Social Incentives for Cooperative Spectrum Sensing in Distributed Cognitive Radio Networks

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Abstract

Cooperative spectrum sensing has been considered as a promising approach to improve the sensing performance in distributed cognitive radio networks. However, there may exist some selfish secondary users (SUs) who are unwilling to cooperate. The presence of selfish SUs could cause catastrophic damage to the performance of cooperative spectrum sensing. Following the social perspective, we propose a Social Tie-based Incentive Scheme (STIS) to deal with the selfish problem for cooperative spectrum sensing in distributed cognitive radio networks. This scheme inspires SUs to contribute sensing information for the SUs who have social tie but not others, and such willingness varies with the strength of social tie value. The evaluation of each SU's social tie derives from its contribution for others. Finally, simulation results validate the effectiveness of the proposed scheme.

Keywords: Cooperative spectrum sensing, cognitive radio networks, incentive, selfish

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1. Introduction

With the rapid growth of wireless communication technology and the huge demand of the capacity for wireless applications, the wireless frequency spectrum has become a scarce resource. However, a large portion of the assigned spectrum is not yet utilized efficiently. According to Federal Communications Commission (FCC) [1], temporal and geographical variations in the utilization of the assigned spectrum range from 15% to 85%. To solve the contradiction between spectrum scarcity and low spectrum utilization, cognitive radio networks (CRNs) [2] have been proposed to make effective use of the electromagnetic spectrum by opportunistically using the spectrum of the licensed users. The licensed users are called primary users (PUs) and the users of the CRNs are known as secondary users (SUs).

Cooperative spectrum sensing (CSS) is one of the key technologies in the realization of CRNs, since it enables SUs to fill in unused spectrum bands without causing harmful interference to PUs. The main idea of CSS is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located SUs [3]. By cooperation, SUs can share their sensing information for making a combined decision more accurate than the individual decisions [4].

However, most of the existing CSS schemes assume all the SUs are willing to collaborate. In reality, some selfish SUs may refuse to provide the sensing results to save energy or transmission time, while still enjoying those from others [5]. Such kind of selfish behaviors may seriously degrade the performance of CSS. To put it concretely, a selfish SU may be reluctant in the cooperation that is not directly beneficial to it, which could make a well designed CSS scheme useless. Therefore, how to efficiently and effectively resolve the selfishness problem for CRNs has become a very challenging issue to achieve better performance of CSS.

To stimulate the possible selfish users to contribute, two forms of incentives [6] can be considered: (1) credit-based (one pays to help and is paid to contribute), and (2) differential service approach (users that contribute more get more help). The monetary payments scheme requires a fictitious currency. However, due to the lack of central authority, it is hard to track various cooperative sensing and charges for them using micropayments in distributed CRNs.

The differential service approach seems more promising as an incentive scheme. Recently, efforts have been made to this approach in CSS using game theory. In [7], the authors modeled CSS as an *N*-player horizontal infinite game and they proposed to use Carrot-and-Stick strategy, which results mutual cooperation as the Nash equilibrium of the game. In [8], the authors proposed mixed strategy Nash equilibrium as the solution of the non-cooperative game among SUs for cooperative spectrum sensing. In [9], the authors formulated the interactive decision on frequency of selfish SUs as a noncooperative game, and Nash equilibrium corresponds to a desired frequency profile. Then, they propose a novel distributed algorithm to lead the SUs to achieve a desired frequency selection outcome. In [10], the authors modeled cooperative sensing framework as an evolutionary game in which each SU makes decision based on its utility history, and takes an action more frequently if it brings a relatively higher utility. However, most of the existing game theory frameworks depend on the assumption that the game between a pair of players is directly played for infinite times. Due to mobility or changes of environment, users will periodically update their partners to achieve better performance, which means that any pair of players is supposed to play for only finite times with the termination time are either known or can be estimated by both players [11]. In addition, these game theory frameworks are mostly related on the central networks and involve complex mathematically analysis and computation. In distributed CRNs, SUs generally have limited computation capability and thus complex game theory is not a suitable solution.

In this paper, we develop the differential service approach from a different point of view. It is worth noting that most SUs are rational and strategic users in the CSS environment. From the social perspective, an SU is willing to help the SUs who have social tie, because he got help from them in the past or will probably get help from them in the future. Conversely, the selfish users who don't help others won't get any help. It should be treated as a design metric to measure this kind of user demand. Based on this, we propose a *Social Tie-based Incentive Scheme* (STIS) to deal with the selfish problem for cooperative spectrum sensing in distributed CRNs.

The organization of this paper is as follows: In section 2, preliminaries related on CSS are described. In section 3, we show how social tie are measured in CSS and construct our STIS scheme in a distributed manner. Simulation analysis of the proposed scheme is given in Section 4. Finally, we conclude the paper in section 5.

