Distributed Clustering in Cognitive Radio Ad Hoc Networks Using Soft-Constraint Affinity Propagation

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Abstract. *Absence of network infrastructure and heterogeneous spectrum availability in cognitive radio ad hoc networks (CRAHNs) necessitate the self-organization of cognitive radio users (CRs) for efficient spectrum coordination. The cluster-based structure is known to be effective in both guaranteeing system performance and reducing communication overhead in variable network environment. In this paper, we propose a distributed clustering algorithm based on soft-constraint affinity propagation message passing model (DCSCAP). Without dependence on predefined common control channel (CCC), DCSCAP relies on the distributed message passing among CRs through their available channels, making the algorithm applicable for large scale networks. Different from original soft-constraint affinity propagation algorithm, the maximal iterations of message passing is controlled to a relatively small number to accommodate to the dynamic environment of CRAHNs. Based on the accumulated evidence for clustering from the message passing process, clusters are formed with the objective of grouping the CRs with similar spectrum availability into smaller number of clusters while guaranteeing at least one CCC in each cluster. Extensive simulation results demonstrate the preference of DCSCAP compared with existing algorithms in both efficiency and robustness of the clusters.*

Keywords

Cognitive radio ad hoc networks, clustering, soft-constraint affinity propagation, robustness.

1. Introduction

Firstly coined by Mitola in 1999 [1], cognitive radio (CR) is a promising technology for solving the problem of the coexistence of spectrum scarcity for new applications and low usage ratio of the allocated spectrum in wireless communication [2]. Based on the latest development of soft-defined radio technologies, CR enabled users (CRs) can dynamically sense the network environment, find idle spectrum, and reconfigure operation parameters to access the temporally unused spectrum opportunistically without insufferable interference to licensed users (also referred as primary users, PUs). This flexibility enables CR networks to increase spectrum efficiency and accommodate to various application requirements through self-organization and dynamic reconfiguration. In the infrastructure-less cognitive radio ad hoc networks (CRAHNs), CRs have to execute multi-hop communications in absence of the central network control utilities. The end-to-end performance is challenged by the distributed multi-hop architecture, dynamic network topology, diverse quality of service (QoS) requirements and time and location varying spectrum availability [3], necessitating extensive research before large-scale deployment of CRAHNs [4].

As the interference to PUs is strictly restricted, CRs should vacate the spectrum on detecting the presence of PUs. Spectrum availability in CRAHNs is determined by the spatial distribution and spectrum usage of PUs, resulting in dynamic spectrum heterogeneity across the network. This dynamic and unreliable spectrum environment proposes special challenges for efficient utilization of idle spectrum in multi-hop collaboration. For media access control, messages with information for resource reservation and competition need to be exchanged among CRs. Yet the dynamic multi-channel environment induces much time and power cost to the process [5]. From routing perspective, the route establishment involves a partial or network-wide route request broadcast and reply process while the constructed routes are expected to be stable and reliable to avoid frequent re-routing which is prone to induce broadcast storm, radio resources waste and degradation of end-to-end network performance such as throughput and delay [6], [7]. Furthermore, partial network information is preferable for local spectrum decision taking control overhead into consideration although it is true that optimal spectrum decision requires whole networks information [8], [9]. Thus it is desirable to construct relatively stable network structure to facilitate local and end-to-end spectrum collaboration.

Clustering is an effective management methodology in ad hoc networks for its capability of guaranteeing system performance in dynamic network environment with benefits of facilitating spatial reuse of spectrum, providing a virtual network backbone and making the network smaller and more stable to each node [10]. Compared with the homogeneous single channel environment in traditional ad hoc networks, the dynamic multi-channel environment makes clustering in CRAHNs fundamentally different from its counterpart in traditional wireless networks. The connectivity of the network depends not only on the geographical locations but also on the spectrum availability, which is likely to be similar for neighboring CRs. Thus clustering in CRAHNs should make use of the inherent grouping property in location and available spectrum of CRs to construct efficient and relatively stable structure in CRAHNs [11].

In CRAHNs, a dedicated common control channel (CCC) is critical for the efficiency of message exchange for clustering as well as the spectrum collaboration in the network after clustering [12]. However, the assignment of CCC is a challenging issue in the dynamic spectrum availability environment. One possible solution is to reserve a global CCC (GCCC) for the whole network, such as in ISM band [13], [14] or guard band of OFDM in the network using OFDM technique [15]. While simple, this method is not very practical since the ISM band has been crowded and large numbers of cognitive radio networks will emerge in the future. Moreover, the GCCC is prone to become the bottleneck of the network even if the reservation can be done. Another approach is to work without CCC and all available channels are checked before communications [16], [17]. While avoiding the disadvantages of GCCC, large communication overhead and end-to-end delay may be caused. On the other hand, CRs may share numerous local CCCs (LCCCs) with neighboring users [18]. Thus it is practical and preferable to investigate the solution that groups CRs into clusters with LCCC(s) while not relying on GCCC.

