Correlation Based Secondary Users Selection for Cooperative Spectrum Sensing Network

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Abstract. Cognitive radio (CR) can significantly enhance spectrum efficiency by dynamical accessing the licensed spectrum. However, single user spectrum sensing may be inaccurate and the second user (SU) may preempt the channel of the primary users (PUs). The appearance of cooperative spectrum sensing (CSS) can effectively improve the spectrum sensing performance by fusing the results of multiple SUs' decisions to yield reliable decisions. Nevertheless, the communication overhead and the energy consumption of SUs bring a heavy burden for the resource limited secondary network. Therefore, in this paper, we propose a correlation based scheme to select representative SUs based on their correlation by using improved Density-Based Spatial Clustering of Applications algorithm (DSCN). First, we set a threshold to screen out SUs with good channel quality. Then, we propose a improved DSCN algorithm to select SUs that participate in CSS. This algorithm can select representative SUs based on their correlations. Simulation results show that the sensing overhead has been greatly reduced and the probability of detection

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and the probability of false alarm are better than the traditional spectrum sensing schemes.

Keywords: Correlation · Cooperative spectrum sensing · Improved DSCN · Sensing overhead

1 Introduction

With the rapid development of wireless communication technologies, a large number of equipments require to utilize the spectrum resources. The available wireless spectrum resources is becoming increasingly scarce. However, the researches show that even in hot spots, many of the authorized bands are idle for most of the time in most of the areas [1]. Therefore, due to the lacking flexibility in wireless spectrum resource management, the current spectrum allocation mechanisms can be improved. To enhance spectrum utilization and alleviate the shortage of spectrum resources, cognitive radio (CR) [2] is proposed to sense and utilize the idle licensed spectrum and dynamically access the spectrum.

Spectrum sensing is the main scheme to discover the available spectrum for utilization. Nevertheless, noise uncertainty, shadowing and multi-path fading significantly decrease the spectrum sensing. Noise uncertainty is caused by the time variability and non-uniformity of noise which decreases the accuracy and stability in spectrum sensing. Normally, the antenna beam of the communication ground station is wide, electromagnetic wave is affected by the surface features and landforms. Therefore, the receiver receives the electromagnetic waves produced by refraction, reflection and direct direction, which lead to a serious impact for the spectrum sensing. Large buildings and other objects block the path of the radio waves and inform a semi-blind area in the receiving area of the transmission, which leads to formation of shadowing.

Cooperative Spectrum Sensing (CSS) is proposed to improve the accuracy of spectrum sensing. In general, CSS uses AND and OR fusion schemes. However, during the fusion process, additional sensing overhead will be incurred because of communication and energy consumption. Moreover, extra information will occupy the storage resources of the fusion center. In [3], Meftah et al. proposed wideband CSS schemes based on the multi-bit hard decision, which could help CRN improve the detection of signal in a wide band and save time. In [4], in order to reduce the complexity of processing, Kartlak et al. presented a method based on the cycle-stationarity by selecting optimal relay to communication. [5] considered using double threshold detection method in CSS and determines whether PU is present by comparing double threshold with statistics. In [6], a dynamic spectrum sensing cycle was proposed by using the convex function of the energy detector's threshold to reduce the delay. [7] focused on the optimal number of secondary users in weighted cooperative spectrum sensing to improved the utility of CRN. These methods improve the detection accuracy to some extent, but there are still a great number of SUs which may cause too much sensing overhead.

In this paper, we propose a correlation based SUs selection scheme to select the representative SUs in CSS. In the proposed scheme, the SUs are clustered together in a given area which have the similar geography and communication conditions. Therefore, one secondary user's perceived results can be representative of the others. Density-Based Spatial Clustering of Applications with Noise (DSCN) is a clustering algorithm based on density. However, DSCN is based on the distance and can not completely reflect correlation among SUs. Thus, we proposed an improved the DSCN algorithm in order to select representative SU in a less dense area based on SUs' correlation. Compared with traditional CSS, this method alleviates the spectrum sensing overhead. Moreover, the probability of false alarm (P_f) and the probability of detection (P_d) in the proposed scheme can be improved. The simulation results show that the proposed improved DSCN enhances the detection performances and decreases sensing overhead compared with traditional spectrum sensing schemes.

The rest of this paper is organized as follows. In Sect. 2, we describe the system model. In Sect. 3, we explain CSS scheme for SU selection and propose the improved DSCN. Section 4 provides performance evaluation and simulation results and Sect. 5 concludes this paper.