2. Preliminaries

In the distributed CRNs, SUs cooperate with each other to achieve a CSS exchange in the self-organizing manner due to the lack of centralized control. In the CSS environment, each SU plays two roles, the role of initiator SU enjoying sensing information and the role of cooperating SU providing sensing information.

The CSS process can be modeled as a parallel fusion network [12]. As shown in **Fig. 1**, each cooperating SU detects the signal of PU individually via the sensing channel, and then reports their sensing information via the reporting channel to SU_1 who combines the received individual sensing information and determines the presence of PU. A sensing channel is the selected licensed frequency band where a physical point-to-point link between the PU transmitter and each cooperating SU for observing the primary spectrum, and a reporting channel is a control channel where a physical point-to-point link between each cooperating SU and the initiator SU for sending individual sensing information [3]. It can be seen that the two types of channels are given by the network. Thus, the CSS process among SUs seems not waste any more spectrums.

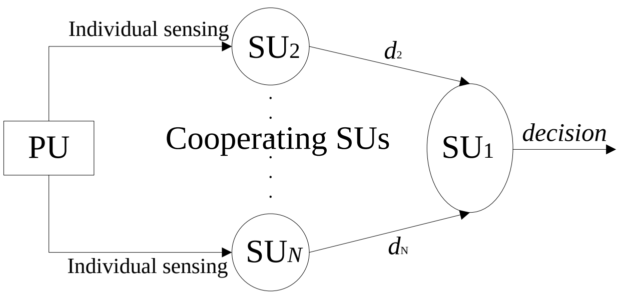


Fig. 1. A round of the CSS exchange launched by SU_1.

During the process of individual sensing, the individual sensing information of each cooperating SU is determined. d_i indicates the sensing information of the i-th cooperating SU, which is expressed as:

$$d_i = \begin{cases} 0, & H_0 \\ 1, & H_1 \end{cases} \tag{1}$$

where H_0 and H_1 denote the hypothesis of the absence and the presence of the PU signal, respectively.

There are several advantages offered by cooperative spectrum sensing over the individual sensing [13]. In the case of deep shadowing and multipath fading, it is very difficult for an SU to distinguish a white space from a deep shadowing effect. Therefore, an individual spectrum sensing system may not work well in this case, and a cooperative scheme can solve the problem effectively by sharing the spectrum sensing information among SUs. However, if the SUs are selfish, they will not collaborate with each other for cooperative sensing without any incentive [14]. Such kind of selfish behaviors may seriously disrupt the cooperative sensing, thus some incentive based solutions are expected to encourage the selfish SUs to contribute more to CSS. Therefore, designing an effective incentive scheme is our main work in this paper.

3. Proposed Incentive Scheme

As like wireless networks, CRNs can be also deployed in centralized and distributed architecture. Unlike centralized networks, distributed CRNs lack a central authority to make the cooperative decision. In this case, SUs communicate among themselves and converge to a unified decision on the presence or absence of PUs. Therefore, the CSS exchange of distributed CRNs has attracted increasing attention. Specially, there is litter literature investigating the selfish behaviors of SUs for distributed CRNs recently. In this paper, we implement our work in distributed CRNs.

3.1 Design Philosophy

The cognitive radio paradigm imposes human-like characteristics (e.g., learning, adaptation and cooperation) in wireless networks [15]. Specially, the self-organizing and distributed natures of distributed CRNs offer an ideal environment for selfish behaviors.

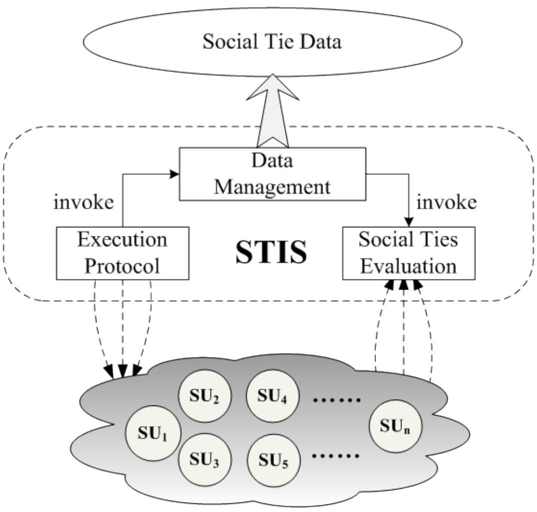


Fig. 2. Functional modules in the STIS scheme

To capture user selfishness in a more realistic manner, there are two observations from the social perspective [16]: 1) A user cooperates with others with whom he has social tie, because he would get help as a return; 2) For those with social tie, a user may give different preferences, namely, provide better service to those with stronger tie than those with weaker tie.