In CRAHNs, practical and efficient clustering algorithm should partition CRs that share similar spectrum into same clusters while do not rely on predefined GCCC. In this paper, we address the clustering algorithm with the following cluster characteristics concerned:

(1) Cluster numbers

In the cluster-based ad hoc networks, a cluster is one unit for distributed spectrum collaboration. Inter-cluster communications require much more control overhead and delay than intra-cluster communications, especially when the delay resulted from CCC switching between different clusters is concerned. As a result, clustering CRs into fewer clusters is beneficial for reducing communications overhead and end-to-end delay.

(2) Usable channel numbers for intra-cluster links

There are two benefits for an intra-cluster link sharing more common usable channels. Firstly, stability of the cluster structure is desirable to guarantee the performance of multi-hop communications. However, the variation of PUs activity may change the spectrum availability in the network. If some local variations cause completely rebuilt of the network, defined as ripple effect of re-clustering in [19], the cluster structure would be too fragile to be used in CRAHNs. Secondly, a CR user is probably to have more information exchange, direct communication or retransmitting for others, with intra-cluster neighbors. Thus it is preferable for both efficiency and reliability to cluster the CRs sharing more spectrum similarity into same clusters.

(3) Intra-cluster LCCC number

Existence of intra-cluster CCC is essential in facilitating local and end-to-end spectrum sharing. But a LCCC may change to unusable if any PU occupies it. Thus it is desirable to construct clusters with more intra-cluster LCCC for robustness of the clusters.

In practice, the after mentioned three aspects are interactional with each other. To minimize cluster number in the network, more CRs are expected to be clustered into same clusters. On the other hand, partitioning more CRs into same clusters may weaken the robustness of clusters because of the reduction of the intra-cluster spectrum similarity and the intra-cluster LCCC guarantee may not be provided. As a sequence, a comprehensive clustering model is needed to cluster the CRs sharing more spectrum similarity into smaller number of clusters. In data clustering community, affinity propagation (AP) [20] is a recently proposed technique with remarkable preference over traditional clustering methods such as K-means and spectral clustering. Soft-Constraint AP (SCAP) is an important improvement of AP to generate hierarchical structure in the cluster [21]. In this paper, we propose a Distributed Clustering algorithm using SCAP message passing model (DCSCAP), which groups neighboring CRs with similar available channels into smaller clusters to provide efficient and robust network architecture in CRAHNs. Following DCSCAP, CRs ascertain neighboring topological information through distributed parallel message exchange following the message passing model of SCAP. On the basis of the accumulated information, clusters are formed with the objective of grouping the CRs with similar spectrum availability into smaller number of clusters while guaranteeing at least one LCCC in each cluster. In summary, the contributions of this paper are three folds:

(1) We analyze the feasibility and advantages of using SCAP in the distributed clustering in CRAHNs theoretically.

(2) We propose a practical clustering algorithm based on SCAP. As it only relies on parallel message exchange on usable channels, the algorithm is thoroughly distributed and scalable for large-scale networks.

(3) Different with original AP and SCAP, the message passing iterations in DCSCAP are small, making the clustering overhead low. Extensive simulations demonstrate the validity of this assignment. This is a key step for the applications of AP because too many iterations as adopted in data clustering are not applicable for distributed collaboration in CRAHNs where message exchange is time and bandwidth consuming.

The remainder of this paper is organized as follows. Section 2 introduces the related work. Section 3 presents the system model and analyzes the feasibility and advantages of using SCAP in CRAHNs theoretically. Section 4 describes the proposed clustering algorithm. Section 5 evaluates the performance of DCSCAP through simulation and section 6 concludes the paper.

2. Related Work

Extensive research has been conducted on clustering in traditional ad hoc networks and a comprehensive survey of the algorithms is presented in [10]. However, the dynamic unreliable spectrum availability in cognitive radio networks introduces new challenges for distributed collaboration in cognitive radio networks. In this section, we review and analyze the existing works on distributed clustering in CRAHNs.

A cluster-based CR network framework and the corresponding topology management algorithm are proposed in [22], [23]. Following the scheme, each un-clustered CR user chooses the channel with the largest number of neighbors as LCCC and constructs a cluster in the initial phase, which is followed by a local minimal dominating cluster merging algorithm (LMDS) to reduce cluster number. This algorithm optimizes the cluster size while guaranteeing one LCCC in each cluster. However, the robustness of the cluster structure is not considered and re-cluster is easily caused by variation in the spectrum availability, resulting in more control overhead in turn. Furthermore, the rough clustering in the initial phase limits its performance in reducing cluster numbers.

