A New Cooperative Spectrum Sensing Scheme for Cognitive Ad-Hoc Networks

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Abstract. As the radio spectrum is becoming more and more crowded, the cognitive radio has recently become a hot research topic to improve the spectrum utilization efficiency. It is well known that the success of cognitive radio depends heavily on fast and efficient spectrum sensing that can be very difficult in practice. Toward this end, this paper introduces a new guard-resident collaborative spectrum sensing topology for a cognitive ad-hoc network. In particular, we classify cognitive nodes as either *resident* or *guard* based on the spectrum neighbor decision and distributed boundary search. The guard nodes sense the spectrum and then inform the resident nodes that are free from spectrum sensing about the environmental changes. The analysis and simulation results show that the proposed algorithm can significantly reduce the total spectrum sensing load and improve the sensing accuracy.

Keywords: cognitive radio, spectrum sensing, ad-hoc, multi-cell, distributed boundary search.

1 Introduction

In order to improve the spectrum utilization, cognitive radio (CR) has recently gained significant attention from the wireless community [1]. In CR, within a tiered access hierarchy, the primary users retain preferential use rights; the secondary users may only use a primary channel when it is identified as unoccupied and must release such a channel whenever a primary user's transmission is detected. As is well known, the success of CR operation depends heavily on fast and efficient spectrum sensing [2]. This seemingly innocuous task can actually be quite difficult in practice due to the large variations in the dynamic range and bandwidth of signals to be detected.

To achieve better performance, people proposed the cooperative spectrum sensing (CSS) concept where each single node collects individual sensing results from its neighbors and combines them to make a better decision [3]. The existing cooperative spectrum sensing research is mostly focused on how to do the combination of sensing

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information collected by cooperative cognitive radio users and the optimization of sensing parameters [4, 5]. Paper [6] modeled the CSS problem as a nontransferable coalitional game where the network of CR users could form cooperating coalitions and interact on whether to merge or split based on the comparison relation for improving their spectrum sensing performance. Paper [7] modeled the CSS problem as an evolutionary game where the payoff was defined as the throughput of a secondary user. Paper [8] proposed a fast spectrum sensing algorithm for a large network which required fewer than the total number of cognitive radios in cooperative spectrum sensing while satisfying a given error bound. However, all existing CSS approaches put additional burden on neighboring nodes for constant spectrum sensing. Another major drawback of the existing CSS solutions is that most of them assume the collaborating nodes are subject to the same frequency exposure, few work consider the multi-cell primary network scenario where the neighboring cognitive nodes have exposure to different frequencies, leaving some open issues such as the well known *hidden node problem* [9] still unsolved.

In this paper, we consider a CR ad-hoc network (CRAHN), where the secondary network has ad-hoc connectivity (such as distributed multi-hop communication, self-organizing and dynamic network topology [10]). In CRAHN, the cognitive (ad-hoc) nodes generally have limited computation capability and thus constant spectrum sensing is not a suitable solution. *The key contribution of this paper is we derive a new guard-resident CSS method that can significantly reduce the overall spectrum sensing load without sacrificing the overall performance.*

The rest of the paper is organized as follows: Section 2 provides system model and the assumptions, followed by detailed discussion of the guard-resident CSS algorithms in Section 3. In Section 4, simulation results are presented. Finally, a conclusion is drawn in Section 5.

2 System Model

In this section, we describe the system model and assumptions. Compared to other existing CSS models, our model has two distinct features: (1) the primary network has multiple frequency zones; (2) cognitive nodes have ad-hoc connectivity so that cooperation is not limited to geographic neighbors.

Consider a multi-cell TV broadcasting (or cellular downlink) primary network as shown in Fig. 1, where we assume no frequency reuse for adjacent cells to avoid inter-cell interference. We define a *frequency zone* as an area covered by the same primary transmission. Ideally, cognitive users within the same frequency zone should have the same spectrum sensing results. Fig. 1 shows a three-cell primary network with seven frequency zones. The cognitive users with different densities are randomly distributed over the whole area. For any particular cognitive node, we define its *geometric neighbor as those* who have direct (one hop) connection with the node. Note that a node's geometric neighbors may be located at different frequency zones, which is particularly true for those who are on the cell edge.

