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Energy-Efficient Cooperative Spectrum Sensing Scheme Based on Spatial Correlation for Cognitive Internet of Things

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ABSTRACT Due to the negative impact from spatial correlation, spatially correlated cognitive radio (CR) based devices participating in cooperative spectrum sensing may be harmful to the detection performance. In this paper, we propose an energy-efficient cooperative spectrum sensing scheme based on spatial correlation for cognitive Internet of Things (CIoT). To mitigate the communication overhead and ensure sufficient sensing accuracy, the CR-based devices (CRDs) can be grouped into several clusters. The member nodes undertake cooperative spectrum sensing tasks in turn, and send the local test statistic to their cluster head nearby. Then, by exploiting the spatial correlation of the members, the cluster head combines the sensing results and makes use of likelihood ratio test to obtain the cluster decision. After receiving the decisions from all clusters, the fusion center employs hard fusion scheme to make the final decision about spectrum occupancy. The simulation results show that our scheme not only provides the better sensing performance, but also improve the energy efficiency.

INDEX TERMS cognitive Internet of Things, cooperative spectrum sensing, spatial correlation, energy efficiency.

I. INTRODUCTION

Owing to the interconnection of different objects via various technologies, the Internet of Things (IoT) can provide abundant services in the fields of intelligent city, smart home, advanced transportation and environmental protection. Due to fixed allocation of authorized frequency band mechanism, most IoT devices have to operate on the industrial scientific medical (ISM) unlicensed spectrum band [1]. By contrast, plenty of licensed bands are idle for most of the time, and spectrum resources are not fully utilized. Owing to regulate the reception or transmission parameters, cognitive radio (CR) has attracted significant attention to solve the above problem of spectrum shortage. Subsequently, the CR-based IoT devices (CRDs) are designed based on software-defined radios to access licensed channels only when there is no interference with primary users (PUs) [3]. They can cope with the changes in the surrounding radio environments, and achieve dynamic spectrum access [2]. By integrating CR technology with the IoT network, CIoT can benefit from CRDs' self-learning and self-adaptation capabilities and enhance the spectrum resources utilization.

The accuracy of spectrum sensing is crucial to conduct intelligent decisions about spectrum usage and make CRDs access idle channels with more opportunities [3]. However, due to penetration loss, shadowing, and multipath fading, it is difficult for CRDs to obtain accurate sensing results in CIoT network [4]. Cooperative spectrum sensing (CSS) is regarded as promising measures to enhance the sensing performance and improve the reliability of detecting the PU's status [39]. However, although CSS can improve the detection performance, too much cooperative CRDs will also produce

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high communication overhead, which will result in increased bandwidth and energy consumption. Therefore, high achievable detection performance and energy efficiency has become vital considerations in CIoT network from the perspective of green communication. Recently, many studies have revealed that cluster-based CSS approach can handle the problem of high overhead during the sensing result collection and less time for data transmission [5]. By dividing all CRs into some clusters and selecting a proper node in each cluster as the cluster head (CH) for reporting to the fusion center (FC), the cluster-based CSS can reduce the reporting time as well as decrease the traffic load in the reporting channel [6]. Moreover, by exploiting the spatial correlation from multiple signal observations at spatially distributed CRDs, the system can select optimal number of nodes for cooperation and improve the effectiveness of CSS [7]. This motivates us to explore the effect of CSS based on spatial correlation for CIoT and design a correlation-aware CRDs selection scheme to reduce the communication overhead and ensure sufficient detection accuracy [40].

In this paper, we propose an energy-efficient cooperative spectrum sensing scheme based on spatial correlation for CIoT. To this extent the main contributions of this paper are as follows:

- proposing a strategy of selecting only uncorrelated CRDs for participating cooperative spectrum sensing.
- using the maximum sensing accuracy criterion to determine the cluster threshold, and deriving the optimal threshold of cluster decision numerically.
- presenting both soft fusion and hard fusion schemes for cluster decision and the global decision to provide better sensing performance and improve the energy-efficiency.

II. RELATED WORK

The accurate result of spectrum sensing is the premise of maximizing the throughput without interference to authorized users. Thus, to perform opportunistic spectrum access, CRDs should make use of the sensing module and employ some rules to decide whether the licensed spectrum can be utilized or not [8]. Several spectrum sensing techniques in the literature can be classified into major categories including energy detection [9], matched filter [10], and cyclostationary feature detection [11], etc. Among them, owing to low computational complexity and unnecessary prior knowledge of characteristics from the PUs, energy detection has been applied in CIoT as one of the most common techniques.

In [12], Lim *et al.* conducted the derivation to obtain the optimal voting threshold of energy detector in cooperative spectrum sensing, and proposed a fast spectrum sensing algorithm. To enhance the general applicability for different signal format or structure, López-Benítez and Casadevall [13] introduced a modified energy detection method to provide an acceptable estimate of the average signal energy in the sensed channel. To improve the spectrum detection performance and reduce the complexity under low signal-to-noise ratio (SNR), Rakovic *et al.* [14] applied capacity-aware CSS optimization method with estimated noise power to maximize the secondary system capacity. However, the sensing performance of the energy detector will be affected seriously by the noise uncertainty, and it will result in high error probability of spectrum sensing. In [15], Michele *et al.* employed the counterproductive characteristics of convex constraints and proposed an alternative optimization approach based on genetic algorithm, which can guarantee the spectrum sensing performance of sub channels as well as improve the throughput.

CSS technologies have been investigated as a means to improve the sensing performance and detect weak PU's signals reliably. Based on the detection results from multiple CR users with spatially distributed, the system can mitigate the effect of multipath effects and shadowing. In [16], Atapattu *et al.* proposed a data fusion strategy with multiple cognitive relays. Although the difference of transmission channel for each cognitive node being considered, it requires all CR users to participate in cooperation with the result of high transmission overload. To minimize the energy depletion, Maleki *et al.* [17] investigated the combination of sleeping and censoring, in which the real-time performance of the system may be impacted with respect of the number of samples for the sake of credible decision. In [18], a cooperative spectrum sensing mechanism based on multiple antennas is introduced, and the tight bounds of the probabilities of false alarm and missed detection are derived. However, such scheme has high computational complexity and needs more sensing time. In [19], Pham *et al.* established a mathematical model to resolve the problem of minimizing perceptual energy consumption based on perception time and number of collaborative users. They proposed an optimization algorithm with the constraint of detection probability for obtaining approximate solutions in polynomial time. In [41], Mahboobi *et al.* proposed a CSS algorithm based on spatio-temporal weighted non-negative Lasso method. However, Due to the requirement of special receiving and decoding equipment for different types of authorized users, the method has high system overhead.

