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# Soft Decision Cooperative Spectrum Sensing With Entropy Weight Method for Cognitive Radio Sensor Networks

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**ABSTRACT** By fully utilizing the spatial gain and exploiting the multiuser diversity, cooperative spectrum sensing can enhance the sensing accuracy. In the actual wireless environment, the effect of shadowing and fading will result in the different features of signals received by the sensing nodes with different distances from primary user. As a result, some cooperative nodes in deep fading will suffer from serious missed detection, which will affect the final results during the fusing operation. To solve the above problems, a soft decision cooperative spectrum sensing with entropy weight method for cognitive radio sensor networks is presented. Initially, the sensor nodes will be organized into logical groups to obtain energy efficiency and improvement of sensing performance. After receiving the soft sensing information from all member nodes, the cluster heads employs the equal gain soft combination for inter-cluster fusion and then forwards the local decision to the fusion center. During the final decision, the entropy weight method is applied to assign optimal weight value to corresponding cluster local decisions. The simulation results show that the proposed method can outperform some typical clustering scheme for cooperative spectrum sensing in terms of the detection probability and the total error probability.

**INDEX TERMS** Cooperative spectrum sensing, soft decision, entropy weight method, cognitive radio sensor networks.

## I. INTRODUCTION

By employing cognitive radio (CR) technology, the sensor nodes in cognitive radio sensor networks (CRSNs) can change its parameters according to the interactions with the environment. The available licensed bands will be utilized efficiently, which can alleviate the problem of spectrum scarcity to some extent [1]. As a kind of network with cognitive ability to spectrum resources, CRSN can make more flexible use of the sensing results. It reduces the unnecessary overhead caused by preemption of spectrum resources with other wireless devices in the common frequency band, and provides a better guarantee for reliable transmission [2]. Owing to work in the unauthorized mode, it is crucial for CRSN to detect the status of authorized users precisely to

avoid interference and possess enough adaptability along with the change of channel conditions. However, during the process of actual spectrum sensing, many kinds of transmission impairments usually occurs, including severe fading [1], shadowing [3], hidden terminal problems [4], *et al.*, which brings about adverse effects on the sensing or reporting channels and causes severe damage of the system's detection performance. More concretely, due to the condition of multi-path fading and shadow effect, the signal attenuation will be too serious for cognitive sensor nodes to distinguish the state of licensed channels under low signal-to-noise ratio (SNR) condition. Besides, the change of interference source will cause the noise uncertainty, and the performance of energy detection will be greatly weakened due to the deviation of noise estimation. Once the SNR of signal received from primary user (PU) is lower than a certain threshold, the detection result of a single sensor node will be unreliable [4].

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Moreover, for cognitive wireless sensor nodes, limited by hardware conditions, their sensing radius and signal processing ability have great limitations. It is difficult for a single sensor to achieve the accuracy of detection results in line with the requirements of the system especially under the imperfect physical environment. Moreover, for hardware-limited sensors, their sensing radius and signal processing ability have great limitations. It is difficult for a single node to achieve sufficient detection accuracy in the above-mentioned physical environment. Cooperative spectrum sensing (CSS) is a promising technique to overcome the above problems in CRSN [5]. By combining various nodes' sensing data, the fusion center (FC) can make use of global test statistic to obtain final sensing decision so as to improve the detection performance [6]. However, it should be noted that under low signal-to-noise ratio, the sensing data of nodes with poor channel conditions will affect the fusion results and lead to the degradation of the overall detection performance. Obviously, the communication channel between the PU and the sensing nodes should be taken as key factors, and the weights in the fusion criteria need to be quantized reasonably. That will effectively improve the contribution of the local test statistics with high reliability, so as to improve the performance of cooperative spectrum sensing.

The main contributes of our work can be summarized as following:

(i) Taking into account the effect of shadowing and fading, we proposed a soft decision CSS scheme based on clustering structure.

(ii) To enhance the sensing performance, we introduce the entropy weight method to assign different weighted factors to corresponding cluster local decisions for the proposed clustering scheme.

The rest of this article is structured as follows: Section II provides a survey of existing cooperative spectrum sensing schemes. Section III defines the hierarchical network model and the energy detection model and analyzes the impacts of weight coefficient of cluster local decision on the sensing performance theoretically. Section IV introduces an optimal weighted combination scheme to address the problem of optimal weight fusion rule. In Section V, simulation results are presented from the point of view of detection performance. Finally, the paper is concluded in Section VI.