To facilitate hierarchical spectrum sharing in CR networks, a clustering algorithm based on spectrum similarity is proposed in [24]. At the initialization state of the algorithm, every CR node computes the degree W of correlation of available channels with neighbors, which plus one if the correlation is higher than a threshold K. Then the degree W is broadcasted and exchanged among neighbors and nodes with maximal local degree are selected as cluster heads to construct clusters. Theoretical analysis and simulation result indicate that clustering stability is ensured only if threshold K is properly selected. However, the determination of appropriate K is not investigated. Furthermore, LCCC is not guaranteed in each cluster.

Li et al. [16] propose a network construction scheme to form clusters and facilitate network management. Following the scheme, the first node that does not detect any active CR node in neighborhood broadcasts a message on the usable channel that has least PUs interference to construct a cluster and the neighbors that hear the message join the cluster if the interference between the node and the leader is less than a threshold. Interference level on the control channel is optimized in this scheme and the existence of LCCC in each cluster can be guaranteed. However, the intra-cluster spectrum similarity and cluster numbers are not optimized.

In [25], a cluster formation protocol (Combo) for CRAHNs is proposed with a network coded control channel for spectrum coordination and cluster management. Neighbor information within k-hops is attained to compute a weighted priority key which successively prefers common channel number, k-degree of connectivity and ID of the node. The user with largest priority key in k-hops is elected as the cluster head. More common available channels are guaranteed in each cluster, which are claimed to be more efficient in control information exchange for their network coded form. However, since the number of intra-cluster common channels is preferred in the optimization, the number of generated clusters by Combo is prone to be small.

A spectrum opportunity-based control channel assignment and clustering scheme (SOC) is proposed in [11], taking maximizing the product of number of common channels and size of cluster as the objective. This algorithm provides a middle course between the number of common channels and the size of clusters. The hopping sequence on the common channels in a cluster is taken as CCC of the cluster, making the cluster effective until all common channels are unavailable. However, the channel hopping phase devotes too much spectrum resource on control function, which limits the throughput of the network.

In [26], we have proposed a clustering algorithm based on local common channel (CLCC) and corresponding dynamic topology management scheme for the environment in which the channel availability changes fast. CLCC optimizes the cluster size on the constraint of two LCCC in each cluster and updates the cluster structure with the channel variation in the networks. Although extensive simulations have demonstrated that CLCC can guarantee the intra-cluster CCC and the cluster numbers are relatively small, the cluster structure cannot be fully optimized as the result of rather limited message exchanged in the fast-changing channel environment. In this study, we investigate the practical clustering algorithm in a slowly changing network environment in which more message exchange is allowed.

As a revolutionary clustering technique, AP has already been used in clustering of ad hoc networks. A distributed clustering algorithm for vehicle ad hoc networks is proposed in [27] with the plus of distance and relative velocity as similarity function. Following the algorithm, fewer and more robust clusters are produced. Yet the algorithm is only suitable for the homogeneous spectrum environment. The AP message passing model is firstly used for clustering in CRAHNs in [28], in which the spectrum comparability is adopted as partition basis. Smaller numbers of clusters are produced with more similar available channels. However, the algorithm requires too many rounds of message passing for convergence, consuming too much time and bandwidth. Furthermore, the existence of LCCC cannot be guaranteed in the clusters. There are two differences in our algorithm compared with existing AP applications in ad hoc networks. Firstly, we use SCAP model to optimize clusters in two hops rather than original AP which is probably to generate only star clusters. Secondly, the message passing iterations are restricted to a much smaller number and extensive simulations have demonstrated its feasibility and advantages. This is essential for the applicability of SCAP and AP in CRAHNs.

3. Assumption and System Model

3.1 System Architecture

We consider CRAHNs that coexist with randomly distributed PUs in the same geographical area. Spectrum in the network is divided into a non-overlapping channel set $\boldsymbol{M} = \{1, 2, \ldots, M\}$. Each PU is assigned a specific channel. Each CR user in the CRAHN is equipped a half-duplex CR transceiver that can turn to different channels for sensing or transmission. A CR user can access only one channel for transmission at the same time. Interference to PUs from CRs is strictly controlled that CRs should immediately vacate the channel once sensing PU activity on it. Fig. 1 depicts a typical example of the concerned CRAHN scenario in this study. The subscripts of PUs indicate their identities as well as the licensed channels and the numbers in the brackets besides the CRs denote their available channels. It can be observed in the figure that different CRs in CRAHNs have different available channel sets because of the channel utilization of PUs.

