selects PU according to (4)

19:                 $\forall j \in \mathcal{S}_i$ conducts selfish group reformation (Algorithm 2)

20:             **else** ▷ Losing case

21:                 i replaces $\mathcal{S}_i$ with $\mathcal{S}_i \cup \mathcal{S}_j$ such that $j \in \mathcal{N}_i, \mathcal{L}_{\mathcal{S}_j} == \emptyset$, and (2) is minimized

22:         **else** ▷ Trying group reformation

23:             $\forall j \in \mathcal{S}_i$ conducts selfish group reformation (Algorithm 2)

24: **until** $\{\mathcal{S}_i \mid i \in \mathcal{N}, \mathcal{L}_{\mathcal{S}_i,\chi} \neq \emptyset\} == \mathcal{T}^{\text{winning}}$

Each losing SU i attempts to perform CSS with other losing SUs (lines 11–21). First, each SU i searches for possible group candidates $\mathcal{W}_i$ for cooperation (lines 12–15). Note that the group candidates must also be losing because winning groups need not to further cooperate with other SUs. If SU i finds appropriate groups with which it can become winning, it selects a PU and forms a group to maximize the expected value of its own communication opportunities according to (4) (line 19). Otherwise, it still stays losing and forms a group with a losing group to minimize the group miss detection probability (line 21). In line 23, each winning SU i conducts selfish group reformation according to Algorithm 2, which will be described in Section 3.3.

Note that this group updating is repeated until the set of winning groups, $\mathcal{T}^{\text{winning}}$, does not change (line 24). Therefore, there exist two cases after Algorithm 1 has converged. In the first case, all SUs become winning and do not have further incentive to form a new group. In the second case, a part of SUs can become winning and the remaining SUs are forced to remain losing, due to lack of appropriate partner(s). The resulting case depends on not only the locations of PUs and SUs but also the processing order of Algorithm 1 among SUs.

3.3 Selfish Group Reformation

SU's primary purpose is to become winning to acquire the communication opportunities. The winning SU further tries to maximize its own communication opportunities and may have a chance to improve its communication opportunities by reforming the group. This is mainly caused by the randomness of acting order among SUs (lines 10–23 in Algorithm 1).

Algorithm 2 shows the selfish group reformation. Given winning group $\mathcal{S}$, each SU i in $\mathcal{S}$ individually calculates $\mathcal{S}_i^{\text{A}}$ that maximizes its own communication opportunities (lines 1–2). The group reformation requires the consensus among all SUs that will form the group. From lines 4–12, each SU i confirms the consensus of group reformation. If SU i can build the consensus with all the other SUs in $\mathcal{S}_i^{\text{A}}$, they leave $\mathcal{S}$ and make new group $\mathcal{S}_i^{\text{A}}$ (line 7). The remaining SUs in $\mathcal{S}$ temporarily form independent groups and confirm the possibility of group reformation in the succeeding iterations (line 8). If SU i fails to build the consensus, the group reformation does not occur (line 11).

Algorithm 2 Selfish group reformation.

Require: winning group $\mathcal{S}$

for all $i \in \mathcal{S}$ **do** ▷ Search for the best group for i

  i calculates new candidate group $\mathcal{S}_i^{\mathrm{A}}$ such that (4) is maximized

$\mathcal{Y} = \mathcal{S}$

repeat ▷ Confirm consensus of group reformation

  $i \in \mathcal{Y}$

  if $\forall j \in \mathcal{S}_i^{\mathrm{A}}, \mathcal{S}_i^{\mathrm{A}} == \mathcal{S}_j^{\mathrm{A}}$ **then** ▷ Consensus is built

    $\forall k \in \mathcal{S}_i^{\mathrm{A}}$ replaces $\mathcal{S}_k$ with $\mathcal{S}_i^{\mathrm{A}}$

    $\forall m \in \mathcal{S} \setminus \mathcal{S}_i^{\mathrm{A}}$ replaces $\mathcal{S}_m$ with $\{m\}$

    $\mathcal{Y} = \mathcal{Y} \setminus \mathcal{S}_i^{\mathrm{A}}$

  else ▷ Consensus fails

    $\mathcal{Y} = \mathcal{Y} \setminus \{i\}$

until $\mathcal{Y} == \emptyset$

4. Simulation Results

We evaluate the effectiveness of the proposed mechanism through several simulation experiments.

4.1 Simulation Settings

We use Netlogo [18] as the simulator. We show the simulation parameters and their default values in Table 1. The values of $N, P_{\mathrm{SU}}, P_l, \sigma^2, \kappa, \mu, m, \lambda$ and P^{false} are determined according to [3], and the value of $\tilde{d}$ is determined according to [8]. Fig. 1 (resp. Fig. 2) illustrates an example of locations in 1-PU (resp. 2-PU) scenario where 1 PU (resp. 2-PUs) and 18 SUs (resp. 20 SUs) exist. In both scenarios, N SUs are uniformly distributed in the area. As for the PU location, one PU is located at the center of simulation area in the 1-PU scenario. On the other hand, in the 2-PU scenario, two PUs are located at $(0.75, 0.75)$ and $(-0.75, -0.75)$ such that the simulation area can be equally divided by the diagonal line.