2 System Model

2.1 Spectrum Sensing Hypothesis

This work considers a centralized CSS system with a primary user (PU), a fusion center (FC) and N SUs. FC is used to collect the perception results of each SU and fuse them. Then FC makes decision and returns the result. SUs detect channel idle condition and look for opportunities to use channel. In the proposed scheme, there is a set $\mathcal{L}\{1, 2, \cdots, L\}$ consisting of L SUs. All SUs are within FC's communication range and FC knows the distances from the SUs to FC. Let distance D from one SU to FC to be $\mathcal{D}\{d_1, d_2, \cdots, d_n\}$.

In CRN, the accuracy of spectrum sensing is to determine whether PU's signals $Si(t)$ appear based on the observed signals $Os(t)$. Therefore, we model it as a binary relationship:

$$Os(t) = \begin{cases} Gsn(t), & H_0 \\ Cg \cdot Si(t) + Gsn(t), & H_1 \end{cases} \tag{1}$$

where $Gsn(t)$ is zero mean additive Gaussian white noise and Cg denotes the channel gain between PU and SU. Hypothesis H_0 represents that PU is idle and hypothesis H_1 indicates that PU is presence. The spectrum sensing algorithm outputs the test statistics Λ from a series of processing of the observed signals in Eq. (1), and determines the availability of the licensed spectrum according to the test statistics Λ and the predetermined decision threshold λ. When $\Lambda > \lambda$, PU is of the presence. Otherwise, the channel is idle.

We use the P_d and P_f to measure performance indicators. They are defined as:

$$P_d = Pr\{E_1|H_1\}, \tag{2}$$

$$P_f = Pr\{E_1|H_0\} \tag{3}$$

where E_1 represents PU is present from the sensing result of the fusion. P_d means when PU signal is present, the probability that SU correctly detects the occurrence of PU signal. Higher P_d means better protection for PU. P_f denotes that PU is absent, the probability that SU incorrectly determines occurrence of PU signal. Higher P_f means lower spectrum efficiency.

2.2 Energy Detector

In this paper, we use energy detector to detect any zero mean and count independent signals. The energy detector determines whether the channel is idle by measuring the strength of the received signal. Equation (4) shows us the received power of user i:

$$P_i = \frac{P_{pu}}{d_i^{\alpha}}\beta_0 \tag{4}$$

where α is the path loss exponent factor; d_i is the distance between PU and SU_i. β_0 is a scalar and P_{pu} is the PU's signal power. Then the signal-noise ratio (SNR) γ_i of SU_i can be obtained as:

$$\gamma_i = \frac{P_i}{\sigma^2} \tag{5}$$

where σ is noise power. After SU_i obtains the SNR and makes decision whether the channel is idle, they send results to the FC. Section 3 will introduce the proposed scheme about the selecting of the representative SUs.

3 The Proposed Scheme of Improved DSCN

3.1 Fusion Algorithm

In this model, fusion center uses OR rules and AND rules. These two rules will use the same received data to get different results.

OR fusion rule means that the FC will declare that the PU is present as long as at least one SU detects the PU. The equations of P_d and P_f can be derived as [9]:

$$P_d = 1 - \prod_{i=1}^{k}(1 - P_{d,i}) \tag{6}$$

$$P_f = 1 - \prod_{i=1}^{k}(1 - P_{f,i}) \tag{7}$$

where k means total SUs participating in the fusion is k. $P_{d,i}$ is the SUs' detection probability and $P_{f,i}$ is SUs' false alarm probability about the licensed spectrum. AND fusion rule means that the FC will declare the PU is absent unless all of SUs detect the PU. The equations of P_d and P_f can be obtained as:

$$P_d = \prod_{i=1}^{k} P_{d,i} \tag{8}$$

$$P_f = \prod_{i=1}^{k} P_{f,i} \tag{9}$$

3.2 Correction of Shadow Fading

In the transmission receiving area, the large buildings and other objects block the path of the wave and form a semi-blind area, which form the electromagnetic shadow. Due to the shadowing effect, adjacent SUs experience almost the same fading effect, which degrades the performance of collaborative spectrum sensing. To improve spectrum sensing performance, we are required to select a representative SU from SUs with high spatial relevance to participate in the CSS.