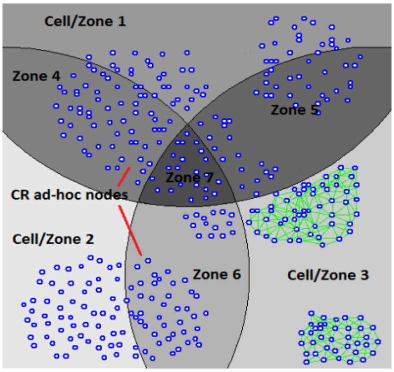

Fig. 1. Multi-cell TV broadcasting primary network

As we mentioned earlier, the benefits (increased sensing accuracy) of the existing CSS methods come at a price (increased sensing load). Furthermore, these methods are problematic for any cell edge cognitive user whose neighbors are from different frequency zones. On the other hand, we realize that cooperation between any two cognitive nodes is possible if they are connected (via single hop or multi-hop) within the same frequency zone, and such cooperation can be used to reduce the overall sensing load and avoid those problems associated with cell edge cognitive users. Toward this end, we propose our new guard-resident CSS scheme. The basic idea is to classify each cognitive node as either *resident* or *guard*, where only the guard nodes sense the spectrum and inform the resident nodes about the environmental changes. As shown by Fig. 2, the polygon formed by the guards becomes a safe zone such that any cognitive node within the safe zone will be free from spectrum sensing.

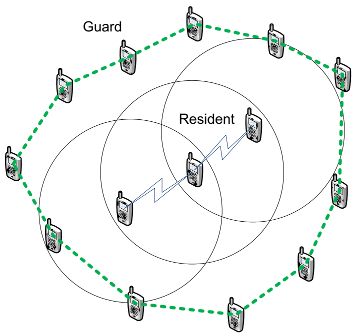

Fig. 2. The guard-resident scheme

In this work, we make the following assumptions: (1) Each CR node has no knowledge about the primary network, but it knows the direction of its geometric neighbor(s), which can be obtained by the positioning devices such as GPS or calculated from some "directional finding" algorithms [11]; (2) The CRAHN has a common control channel (CCC) that is dedicated to coordination and control information exchange among CR users [12].

3 Guard-Resident Scheme

The guard-resident cooperative spectrum sensing (GRCSS) scheme can be illustrated by the flow chart in Fig. 3. In this section, we'll explain it step by step.

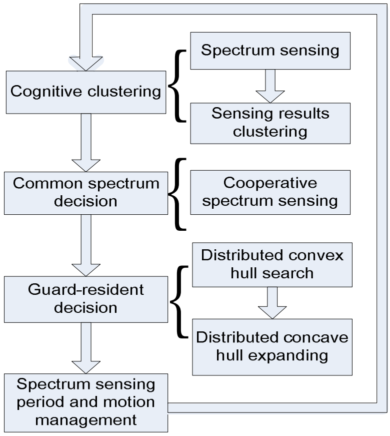

Fig. 3. Guard-resident scheme frame

3.1 Cognitive Clustering

The goal of this step is to divide cognitive users into *clusters* such that nodes within the same cluster are fully connected and located in the same frequency zone. For example, in Fig. 1, there are two cognitive clusters in zone 3. The cognitive cluster is the basic unit to make guard-resident decision, i.e., each cognitive cluster will form a connected guard boundary to "protect" the inside residents.

Initially, all cognitive nodes should sense the spectrum. According to their sensing results, each node is only connected to its *spectrum neighbors,* which are the geometric neighbors within the same frequency zone. As shown in Fig. 4, node *A* has seven geometric neighbors. Among them, node *B*, *C*, *D* and *J* are also spectrum neighbors of *A*.