We use three evaluation criteria. The first one is the ratio of winning SUs, which is the ratio of the number of winning SUs to that of all SUs. The second one

Table 1: Simulation parameters.

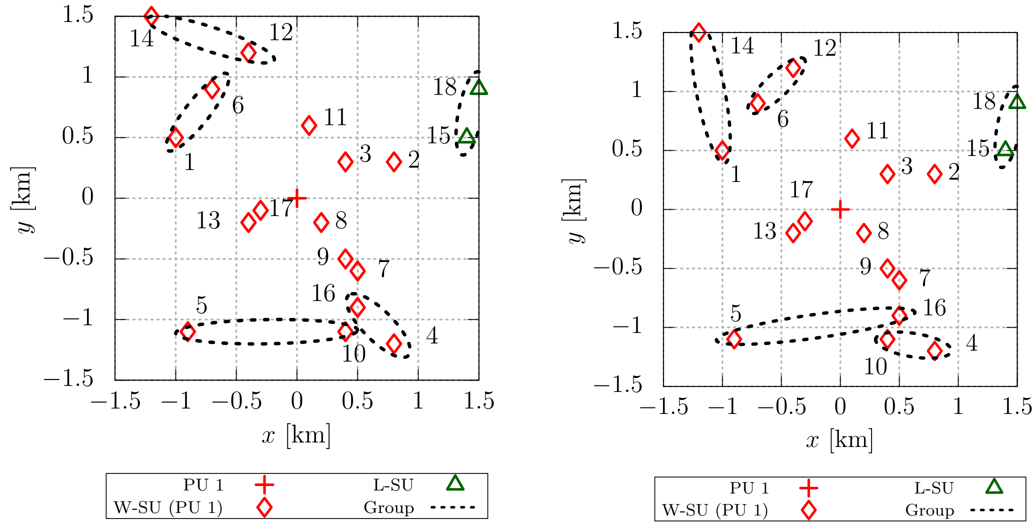
Parameter	Value
Simulation region	3 [km] $\times$ 3 [km] square area
The number of SUs, N	$2, 3, 4, 5, 6, 7, 10, 15, 20, 30, 40, 50$
Transmit power of SU, P_{SU}	10 [mW]
Transmit power of PU l, P_l	100 [mW]
Gaussian noise variance σ^2	-90 [dBm]
Path loss constant κ	1
Path loss exponent μ	3
Time-bandwidth product m	5
Energy detection threshold λ	21.51 [mW]
False alarm probability P^{false}	0.018 (1.8%)
Upper limit of miss detection probability, χ	0.05
Transmission range of SU, $\tilde{d}$	2,154 [m]

is the average false alarm probability. The third one is the relationship between PU-SU distance and winning frequency. The winning frequency describes how often SUs with certain PU-SU distance can become winning through independent simulation runs. In what follows, we show the average of 5000 independent simulation runs.

4.2 Performance of Proposed Mechanism in 1-PU Cognitive Radio Network

We first evaluate the effectiveness of the proposed mechanism in 1-PU cognitive radio networks by comparing the results with CF-PD [3], which is the CSS scheme designed for 1-PU cognitive radio networks. Recall that CF-PD mainly focuses on CSS itself and thus SUs in a group have the same objective. CF-PD forms groups by taking account of the trade-off between group detection probability and group false alarm probability through the following group-based utility function:

$$v(\mathcal{S}) = (1 - Q_{\mathcal{S}}^{\mathrm{miss}}) - C(Q_{\mathcal{S}}^{\mathrm{false}}, \alpha), \tag{5}$$



(a) CF-PD (b) Proposed mechanism

Figure 1: An example of PU selection and group formation in 1-PU cognitive radio networks when $N = 18$ (W-SU (PU l) means winning SU selecting PU l and L-SU means losing SU).

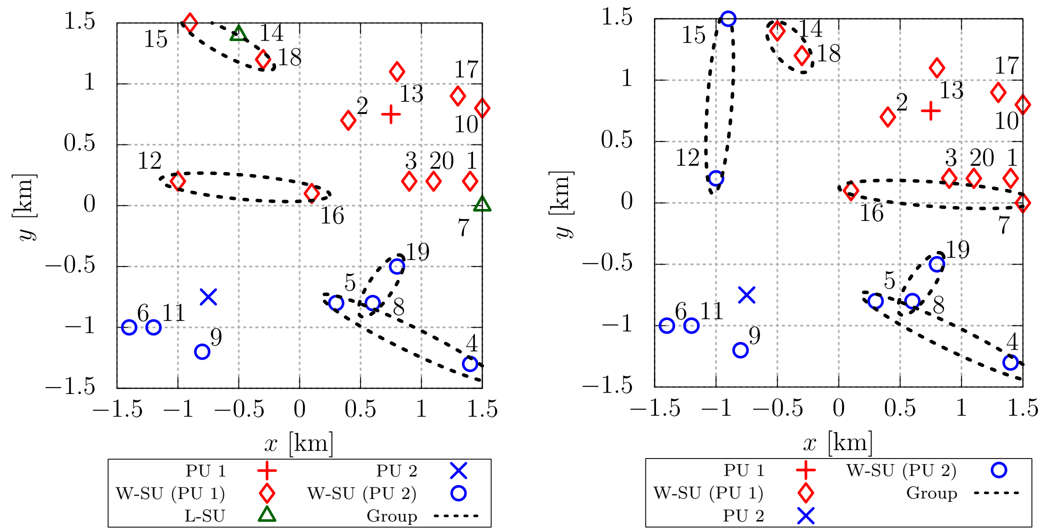
where $Q_{\mathcal{S}}^{\text{miss}}$ is group $\mathcal{S}$'s miss detection probability and $Q_{\mathcal{S}}^{\text{false}}$ is $\mathcal{S}$'s false alarm probability. These are the same as (2) and (3), respectively. Moreover, α is a constraint on the false alarm probability and $C(,)$ represents the cost function for false alarm probability given by