## II. RELATED WORK

By using the spatial diversity of nodes in different geographical locations, CSS can reduce the impact of detection performance caused by shadow fading or multipath fading. In addition, it is also conducive to reducing the pressure required by the sensitivity of the system and alleviating the problems caused by hardware limitations [7]. In the recent years, the explosion of research related to the CSS technologies have been emerged in an endless stream. Althunibat *et al.* [8] conducted the comparison between soft-data combination and hard-decision spectrum sensing schemes and analytically proved that the soft scheme be

effective solution especially with the limitation of the sensing time. Nallagonda *et al.* [9] analyzed the performance of soft-data fusion and hard-decision schemes for various sensing channels, and derived the closed-form analytic expressions of detection probability under various soft schemes in Rayleigh fading channel. By optimizing the sensing period and the searching time, Hu *et al.* [10] proposed a periodic cooperative spectrum sensing model with weighted data fusion, which optimized the perception interval and search time. By optimizing the sensing time and the threshold of energy detection jointly, Hu *et al.* [10] achieved a compromise between spectrum efficiency and energy efficiency. Jiao *et al.* [11] put forward a cooperative spectrum sensing optimization strategy based on clustering, in which hard decision rules are applied to achieve high energy efficiency. Under the constraint of limited control channel bandwidth, Rakovic *et al.* [12] presented a cooperative spectrum sensing algorithm to further enhance the spectrum detection. In CSS, the important content of the research is to choose the parameters of cooperative sensing and design the proper fusion rules to obtain the optimal detection performance.

The distribution and geographical position of cooperative sensor nodes, as well as the quality of the reporting channel, the fusion strategy of sensing results and other factors will affect the detection performance. In [13], Chavali *et al.* proposed a novel collaborative sensing method to gather the local decision results of sensing nodes and their SNR estimation, and select the sensing nodes with high SNR according to certain criteria for final decision. In [14], Ejaz *et al.* adopted the average received SNR of each cognitive user to define the detection reliability, and then optimize the detection threshold to obtain a lower total error probability. From the perspective of maximizing the detection probability, Xin *et al.* [15] proposed a cooperative spectrum sensing algorithm with weighted soft fusion, and allocate the sensing nodes with high SNR or low channel gain in term of the coordinator, proportion of the sensing information. To reduce the interference to authorized users and improve the network throughput, Kan *et al.* [16] introduced an interference-aware model for CSS and investigated the issue of sensing-throughput tradeoff. Based on comprehensive consideration of cooperative gain, nodes' residual energy, and distance from PU, and the cost of data sensing and reporting, Muthukkumar and Manimegalai [17] proposed a distributed dynamic load-balanced clustering algorithm to improve the sensing accuracy. By taking into account of the variance and geographical position and topological structure among the cooperative sensors, Abozarib *et al.* [18] proposed an optimum fusion rule based on location reliability. Most of the related literature assumes that the SNR environments between the cognitive sensor nodes and the authorized users are the same and ideal, while the actual cognitive users are randomly distributed with different SNR. The accuracy of the local spectrum detection results of the sensing node has a great impact on the spectrum detection performance. Reasonable selection of cognitive users and reasonable fusion strategy

can effectively alleviate the impact of channel fading and noise uncertainty, thus obtaining a low error probability.

However, most of the related literature has endeavored to increase the sensing performance under the assumption of perfect spectrum sensing, which are unable to meet the requirement of realistic scenarios [19]–[21]. Cooperative sensor nodes with low SNR will negatively affect gathering global sensing data, and the total error probability due to imperfect sensing need to be formulated precisely.

### III. SYSTEM MODEL

Assuming the PU and plenty of sensor nodes being random distributed in large areas, as shown in Fig. 1. Each sensor node will sense the channel opportunistically for monitoring the status of PU whether occupies in the authorized channel. To restrict the interference to PU and improve the energy efficiency, spectrum-aware clustering scheme is employed in this paper, and the system model of the two-layer hierarchical CRSN is depicted in Figure 1. Several sensor nodes, who are referred to as member nodes, can be organized into a logical group and sent their local sensing information to a cluster head (CH).