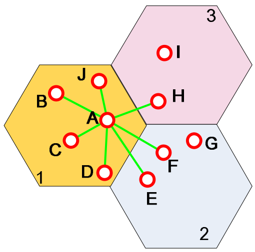

Fig. 4. Geometry neighbors and spectrum neighbors

Due to the noise and other imperfections, nodes in the same frequency zone may have different sensing results. Then the question is how to decide a node's spectrum neighbors with sensing errors. In this paper we use *cluster analysis* to partitions the cognitive nodes into a certain number of clusters so that the sensing results in the same cluster are similar while those from different clusters are quite different. We aim to maximize both the cluster internal homogeneity and the external separation. Among many clustering algorithms, we choose hierarchical clustering algorithm (HCA) [13] because it doesn't need the prediction of the number of clusters and yields good performance in our cognitive clustering.

There are two design parameters when applying HCA to our cognitive clustering: one is the *distance* among cognitive nodes and the other is the *threshold* for cutting the hierarchical tree. For example, in Fig. 5, we have a hierarchical tree with three clusters (10, 12, 5, 1, 8, 11, 14), (2, 6, 7, 3) and (4, 9, 13) using the threshold of 0.25. There are no fixed criteria for choosing the distance and the threshold because they depend on the specific application.

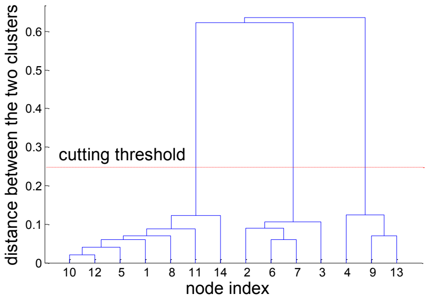

Fig. 5. The dendrogram of a hierarchical tree

Note that the specific spectrum sensing technique is not the focus of this paper. For the convenience of the discussion, we use energy detection based spectrum sensing (EDSS) technology to illustrate how to define the distance and threshold in HCA. The EDSS approach has the following two hypotheses:

$$\begin{cases} H_0 : Y = N \\ H_1 : Y = S + N \end{cases} . \tag{1}$$

where Y is the overall sensed signal on a particular frequency channel; S is the primary signal to be detected; N is the additive white Gaussian noise (AWGN).

Assuming a node has *n-1* geometric neighbors and *m* channels to sense, we use the following *n*-by-*m* matrix $X\{x_{ij}\}_{n\times m}$ to denote the sensing results:

$$X = \begin{pmatrix} 1 & 0 & 0 & 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 0 & 0 & 1 & 0 & \cdots & 0 \end{pmatrix}_{n\times m} . \tag{2}$$

where x_{ij} =1 or 0 means the channel *j* is sensed by node *i* as available or occupied. In *X*, each row vector represents the sensing results of a particular node. For any two nodes *r* and *s*, we use normalized Hamming distance (NHD) as the distance metric:

$$d_{rs} = \frac{1}{m}\sum_{j=1}^{m} x_{rj} \oplus x_{sj} \quad . \tag{3}$$

Note that the symbol "$\oplus$" is the mod operation, which can give erroneous result because each node may have detection errors. For node *i*, we denote the detection error rate for a particular channel *j* as $P_E(i, j)$. In order to maximize both the cluster internal homogeneity and the external separation, the *threshold* for cutting the hierarchical tree can't be either too large or too small. We denote the *threshold* as λ_{cut} and it should satisfy $\lambda_{\min} < \lambda_{cut} < \lambda_{\max}$ .We have derived both $\lambda_{\min}$ and $\lambda_{\max}$ (derivation is omitted due to space limit):

$$\lambda_{\min} = 2E\{P_E\}(1 - E\{P_E\}) \quad . \tag{4}$$

$$\lambda_{\max} = (1 - 2E\{P_E\}(1 - E\{P_E\}))d_z + 2E\{P_E\}(1 - E\{P_E\})(1 - d_z) \quad . \tag{5}$$