First, Eq. (4) shows us that the received power of user i is inversely proportional to the distance d_i. It means that excessive distance causes SNR to be extremely low and significantly decreases SU_i's accuracy of detection. That is to say, the results from FC may be greatly influenced by SUs with low SNR. Therefore, we set a threshold ϵ to remove SUs with a SNR less than ϵ.

Then, according to the Logarithmic Distance Path Loss Model, the average received power decreases logarithmically with distance in both indoor and outdoor. For any send-receive (S-R) distance, the average path loss is expressed as [10]:

$$\overline{PALO}(dB) = \overline{PALO}(d_0) + 10nlog(\frac{d}{d_0}) \tag{10}$$

where d_0 is near ground reference distance determined by the test. n is the path loss index, indicating the growth rate of path loss with distance. d is the distance between receiver and transmitter. Therefore, to model the correlation properties we have used a decreasing correlation function as follows:

$$Crl(d) = e^{-d\theta} \tag{11}$$

where d is distance between two SUs and we define $d_{i,j}$ is the distance between SU_i and SU_j; θ is an environment based parameter and we set $\theta \approx 0.02/m$. When $d_{i,j} = 0$, $Crl(d_{i,j}) = 1$, it means SU_i and SU_j have full correlation. However, SU_i and SU_j have empty correlation if $d_{i,j} \rightarrow \infty^+$. Therefore, we set a threshold value δ $(0 < \delta < 1)$ to determine whether there is a good correlation between two SUs. Then we use 0 and 1 to represent the correlation between two SUs and we obtain the equation [11]:

$$Crl'(i,j) = \begin{cases} 1, & Crl(d_{i,j}) \geq \delta \\ 0, & Crl(d_{i,j}) < \delta \end{cases} \tag{12}$$

$Crl(i,j) = 1$ represents that SU_i and SU_j have a good correlation. This method also saves storage space of the FC. Then, we use a $\mathcal{A} \times \mathcal{A}$ matrix ζ to show the relationships among all SUs, it can be obtained as follows:

$$\begin{bmatrix} Crl'(1,1) & Crl'(1,2) & \cdots & Crl'(1,\mathcal{A}) \\ Crl'(2,1) & Crl'(2,2) & \cdots & Crl'(2,\mathcal{A}) \\ \vdots & \vdots & \ddots & \vdots \\ Crl'(\mathcal{A},1) & Crl'(\mathcal{A},2) & \cdots & Crl'(\mathcal{A},\mathcal{A}) \end{bmatrix} \tag{13}$$

3.3 Improved DSCN

DSCN defines the cluster as the largest set of points connected by density and can divide regions with sufficient density into clusters. We improve DSCN so that it can be applied to SUs selection in cooperative sensing mainly reflects in two aspects.

Using Correlation of SUs. Traditional DSCN uses radius of neighborhood to count the number of points that a point contains to determine whether it is a core point or a noise point. However, besides distance, other factors such as shadow fading also affect the detection performance. Therefore, it is better to use correlation to correct shadow fading hereinbefore. Improved DSCN uses correlation of SUs instead of radius of neighborhood. Each radius of neighborhood r corresponds to a unique $Crl(r)$ because Eq. (11) is monotonically decreasing. SU_i and SU_j are considered to be SUs of mutual inclusion if $Crl'(i,j) \neq 0$.

Two-Stage Core Point Judgement Threshold. Traditional DSCN sets a threshold η to determine whether a point is a core point. When considering the actual situation, the SUs who close to PU is denser and SUs who far from PU is looser. Therefore, most of the boundary SUs will be excluded if set a large η. Moreover, there will be very few representative SUs selected internally if set a small η.

Based on the above considerations, we use two-stage core point judgement threshold to solve the problem. When the first judgement is made on a selected point, we set a short η_1 to ensure that most boundary points are also taken into account. Then, we set a large η_1 to avoid too few internal representative points.

Our proposed improved DSCN is summarized in Algorithm 1. This algorithm considers many factors among SUs and selects representative SUs based on the correlation. Moreover, the number of SUs selected can be changed by setting threshold η_1 and η_2, which can significantly improve the accuracy of sensing.