In the process of CSS, social tie may affect SUs' behaviors. For instance, an SU is reluctant to report sensing information to those without social tie value, and he gives preference to those with stronger social tie value. Therefore, our underlying philosophy is that social tie should be treated as a design metric to measure social tie and inspire selfish SUs. In view of this analysis, we propose the STIS scheme to resolve the selfish problem for CSS.

In this paper, we design our STIS scheme, as shown in **Fig. 2**, with three functional modules, such as the *social tie evaluation* module, *data management* module and *execution protocol* module. The *social tie evaluation* module is employed to evaluate the social tie. The *data management* module (as shown in **Fig. 3**) is used to manage and update social tie data for each SU in a distributed CRN by invoking the first module. The *execution protocol* module (as shown in **Fig. 4**) is in charge of implementing the STIS scheme in a distributed manner.

3.2 Social Tie Evaluation

From the angle of game theory, a selfish SU wants to get more gains when he pays. Thus, social tie can be viewed as the user utility of an SU, which is a design idea from the social perspective to suppress selfish behaviors. Once an SU often helps other SUs by contributing its sensing information, it would get a good social tie value. Or else, he would get a bad social tie value. With a good social tie value, this SU can request other SUs to help him easily. For a specific SU, "other SUs" may refer to the SUs who want to enjoy sensing information from the specific SU when this SU plays the role of cooperating SU. Or else, "other SUs" may refer to the SUs who provide sensing information to the specific SU when this SU plays the role of initiator SU.

In our STIS scheme, we find that the evaluation of social tie depends on four parameters. Take ***i***-th SU (SU_i) as an example, its social tie value can be defined as:

$$s_i = f\left(r_i, q_i, \omega_i^h, \sigma_i\right) \tag{2}$$

- r_i denotes the number of "helping" performed by SU_i. The more SU_i helps other SUs, the higher social tie value SU_i will get.
- q_i denotes the number of "helped" queried by SU_i. This parameter is inversely proportional to the evaluation of social tie. If SU_i often queries CSS help from other SUs rather than contribution, its social tie value will be reduced.
- $\omega^h{}_i$ is the reward index to SU_i at time h when he participates in CSS. Sening the primary spectrum would cause a certain cost consumptions. To stimulate SU_i to help other SUs via CSS, a reward index related on cost consumptions should be considered in the evaluation of social tie.
- σ_i is the penalizing parameter to the evaluation of social tie. In order to enhance social tie, some SUs may send false sensing information. The more SU_i reports false sensing information, the higher penalizing parameter SU_i will get, and thus leading to a rapid reduction in s_i.

The two parameters (r_i, q_i) can be collected directly during the process of CSS. Then, how to evaluate the reward index and penalizing parameter becomes the main task of the *social tie evaluation* module.

- **Cost-Reward Evaluation**

In distributed CRNs, SUs are generally the wireless devices with limited computation and battery energy. We cannot ignore the fact that sensing the primary spectrum would consume a certain amount of cost, such as time, energy and memory. The more an SU participates in CSS for other SUs, the more cost he will consume. As the cost of sensing increases, some diligent SUs may tend to contribute nothing. In this case, a cost-reward mechanism is essential in social tie evaluation to inspire contribution.

Let $O^h_i=\{o^h_{i1}, o^h_{i2}, \ldots, o^h_{im}\}$ denote the set of cost spent in sensing the primary spectrum by SU_i at time h. The reward index of SU_i in regard to participation of CSS can be estimated by its consumption at time h.

$$\omega_i^h = \sum_{j=1}^{m} \frac{o_{ij}^h}{o_{ij}} \tag{3}$$

where m is the number of cost spent by SU_i and o_{ij} is the total capacity hold by the wireless device, such as overall run time, overall battery energy and overall computation memory.

To ensure the reliable estimation of ω^h_i, two constraints should be considered in the cost-reward mechanism: 1) SU_i cannot estimate ω^h_i by himself, because it would fake this index to maximize its social tie value; 2) The reward index must be tamper-resistant during the transmission, or else anyone may slander SU_i by tampering this index. Therefore, a small software is required in the wireless device to measure O^h_i and the total capacity synchronously as SU_i sensing the primary spectrum. This software, uncontrolled by SU_i, then estimates the reward index ω^h_i that is set as read-only and sent automatically as well as the sensing information provided by SU_i.