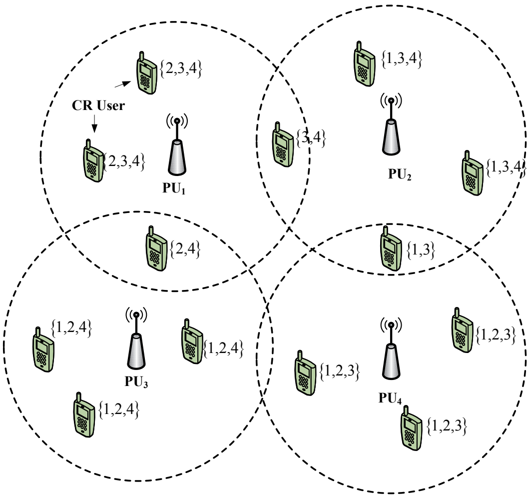

Fig. 1. A CRAHN scenario with spectrum heterogeneity.

We assume the network is time-slotted with perfect synchronization. Every node knows its coordinates which are embedded in the interaction message and implied in their IDs hereafter for illustration concision. Node mobility is assumed to be slow and the channel availability changes at a relatively low rate such that the topology does not change during the clustering process.

3.2 Problem Formulation

The network is modeled as an undirected graph $G=(N, E)$, in which N denotes the node set of CRs and E are the edge set corresponding to the bidirectional links between nodes. Each node in CRAHNs is assigned a unique ID i ($i = 1, 2, \ldots |N|$). The channels without PUs activity are regarded to be available for CRs and node i determines its available channel set $C_i = \{i_1, i_2, \ldots, i_k\}$ ($k \geq 0$) by independent spectrum sensing. Due to the heterogeneous distribution and channel utilization of PUs, C_i may be different for different nodes in the network. All nodes are assumed to have same radio range L. Thus adjacent nodes i and j are neighbors for each other if and only if:

$$C_i \cap C_j \neq \varnothing, \tag{1}$$

$$l_{ij} \leq L \tag{2}$$

where l_{ij} denotes the geographical distance between the two nodes. We designate a set e_{ij} to indicate the neighbor relationship of two node i and j, such that

$$e_{ij} = \begin{cases} C_i \cap C_j & l_{ij} \leq L \\ \varnothing & otherwise \end{cases} \tag{3}$$

The precondition of clustering is to acquire the information of neighbors, defined as neighbor discovery. Yet neighbor discovery is itself a challenging issue in CRAHNs, details of which are out of the scope of this paper. In the following, we assume the neighbor information has been attained through some neighbor discovery algorithm, such as that in [11], including 1-hop neighbor list N_i, available channel set of neighbors $C_k\,(k \in N_i)$ and 1-hop neighbor list of the 1-hop neighbors $N_k\,(k \in N_i)$.

Suppose that the network is clustered into cluster set $\{G_1, G_2, \ldots G_k\}$ based on the neighbor information and a cluster head h_l is chosen for each cluster $G_l\,(l = 1, 2, \ldots k)$ as the local manager. A LCCC shared by all the members of a cluster is assigned as the Cluster ConTrol Channel (CCTC) of the cluster. To guarantee the existence of CCTC, the following constraint should be satisfied

$$\left| \bigcap^{i \in G_l} C_i \right| \geq 1,\ l = 1, 2, \ldots k \tag{4}$$

in which the operator $|\cdot|$ denotes the cardinality of a set.

In the clustered CRAHNs, the more channels available for a link between two nodes in the same cluster, the more robust the link is in the unpredictable or hard predictable PUs activity environment. And it is reasonable to regard the cluster with more robust intra-cluster link to be more stable. On the other hand, fewer clusters are preferable in communication overhead and end-to-end delay. Considering both of the two factors, we formulate the clustering problem in CRAHNs as follows:

$$\max \quad \frac{\sum_{l=1}^{k} \sum_{i \in G_l} \sum_{j \in G_l \cap N_i} |e_{ij}|}{\sum_{l=1}^{k} \sum_{i \in G_l} |G_l \cap N_i^{'}|} - \lambda \cdot k \tag{5}$$

$$s.t. \quad \left| \bigcap^{i \in G_l} C_i \right| \geq 1, \qquad l = 1, 2, 3, \ldots k$$

$$\lambda > 0$$

where λ is a parameter to coordinate the number and robustness of clusters. In the former term of the objective function (5), the numerator indicates the sum of all usable channels for intra-cluster links in the network and the denominator stands for the number of intra-cluster links, making the term represent the average number of available channels of each intra-cluster link. The latter term is a penalty term related to generated cluster numbers. The penalty term is imported to improve the efficiency and bigger λ results to heavier penalty on increasing numbers of cluster. Thus the objective function (5) makes a middle course between communication efficiency and robustness of the generated clusters.

Problem (5) is NP-hard in general [29] and the choice of λ is complex in different network environment. In the following, we will analyze the feature of SCAP to investigate a practical and preferable clustering algorithm in CRAHNs.