For densely deployed CIoT, all CRDs participating in the cooperation does not necessarily achieve the optimum sensing performance. By exploiting the spatial correlation, Cacciapuoti *et al.* [20] presented a solution for uncorrelated CR users selection in mobile cognitive radio ad hoc networks, in which spatial correlation coefficient is defined to estimate the correlation degree of mobile CRs in different scenarios. In [21], Wu *et al.* defined the maximum interference constrained transmission power to metric the spatial-temporal opportunity detection and proposed a two-dimensional sensing framework with heterogeneous spectrum availability among CRDs. However, the solution for such multi-objective problem shows relatively high computational complexity. In [22], by using location awareness, Zhou *et al.* estimated the channel gain and magnitude between the PUs and the CR nodes and proposed a method to evaluate the transmission reliability. In [23], Mustapha *et al.* presented a weighted hard combination scheme to minimize energy cost for reporting sensing result, which allows the CR node to share its local test statistics with other cooperative nodes and collectively decide on existence or otherwise of PU in the channel. However, due to the limitation of hard fusion, the detection accuracy is bound to be affected in complex network environment [24]. In [42], Bhatti *et al.* proposed a CSS scheme with Fuzzy C-means clustering to overcome the shadowing and fading effect. This scheme can reduce the shadowing correlation to a certain extent. However, the secondary users with high correlation to each other still exist in selected set, which may degrade the energy efficiency.

Although the optimization of –CSS has already been considered in many studies for CIoT, there are still numerous vital issues to be solved. The spatially correlated CRDs participating in the cooperation should be analytically considered, and the impact on the overall performance of CSS under spatial correlation should be exploited.

III. SYSTEM MODEL

We consider a CIoT network composed of CRDs distributed uniformly over a rectangular region. The whole network can be divided into several clusters, each of which comprises multi closely CRDs. The steps of our clustered-based CSS mechanism include spectrum sensing, intra-cluster fusion and final decision-making. In the spectrum sensing stage, the member node inside the cluster will independently observe the band of interest, and forward the local test statistics to its corresponding CH. For simplicity, the reporting channel is assumed to be error-free. Next, during the phase of intra-cluster fusion, the CH collects all local test statistics without information loss, and then conducts a soft decision combining strategy to make the cluster decision about PU's presence or not. In order to decrease the load of sharing bandwidth, only CHs send the one-bit cluster decisions to the fusion center. Finally, the final decision is conducted at the FC, which uses certain criteria to fuse the received decision results from all clusters. Also, we assume that the reporting links between the CRDs and the FC will be perfect and the data fusion rules are implemented.

Suppose that n CRDs in the network can be grouped into k clusters, and N member nodes in the c-th cluster. Assuming that the local sensing process of each cognitive user is independent, and the energy detection method will be exploited for decision making. For the i-th member node of c-th cluster, the local test statistics can be estimated as

$$y_{ci}(m) = \begin{cases} n_{ci}(m), & H_0 \\ h_{ci}s_{ci}(m) + n_{ci}(m), & H_1 \end{cases} \tag{1}$$

where $s_{ci}(m)$ denotes the m-th sample of the signal being received by CRD u_{ci}. $n_{ci}(m)$ represents the observation noise, and it can be referred to as identical independent distributed (i.i.d) Gaussian random process with mean zero and variance σ_{ci}^2. Besides, h_{ci} is channel gain between SU_{ci} and the PU.

Each CRD, after collecting M samples from the channel during the sensing process, can add up the observations as

$$v_{ci} = \sum_{m=1}^{M} |y_{ci}(m)|^2 \tag{2}$$

Under hypothesis H_0, the probability density function of v_i will obey the central chi square distribution with $2M$ degree of freedom. Otherwise, it follows non-central chi square distribution with $2M$ degree of freedom under hypothesis H_1 [25]. If the value of M is large enough, the test statistics can be written as

$$v_{ci} \sim \begin{cases} \mathcal{N}(M\sigma_{ci}^2, 2M\sigma_{ci}^4), & H_0 \\ \mathcal{N}(M(1+\gamma_{ci})\sigma_{ci}^2, 2(M+2\gamma_{ci})\sigma_{ci}^4), & H_1 \end{cases} \tag{3}$$

where $\gamma_{ci} = \sigma_s^2/\sigma_{ci}^2$ represents the instantaneous signal-to-noise ratio of CRD u_{ci}.

IV. PROPOSED METHOD

A. COOPERATIVE SPECTRUM SENSING UNDER SPATIAL CORRELATION

In CSS, the local sensing results of CRDs are combined at the FC by two schemes: Hard decision fusion (HDF) [26] and Soft decision fusion (SDF) [27]. HDF can effectively reduce the amount of data transmission in the reporting channel, but it is easy to cause the loss of the original signal when making local decisions. Especially when the average SNR of the receivers is low, the accuracy of the PU's detection will be very unsatisfactory as a result of the distance or shadow effect. By contrast, due to local sufficient statistic, SDF-based CSS schemes can achieve better performance than HDF-based CSS schemes [28]. However, the observations without any processing may result in a significant overhead of the channels between the CRDs and the FC. Moreover, it will take a long time to obtain the final decision. Since the wireless channel is usually complex and changeable, the decision result may be out of date.

For clustered structured CIoT, the potential advantages of HDF and SDF can be exploited. In single cluster, energy observations measured by member nodes will be forwarded to CH in short-range transmission mode, which can cause less interference to the PU far away from. After soft combining of the intra-cluster sensing information, only one bit solution will be sent to the FC for final decision by each CH. Obviously, the manner of soft-hard combination can reduce the demand of bandwidth for reporting channel in process of intra-cluster soft decision and achieve low energy consumption among sensor nodes in the premise of ensuring the sensing quality.