$$C(Q_{\mathcal{S}}^{\text{false}}, \alpha) = \begin{cases} -\alpha^2 \cdot \log(1 - (\frac{Q_{\mathcal{S}}^{\text{false}}}{\alpha})^2), & \text{if } Q_{\mathcal{S}}^{\text{false}} < \alpha, \\ +\infty, & \text{otherwise.} \end{cases}$$

The winning SUs, which meet both constraints on miss detection probability and false alarm probability, are defined by the following adjunct utility function,

$$u(\mathcal{S}) = \begin{cases} 1, & \text{if } Q_{\mathcal{S}}^{\text{detect}} \geq (1 - \chi) \text{ and } Q_{\mathcal{S}}^{\text{false}} < \alpha, \\ 0, & \text{otherwise,} \end{cases}$$

where $Q_{\mathcal{S}}^{\text{detect}}$ represents group $\mathcal{S}$'s detection probability, i.e., $1 - Q_{\mathcal{S}}^{\text{miss}}$, and χ represents the upper limit of miss detection probability. If $u(\mathcal{S}) = 1$, group $\mathcal{S}$ is winning. In addition, each winning group performs an adjust operation such that the corresponding group can keep winning with the minimum number of SUs.



(a) Proposed mechanism without user incentive

(b) Proposed mechanism

Figure 2: An example of PU selection and group formation in 2-PU cognitive radio networks when $N = 20$ (W-SU (PU l) means winning SU selecting PU l and L-SU means losing SU).

In this evaluation, we set the probability that PU 1 uses its own spectrum, $R_1^{\text{use,PU}}$, to be 0.3. To compare the proposed mechanism with CF-PD, we set α of CF-PD to be 0.3, which is the maximum false alarm probability that was observed in the case of the proposed mechanism.

4.2.1 Ratio of Winning SUs

Fig. 3 illustrates the relationship between the number of SUs, N, and ratio of winning SUs for the proposed mechanism and CF-PD. We observe that the proposed mechanism can improve the ratio of winning SUs for $N \geq 6$, compared with CF-PD. For example, the improvement ratio becomes about 4% in the case of $N = 50$. To analyze this difference deeply, we further investigate the relationship between upper limit χ of miss detection probability and average miss detection probability among winning groups in the case of $N = 50$. The average group miss detection probability of the proposed mechanism is 0.0284, which is closer

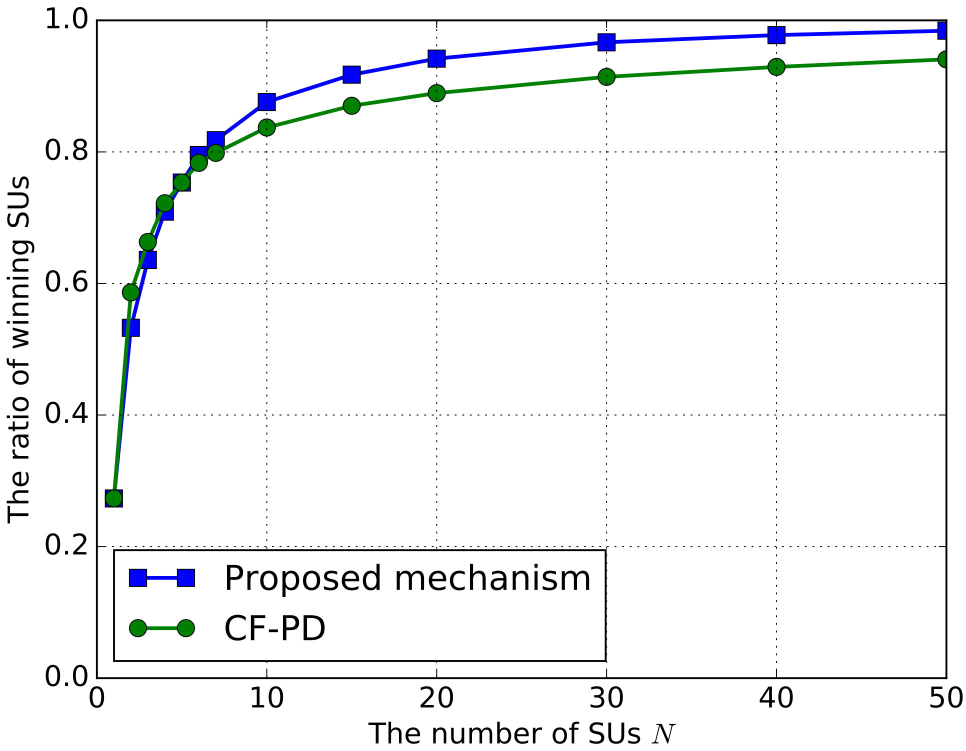


Figure 3: Relationship between the number of SUs, N, and ratio of winning SUs (1-PU scenario).