where $E\{\cdot\}$ is expectation and d_z is the average frequency diversity rate of two adjacent frequency zones. The optimal threshold is given by $\lambda_{cut} = \frac{1}{2}(\lambda_{\min} + \lambda_{\max})$. Another question is whether or not we can always find a solution for λ_{cut}. Obviously, λ_{cut} always has a solution if $\lambda_{\max} - \lambda_{\min} \geq 0$. Plugging above results, we have

$$\lambda_{\max} - \lambda_{\min} = d_z(2E\{P_E\} - 1)^2 \geq 0 \quad . \tag{6}$$

Therefore, λ_{cut} always exists.

Once the cognitive clustering is done, cooperative spectrum sensing will be done within each cluster, which includes the common spectrum decision shown in Fig. 3.

3.2 Guard-Resident Decision

The most important step in GRCSS is to make guard-resident decision for each cognitive cluster. Intuitively, the boundary nodes of each group can serve as the guards and "protect" the inside residents. For example, Fig. 6 shows a cognitive cluster where the square and round nodes are marked as guard and residents respectively. It is a concave hull of the CR nodes. However, the challenge is how to determine the boundary nodes considering the ad-hoc nature of the network. A major contribution of this work is that we derive efficient distributed algorithm to find the connected boundary of any arbitrary cognitive cluster.

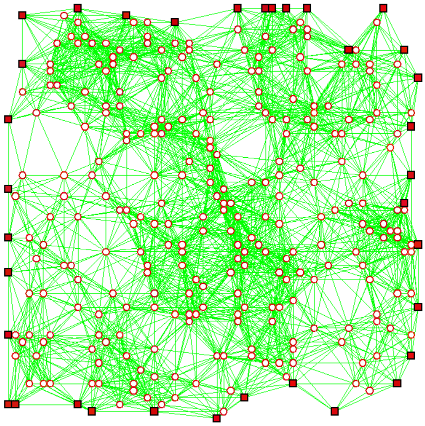

Fig. 6. A simulation of Guard-Resident Decision

Note that in CRAHN, each node can only decide its state (guard or resident) according to the limited local information. Most existing work on concave hull searching is not distributed and needs position information. Paper [14] proposed a distributed boundary search method but it assumed dense node connectivity, which only has limited applications. The distributed boundary search algorithm we present in this paper assumes each node only has its neighbor's direction information, which is represented by the counter-clockwise angle θ from one edge to another (see Fig. 7).

The guard-resident decision contains two steps, the first is distributed convex hull searching aimed to find a rough boundary and the second is distributed concave hull expanding aimed to expand some nodes as the boundary nodes for the final concave hull (Fig. 8).

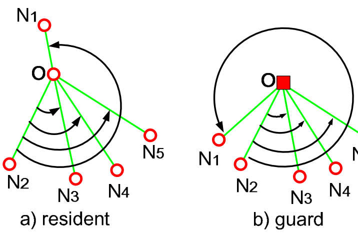

Fig. 7. Guard and resident

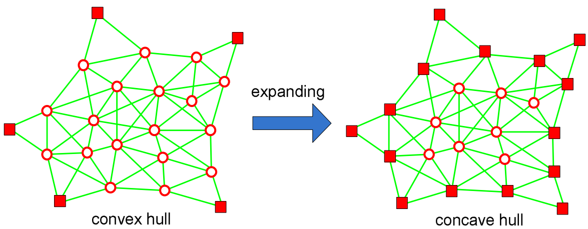

Fig. 8. Distributed boundary search algorithm

3.2.1 Distributed Convex Hull Search

As shown in Fig. 7. The spectrum neighbor of node O is denoted by N_i, i=1, 2, 3… Select an arbitrary edge ON_j, the counter-clockwise angle from ON_j to ON_i is $\{\theta_i | i = 1,2,3...\}$, define:

$$\Delta\theta = \min\{\theta_i \cup 2\pi | \pi < \theta_i \le 2\pi\} - \max\{\theta_i \cup 0 | 0 \le \theta_i \le \pi\} \tag{7}$$