After periodic sensing slot, the CH will aggregate the positive test statistics from its members to perform soft decision fusion. By employing equal gain combining (EGC) method [29], the sensing measurements of all member nodes can be formed to a cluster test statistic, which is also known as the estimation of received primary signal power. At the c-th CH, the cluster test statistic will be given as

$$v_c = \sum_{i=1}^{N} v_{ci} = \sum_{i=1}^{N}\sum_{m=1}^{M} |y_{ci}(m)|^2. \tag{4}$$

Given that CRDs are spatially correlated, the means and variances of the sensing measurements of all CRDs under hypothesis H_0 and H_1 can be expressed, respectively, as

$$\begin{cases} \mu_{c,0} = M \sum_{i}^{N} \sigma_{ci}^2, & H_0 \\ \mu_{c,1} = M(\sum_{i}^{N} \sigma_{ci}^2 + \sum_{i}^{N} \sigma_s^2), & H_1 \end{cases} \tag{5}$$

$$\begin{cases} \sigma_{c,0}^2 = 2M \cdot [1^T \Sigma 1], & H_0 \\ \sigma_{c,1}^2 = 2M \cdot ([1^T \Sigma_c 1] + 4 \cdot [1^T \Sigma_c \Lambda_c & H_1 \end{cases} \tag{6}$$

where $\Lambda_c = diag(\gamma_{c1}, \gamma_{c2}, \cdots, \gamma_{cN})$, $1^T \Sigma_c 1$ represents the summation of the covariance matrix, and Σ_c can be defined as

$$\Sigma_c = \begin{bmatrix} \sigma_{c1}^4 & \sigma_{c2,c1}^2 & \cdots & \sigma_{cN,c1}^2 \\ \sigma_{c2,c1}^2 & \sigma_{c2}^4 & \cdots & \sigma_{cN,c2}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{cN,c1}^2 & \sigma_{cN,c2}^2 & \cdots & \sigma_{cN}^4 \end{bmatrix} \tag{7}$$

In CSS, the sensing results of the adjacent CRDs will be correlated, and the spatial correlation will affect the sensing performance by the same environmental conditions [30]. Specifically, for the channel correlation between the sensing nodes, Gudmundson model is widely applied to estimate the spatial correlation coefficient between CRDs [31]: $\rho^{|i-j|} = e^{-\varepsilon d_{ij}}$, where d_{ij}. represents the distance between CRD i and j. ε denotes the environment dependent constant.

To simplify the analysis, we assume an equal distance between each pair of neighboring nodes, and $\rho_{ij} = \rho^{|i-j|}, (i,j = 1, 2, \cdots, N)$. Without loss of generality, the CRDs are positively and negatively indexed in the matrix in the order as the correlation increases.

Thus, the covariance matrix Σ can be expressed as

$$\Sigma_c = \begin{bmatrix} \sigma_{c1}^4 & \sigma_{c1}^2\sigma_{c2}^2\rho^2 & \cdots & \sigma_{c1}^2\sigma_{cN}^2(\rho^{|N-1|})^2 \\ \sigma_{c2}^2\sigma_{c1}^2\rho^2 & \sigma_{c2}^4 & \cdots & \sigma_{c2}^2\sigma_{cN}^2(\rho^{|N-2|})^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{cN}^2\sigma_{c1}^2(\rho^{|N-1|})^2 & \sigma_{cN}^2\sigma_{c2}^2(\rho^{|N-2|})^2 & \cdots & \sigma_{c2}^4 \end{bmatrix} \tag{8}$$

Then, the hypothesis can be written as (9), shown at the bottom of the page.

Since the covariance matrix Σ_c is a symmetric Toeplitz matrix known as the Kac–Murdock–Szego matrix, according to its characteristic [32], the inverse matrix Σ_c^{-1} can be given as

$$\Sigma_c^{-1} = \frac{1}{1-\rho^4} \begin{bmatrix} \frac{1}{\sigma_{c1}^4} & -\frac{\rho^2}{\sigma_{c1}^2\sigma_{c2}^2} & 0 & 0 & \cdots & 0 & 0 \\ -\frac{\rho^2}{\sigma_{c1}^2\sigma_{c2}^2} & \frac{1+\rho^4}{\sigma_{c2}^4} & -\frac{\rho^2}{\sigma_{c2}^2\sigma_{c3}^2} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \frac{1+\rho^4}{\sigma_{cN-1}^4} & -\frac{\rho^2}{\sigma_{cN-1}^2\sigma_{cN}^2} \\ 0 & 0 & 0 & 0 & \cdots & -\frac{\rho^2}{\sigma_{cN-1}^2\sigma_{cN}^2} & \frac{1}{\sigma_{cN}^4} \end{bmatrix} \tag{10}$$

and

$$1^T \Sigma_c^{-1} 1 = \frac{1}{1-\rho^4} \times \begin{bmatrix} \left(\sum_{i=1}^{N} \frac{1}{\sigma_{ci}^4}\right) - 2\rho^2 \left(\sum_{i=2}^{N} \frac{1}{\sigma_{ci}^2\sigma_{ci-1}^2}\right) \\ +\rho^4 \left(\sum_{i=1}^{N} \frac{1}{\sigma_{ci}^4} - \frac{1}{\sigma_{c1}^4} - \frac{1}{\sigma_{cN}^4}\right) \end{bmatrix} \tag{11}$$

B. OPTIMAL DECISION THRESHOLD

Next, based on the cluster test statistic v_c, each CH will perform soft fusion to make the cluster decision on the absence or present of the PU's signal. The log-likelihood ratio test [33] will be conducted by CH, and the information-combining strategy can be given as

$$\varphi_c = \log \frac{f_v(v_c|H_1)^{H_1}}{f_v(v_c|H_0)_{H_0}} \lessgtr \lambda_c \tag{12}$$

where λ_c represents the threshold of decision making in likelihood ratio test, and the conditional probability density function of the received signal power under hypothesis H_i, $i \in \{0, 1\}$, can be defined as

$$f_v(v_c|H_i) = \frac{1}{\sqrt{2\pi}\sigma_{c,i}} \exp\left[-\frac{(v_c - \mu_{c,i})^2}{2\sigma_{c,i}^2}\right] \tag{13}$$