to the value of χ, i.e., 0.05, compared with that of CF-PD, i.e., 0.0228. In the proposed mechanism, each SU tries to form a group such that the group miss detection probability of group does not exceed χ. CF-PD also guarantees this condition but prefers smaller group miss detection probability according to (5). As a result, in CF-PD, each group tries to include SUs that are close to a PU as shown in Fig. 1a, e.g., SU 1. On the contrary, the proposed mechanism can alleviate this problem by introducing the user incentive, which encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa, as shown in Fig. 1b, e.g., SU 1.

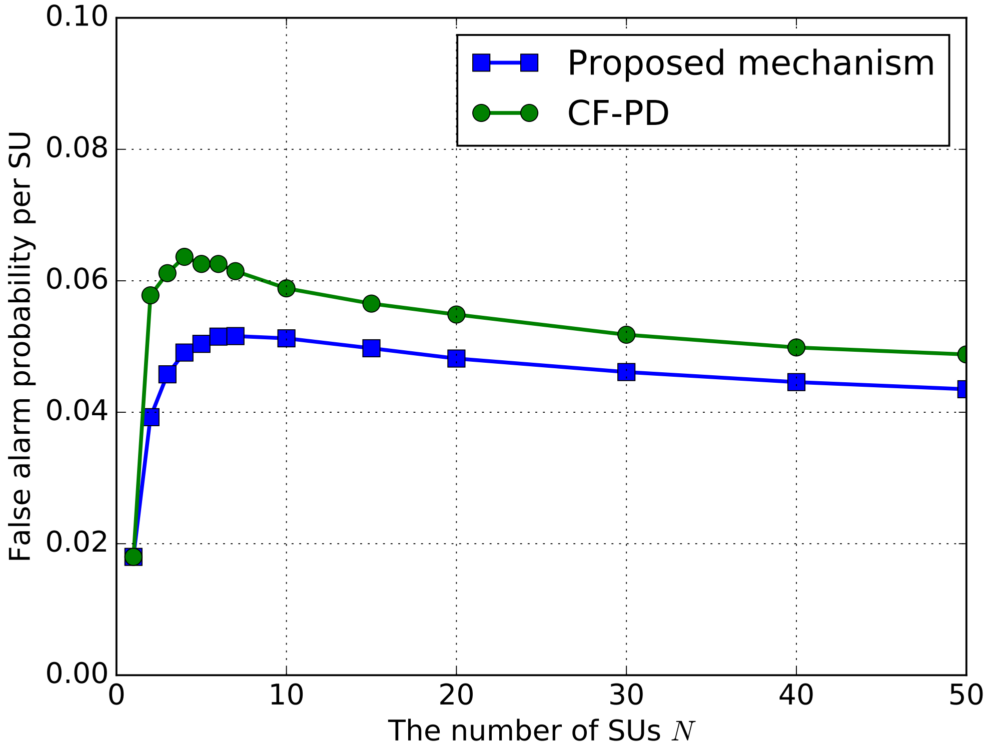


Figure 4: Relationship between the number of SUs, N, and average false alarm probability (1-PU scenario).

4.2.2 Average False Alarm Probability

As mentioned in Section 3.1, there is a trade-off between the group miss detection probability and the group false alarm probability. Next, we focus on the false alarm probability. Fig. 4 illustrates the relationship between the number of SUs, N, and average false alarm probability. As we expected, the average false alarm probability of the proposed mechanism becomes lower than that of CF-PD. (Recall that the group miss detection probability of the proposed mechanism becomes slightly higher than that of CF-PD, under the constraint of χ, as mentioned in Section 4.2.1). In CF-PD, SUs close to a PU want to cooperate together to achieve smaller group miss detection probability. As a result, SUs distant from a PU will be forced to make groups among them, which tends to