Algorithm 1: Optimal SUs selection

```
begin
    bool Visit[m] = false, w[m], int Nps[m] = 0, q = 0
    INPUT: Finite set of SUs L: {1, ··· , L} and A : Set of A SUs' SNR > ϵ
    Calculate SNR λ_i of every SU_i using Equation (4)
    Select SUs based on the SNR and store in A
    for int m = 1 to A do
        for int n = 1 to A do
            Crl(m, n) = e^{-xy}
            if Crl'(m, n) < γ then
                Crl'(m, n) = 0
            end
            else
                Crl'(m, n) = Crl(m, n)
            end
        end
    end
    for int m = 1 to A do
        for int n = 1 to A do
            if Crl'(m, n) ≠ 0 then
                Nps[m] + +
            end
        end
    end
    for int m = 1 to A do
        if Visit[m] = true then
            continue
        end
        else
            if Nps[m] < η_1 then
                Visit[m] = true
                w[m] = 0
            end
            else
                Visit[m] = true
                w[m] = 1
                establish new cluster C[q + +]
                add the neighborhood of the ith point into C[q]
                for int n in C[q] do
                    if Nps[n] > η_2 then
                        add the neighborhood of the nth point into C[q]
                    end
                end
            end
        end
    end
    Select SU_T with maximum Nps[t] in C[t]
    add SU_T into R[t]
    OUTPUT : T : Set of selected t SUs
end
```

Selected SUs send decision (H_0 or H_1) to the FC. FC uses OR and AND fusion rules to aggregate the fusion results and make final decision. Then FC sends the decision to SUs that need idle channel and have access to it.

4 Simulation Results

In the simulation, the performance evaluation mainly depends on the sensing overhead (number of participating communication SUs), P_d and P_f in Matlab. Initially, 400 SUs are randomly distributed in a 100 km × 100 km coordinate system. PU is at the center of the coordinate system and can communicate with all SUs. The result is shown in Fig. 1.

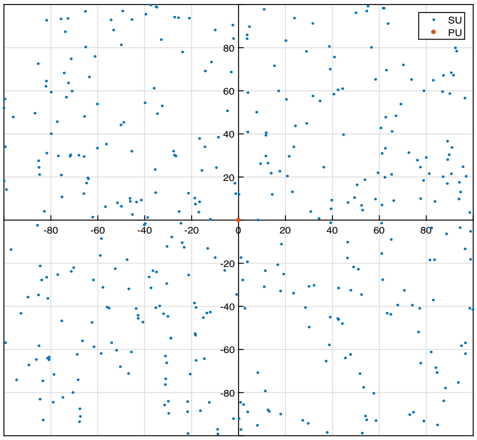

Fig. 1. The distribution of randomly SUs

During the sensing period, the number of received signal samples at each SU is set at 5000 samples. The path loss exponential factor a is set at 3. Set β_0 and P_{pu} to a value so that the SNR of the SUs at 100 km from PU is −16 dB. Then we set threshold ϵ to ensure SUs with good SNR and exclude all SUs with SNR less than threshold. The result is shown in Fig. 2.

In the next phase, we use improved DSCN to select representative SUs. The value of η_1 is set at 5 and η_2 is set at 10. Typically, there are 26 SUs left. The distribute of SUs involved in CSS is shown in Fig. 3.

Next, considering the P_d and P_f, we use AND fusion rule for performance evaluation of P_d because it can reduce the probability of secondary users' interference while primary user is present. OR fusion rule is selected for P_f because when the PU is absent, as long as one SU senses the channel is idle, it can occupy the channel and utilize the spectrum. The simulation considers a total of 100 SUs. Starting from the SU nearest to PU, select SUs by distance from smallest to largest and use improved DSCN and unfiltered SUs for CSS respectively.

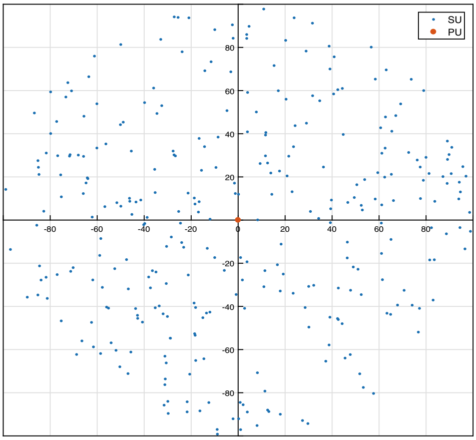

Fig. 2. The distribution after screening SUs with too low SNR

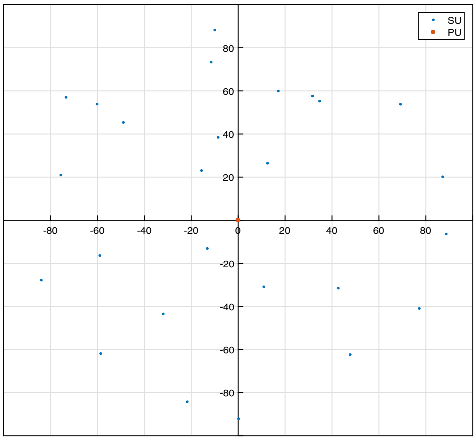

Fig. 3. The distribution of SUs involved in cooperative spectrum sensing

According to the Monte Carlo rule, we run 1000 times simulations and take the mean to evaluate the P_d and P_i of the original CSS method and the CSS method based on improved DSCN. For P_d, target P_i is set at 0.001 and 0.002, the result of simulation is shown in Fig. 4.