Note that v_c is the random variable about the test statistic of log-likelihood ratio test (LRT) at CH_c, the LRT value can be derived using Eq. (12) and (13) as

$$\varphi_c = \log \frac{\sigma_{c,0}}{\sigma_{c,1}} + \frac{1}{2} \times \left(\frac{(v_c - \mu_{c,0})^2}{\sigma_{c,0}^2} - \frac{(v_c - \mu_{c,1})^2}{\sigma_{c,1}^2}\right) \tag{14}$$

By substituting (5) and (6) into (14), the LRT value can be given as

$$\varphi_c = g(v_c) = V\left(v_c^2 + Wv_c + U\right) \tag{15}$$

$$v_c \sim \begin{cases} \mathcal{N}\left(M \sum_{i}^{N} \sigma_{w,ci}^2, 2M \cdot [1^T \Sigma 1]\right), & H_0 \\ \mathcal{N}\left(M(\sum_{i}^{N} \sigma_{w,ci}^2 + \sum_{i}^{N} \sigma_s^2), 2M \cdot [1^T \Sigma_c 1] + 4 \cdot [1^T \Sigma_c \Lambda_c 1]\right), & H_1 \end{cases} \tag{9}$$

where

$$U = \frac{M}{2\sum_{i=1}^{N}\gamma_{ci}} \times \left(\begin{array}{l} 2M\sum_{i=1}^{N}\gamma_{ci}\left(\sum_{i}^{N}\sigma_{w,ci}^{2}\right)^{2} + 2M\sum_{i}^{N}\sigma_{w,ci}^{2}\sum_{i}^{N}\sigma_{w,ci}^{2}\gamma_{ci} \\ -\left(\sum_{i}^{N}\sigma_{w,ci}^{2}\gamma_{ci}\right)^{2} + \sigma_{c,1}^{2}\times\log\left(1+\frac{2}{M}\sum_{i=1}^{N}\gamma_{ci}\right) \end{array} \right),$$

$$V = \frac{[1^{T}\Sigma_{c}^{-1}1]}{2M(M/\sum_{i=1}^{N}\gamma_{ci}+2)}, \text{ and}$$

$$W = \frac{M\sum_{i=1}^{N}\sigma_{w,ci}^{2}\gamma_{ci}}{2\sum_{i=1}^{N}\gamma_{ci}} + M\sum_{i=1}^{N}\sigma_{w,ci}^{2}.$$

By applying fundamental theorem [34] the probability density function of the LRT value can be derived using Eq. (9) and (12) as

$$f_{\varphi_c}(\varphi_c) = \sum_{r}^{f_{v_c}(v_c^r)/} \left|g'(v_c^r)\right| \tag{16}$$

where v_c^r is the r-th real root of (14) and $g'(v_c^r)$ is the derivative of $g(v_c)$.

After some algebra, the probability density function of the LRT value can be derived as

$$f_{\varphi_c}(\varphi_c) = P(H_0)f_{\varphi_c}(\varphi_c|H_0) + P(H_1)f_{\varphi_c}(\varphi_c|H_1) \tag{17}$$

where $P(H_0)$ and $P(H_1)$ represents the probability of present and absence of the PU's signal.

The conditional probability density function of LRT value under hypothesis H_j, $i \in \{0, 1\}$, can be estimated as

$$f_{\varphi_c}(\varphi_c|H_0) = \frac{b}{2\sqrt{2\pi(a+b\varphi_c)}\sigma_{c,0}} \times \exp\left[-\frac{\left(\sqrt{a+b\varphi_c}-N/2-\mu_{c,0}\right)}{2\sigma_{c,0}^2}\right] \tag{18}$$

$$f_{\varphi_c}(\varphi_c|H_1) = \frac{b}{2\sqrt{2\pi(a+b\varphi_c)}\sigma_{c,1}} \times \exp\left[-\frac{\left(\sqrt{a+b\varphi_c}-N/2-\mu_{c,1}\right)}{2\sigma_{c,1}^2}\right] \tag{19}$$

where $a = N^2/4 - U$, $b = 1/V$.

Then, we can obtain the expression of false alarm probability $P_{f,c}$ and detection probability $P_{d,c}$ for c-th cluster, respectively, as

$$\begin{cases} P_{d,c} = \int_{\lambda_c}^{\infty} f_{\varphi}(\varphi_c|H_1)d\varphi \\ P_{f,c} = \int_{\lambda_c}^{\infty} f_{\varphi}(\varphi_c|H_0)d\varphi \end{cases} \tag{20}$$

From the above discussions, we can see that the false alarm probability and detection probability of each cluster are determined by the channel condition, i.e., the average SNR, and the cluster threshold. In this paper, we adopt the maximum sensing accuracy criterion to determine the cluster threshold. Thus, the objective function to determine the cluster threshold of c-th cluster can be defined as: $g(\lambda_c) = P(H_0)(1 - P_{f,c}) + P(H_1)P_{d,c}$. Then, the optimal sensing threshold of c-th cluster can be estimated as

$$\lambda_{c,opt} = \arg\max\{P(H_0)(1 - P_{f,c}) + P(H_1)P_{d,c}\} \tag{21}$$

To obtain the approximated solution, Newton iteration method is applied and the algorithm is described as follows:

Algorithm 1 Finding the optimal decision threshold in a cluster.