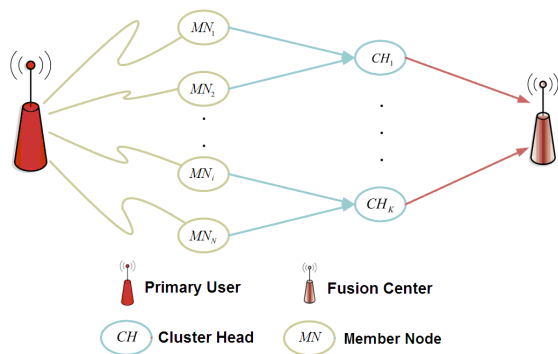


FIGURE 1. System model of a two-layer hierarchical CRSN.

#### A. HIERARCHICAL NETWORK MODEL

It is assumed that the system meets the following preconditions: (1) The cognitive sensor nodes know the instantaneous information of the channel; (2) The channels among the cooperative sensor nodes in each cluster is ideal; (3) Before spectrum sensing, the upper layer has divided all sensor nodes into several clusters according to clustering protocol. Based on the above assumption, the design of clustering spectrum sensing can be summarized as follows: firstly, to achieve the balance of the energy depletion, the sensor nodes will be selected as CHs in turn. During the phase of spectrum sensing, the member nodes in all clusters should reports their local sensing data to the cluster head through the local communication channel, and the CH makes local cluster decision. Finally, the cluster head transmits the decision result to FC, which makes the final decision according to the data gathered from all CHs.

Consequently, the cluster decision and final decision should be discussed according to the relevant fusion

strategies. Generally speaking, either hard-decision or soft-data fusion scheme can be employed for intra-cluster decision. Some research proved that soft-data combination demonstrates better cooperative sensing performance than hard-decision schemes, especially in low SNR regimes [22]. Moreover, from the perspective of data transmission, the hard-decision will produce binary results and be fewer than soft-data fusion [23]. By directly sending all member nodes' local observations to CH, Intra-cluster employing soft-data fusion scheme can make better use of the characteristics of high sensing accuracy. Furthermore, the hard-decision scheme can be applied to inter-cluster fusion. It will not only reduce the communication cost of long-distance transmission, but also be easy to implement. To enhance the detection accuracy and energy efficiency, soft-data fusion by using equal gain combining (EGC) will be conducted at CH in each cluster, and weighted hard-decision combination will be made by the FC to make the final results.

#### B. ENERGY DETECTION MODEL

The cooperative sensor nodes are divided into  $K$  clusters, and  $S_k$  represents the number of member nodes in  $k$ -th cluster. For the member node  $n_{k,i}$  in the  $k$ -th cluster, the  $l$ -th sensing sample can be represented by binary hypothesis [24] as:

$$\begin{cases} H_1 : x_{k,i}(l) = h_{k,i}s(l) + n(l), \\ H_0 : x_{k,i}(l) = n(l), \end{cases} \quad (1)$$

where  $s(l)$  represents the transmitting signals for authorized users,  $x_{k,i}(l)$  represents the signals observed for the  $i$ -th cognitive user, and  $n(l)$  is a Gaussian, independent and identically distributed (i. i. d) random process with zero mean and variance  $\sigma_n^2$ . Besides,  $h_{k,i}$  denotes the channel gain between the authorized user and the cognitive node  $n_{k,i}$ . In addition,  $H_1$  and  $H_0$  indicate that the authorized user exists or not, respectively.

According to the accumulated value of  $M$  samples of the signal from the receiver, the test statistic of energy detection can be given as [25]:

$$T_{k,i} = \frac{1}{M} \sum_{l=1}^M |x_{k,i}(l)|^2. \quad (2)$$

By omparing  $T_{k,i}$  with the predefined threshold  $\lambda_{k,i}$ , the status of the authorized user exist or not can be deduced. If  $H_0 : T_{k,i} > \lambda_{k,i}$ . Otherwise,  $H_1 : T_{k,i} < \lambda_{k,i}$ .

When  $M > 100$  and on the basis of the Central Limit Theorem,  $T_{k,i}$  approximates to Gaussian distribution. Hence, the mean value  $\mu_{k,i,j}$  and variance  $\sigma_{k,i,j}^2$  of  $T_{k,i}$ , under the hypothesis conditions  $H_j(j = 0 \text{ or } 1)$ , can be given as:

$$H_0 : \begin{cases} \mu_{k,i,0} = \sigma_n^2 \\ \sigma_{k,i,0}^2 = \frac{2}{M} \sigma_n^4 \end{cases} \quad (3)$$

$$H_1 : \begin{cases} \mu_{k,i,1} = (1 + \gamma_{k,i})\sigma_n^2 \\ \sigma_{k,i,1}^2 = \frac{2}{M}(1 + 2\gamma_{k,i})\sigma_n^4 \end{cases} \quad (4)$$

where  $\gamma_{k,i}$  represents the SNR of the  $i$ -th member node's receiver in the  $k$ -th cluster.