3.3 SCAP Messaging Passing Model

AP is a recently proposed and widely concerned clustering technique for finding good partitions of large data sets [20]. Although AP has been validated to be more accurate and efficient than traditional clustering algorithms, the hard constraint which requires each exemplar (cluster head) point to itself forces the clusters to appear as stars with radius one, resulting in the loss of all information about both the internal structure and hierarchical merging/-dissociation of clusters. Regarding of this disadvantage, Leone et al [21] replace the hard constraint with soft constraint and propose an improved algorithm SCAP. Taking all data points as potential exemplars, SCAP relies on the parallel message passing among points to solve the following optimization problem

$$\arg\max(E[\mathbf{c}]) \tag{6}$$

subject to
$$E[\mathbf{c}] = \sum_{i=1}^{N} s(i, c_i) - \delta \times \sum_{j=1}^{N} \ln \chi_j \tag{7}$$

$$\chi_j = \begin{cases} \beta & if\ c_j \neq j,\ \exists i,\ s.t.\ c_i = j, \\ 1 & otherwise \end{cases} \tag{8}$$

where N is the number of data points, $\mathbf{c} = (c_1, c_2, \ldots c_N)$ is the mapping between the data and their exemplars, $\delta > 0$ is a penalty coefficient for clusters, $\beta \in [0,1]$ is a penalty if data i is chosen as an exemplar by some other data point without being a self-exemplar itself, and $s(i, c_i)$ is the similarity between data point i and its exemplar c_i. The first term in (7) denotes the sum of similarities between data points and their exemplars and the second term constrains the number of generated clusters. With the optimization function (6), SCAP aims to cluster data points that share most similarities into fewer groups while allows hierarchical intra-cluster architecture by using nonzero penalty β. When the parameter β is set to zero, SCAP degenerates to AP.

SCAP takes the similarity matrix $\boldsymbol{S} = [s(i,j)]_{N \times N}$ as input, where the similarity $s(i, j)$ indicates the appropriateness of serving as the exemplar of each other for the two points. The self-similarity $s(i,i)$ is also defined as preference with $p(i) = s(i,i)$, indicating the preference of i to be an exemplar. The choice of preference vector $\mathbf{P} = (p(1), p(2), \ldots p(i))$ influences the generated exemplars and larger preference results in fewer exemplars.

Based on the similarity matrix, two kinds of messages are passed among data points iteratively. The responsibility $r(i,k)$, sent from point i to candidate exemplar k, reflects the accumulated evidence for how well-suited point k is to serve as the exemplar of i, taking into account other potential exemplars for point i. The availability $a(i,k)$, sent from candidate exemplar k to data point i, reflects the accumulated evidence for how appropriate it would be for point i to choose point k as its candidate, taking into account the support from other points that k should be an exemplar. The iterative exchange of responsibility and availability are illustrated in Fig. 2. As can be seen in the figure, based on the availability information from other potential exemplars (k' and k''), node i sends $r(i,k)$ to node k to indicate the preference of choosing k as its exemplar. Similarly, node k sends $a(i,k)$ to node i to indicate the preference of i to choose k as its exemplar.

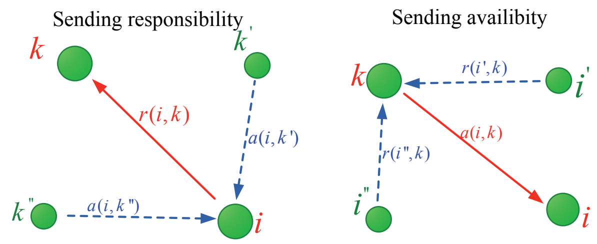

Fig. 2. Responsibility and availability exchange.

All availabilities are initialized to zero and then responsibilities and availabilities are updated iteratively using

$$\underset{i \neq k}{r(i,k)} \leftarrow s(i,k) - \max_{k' \neq k}[a(i,k') + s(i,k')], \tag{9}$$

$$r(i,i) \leftarrow \max\{-\gamma, s(i,k) - \max_{k' \neq k}[a(i,k') + s(i,k')]\}, \tag{10}$$

$$\underset{i \neq k}{a(i,k)} \leftarrow \min[0,\ r(k,k) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))], \tag{11}$$

$$a(k,k) \leftarrow \min[\gamma, \sum_{i' \neq k} \max(0, r(i',k))] \tag{12}$$

where γ is an additional threshold (compared with AP) on the self-availability and self-responsibility. In practice,

γ indicates that data points are discouraged to be self exemplars beyond a given threshold even being chosen by some other points.

After each iteration, the exemplar of any data point i is chosen following

$$c_i = \arg\max_j [r(i,j) + a(i,j)]. \tag{13}$$

The algorithm converges if there is no change in the exemplars for a large number of iterations (typically 10~100 iterations) or the maximal iteration (typically 100~1000 iterations) is reached.