$\lambda_{c,\min} = 0$, $\lambda_{c,\max} = C$, $i = 0$.
$\lambda_c = random\{\lambda_{c,\min}, \lambda_{c,\max}\}$
while $i < count$
  $\tilde{\lambda}_c = \lambda_c - \mu g(\lambda_c)/g'(\lambda_c)$
  if $\left|g(\tilde{\lambda}_c)\right| < |g(\lambda_c)|$ then
    if $\left|\tilde{\lambda}_c - \lambda_c\right| < \varepsilon$ then
      $\lambda_{c,opt} = \tilde{\lambda}_c$, break;
    else $\lambda_c = \tilde{\lambda}_c$, continue;
    end if
  else $\lambda_c = \lambda_c/2$, continue;
  end if
end while

C. NUMBER OF CLUSTERS

The CHs will send their decision bits to the FC, and then, the FC can make the final decision on the state of channel based on the combination of the decisive results of the selected CRDs. It is assumed that the FC uses the logic-OR rule or logic-AND rule to combine the decisions of clusters. According to the logic OR fusion rule, if at least one CH detects the PU is transmitting on the channel, the final decision indicates that the channel is busy [35]. Compared to AND rule, OR rule is adopted in this paper due to requiring a smaller number of clusters to satisfy the detection performance constraints. Next, we will deduce the optimal number of clusters according to the fusion criteria.

By employing OR rule, the global Q_d and Q_f of the final decision that made at the FC can be written as

$$\begin{cases} Q_d = 1 - \prod_{i=1}^{k}(1 - P_{d,i}) \\ Q_f = 1 - \prod_{i=1}^{k}(1 - P_{f,i}) \end{cases} \tag{22}$$

where $P_{d,i}$ and $P_{f,i}$ represent the false alarm probability and detection probability for i-th cluster, respectively.

Let α and β represent the desired detection and false alarm probabilities, respectively. Since $Q_d \geq \alpha$ and $Q_f \leq \beta$, we can get

$$\begin{cases} \prod_{i=1}^{k}(1-P_{d,i}) \le 1-\alpha \\ \prod_{i=1}^{k}(1-P_{f,i}) \ge 1-\beta \end{cases} \tag{23}$$

Suppose that $P_d^{\max}$ and $P_f^{\min}$ are the maximum detection probability and the minimum false alarm probability among all clusters, respectively. Then, the following conditions should be satisfied:

$$\begin{cases} (1-P_d^{\min})^k \le 1-\alpha \\ (1-P_f^{\max})^k \ge 1-\beta \end{cases} \tag{24}$$

By taking the logarithm of both sides of inequality (24), we have

$$\left\lceil \frac{\log(1-\alpha)}{\log(1-P_d^{\min})} \right\rceil \le k \le \left\lfloor \frac{\log(1-\beta)}{\log(1-P_f^{\max})} \right\rfloor \tag{25}$$

Since the OR rule can acquire better protection of the PU's transmission and enhance the system reliability, the detection probability will be greatly improve. However, the false alarm probability is also significantly increased, and it results in reducing the probability of accessing the idle authorization band for CRDs. Therefore, the number of clusters should be set as few clusters as possible, and the optimal cluster number can be achieved as follows:

$$k = \left\lceil \frac{\log(1-\alpha)}{\log(1-P_d^{\min})} \right\rceil \tag{26}$$

Next, the correlation-aware selection algorithm is summarized as following:

In algorithm 2, $\{u_1, u_2, \cdots, u_N\}$ indicates the set of member nodes in the cluster, which are arranged in descending order by the received power. US_c, S_c and T_c represent the set of unprocessed nodes, the set of uncorrelated CRDs being selected, and the set of non-selected CRDs, respectively. $corr(u_i, u_j)$ denotes the correlation between the node u_i and u_j, and $corr(u_i, u_j) = \rho_{ij}$. During the initialization of each round, the FC performs a random selection of k CRDs as CHs in the set T_c of the last round. Then, each CH requests its member nodes to send a probing signal and calculates the received power. After receiving the acknowledgement, the CH makes an array $\{u_1, u_2, \cdots, u_N\}$ and arranges the member nodes into an ascending order set US_c according to the received power. During the selection process, the CRDs of set US_c will be compared with all users of set S_c. If the correlation is greater than threshold ρ_{th}, the CRD will be shifted into T_c meanwhile be removed from the array. Eventually, the uncorrelated CRDs with highest power will be selected for performing cooperative spectrum sensing.

Algorithm 2 Selection of uncorrelated CRDs.

for $1 \le i \le n$
  SUs compete for being CH randomly;
  the non-CH chooses the adjacent CHs to join in;
  select k CRDs as CHs;
end for
for $1 \le c \le k$ do
  $S_c = \emptyset$, $T_c = \emptyset$;
  CH_c requests the CRDs within its communication range to send a prob signal;
  $US_c = \{u_1, u_2, \cdots, u_N\}$;
    while $US_c \ne \emptyset$
     for $u_i \in US_c$
       for $u_j \in S_c$
         if $corr(u_i, u_j) > \rho_{th}$ then
           $T_c \leftarrow u_i$;
         else
           continue;
         end if
       end for;
    $S_c \leftarrow u_i$;
    $US_c = US_c - u_i$;
    end for
  end while
end for

D. CLUSTER FORMATION

Firstly, the communication process of CRDs in the network is assumed as follows:

(1) The CRDs can be heterogeneous, but they should provide accurate geographical location information.

(2) The communication channel between nodes in the network has symmetry, and all CRDs can dynamically adjust their transmission power according to the communication distance.

(3) The energy of the FC is sustainable, and all nodes have accurate clock synchronization

The process of cluster formation is described as follows.

Step 1: At the beginning of each round, the FC broadcasts HELLO_msg to all nodes at a certain power. And then, each CRD responds to the FC with RES_msg containing its own residual energy. After the aggregation at the FC, the optimal number of clusters can be obtained according to the detection probability and false alarm probability of each cluster in the last round, and then k nodes with the largest residual energy will be chosen as the CHs of current round. Subsequently, the FC sends HEAD_DEC_msg to the corresponding the nodes to be CHs, and MEM_DEC_msg to other nodes.