Therefore, the false alarm probability and detection probability of the cognitive sensor node  $n_{k,i}$  in Gaussian channel can be given, respectively, as:

$$P_{f,k,i} = P(T_{k,i} > \lambda_{k,i} | H_0) = Q\left(\left(\frac{\lambda_{k,i}}{\sigma_n^2} - 1\right)\sqrt{\frac{M}{2}}\right), \quad (5)$$

$$P_{d,k,i} = P(T_{k,i} > \lambda_{k,i} | H_1) = Q\left(\left(\frac{\lambda_{k,i}}{\sigma_n^2} - \gamma_{k,i} - 1\right)\sqrt{\frac{M}{4\gamma_{k,i} + 2}}\right), \quad (6)$$

where  $Q(\cdot)$  is Gaussian tail function, and it can be defined as  $Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty \exp\left(-\frac{x^2}{2}\right) dx$ .

The energy threshold  $\lambda_{k,i}$  can be determined by false alarm probability and detection probability, and then  $P_{f,k,i}$  and  $P_{d,k,i}$  will be given by

$$P_{f,k,i} = Q\left(Q^{-1}(P_{d,k,i})\sqrt{2\gamma_{k,i} + 1} + \gamma_{k,i}\sqrt{\frac{M}{2}}\right), \quad (7)$$

$$P_{d,k,i} = Q\left(Q^{-1}(P_{f,k,i})/\sqrt{2\gamma_{k,i} + 1} - \gamma_{k,i}\sqrt{\frac{M}{4\gamma_{k,i} + 2}}\right). \quad (8)$$

Since the detection probability is related to the function of SNR  $\gamma_i$ , under Rayleigh channel the SNR of cognitive radio will be expressed as following [26]:

$$f(\gamma_{k,i}) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma_{k,i}}{\bar{\gamma}}\right) \quad (9)$$

where  $\bar{\gamma}$  represent the average SNR.

Thus, in Rayleigh channel the detection probability  $P_{d,k,i}$  can be estimated as:

$$P_{d,k,i} = \int_0^{+\infty} P_d(\gamma_{k,i}) f(\gamma_{k,i}) d\gamma_{k,i} \quad (10)$$

After each member mode makes local observation, the energy statistics of the authorized user signals being observed will be sent to the CH, and then the CH conducts the local cluster fusion according to weighted soft fusion. During the phase, the test statistic of energy detection will compare with the threshold  $\lambda_{k,g}$  of the cluster to decide whether PU is busy or idle state.

The test statistics of member node being sent to the cluster head can be given as:

$$Y_{k,i} = g_{k,i}T_{k,i} + v_k, \quad i = 1, 2, \dots, S_k \quad (11)$$

where  $g_{k,i}$  is channel gain from member node  $i$  to  $k$ -th CH.  $v$  represents additive white Gaussian noise, and  $v_k$  is a Gaussian, independent and identically distributed (i. i. d) random process with zero mean and variance  $\sigma_{v,k}^2$ .

Hence, the aggregated statistics of  $k$ -th CH is given by

$$Z_k = \sum_{i=1}^{S_k} \omega_{k,i} Y_{k,i}, \quad (12)$$

where  $\omega_{k,i}$  represents the weight value of  $i$ th member node.

The soft fusion in the cluster employs equal gain combining [27], and the weight of each member node is equal, i. e.,  $\omega_{k,i} = \omega_k = 1/\sqrt{S_k}$ . Suppose that  $\omega_i$  and  $Y_{k,i}$  are independent of each other,  $Z_k$  obeys Gaussian distribution. Thus, the mean value  $\mu_{Z_k,j}$  and variance  $\sigma_{Z_k,j}^2$  of the aggregated test statistics under the assumption  $H_j$  can be given, respectively, by

$$H_0 : \begin{cases} \mu_{Z_k,0} = \sum_{i=1}^{S_k} \omega_k g_{k,i} \sigma_n^2 \\ \sigma_{Z_k,0}^2 = \frac{2}{M} \sum_{i=1}^{S_k} \omega_k g_{k,i} \sigma_n^2 + \sigma_{v,k}^4 \end{cases} \quad (13)$$

$$H_1 : \begin{cases} \mu_{Z_k,1} = \sum_{i=1}^{S_k} \omega_k g_{k,i} (1 + \gamma_{k,i}) \sigma_n^2 \\ \sigma_{Z_k,1}^2 = \frac{2}{M} \sum_{i=1}^{S_k} \omega_k g_{k,i} (1 + 2\gamma_{k,i}) \sigma_n^4 + \sigma_{v,k}^4 \end{cases} \quad (14)$$