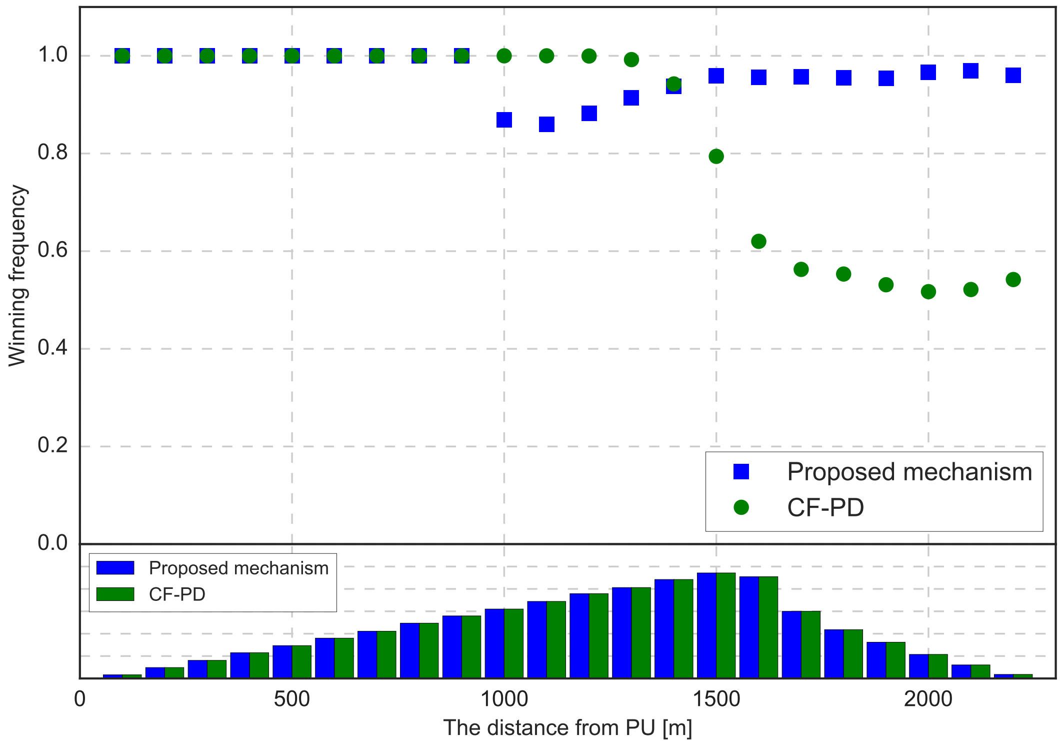


Figure 5: Relationship between PU-SU distance and winning frequency (1-PU scenario, $N = 50$).

increase the group size, due to high miss detection probability of each SU. This results in the increase of average false alarm probability. On the other hand, the proposed mechanism considers the false alarm probability as a part of SU's communication opportunities given by (4). As a result, the proposed mechanism can suppress the increase of average false alarm probability, compared to CF-PD.

4.2.3 Relationship between PU-SU Distance and Winning Frequency

Finally, Fig. 5 illustrates the relationship between PU-SU distance and winning frequency in the case of $N = 50$. Note that we set the granularity of distance to be 100 [m]: PU-SU distance d_i of SU i is replaced with $d_i' = \lceil d_i/100 \rceil \cdot 100$, e.g., $d_i' = 100$ for $d_i = 50$. We also show the histogram of the number of SUs located at the corresponding distance. We first observe that the winning frequency of both schemes becomes 100% when PU-SU distance is equal or less than 900 [m]. We also find that the proposed mechanism can significantly improve the winning frequency for SUs with larger PU-SU distance, i.e., 1500–2300 [m], compared with CF-PD, with the small sacrifice of winning frequency for SUs with moderate PU-SU distance, i.e., 1000–1400 [m]. As a result, the proposed mechanism can improve the ratio of winning SUs compared to CF-PD as in Fig. 3.

4.3 Impact of Cooperation Based on User Incentive in 2-PUs Cognitive Radio Network

We evaluate the effectiveness of the proposed mechanism in 2-PU cognitive radio networks. For comparison purpose, we use the proposed mechanism without user incentive, which equally allocates communication opportunities to winning SUs, regardless of their detection performance. This can be achieved by replacing (4) with the following objective function:

$$\max_{\mathcal{S}_i \in \mathbf{S}_i,\ l \in \mathcal{L}_{\mathcal{S}_i,\chi}} (1 - R_l^{\text{use,PU}})\ (1 - Q_{\mathcal{S}_i}^{\text{false}})\ \frac{1}{N_l^{\text{winning}}}, \tag{6}$$

where N_l^{winning} is the number of winning SUs selecting PU l.

In this section, we evaluate through the above mentioned three criteria. In the following evaluation, we set $R_1^{\text{use,PU}}$ and $R_2^{\text{use,PU}}$ to be 0.3 and 0.5, respectively.

4.3.1 Ratio of Winning SUs

As mentioned in Section 3.2, the proposed mechanism introduces user incentive, which encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa, as shown in Fig. 2b, e.g., SU 12. On the other hand, in the proposed mechanism without user incentive, each SU tends to form the group among nearby SUs as shown in Fig. 2a, e.g., SU 12, because reducing the group false alarm probability has a large impact on maximizing (6).

Fig. 6 illustrates the relationship between the number of SUs, N, and ratio of winning SUs for the proposed mechanism and that without user incentive. We observe that the proposed mechanism can slightly improve the ratio of winning SUs, compared to that without user incentive, e.g., 1.6% improvement at $N = 50$. As in Section 4.2.1, we investigate the relationship between upper limit