Step 2: The node receiving HEAD_DEC_msg will broadcast the message CH_BRD_msg to declare as the CH, which contains its ID information. In addition, the other nodes select the adjacent CH according to the signal's power and send JOIN_INQ_msg. By receiving JOIN_ INQ_msg, the CH adds the corresponding node to its member list, and replies the confirmation message JOIN_ ACK_ msg, which contains the information of mem_ID. Once the number of members exceeds the upper limit N, the CH will send JOIN_REJ_msg to the node submitting the request. Then, the corresponding CRDs will turn to other CHs until join a cluster.

Step 3: According to the node selection algorithm, the CH selects the uncorrelated nodes for spectrum sensing and send them the message ACTIVE_SEN_msg with the node's identification. Those active member nodes will perform local sensing within a certain period of time, and upload the results to the CH in the sub-frame. Based on the members' observations, the CHs conduct the local cluster decision and convey these one-bit decisions to the FC.

Step 4: by combining all the cluster decisions, the FC employs OR fusion rule to make the final decision and broadcasts the result to the all CRDs in network.

E. ENERGY EFFICIENCY ANALYSIS

In this subsection, we conduct mathematical analysis in terms for throughput, energy consumption and energy efficiency. Herein, the energy efficiency metric is defined as the ratio of average throughput over the average consumed energy. Typically, the energy consumption of each CRD is due to sensing power and transmission power for reporting the sensed data. Moreover, the total frame time T can be divided into three parts: sub-frame T_s for spectrum sensing, T_r sub-frame for result reporting, and sub-frame T_d for data transmission. Among them, $T_s = Mf_s, f_s$ is the sampling frequency. During the sensing time, every selective CRDs collects M samples from the channel, and then reports them to the CH by a quantised form of θ bits [36]. Hence, $T_r = N\theta/v$, where v denotes the reporting data rate. Besides, e_s and e_r represent the sensing power and transmission power of each CRD for reporting, respectively. Assuming that the transmission power of reporting from the CH to the FC is e_t and reporting time is same as reporting time of CRDs to report their decision to CH. Four possible cases of the activity between CRDs and the PU should be discussed.

Case 1: the PU is present and CRDs can detects it, which means the spectrum will be occupied by the PU and CRDs can only send sensing information to CH instead of transmitting useful data. In this case, the total energy consumed for one cluster can be estimated as:

$$E_1 = NT_s e_s + T_r e_r \tag{27}$$

where e_s and e_r are sensing power and transmission power of each CRD, respectively.

Case 2: The actual state of the PU is absent, but CRDs detect it as a present. In this case, no data can be transmitted and total energy consumed will be the same as in the previous case.

Case 3: the PU is present but CRDs can not detect it successfully. In this case, the miss detection occurs and the data transmission will be invalid due to the interference with the PU's signal. Thus, the total energy consumed by one cluster is given as:

$$E_2 = NT_s e_s + T_r e_r + (T - T_s - T_r)e_r \tag{28}$$

Case 4: the PU is absent, and the CRDs can detect it successfully. In this case, the data transmission will be valid and energy consumption is the same as in the previous case.

Apart from these four cases, the energy will be consumed during reporting of the cluster decision by the CH to the FC. For k clusters, the energy consumption is given by

$$E_3 = \frac{kT_r e_t}{N} \tag{29}$$

Therefore, the total energy consumption E_{total} can be given by

$$\begin{aligned} E_{total} &= kNT_s e_s + \frac{N-1}{N} kT_r e_r + \frac{kT_r e_t}{N} \\ &\quad + \left[P(H_0)(1 - P_{f,c}) + P(H_1)P_{d,c}\right](T - T_s - T_r)e_r \end{aligned} \tag{30}$$

There are two cases when CRDs are allowed to transmit data. In the first case, the CRDs can successfully detect the absence of the PU. And yet, in the second case, the CRDs miss detects it. The corresponding throughputs of above cases are discussed below:

Case 1: the PU is absent and the CRDs succeed in detecting the state of the PU.

$$R_1 = C_0 P(H_0)(1 - Q_f)(T - T_s - T_r) \tag{31}$$

where $C_0 = \log_2(1 + \gamma_s)$ is the achievable bit/s/Hz of the CRD operating at the absence of the PU, and $C_1 = \log_2\left(1 + \frac{\gamma_s}{1+\gamma}\right)$ is the achievable bit/s/Hz of the CRD when it does not correctly detect the presence of the PU according to the Shannon theorem. Besides, γ_s and γ are the SNR value of secondary link and the primary link, respectively.

Case 2: the PU is active but the CRDs fails to detect the active state of the PU.

$$R_2 = C_1 P(H_1)(1 - Q_d)(T - T_s - T_r) \tag{32}$$

Thus, the overall throughput for both the cases is given by:

$$\begin{aligned} R_{total} &= \left[C_0 P(H_0)(1 - Q_f) + C_1 P(H_1)(1 - Q_d)\right] \\ &\quad \times (T - T_s - T_r) \end{aligned} \tag{33}$$

Therefore, the achievable energy efficiency can be expressed as

$$EE = \frac{R_{total}}{E_{total}} \tag{34}$$

V. EXPERIMENTAL RESULTS

In this section, we evaluate the performance and present some experimental results to verify the feasibility of our proposed scheme. In the experiments, the CRDs are uniformly distributed in the square field with the length of 800m. The FC is located in the center of the square, and the PU is randomly located in the region. In addition, we assume that the instantaneous SNR is available for each node. The noise samples are independent to each other and uncorrelated between each CRD. Besides, additive white Gaussian noise channel is assumed between the PU and each CRD.

TABLE 1. Parameter values used in the simulation.

Parameter	Value
environment dependent constant ε	0.002
number of samples M	100
sampling frequency f_s	$6MHz$
sensing power e_s	$10mW$
intra-cluster transmission power e_r	$10mW$
transmission power e_t for reporting from the CH to the FC	$100mW$
total frame time T	$50ms$
quantised form of multiple bits θ	8
reporting data rate v	$10kbps$
SNR for the secondary link γ_s	$20dB$
occurrence probability $P(H_0)$	0.5
occurrence probability $P(H_1)$	0.5

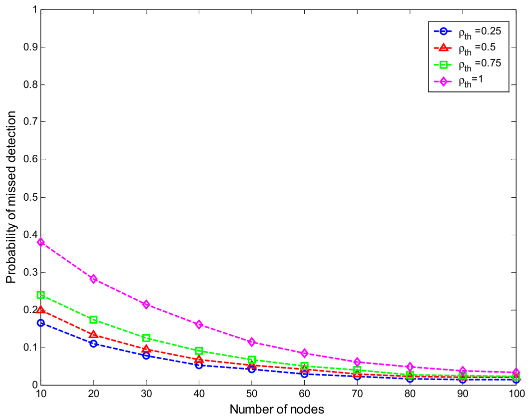

FIGURE 1. Probability of missed detection versus the correlation coefficient.