Therefore, the false alarm probability and detection probability in the cluster can be obtained as following:

$$P_{f,k} = Q\left(\frac{\tilde{\lambda}_k - \sum_{i=1}^{S_k} \omega_k g_{k,i} \sigma_n^2}{\sqrt{\frac{2}{M} \sum_{i=1}^{S_k} \omega_k g_{k,i} \sigma_n^2 + \sigma_{v,k}^4}}\right), \quad (15)$$

$$P_{d,k} = Q\left(\frac{\tilde{\lambda}_k - \sum_{i=1}^{S_k} \omega_k g_{k,i} (1 + \gamma_{k,i}) \sigma_n^2}{\sqrt{\frac{2}{M} \sum_{i=1}^{S_k} \omega_k g_{k,i} (1 + 2\gamma_{k,i}) \sigma_n^4 + \sigma_{v,k}^4}}\right). \quad (16)$$

Each CH forwards the fusion result to the FC for further process and attaining the final decision. If sensing result shows that the PU is idle, the sensor nodes of the network can deliver their monitoring data during the transmission phase. Otherwise, they should keep silent and perform spectrum sensing for idle spectrum band [28], [29].

Let  $U_{k,j}$  denote the result of hard decision transmitted from the  $k$ -th cluster head to FC, and then weighted combination will be made as following:

$$DF = \sum_{j=1}^K w_k U_{k,j} \quad (17)$$

where  $w_k$  represents the weight value of  $k$ -th cluster.

The decision threshold is set to 1/2, i. e., when the sum of weighted hard decision result with 1 is greater than the sum of weighted result 0, the PU's activity will be determined as present. Otherwise, the PU's status will be considered as absent [30], [31]. The detection probability and false alarm probability of the  $k$ -th cluster are  $P_{d,k}$  and  $P_{f,k}$  respectively. Thus, the global false alarm probability and



detection probability can be calculated as:

$$Q_f = \sum_{\sum U_{k,j}=1}^K \sum_{\sum U_{k,j}w_k \geq 1/2} \prod_{k=1}^K (P_{f,k})^{U_{k,j}} (1 - P_{f,k})^{1-U_{k,j}} \quad (18)$$

$$Q_d = \sum_{\sum U_{k,j}=1}^K \sum_{\sum U_{k,j}w_k \geq 1/2} \prod_{k=1}^K (P_{d,k})^{U_{k,j}} (1 - P_{d,k})^{1-U_{k,j}} \quad (19)$$

Obviously, the weight value of each cluster is very important for the detection performance of the system. Next, we will discuss the determination of the weight value of each cluster according to the corresponding contribution to the performance.

#### IV. OPTIMAL WEIGHT VALUE

##### A. MULTIPLE FACTORS

During the phase of inter-cluster decision fusion, all cluster decisions should be allocated based on multiple weighted factors corresponding to their sensing reliabilities. To obtain better performance, we should conduct the analysis on the critical factors with regard to the quality of CH's channel [32], [33]. For the clusters, some factors will contribute to the global detection, which includes the channel's SNR, the location-aware sensitivity, the deviation of sensing result and the maximum throughput with interference tolerance [34], [35]. The specific definitions of above factors are given below.

*Definition 1:* The channel's SNR. On the premise that each cluster head node can measure its distance from PU, the SNR of the  $k$ -th CH can be expressed as:

$$f_1(k) = \frac{W_{pu}}{(d_{k,pu})^\alpha \sigma_n^2} \beta \quad (20)$$

where  $W_{pu}$  denotes the signal power of the authorized user, and  $d_{k,pu}$  denotes the distance between the  $k$ -th CH and the authorized user. Besides, parameter  $\alpha$  is the path loss factor and  $\beta$  is a channel dependent constant.