The consistency of the objective of SCAP and the clustering formulation (5) and the justified superiority of SCAP make it profitable to investigate efficient clustering algorithm for CRAHNs based on SCAP model. Furthermore, the distributed characteristic of SCAP is suitable in the application of CRAHNs. In the next section, we present a distributed clustering algorithm based on SCAP clustering model to give a desirable solution of problem (5).

4. DCSCAP

The proposed algorithm is a distributed application of SCAP message passing model in CRAHNs. Each node in the network transmits messages which include the responsibility and availability to its neighbors and then makes decisions independently based on the received messages.

4.1 Overview of the Algorithm

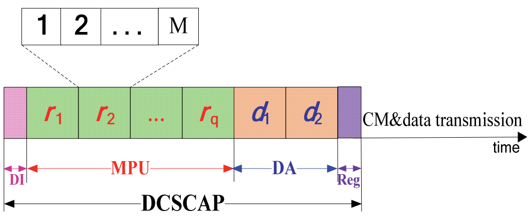

Fig. 3. Overview of DCSCAP.

Based on the neighbor information attained from neighbor discovery process, the objective of DCSCAP is to group CRs that share similar available channels into smaller number of clusters while guaranteeing at least one LCCC in each cluster. To achieve that, the operation of the algorithm is composed of four phases as illustrated in Fig. 3: definition and initialization (DI), message passing and update (MPU), decision and announcement (DA) and registration (Reg). After cluster formation, multi-hop data transmission can be served while cluster maintenance (CM) function is executed to accommodate to the variation in the network.

4.2 Definition and Initialization

The definition of similarity and preference of SCAP is the basis of clustering. In the spectrum diversity environment of CRAHNs, grouping the nodes that share a relatively high number of common available channels into same cluster would benefit local and global spectrum collaboration as well as the robustness of the clusters. On the other hand, the generated clusters may larger if the neighboring two nodes share more common neighbors. Thus the similarity of two nodes i and j in DCSCAP is defined as

$$s(i,j) = |e_{ij}| \times (|N_i \cap N_j| + 2) \tag{14}$$

in which e_{ij} is defined in (3). It can be observed from (14) that the similarity is bigger for the nodes that share more common available channels and common neighbors, which is essential for the optimization of DCSCAP.

The preference is another important parameter that influences the generated network structure. The relative difference among the preferences of different nodes results in different chances to be selected as cluster heads. Therefore, different from the same definition in the existing applications of AP (such as that in [27], [28]), preferences defined in DCSCAP are node-specific. For clustering in CRAHNs, the nodes with more available channels are preferable to be selected as cluster heads since such nodes can serve intra-cluster management and inter-cluster communications better. On the other hand, to generate fewer clusters, each cluster head should select the channel with most neighbors as CCTC and constructs the cluster in the decision and announcement phase. Thus the preference in DCSCAP for node i is defined as

$$p(i) = -|C_i| \times \max_{m \in C_i} \{|N_i^m|\}. \tag{15}$$

Based on the limited neighbors information N_i, C_k and N_k $(k \in N_i)$ (as illustrated in subsection 3.2), node i computes its preference and the similarities with neighbors according to (14) and (15), respectively. Then the responsibility and availability are initialized as $r(i,j)_0 = s(i,j)$ and $a(i,j)_0 = 0$ for all $j \in N_i \cup \{i\}$.

4.3 Message Passing and Update

During this phase, each node i maintains and updates a neighbor information table T_i which has an entry t^i_j for each neighbor j $(j \in N_i)$.The contents contained in t^i_j are listed in Tab. 1.

Field	Content
$s(i,j)$	latest responsibility received from j
$a(i,j)$	latest availability received from j
$s(j,i)$	latest responsibility sent to j
$a(j,i)$	latest availability sent to j

Tab. 1. Content of t^i_j.

As there is no predefined GCCC or central control utilities to dominate the clustering process, all CRs in the networks hop on the global channel set M to exchange messages for clustering. As illustrated in Fig. 3, this phase consists of q rounds of common hopping sequence on $\boldsymbol{M}$. And during each round, nodes in the network turn to each channel $m \in M$ successively in the slot corresponding to channel m.

If $m \in C_i$, node i broadcasts a message with its neighbor information table T_i embodied following a 1-persistent CSMA mode. Meanwhile, the neighbor information tables of neighbors are also collected on the channel.

If $m \notin C_i$, node i just stays idle in the slot to avoid interference to PUs.

At the end of each round, the neighbor information table of each node is updated using (9) ~ (12). And the new table will be exchanged in the next round.

The number of rounds is a predefined parameter q which is known by every node, guaranteeing synchronous termination of the message passing process in the network. The simulation in section 5 will demonstrate that the value of q can be set to be a relatively small number for time and energy efficiency.