The PU's signal is modeled as Gaussian random numbers with mean 0 and variance γ, which will be varied in the range of $[-20dB, -10dB]$. Other simulated parameters are summarized in Table 1.

The probability of missed detection under different correlation coefficients is depicted in Fig. 1 for different number of CRDs. According to the definition of the correlation coefficient, it will reduce the spatial diversity gain and increase the sensing cost. The value of ρ_{th} determines that the sensing results of the CRDs in close proximity will be correlated. If the correlation coefficient tends to 1, all CRDs should be required to participate in sensing activity. However, many studies have proved that spatial correlation affects the performance of cooperative spectrum sensing, and only increasing the number of CRDs does not always lead to the maximum performance. From the results, it can be observed that the number of spatially correlated CRDs participating in the cooperation can make significant impact on the detection performance. It also can verify that spatial correlation between the CRDs has the negative impact on cooperative spectrum sensing. For the selection of uncorrelated CRDs, the probability of missed detection can maintain at a relatively lower level. It is obvious to observe that the performance, when

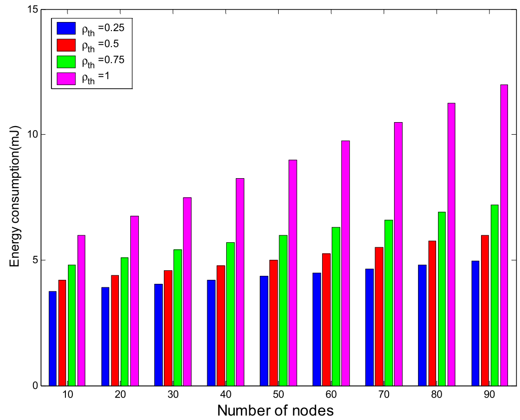

FIGURE 2. Energy consumption versus the correlation coefficient.

correlation coefficients are set to 0.5 and 0.75, demonstrate slightly the same and they both outperform other cases.

Fig. 2 illustrates the effect of increasing correlation on energy consumption with different number of CRDs. The cooperative spectrum sensing under spatial correlation can activate only partial nodes rather than all members in the clusters so as to reduce the energy consumption. The small value of correlation coefficient indicates that the distance of the non-correlated nodes will be increased. It means that the CRDs will be more spatially distributed. Too much cooperative CRDs will results in high overhead during the sensing result's collection and report, and then lead to high energy consumption for data transmission. From the experimental results, we can see that when all nodes participate in cooperative awareness, the overall energy consumption increases significantly with the increase of nodes' density. It demonstrates that the correlation threshold can regulate the number of active member nodes and the distance between members and CHs, so as to optimize the cost of sample collection and reporting in the cluster and reduce the energy consumption of the whole system.

The effect of increasing correlation on energy efficiency with different number of CRDs is shown in Fig. 3. In general, energy efficiency increases initially as the number of CRDs increases. It is worth noting that as the number of CRDs increase, the energy efficiency will reach at a certain point and starts to decline. The reason is that false alarm can be reduced owing to more cooperative CRDs and low false alarm will lead to high throughput. Nevertheless, if the number of CRDs further increases, there will be more energy consumption due to large overhead. Hence, energy efficiency decreases. Therefore, it is important to selects optimal uncorrelated CRDs among all CRDs. Besides, higher value of ρ_{th} can make more spatially correlated CRDs participate in the cooperation and obtain better sensing performance, especially in case of sparse distribution. However, with the increase of node's density, a relatively small value of ρ_{th} can achieve higher energy efficiency.

Furthermore, we compare the performance of proposed scheme with SDF [37] and DDLBC [38] in aspects of global

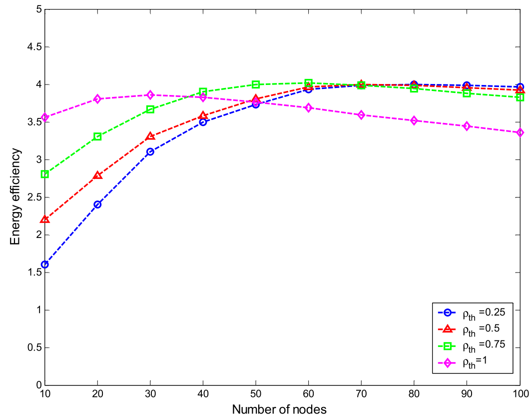

FIGURE 3. Energy efficiency versus the correlation coefficient.

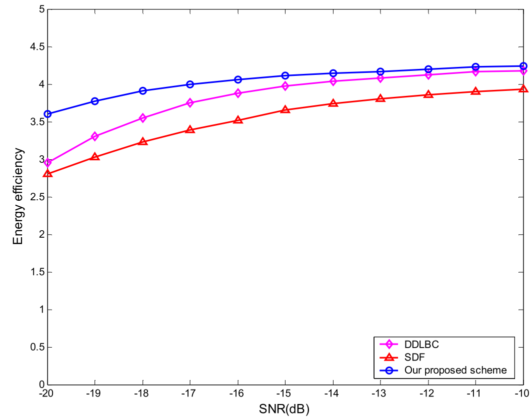

FIGURE 5. Energy efficiency for different value of SNR.