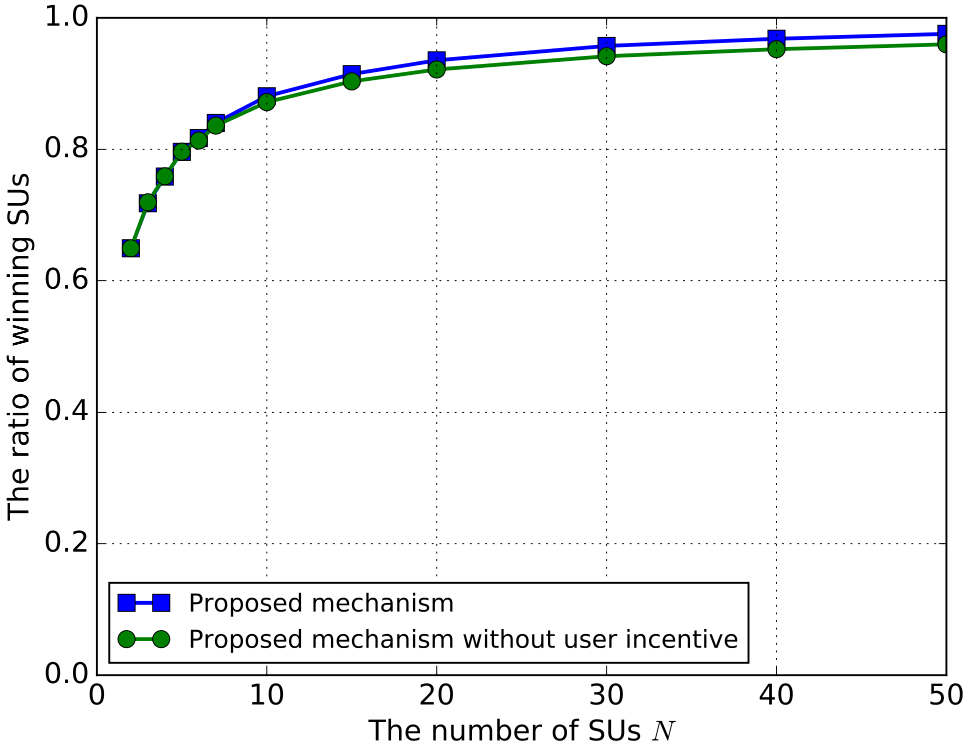


Figure 6: Relationship between the number of SUs, N, and ratio of winning SUs (2-PU scenario).

χ of miss detection probability and average group miss detection probability among winning groups in the case of $N = 50$. The average group miss detection probability of the proposed mechanism is 0.033, which is closer to the value of χ, i.e., 0.05, compared to that of the proposed mechanism without user incentive, i.e., 0.027.

Fig. 7 illustrates the relationship between PU-SU distance and winning frequency in the case of $N = 50$. As in Section 4.2.3, Fig. 7 shows the proposed mechanism can significantly improve the winning frequency for SUs with larger PU-SU distance, i.e., 1500–2500 [m], compared with the proposed mechanism without user incentive. Recall that the proposed mechanism without user incentive encourages each SU in forming a group with nearby SUs. If SUs close to a PU make groups among them, it is difficult for SUs distant from a PU to become

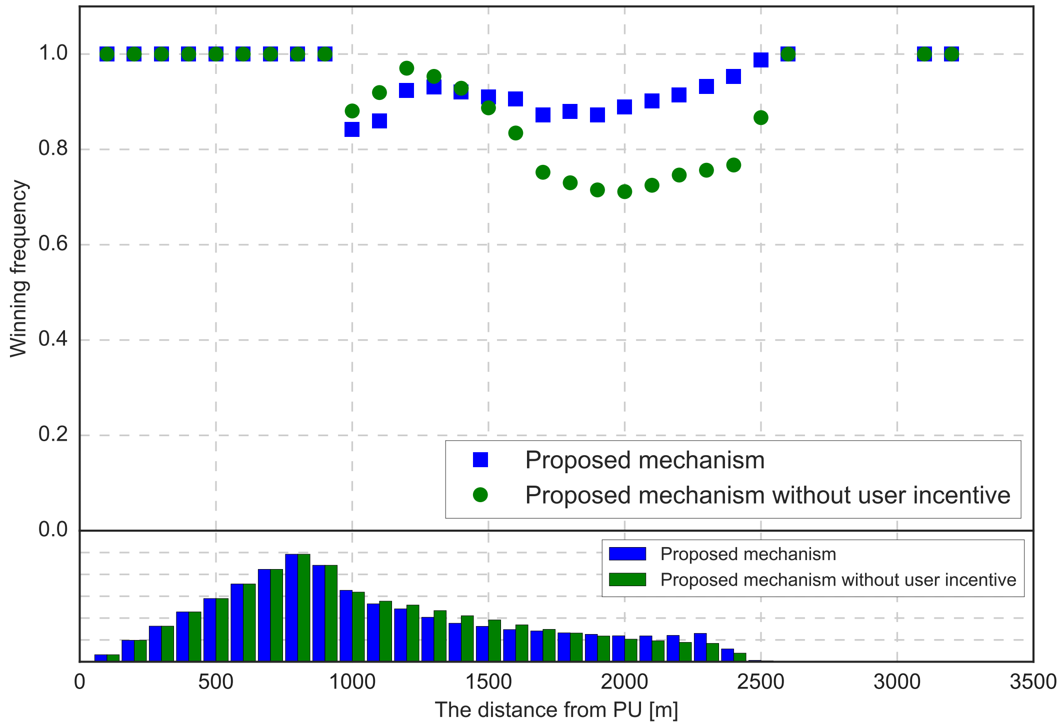
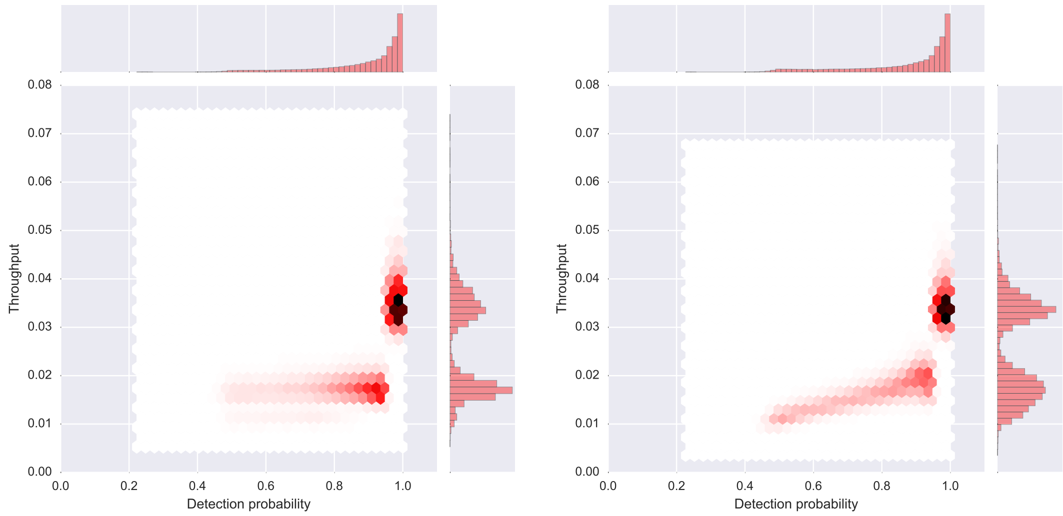