For SU_i, its social tie value will be increased by the reward index if he often participates in CSS. Thus, the cost-reward value after r_i-th sensing performed by SU_i can be represented as:

$$w_i = r_i * \omega_i^h, \ 1 \le h \le r_i \tag{4}$$

- **Penalizing Parameter Evaluation**

It is possible that some SUs may maintain a good social tie value by sending false sensing information. To suppress such fraudulent behavior, two measures can be adopted in the STIS scheme. First, as we know from the cost-reward evaluation metric, the cost data are measured in the processing of sensing the primary spectrum. So, the behavior of SU_i can be detected to as fraudulent if ω^h_i is not received automatically as well as the sensing information. To insure the accurate final decision of the primary spectrum from CSS, such false sensing information should be discarded.

However, an SU may also send false sensing information to misguide other SUs that the PU signal is present if he likes the primary spectrum after individual sensing. Given this, the second measure is presented following the view of punishment is. Assuming r_i^C be the number of correct sensing information reported by SU_i, the penalizing parameter σ_i is defined as:

$$\sigma_i = \frac{r_i^C}{r_i\left(1 + r_i - r_i^C\right)} \tag{5}$$

This penalizing parameter is used as a multiplicative decay coefficient to reduce the social tie value of SU_i. The index (r_i -r_i^C) denotes the number of false sensing information reported by SU_i. Obviously, the more SU_i reports correct sensing information, the lower reduction will get in s_i, and vice verse. Specially, σ_i will accelerate the growth of s_i when r_i -r_i^C=0.

Of course, the negative effect caused by a handful of false sensing information on final decision is limited sometimes in CSS. For example, the *Majority* fusion rule requires at least a half of SUs to report H_0 (H_1) before the final decision H_0 (H_1) is determined [3]. That does not mean the punishment to social tie value is not important. Without punishment, more and more SUs would fake sensing information to increase their social tie value, resulting in seriously hurting the performance of CSS.

Then, another question is how to identify the correct sensing information. We have already known that an initiator SU requests a CSS exchange under the condition of failing to sense the primary spectrum. In the process of CSS, it is impossible to identify the correct sensing information without prior knowledge, but an initiator SU can differentiate between the correct and false sensing information when the final decision is determined. Afterwards, the false sensing information will lead to a rapid reduction in cooperating SUs' social tie value. It is difficult for those SUs to get CSS help from others when their social tie value decay below a certain value. It also shows that the punishment is very essential to social tie evaluation.

- **General Evaluation Metric**

By introducing the reward index and penalizing parameter into the evaluation of social tie, the social tie value of SU_i can be evaluated as:

$$s_i = r_i * \omega_i^h + \sigma_i \frac{r_i}{q_i}, \ 1 \le h \le r_i \tag{6}$$

Similarly, we can evaluate the social tie value of each SU in a distributed CRN and consequently derive a social tie vector:

$$S = \left[s_1, \ \cdots, s_i, \cdots \ s_n \right]$$

It is necessary to normalize the social tie value in *S*. Otherwise, some SUs may be assigned arbitrarily high social tie value (much more than 1), and arbitrarily low local social tie (much less than 1) to another SUs, which brings a difficulty in comparing them. To ensures that all social tie value lie in [0, 1], the social tie value are normalized with max(*S*) which can be updated adaptively by the following procedure.

Procedure Updating max(*S*)

Input: *S*
Output: max(*S*)
At h=0, initialize max(S)=1;
for h≥1 **do**
  for each SU_i **do**
    if (s_i>max(S)) **then**
      max(S)=s_i;
    end if
  end for
  h++;
end for

Such factor can inspire SUs to learn from the SU with best behaviors. If selfish SUs often contribute nothing to others, he will get less normalized social tie than other SUs. For SU_i, its social tie value can be normalized as follows:

$$s_i' = \frac{s_i}{\max(S)} \tag{7}$$

- If $s_i' >= \delta$, SU_i will be looked as a non-selfish SU, and other SUs will share sensing information with SU_i.
- If $s_i' < \delta$, SU_i will be looked as a selfish SU, and other SUs will not share sensing information with SU_i.

It can be seen that the key to deciding whether an SU is selfish depends on the threshold of social tie value (δ). In order to guarantee the performance of CSS, δ should satisfy three requirements: 1) P_d ($0 \le P_d \le 1$) represents the probability of detecting the presence of PU singal under hypothesis H_1 [17], and hence δ needs to be able to inspire SUs to keep a higher P_d by providing correct sensing information; 2) δ should be a moderate value between 0 and 1 in correspondence with the normalized social tie value; 3) δ can also inspire SUs to maximize the throughput of a netwwork, which is viewed as the network utility of all SUs in a time slot. Such index reflects the degree of contribution that all SUs provide sensing information via CSS. To stimulate cooperation among SUs, we can set the minimum required for the throughput in a time slot to adjust the size of δ. Here, the time is divided into L time slots of equal length, where L is a large positive integer. The throughput is defined as the ratio of the number of "helping" performed by all SUs to the number of "helped" queried by all SUs in a time slot. Let Ψ denote the set of all SUs in a network, the j-th throughput can be calculated as:

$$t_j = {\sum_{i\in\Psi} r_i} \Big/ {\sum_{i\in\Psi} q_i}, \quad 1 \le j \le L \tag{8}$$