*Definition 2:* the location-aware sensitivity. The closer the cluster is far from the authorized user, the better the effect of noise uncertainty and fading can be reduced. In addition, the CH close to the FC can obtain relatively lower of the error rate for data forwarding in reporting channel. Therefore, the location-aware sensitivity can be defined by the distance from the CH to the authorized users and the FC.

Let  $d_{k,pu}$  and  $d_{k,FC}$  denote the distance from the  $k$ -th CH to the authorized users and the FC, respectively, then the location-aware sensitivity can be defined as:

$$f_2(k) = \exp\left(-\sqrt{(d_{k,pu})^2 + (d_{k,FC})^2}\right) \quad (21)$$

*Definition 3:* the deviation of sensing result. Generally speaking, the propagation condition of the PU's signal will not vary significantly among the sensor nodes in the neighboring region, which means that the sensor nodes in a certain

range should not produce significant estimation errors. The deviation of sensing result can be defined as the difference between the average value of test statistics of  $k$ -th cluster and other clusters, which can be expressed as:

$$f_3(k) = \left| Z_k - \frac{1}{K} \sum_{k=1}^K Z_k \right| \quad (22)$$

*Definition 4:* the maximum throughput with interference tolerance. When the interference tolerance is not exceeded, the channel capacity increases gradually as well as the bandwidth or interference temperature redundancy in a certain range. The reason is that the reliable transmission capacity will increase with the interference tolerance, and then play a corresponding role in the overall throughput [36], [37]. As improving the throughput, we should also ensure that the resulting interference to the PU below a predefined threshold. Thus, the throughput with interference tolerance can be expressed as:

$$f_4(k) = \Pr(H_1) C_k \left( 1 - Q \left( \frac{Q^{-1}(\alpha)}{\sqrt{1+2\gamma}} - \sqrt{\frac{M}{2} \sum_{i=1}^{S_k} \frac{\gamma_{k,i}^2}{1+2\gamma_{k,i}}} \right) \right) \quad (23)$$

where  $C_k$  denotes the capacity of  $k$ -th CH and  $C_k = 1 + \frac{W_{pu}}{P_{s,k} + \sigma_n^2}$ ,  $P_{s,k}$  is the average power of receiver.

Considering the different evaluation standards of the above indicators, it is necessary to standardize the measurements from above factors, and then use entropy weight method to determine the corresponding weights objectively.

##### B. WEIGHT VALUE BASED ON ENTROPY THEORY

Based on the entropy theory, the entropy weight method can be applied for the subjective assignment. To determine subjectively weight coefficient, the entropy weight method can avoid the interference of subjective judgment and ensure that the established metrics reflects most of the original information [38], [39]. In this paper, we employs the entropy weight method to determine the weight value of above multiple factors corresponding to their contributes for sensing reliabilities. Generally, the entropy weight method includes several steps of object gathering, normalization of index value, determination of index weight, and calculation of synthetic index [40], [41].

Let  $S = \{s_1, s_2, \dots, s_K\}$  denote the set of CHs in the network, and  $F = \{f_1, f_2, \dots, f_N\}$  be the set of multiple factors, we can construct the matrix  $X$  as

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2N} \\ \dots & \dots & \ddots & \dots \\ x_{K1} & x_{K2} & \dots & x_{KN} \end{bmatrix} \quad (24)$$

where  $x_{kn}$  is the  $n$ -th index value of the  $k$ -th CH.

To eliminate the influence caused by the different dimension of each factor and deal with some decision-making problems with negative index values, the decision matrix should be standardized. According to the nature of the index, the index is divided into two categories: benefit index and cost index [42], [43]. Among the above factors, the channel's SNR, the location-aware sensitivity and the maximum throughput with interference tolerance can be regarded as benefit index. Besides, the deviation of sensing result should belong to cost index. Suppose  $\rho_{kn}^+$  and  $\rho_{kn}^-$  be the result of data standardization for benefit index and cost index, and  $0 \leq \rho_{kn} \leq 1$ , we have

$$\begin{cases} \rho_{kn}^+ = \frac{x_{kn} - \min\{x_n\}}{\max\{x_n\} - \min\{x_n\}} \\ \rho_{kn}^- = \frac{\max\{x_n\} - x_{kn}}{\max\{x_n\} - \min\{x_n\}} \end{cases} \quad (25)$$

where  $\rho_{kn}$  is the normalized value of  $x_{kn}$ .  $\max\{x_n\}$  and  $\min\{x_n\}$  are the maximum value and the minimum value of the  $n$ -th index respectively.