Figure 7: Relationship between PU-SU distance and winning frequency (2-PU scenario, $N = 50$).

winning. On the other hand, the proposed mechanism can alleviate this problem by introducing user incentive such that each SU close to a PU wants to form a group with SUs distant from the PU, and vice versa.

4.3.2 Relationship between Detection Performance and Throughput

We use the following time-slot based access model for the usage of PU's spectrum. In each time slot, PU l transmits data according to probability that it uses its own spectrum, $R_l^{\mathrm{use,PU}}$, and transmission request for each SU occurs with probability 0.1. When multiple winning groups detect the idle state of PU's spectrum, one of the groups is selected at random, and then an SU in the group wins the transmission opportunity based on the contribution to detection performance. If a collision occurs between the PU and SU(s), both of them do not conduct retransmission.



(a) Proposed mechanism without user incentive

(b) Proposed mechanism

Figure 8: Relationship between detection probability and throughput for PU 1's spectrum (2-PU scenario, $N = 50$).

Fig. 8 illustrates the relationship between detection probability and throughput for each winning SU selecting PU 1 in the case of $N = 50$. We also show the histogram of the number of SUs with the corresponding detection probability (resp. throughput) in the upper (resp. right) area of Fig. 8. As shown in Figs. 8a and 8a, each single SU i with $P_{i,1}^{\text{detect}} \leq (1 - \chi)$ obtains about 0.03–0.04 throughput in both schemes. On the other hand, remaining SUs with $P_{i,1}^{\text{detect}} > (1 - \chi)$ form a group with other SUs. In the proposed mechanism without user incentive, such SUs obtain almost the same throughput (Fig. 8a). In the proposed mechanism, Fig. 8b shows that SUs with high detection probability can obtain the high throughput because communication opportunities are allocated to SUs according to their contribution to detection performance. We also confirmed that the similar tendency is satisfied in the case of SUs selecting PU 2.

4.4 Robustness against Selfish Group Reformation

In this section, we investigate how the proposed mechanism is robust against SUs' selfish behavior. As mentioned in Section 3.3, the proposed mechanism includes the selfish group reformation scheme where each SU has a chance to remake the belonging group to increase its own communication opportunities. Through simulation experiments, however, we observed that the group reformation occurred at less than 1% of the winning groups, regardless of N. This is because the selfish group reformation occurs only when the SUs joining the new group can build a consensus where all of them can increase their own communication opportunities by the group reformation. This condition is severe and each winning group tends to reach a deadlock. As a result, the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

4.5 Convergence Property and Adaptability to Environmental Change

Finally, we evaluate the convergence property and adaptability to an environmental change of the proposed mechanism. In the proposed mechanism, each SU tries to improve its communication opportunity according to Algorithms 1. We define a time step where one SU conducts group update (lines 11–23 in Algorithm 1). Fig. 9 illustrates how the ratio of winning SUs, average throughput of winning SUs, and the frequency of group update vary with time step when the PUs' spectrum utilization are initially set to be $R_1^{\text{use,PU}} = 0.3, R_2^{\text{use,PU}} = 0.5$ and change at step 150, i.e., $R_1^{\text{use,PU}} = 0.5, R_2^{\text{use,PU}} = 0.3$.