Based on the above three requirements, we use the following function for δ:

$$\delta = \left(\frac{T}{\max(S)} \right)^{P_d} \tag{9}$$

The detection probability P_d is recognized as the exponential weight to determine the threshold dynamically. A higher value is required in P_d, a larger threshold is determined. To avoid being identified as selfish, SUs must report more correct sensing information in the process of CSS. Meanwhile, a higher value in T also means that SUs must often participate in CSS at every time slot. In the STIS scheme, T is the minimum required for the throughput in a time slot. When some SUs are not enthusiastic about helping others in a time slot, T is set to a higher value aiming to motivate them to contribute sensing information. After they behave well, T is decreased to allow more SUs to obtain sensing information via CSS. Once the selfish behaviors of some SUs reappear, T is adaptively adjusted to a higher value again.

3.3 Data Management

Without a central database, social tie data need to be stored among SUs in a distributed manner. **Fig. 3** gives a sketch of the system architecture of the *data management* module.

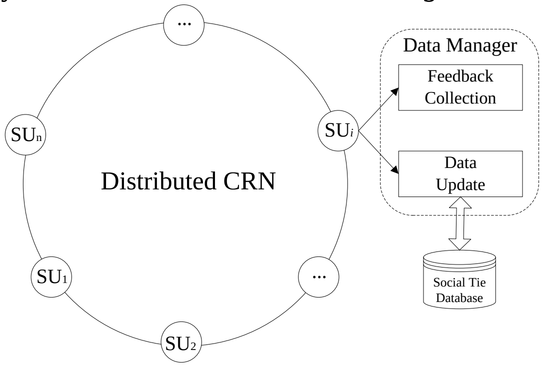


Fig. 3. System architecture of data management module

The callout shows that each SU has a data manager that is responsible for collecting the feedback message related to the SU and updating its social tie data, in which a small database (as shown in **Table 1**) stores the social tie data.

Table 1. Description of Social tie database

ID	Number of "helping"	Number of correct sensing	Number of "helped"	Total cost-reward	Social tie value
SU$_1$	r_1	r_1^C	q_1	t_1	s_1
SU$_2$	r_2	r_2^C	q_2	t_2	s_2
…	…	…	…	…	…
SU$_n$	r_n	r_n^C	q_n	t_n	s_n

Specially, due to the limited computation capability, each SU cannot store the social tie data for all SUs of the whole network. Only when an SU becomes some SUs' data manager can the SU store their social tie data.

In our approach, an SU's data manager is located by mapping a unique ID of the SU. Take SU$_j$ as an example, we can find the ID of its data manager by the following map function.

$$ID_i = k \times ID_j \left(\bmod \; n+1\right), \; k > n+1 \,\&\&\, ID_i \neq ID_j \,\&\&\, ID_i \neq 0 \quad (10)$$

where k is an integer generated by the network and is distributed to each SU uniformly.

As shown in **Fig. 3**, let SU$_1$ be a requestor for a CSS exchange and SU$_2$ is one of SU$_1$'s possible cooperating SUs. Assuming ID_1=1, k=13 and n=6. Then, 1*13 (mod 6+1)=6.With the map function, the unique ID of SU$_1$, ID_1, is mapped into 6. Thus, SU$_6$ becomes SU$_1$'s data manager who sends SU$_1$'s social tie value to SU$_2$ and updates the q_1 value by adding 1 in its social tie database. Similarly, if k is assigned to several values, several data mangers of SU$_1$ can be found by different k value.

According to the social incentive scheme, if SU$_1$'s social tie value is greater than the threshold, SU$_2$ will join in the CSS exchange launched by SU$_1$ and provide sensing information to SU$_1$, and vice verse.

In the module, to cope with the inherent dynamics of a distributed CRN, several data managers are responsible for the social tie value of SU_1. If a cooperating SU needs the social tie value of SU_1, he can query all SU_1's data managers for the value.

In addition, a majority vote on the social tie value should be adopted to settle the conflicts among the data managers. For example, there are five data managers of SU_1, in which three of them think that SU_1 is active and two of them think that SU_1 is selfish. According to the majority vote, SU_2 decides that SU_1 is active. This is because the truth is often in the hands of the majority.

3.4 Execution Protocol

It is important to note that the effectiveness of supporting social tie in CSS depends not only on the factors and metric for evaluating social tie, but also on the implementation of the STIS scheme in a distributed CRN.