4.4 Decision and Announcement

This phase consists of two rounds on global channel set $\boldsymbol{M}$ as that in the last phase. Through this phase, nodes determine their roles in the cluster structure and form clusters based on the information attained from the message passing in the last phase.

At the beginning, if node i figures out (from the neighbor information tables) that the following condition can be satisfied

$$r(i,i)+a(i,i) \geq r(i,k)+a(i,k),\ \forall k \in \{N_i \cup N_k, k \in N_i\} \quad (16)$$

it chooses itself as a cluster head and selects channel $m \in C_i$ that has most one hop neighbors on it, i.e.,

$$m = \arg\max_{m \in C_i} \{|N_i^m|\} \quad (17)$$

as CCTC of the cluster. Otherwise, node i ascertains that it is better to choose some other node as cluster head.

In the first round of this phase (d_1 in Fig. 3), each cluster head i broadcasts a cluster head announce message (CHAM) with its ID and CCTC embodied on all their available channels following similar way in the last phase. At the same time, all nodes collect CHAMs from neighbors. At the end of this round, non-head nodes that have received one or several CHAM(s) in the round choose their cluster heads following the criterion in (13). The chosen CHAMs are rebroadcast in the second round to announce their choice. At the end of the round, nodes that have received the rebroadcasted CHAMs determine their cluster membership as that in the first round.

There is a possibility that some nodes have not received any CHAM by the end of this phase. These nodes will ascertain their roles in the next phase.

4.5 Registration

Cluster members register to their cluster heads in this phase. As the clustered nodes have known the CCTCs of their clusters, it is not necessary to hop on $\boldsymbol{M}$ any more. Each cluster head waits on its CCTC and cluster members send registration message to their heads on CCTCs to affirm their membership.

The nodes that have not received any CHAMs in the last phase listen on the channel with most neighbors. If some registration messages are received, they conclude that there is at least one cluster head within two hops and try to join the most appropriate one. If none registration message have been received by the end of the phase, the nodes will select themselves as cluster heads and assign the channels with most one hop neighbors as CCTCs.

Through the above assignment, we restrict the maximal hops between the cluster member and its cluster head to three in DCSCAP. And it is straightforward to very the constraint by changing the assignment in subsection 4.3.

4.6 Cluster Maintenance and Re-clustering

After cluster formation, cluster heads in the networks take charge of cluster maintenance by broadcasting on CCTCs. The local spectrum reservation and multi-hop route establishment and maintenance can also negotiated on CCTCs.

However, re-cluster is unavoidable and may be preferable in overhead reduction if the change of network accumulates to some degree. Thus the clustering process should be repeated periodically. The preference of the DCSCAP lies in the fact that the interval between two clustering process can be much longer because of the robustness of the structure.

5. Performance Evaluation

In this section, we adopt simulation to evaluate the performance of the proposed clustering algorithm. We consider a CRAHN scenario in which CRs are randomly deployed in a 200 m × 200 m square domain. The number of channels in the network is 20. To simulate spectrum heterogeneity, 50 PUs locate randomly in the same area and each is randomly assigned a channel. The interference range of PUs is 15 m in which domain the channels used by PUs cannot be used by CRs. The communication range of CRs is set to 10 m and each CR user can access one idle channel for communication at the same time. The simulation results in this section are the average on 100 randomly generated topologies.

As references, DCSCAP is compared with two recently proposed distributed clustering algorithms in CRAHNs: a) Combo-2 in [25] and CLCC in [26]. In the simulation, the parameter γ of DCSCAP is set to 10 and we vary the number of round q in DCSCAP to observe its influence on the performance of the clustering algorithm. The metrics to evaluate the performance of the clustering algorithms include: a) cluster numbers, b) average number of available channels for each intra-cluster link, c) number of LCCCs in each cluster, and d) cluster survival ratio, in which the former two metrics indicate the efficiency of the generated cluster architecture in serving multi-hop communications, the later two reflect the robustness of the clusters.

In Fig. 4, we compare the generated cluster numbers with the variation of CRs numbers in the network. It can be observed from the figure that DCSCAP always generates fewer clusters than its counterparts, which results from the feature of SCAP algorithm. As to the influence of the q to DCSCAP, it can be observed that the cluster numbers are almost the same when q=10, 15, and 100.

In the second simulation, we compare the number of available channels for each intra-cluster link which influences the robustness of clusters and the ability of serving intra-cluster communications. It can be observed from the results in Fig. 5 that the numbers of available channels do not change obviously with the variation of CRs density in the networks. The performance of DCSCAP is better than CLCC and almost the same as that of Combo-2, which prefer more intra-cluster common channels.