We first evaluate the convergence property by focusing on the first half period of $[0, 149]$. We observe that the total ratio of winning SUs and average throughput of winning SUs for respective PUs almost converges when all 50 SUs try group formation at once, i.e., step 50. Moreover, average throughput of winning SUs for PU 1 can be almost the same as that for PU 2. We also confirm that the system finally reaches the steady state at step 120. Next, we focus on the remaining half period of $[150, 300]$ to evaluate the adaptability to the environmental change. We find that the proposed mechanism can smoothly converge to the new steady state while keeping the total ratio of winning SUs among two PUs. In ideal, average

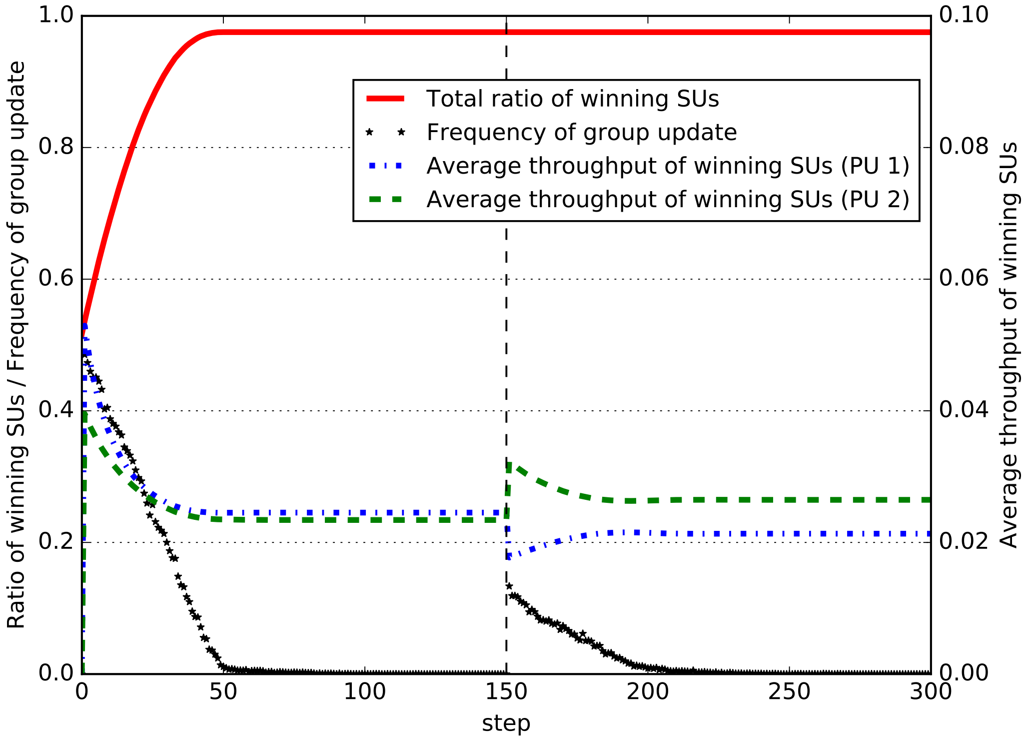


Figure 9: Relationship between the number of step and ratio of winning SUs (2-PU scenario, $N = 50$).

throughput of winning SUs for PU 1 should be equal to that for PU 2 after the environmental change at step 150, where $R_1^{\mathrm{use,PU}}$ and $R_2^{\mathrm{use,PU}}$ are counterchanged with each other. We, however, observe that there is a gap between average throughput of winning SUs for PU 1 and that for PU 2. This is because some SUs (groups) located near PUs will not be affected by the environmental change. As a result, group update will partially occur among SUs.

5. Conclusion

In this thesis, we proposed the CSS mechanism based on user incentive for multi-PU cognitive radio networks, in which communication opportunities are allocated to each SU according to its detection performance. In the proposed mechanism, the SU with high detection performance can acquire more communication opportunities by forming a group with SUs with low detection performance. On the other hand, there is also user incentive for the SU with low detection performance because it can become a winning SU by forming the group. We formulated the group formation as the optimization problem where each SU aims to maximize its own communication opportunities under the constraint on the upper limit of miss detection probability, by selecting an appropriate PU and forming a group with appropriate SUs. We further proposed the selfish group reformation where each SU aims to improve its communication opportunities by reforming the group.

Through simulation experiments, we evaluated the performance of the proposed mechanism. We first showed that the proposed mechanism can increase the ratio of winning SUs compared to the existing scheme, CF-PD, through the evaluation under 1-PU scenario. We further investigated the performance of proposed mechanism in terms of the impact of user incentive based cooperation and robustness against SUs' selfish behavior. We demonstrated that the proposed mechanism can improve the ratio of winning SUs compared to that without user incentive while allocating the throughput to SUs according to their detection performance. In addition, we also showed that the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

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International Conference

1. Tomohiro Nishida, Masahiro Sasabe, Shoji Kasahara, "Maximizing Communication Opportunity for Collaborative Spectrum Sensing in Cognitive Radio Networks," Proc. of 27th International Telecommunication Networks and Applications Conference (ITNAC), Melbourne, Australia, 2017.

Domestic Conference

1. 西田 知弘, 笹部 昌弘, 笠原 正治, "複数プライマリ・ユーザ型コグニティブ無線における協調センシングのための通信機会を考慮したセカンダリ・ユーザ間グループ形成手法," 信学技報, vol. 116, no. 484, pp. 499–504, Mar. 2017.
2. 西田 知弘, 笹部 昌弘, 笠原 正治, "コグニティブ無線におけるシステム負荷と検知率貢献度を考慮した協調センシングメカニズムの一検討," 信学技報, vol. 117, no. 204, pp. 61–66, Sep. 2017.
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