When an initiator SU tries to use a primary spectrum, at first this SU needs to check whether the PU signal band is free or in using. In the STIS scheme, the execution protocol is responsible for the interaction between the initiator SU and its cooperating SUs as well as their data managers. From **Fig. 4**, it can be seen that the whole protocol is composed of three steps.

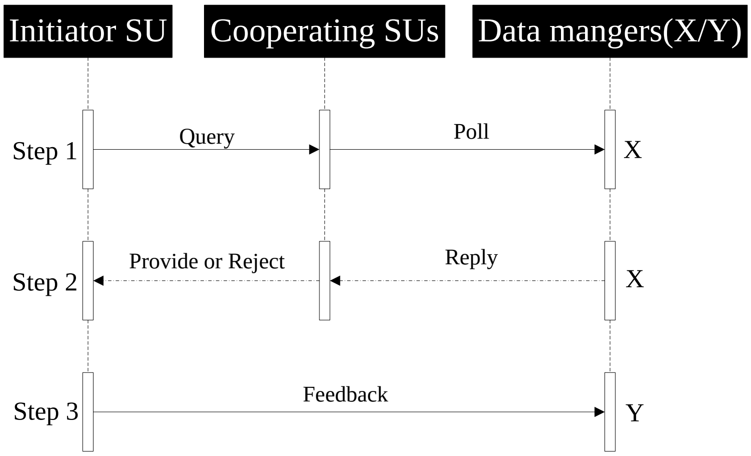


Fig. 4. Message flow for the Execution Protocol

Step 1. An initiator SU, such as SU_i, sends a Query message (ID<PU>, r, t) to request a CSS exchange related on a primary spectrum. A random number r in the message is added to mark the CSS action, and h is the current system time. Meanwhile, the cooperating SUs broadcast a Poll message (SU_i, r, h) to the initiator SU's data managers (X).

Step 2. Upon receiving the reply message(s_i, q_i, r, $\omega^h{}_i$), the cooperating SUs check whether SU_i's social tie value outweighs δ. For $s_i>\delta$, the cooperating SUs provide sensing information to SU_i, and vice verse. Of course, the STIS scheme also should give the newcomers one chance. For s_i=0&&q_i=1, SU_i can referred to as a newcomer. In this case, the cooperating SUs would share its sensing information to SU_i. Afterwards, if SU_i would like to get help from again, he must continue to help others.

Step 3. The initiator SU sends the feedback message (fb(cooperating SUs), r, $\omega^h{}_i$) to the cooperating SUs' data managers (Y). Take a cooperating SU as an example, such as SU_j, if he provides corrected sensing information, $fb(SU_j)=(r_j{}^C+1)$. Its data managers will update the $r_j{}^C$ value by adding 1 in their social tie database. Otherwise, $fb(SU_j)=(r_j{}^C+0)$. SU_j's data managers will not update the $r_j{}^C$ value. Also, upon receiving the feedback message $\{fb(SU_j)\}$, SU_j's data managers will update the r_j value by adding 1.

4. Simulation Analysis

We would perform four simulations to validate the STIS scheme and show its effectiveness, and robustness.

4.1 Simulation Setup

We consider a distributed CRN with 60 SUs and 5 PUs, where the SUs are split into two types: non-selfish SUs and selfish SUs. The percentage of selfish SUs is set to 50%.

The behavior pattern for good SUs is to always cooperate in CSS and provide honest sensing information. While it is a challenging task to model SUs' selfish behavior realistically, we start with two selfish behavior patterns to study the robustness of STIS, namely, active setting and inactive setting. In the active setting, selfish SUs would share their sensing information with incentive measures. In the inactive setting, selfish SUs may maintain a good behavior by contribution, and then reject to share their sensing information as their social tie value outweigh the threshold δ.

The simulations are executed by cycle-based fashion. At each cycle, all SUs are selected to perform CSS random exchanges with each other. After a few cycles, an incentive network topology is gradually formed by social tie value. The participating SUs then use the STIS scheme to perform CSS exchanges at each cycle, and update social tie data on the corresponding SUs. In this simulation fashion, the h-th cycle denotes time h and a time slot consists of 8 cycles.

4.2 Simulation Results

The first three simulations validate the effectiveness of STIS in the active setting by compared with a latest evolutionary game-based incentive scheme [10] (hereinafter "EGIS"). Finally, we evaluate the robustness of STIS by observing the variation of social tie value at a selfish SU who behaves two selfish behavior patterns respectively including the active setting and the inactive setting.