The value range of P_d without selection is from 0.1 to 1. Moreover, as the numbers of SUs increases, the value of P_d decreases rapidly. The value range of P_d with selection is from 0.9 to 1, and the downward trend is slow. Furthermore, P_d will increase as the target P_f increases. For P_f, target P_d is set at 0.999 and 0.998, Fig. 5 shows us the simulation result.

The value range of P_f without selection is from 0.08 to 0.1, which increases with the increase of the numbers of SUs. The value range of P_f with selection is

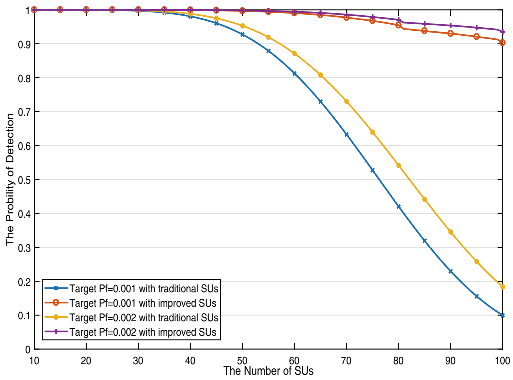

Fig. 4. P_d with Numbers of SUs participating in CSS

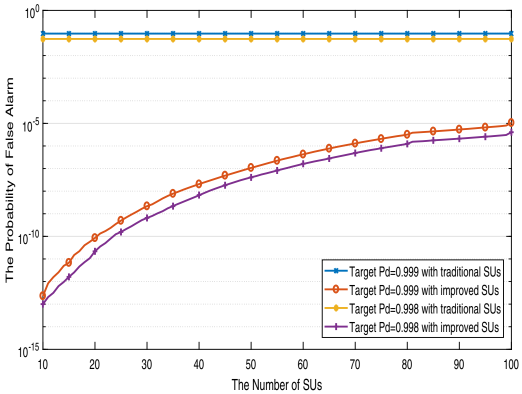

Fig. 5. P_f with Numbers of SUs participating in CSS

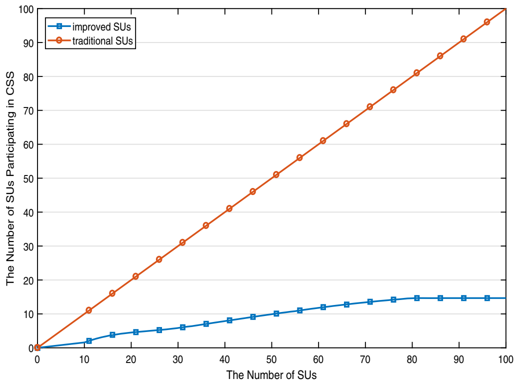

Fig. 6. Numbers of SUs participating in CSS

from 10^{-13} to 10^{-5}, which is much less than the value of P_f without selection. Moreover, P_f will increase as the target P_d grows. In cooperative spectrum sensing, information exchange between SUs and FC result in sensing overhead. Using improved DSCN can greatly reduce the sensing overhead. The simulation result is shown in Fig. 6. For 100 SUs, there are only less than 20 SUs participating in CSS.

5 Conclusion

In this paper, we proposed a correlation based spectrum sensing scheme and designed the improved DSCN to select representative SUs in cooperative spectrum sensing. In the proposed scheme, SUs were selected based on their correlation and the density of distribution. This method could significantly reduce sensing overhead and shadow fading under the premise of ensuring the detection effect. Two-stage core point judgement threshold made the improved SU more representative. Simulation results show that for 100 improved SUs, P_d stays above 0.9 under the circumstance of target $P_f = 0.001$ and P_f is controlled under 0.01 in case of target $P_d = 0.998$. This approach significantly improves the P_d and decreases the P_f compared with traditional spectrum sensing schemes.

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