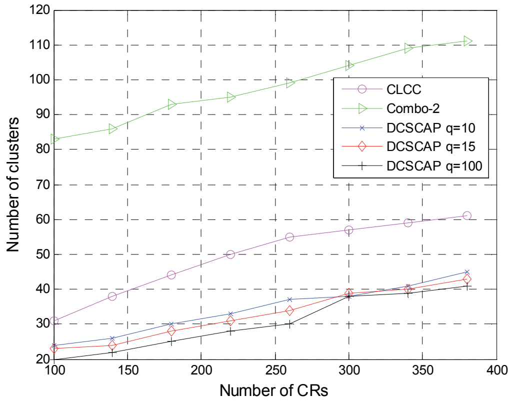

Fig. 4. Comparison of cluster numbers.

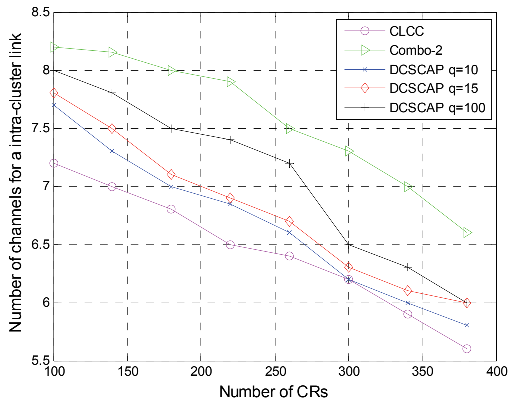

Fig. 5. Comparison of available channels for intra-cluster link.

Then we compare the number of LCCCs in each cluster, which is critical for the local and multi-hop communications in the clustered architecture. As can be seen from the results in Fig. 6, the clusters generated by Combo-2 have most LCCC numbers since it take more LCCCs as optimization goal. DCSCAP perform better than CLCC in this metric.

In the last simulation, cluster survival ratios are compared with the variation of channel availability in the network. To observe this metric, the simulation time is equally partitioned into unit period. At the end of each unit period, both the probability of a usable channel changing to unusable and the vise probability are set to 0.1. A cluster is regarded to be invalid if no LCCC can be used. As can be seen from the results in Fig. 7, the cluster survival ratio reduces as time elapses. Through dynamic topology management, i.e., re-selecting LCCCs in the clusters, CLCC performs best in the three algorithms. And the performance of DCSCAP is close to Combo-2.

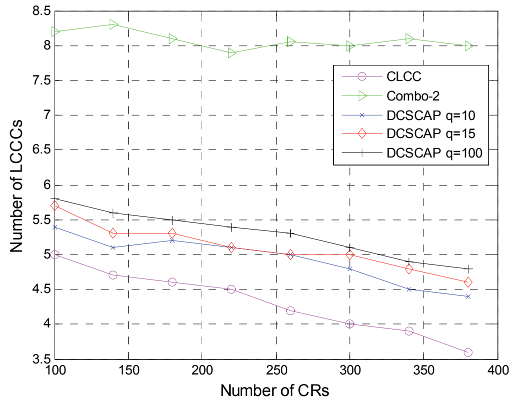

Fig. 6. Comparison of LCCCs in each cluster.

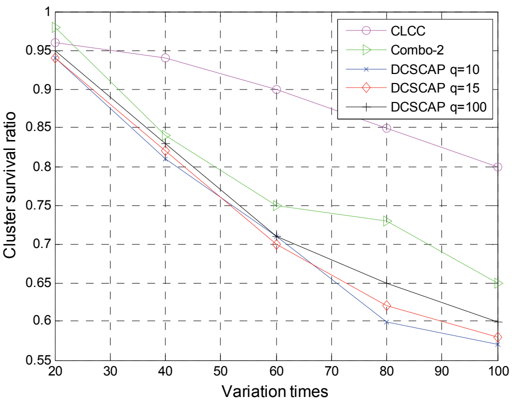

Fig. 7. Comparison of cluster survival ratio.

From the simulations in this section, two conclusions can be obtained. Firstly, DCSCAP generates much fewer clusters with similar or preferable number of LCCCs and usable channels of intra-cluster links. Secondly, a rather small number of message passing iterations of DCSCAP can generate close performance with large number of iterations. Thus q can be set to be relatively small for time and energy efficiency while not degrading the performance of DCSCAP a lot.

6. Conclusions

In this paper, we address the network management problem in CRAHNs and propose a distributed clustering algorithm based on the message passing model of SCAP. The objective of the algorithm is to group neighboring CRs with similar spectrum availability into smaller number of clusters. The algorithm does not rely on infrastructure or predefined GCCC, which make it scalable and applicable in CRAHNs. Simulation results demonstrate the preference of the proposed algorithm in both robustness and efficiency of the structure. The cluster structure is beneficial for multi-hop spectrum collaboration and our future work will focus on cognitive routing on this basis.

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