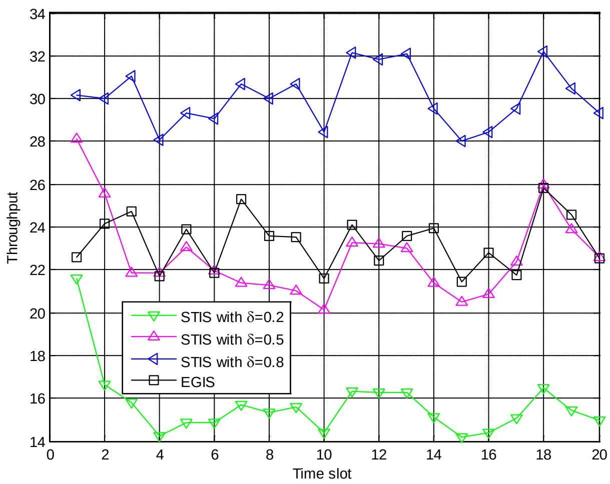


Fig. 5. Throughput of STIS vs. EGIS

The throughput of STIS is compared with EGIS in the first simulation. To acquire an ideal throughput in STIS, we set the detection probability P_d to 0.98 and then vary the T factor to slide δ dynamically in [0.2, 0.5, 0.8]. As shown in **Fig. 5**, both STIS and EGIS can enhance the throughput effecively. Specially, STIS behaves better than EGIS when δ=0.8. As we know from section 3.1, δ is correlative to the T factor that is the minimum required for the throughput in a time slot. Thus, a larger δ can stimulate some selfish SUs to change their past behaviors more easily, and then share sensing information to improve their social tie value. However, if the T factor is set to a lower value, some selfish SUs would be not interested to share sensing information since they can make their social tie value easily outweigh δ. Of course, EGIS modes CSS as an evolutionary game in which each SU participates in CSS based on its utility history, and takes an participation more frequently if a relatively higher utility achieves. In this case, EGIS can also maintain an ideal throughput to some extent.

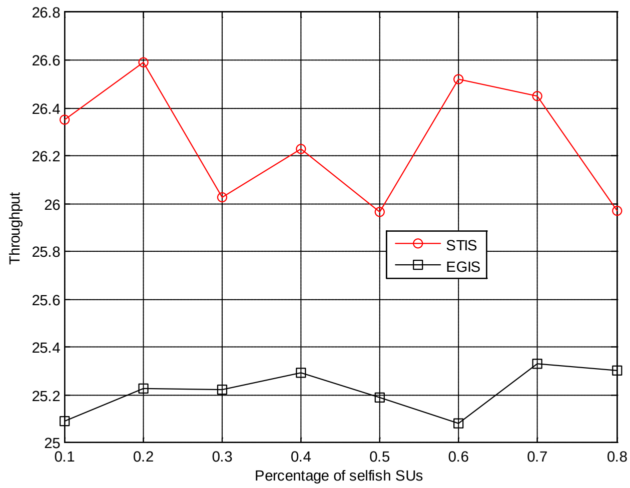


Fig. 6. STIS vs. EGIS under the different percentage of selfish SUs

Next, the threshold δ is fixed at 0.8. We vary the percentage of selfish SUs in the second simulation to observe the throughput of STIS compared with EGIS in the tenth time slot. As shown in **Fig. 6**, we can also validate that STIS is better than EGIS due to its strict requirement for the throughput.

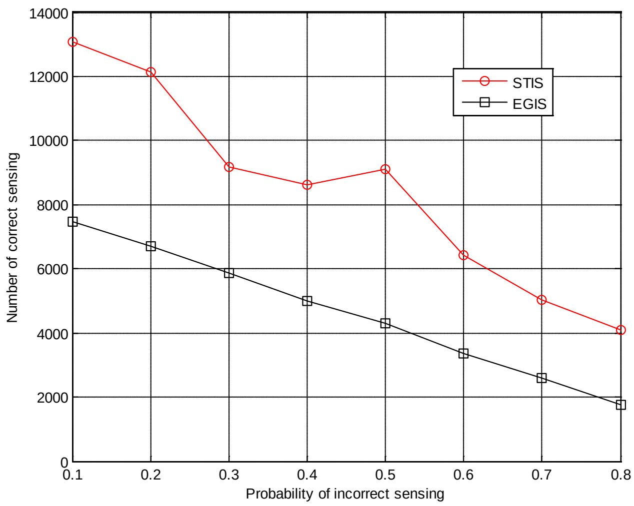
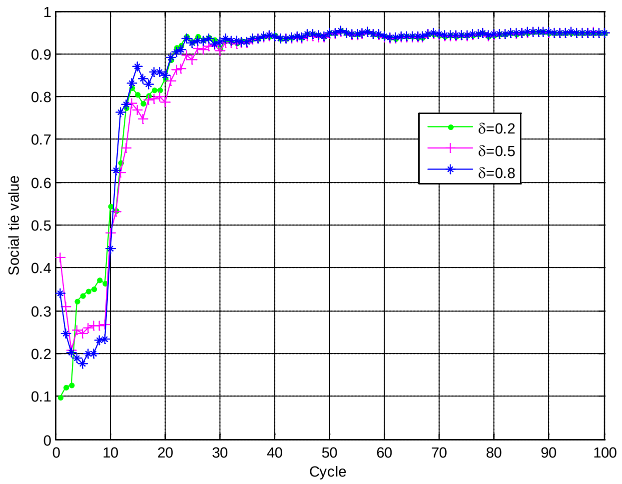