Node O is called *guard* (boundary node) if $\Delta\theta > \pi$ (Fig. 7b). Otherwise, it is *resident* (interior node, Fig. 7a). The spectrum neighbors that achieve the "min" and "max" value in (7) are called the *left* and *right* spectrum neighbors of node O respectively. For example, for the guard node O in Fig. 7b, N_1 and N_5 are its left and right spectrum neighbors.

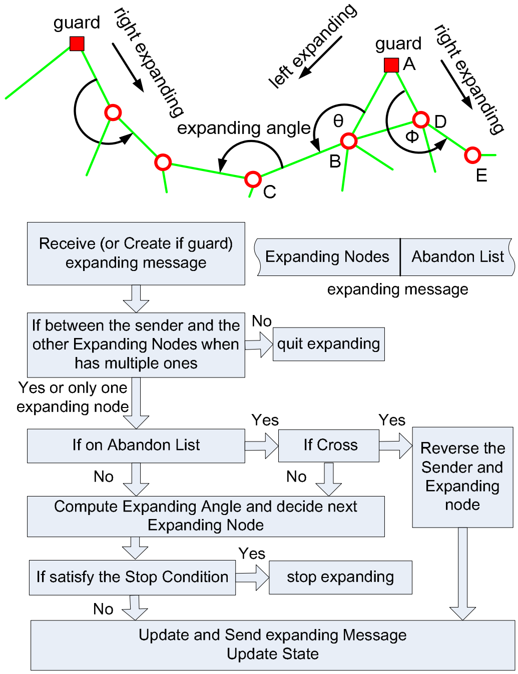

Fig. 9. Guard expanding procedure

3.2.2 Distributed Concave Hull Expanding

To better protect the residents and facilitate information exchange, we need to expand the rough guard boundary obtained from Section *3.2.1* to make it fully connected. As shown in Fig. 9, guard node *A* first expends to both its left spectrum neighbor *B* and right spectrum neighbor *D* so that node *B* and *D* change their status from resident to guard. Then node *B* further expands the guard boundary to *C* and *E*, where node *C* is called the *left expanding node* of *B* (*E* is the *right expending node* of *D*). The angel θ and ϕ are called *expanding angles* of the node *B* and *D*. The same procedure will continue till a stopping condition is met.

4 Simulation

To evaluate the performance of the proposed GRCSS scheme, we consider a rectangular service area with dimensions 1000m×1000m. There are totally 100 frequency channels. The communication radius of the node is 30m.

4.1 Single Cell Scenario

As shown in Fig. 10, we scatter 500 nodes in a given area. The *SNR* is set as 5db. After running our distributed guard-resident algorithm, overall 82 percent of the nodes become residents (hollow round node) (see Table 1), which means the majority of the nodes are released from constant spectrum sensing.

Table 1. The resident ratio of single cell scenario

Color	red(small group)	red(large group)	total
Guard	23	66	89
Resident	22	389	411
Ratio	49%	85%	82%

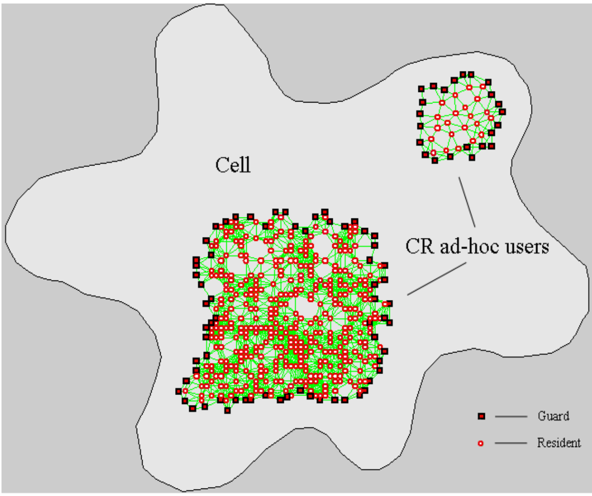

Fig. 10. Single cell scenario

When the detection error rate goes to 40%, we show the result in Fig.11, where many nodes make incorrect clustering decisions.