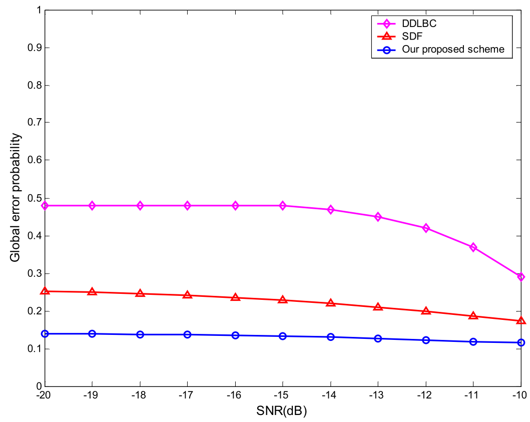

FIGURE 4. Global error probability for different value of SNR.

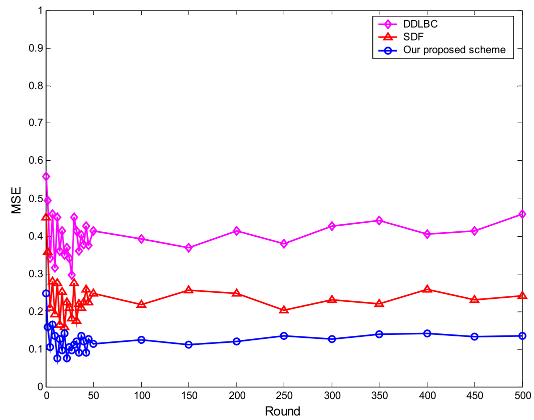

FIGURE 6. MSE in different rounds.

error probability and energy efficiency. The global error probability is defined as $P_e = P(H_0)(1 - P_f) + P(H_1)P_d$, where P_f and P_d refer to the global false alarm and detection probability respectively. It is plotted with respect to average SNR varying from -16 to 0 dB. In our scheme, ρ_{th} is set as 0.75 and it means that any pair of CRDs will be considered as correlated nodes if they located within 150m. It can be observed from Fig. 4 that as the value of SNR increase, global error probability decreases because the detection of the PU's signal is more reliable than in worse radio conditions. It is also observed from the result that the global error probability can be well-maintained within 12% in our proposed scheme. In contrast, our proposed scheme can attain marginally lower error probability than the proposed scheme in [38] even in low SNR region. Since the spatial correlation of cooperative CRDs is utilized and the detection threshold of each cluster is optimized, it can guarantee the detection accuracy and reduce the overall error probability effectively.

Fig. 5 depicts the fact of different SNR on energy efficiency of the proposed and other schemes. The results show that our proposed scheme always provides higher energy efficiency than other schemes. In conventional soft fusion scheme, the correlation between cooperative CRDs will reduces the spatial diversity gain and affect the sensing performance harmfully, especially with respect to the overhead of sensing data reporting and the energy consumption for data transmission. Due to the clustered structure for CSS, our proposed scheme and the proposed scheme in [38] can achieve better performance of energy consumption by forwarding the soft sensing data of members to CH. They utilize the sensing information to perform spectrum sensing as well as ensure the low energy consumption during the process of the CH's collection. At low SNR regime, it is demonstrated that our proposed scheme can obtain dynamic decision threshold to compensate for the channel losses and improve the sensing accuracy.

Finally, we make the comparison of the decision accuracy among those schemes in different rounds. Herein, the mean squared error (MSE) will be employed as the performance measurement, which is equivalent to the probability of error detection statistically. The MSE can be defined as follows:

$$MSE_{round} = \frac{1}{rounds} \sum_{j=1}^{rounds} \left| D_j - H_j \right|^2, \tag{35}$$

where D_j represents the decision result of j-th round, and H_j is the actual state of the PU in j-th round. When $D_j = 0$ and $H_j = 1$, the missed detection occurs. Besides, $D_j = 1$ and $H_j = 0$ indicate the false alarm situation.

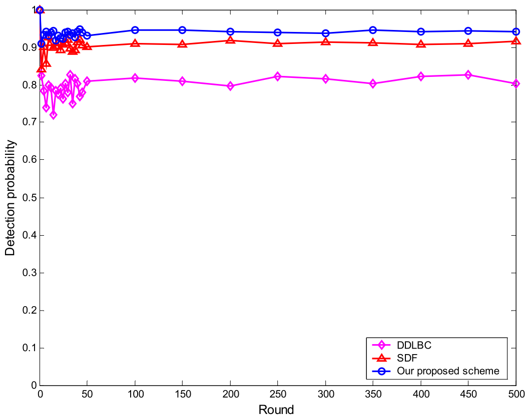

FIGURE 7. Detection probability in different rounds.

Figure 6 shows the comparison of MSE in different rounds. From the experimental results, we can observe that our proposed scheme can obtain the lower mean square error value than other schemes. It demonstrates that our scheme can help the sensing system to gain lower error rate in terms of the PU's signal detection. That is because that our proposed scheme fully takes into account of the effectiveness and reliability of the CSS. On the one hand, intra-cluster soft fusion can ensure the accuracy and consistency of local sensing results. On the other hand, the optimization of the number of clusters can play a crucial role in reducing the global false alarm probability in the process of hard fusion between clusters.

Figure 7 shows the comparison of detection probability among the schemes in different rounds. It can be found that the detection rate of our scheme and SDF in each round is relatively stable and can maintain at a high level. By assigning different weights to the test statistics of each cluster, SDF employs weighted soft combination to determine the optimal decision threshold. Comparatively, due to the joint optimization of uncorrelated node's selection and optimal decision threshold, our proposed scheme can achieve better local sensing results and enhance the detection accuracy.

VI. CONCLUSION

In this paper, we propose an energy-efficient cooperative spectrum sensing scheme based on spatial correlation for CIoT. By analyzing the impact of the spatially correlated CRDs on the detection performance, we presenting both soft fusion and hard fusion schemes for cluster decision and the global decision to provide better sensing performance and improve the energy-efficiency. During the process of intra-cluster soft fusion, the impact of correlated CRDs' observations on the performance of the PU's detection is analyzed and the algorithm is introduced to select optimal uncorrelated CRDs for CSS. Besides, the fusion strategy is discussed and the optimal number of CHs is estimated in the stage of hard fusion. The simulation results show that the proposed scheme can lead to significant improvement in terms of energy efficiency and global error rate.

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