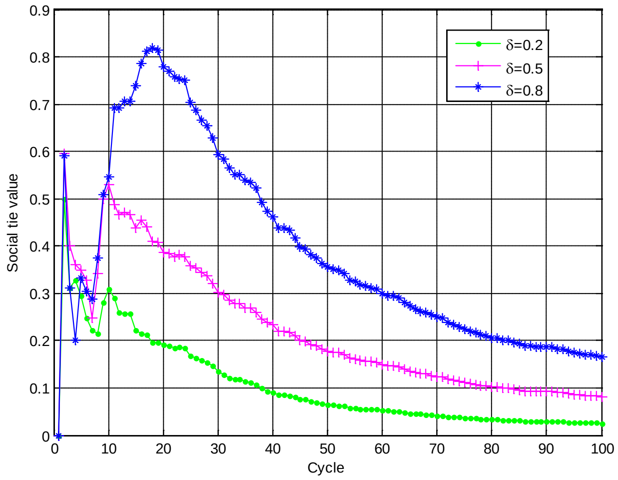
Fig. 7. STIS vs. EGIS under the different probability of incorrect sensing

In the third simulation, we find that the incorrect sensing behavior can hurt the performance of STIS and GEIS seriously. **Fig. 7** shows that the number of correct sensing decreases with the increase of the probability of incorrect sensing. Fortunately, STIS decreases slower since the penalizing parameter is introduced to suppress such fraudulent behavior, whereas the curve of EGIS drops rapidly without punitive measures. Although the curve of STIS turns bad after the probability of incorrect sensing outweighs 0.5, such extreme case appears rarely in the CSS environment driven by STIS. In our scheme, the evaluation of social tie value for an SU is highly dependent on its histroy of correct sensing. The less number of correct sensing will lead to a lower social tie value. Thus, the SUs with fraudulent behavior can get nothing from CSS.

We have known that the social tie value is the key factor in our STIS scheme to inspire the contribution of selfish SUs. The fourth simulation shows the variation of social tie value at a selfish SU in the active setting and the inactive setting respectively. As shown in **Fig. 8(a)**, a selfish SU's social tie value increase gradually by 30 cycles in the active setting, and then tends to stable. In the simulations, the parameters of Eq.(6) and the max(S) of all SUs are used to evaluate each SU's social tie value at different cycles. The reward index of each SU in regard to participation of a CSS action is assumed to 0.01. Such index can boost the social tie value with the increase of correct sensing. Since the selfish SU persistently reports correct sensing information in the active setting, its social tie value normalized by max(S) will tend to 1 along with cycles.



(a)



(b)

Fig. 8. Variation of social tie value at a selfish SU. (a) Active setting. (b) Inactive setting

Is its social tie value will decrease if the selfish SU rejects the contribution when its social tie value is greater than δ ? We can see in **Fig. 8(b)** that the social tie value will decrease gradually once a selfish SU does not provide sensing information. In the inactive setting, as a selfish SU declines to participate in CSS, its reward index and the number of correct sensing information will stop to rise. Then, its social tie value will decrease with the increase of its query corresponding to CSS. After normalization, its social tie value tends to 0.

The fourth simulation also shows that, no matter how δ is set, a selfish SU's social tie value will tend to 1 by its persistent sensing behaviors in the active setting. However, in the inactive setting, the social tie value only arrives at the given δ instantaneously and then drops sharply without any contribution.

5. Conclusion

In this paper, we propose an incentive scheme based on social tie (STIS) for cooperative spectrum sensing in distributed CRNs. Following the social perspective, this scheme inspires SUs to contribute sensing information for the SUs who have social tie but not others, and such willingness varies with the strength of social tie value. The evaluation of social tie is given by this underlying philosophy. Meanwhile, we design a *data management* module and *execution protocol* module to implement the STIS scheme in a distributed manner. Through the simulation analysis, we have demonstrated that the STIS scheme can effectively inspire selfish SUs to contribute sensing information for increasing their social tie value.

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