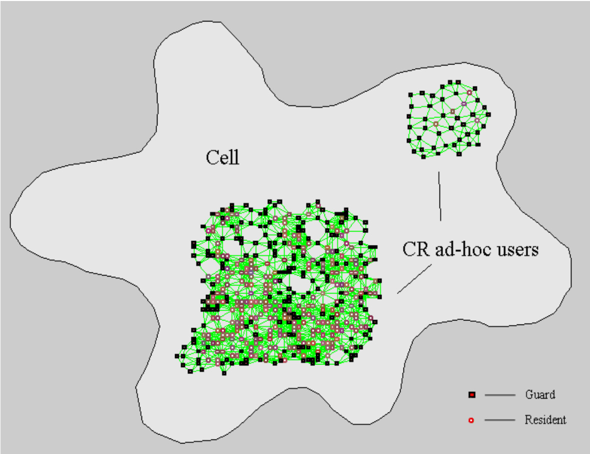

Fig. 11. Clustering error caused by detection error

4.2 Multi-Cell Scenario

As shown in Fig.12, the frequency channels are evenly allocated to three cells with overlap but no frequency reuse. The whole area forms seven different spectrum zones and the NHD between every two adjacent zones equals 0.33; the *SNR* is 5db. We can get the result in Fig. 12 (Different colors denote different sensing results) and Table 2.

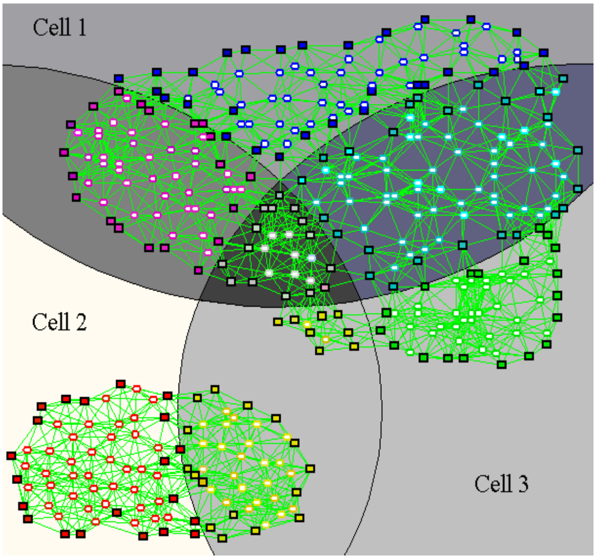

Fig. 12. Multi-cell scenario

Table 2. The resident ratio of multi-cell scenario

Color	purple	blue	cyan	gray	yellow	green	red	total
Guard	20	29	25	15	24	19	21	153
Resident	37	39	54	8	27	31	39	235
Ratio	65%	57%	68%	35%	53%	62%	65%	61%

Obviously, from the computation point of view, larger node density yields better performance. On the other hand, we also want to control the size of the cluster to make sure communications are effective within the same cluster.

5 Conclusion

This paper proposed a new guard-resident cooperative spectrum sensing method based on cluster theory and distributed boundary search. We grouped the nodes into two types: guard nodes and resident nodes. The guard nodes will constantly sense the spectrum and inform the environmental changes to their residents. Within the coherent time period, the area formed by the guards becomes a safe zone and the residents can be free from spectrum sensing. The analysis and simulation results suggest that the proposed scheme can reduce the total sensing load of the CRAHN significantly.

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