For a certain index, the greater the value difference of  $\rho_{kn}$  is, the greater the influence of the index on the final fusion result will be [44], [45]. According to the definition of entropy, the increase of its value means the decrease of entropy. Therefore, the entropy value of the index can be expressed as:

$$\kappa_n = -\frac{1}{\ln N} \sum_{k=1}^K \theta_{kn} \ln \theta_{kn} \quad (26)$$

where  $\theta_{kn} = \frac{\rho_{kn}}{\sum_{n=1}^N \rho_{kn}}$ .

Next, the entropy weight of  $n$ -th index can be given by

$$\psi_n = \frac{1 - \kappa_n}{\sum_{n=1}^N (1 - \kappa_n)} \quad (27)$$

Therefore, the weight value of each cluster for final decision can be given by

$$w_k = \sum_{n=1}^N \psi_n \rho_{kn} \quad (28)$$

### V. SIMULATION RESULTS AND DISCUSSIONS

To verify the effectiveness of the proposed algorithm, we conduct the experiments and the results are obtained through Monte-Carlo simulations over 1,000 runs. In the scenario, the sensing channel is a Gaussian fading channel, and the average SNR is set as a constant value. The attenuation coefficient of each channel is randomly generated based on the average SNR.

Figure 2 and Figure 3 show that the detection probability versus the false alarm probability with different number of cooperative sensing nodes. In this scenario, we assume that the channel's SNR is about  $-8\text{dB}$  and  $-15\text{dB}$ . The typical number of clusters  $K$  varies from 5 to 10 in the simulations.

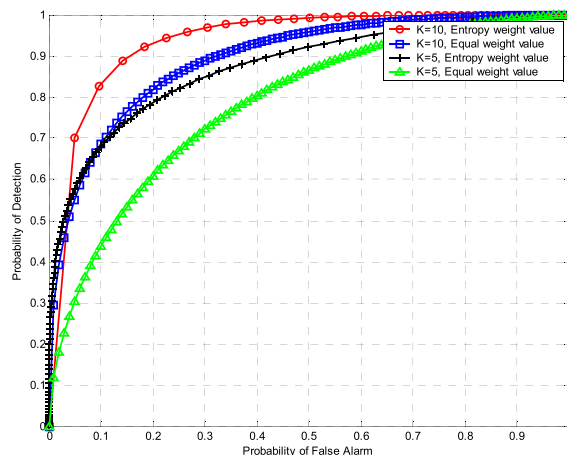


FIGURE 2. The detection probability versus the false alarm probability (average SNR= $-8\text{dB}$ ).

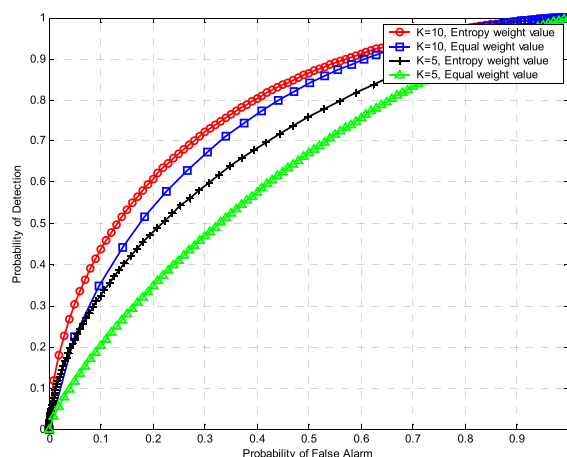


FIGURE 3. The detection probability versus the false alarm probability (average SNR= $-15\text{dB}$ ).

and each cluster consists of 10 member nodes. It can be seen that the network with more sensor nodes' distribution can bring better cooperative sensing gain. Based on the local sensing results of each cluster, the SNR of CHs and other factors may exert a great influence on the overall performance of cooperative detection.

Figure 4 and Figure 5 show the missed detection probability versus the false alarm probability with different number of cooperative sensing nodes. It can be seen from the results that under different SNR conditions, the difference of the missed detection probability is relatively small by using either equal weight or entropy weight respectively. In general, under the same constraint of false alarm probability, the cooperative sensing with weight optimization method can adaptively reduce the contribution of the clusters with poor channel conditions to the final decision of the system. Thus, it can effectively reduce the system's missed detection probability.

From the experimental results, it also can be seen that when all clusters are combined with equal weights, once some sensing nodes are in a poor SNR environment, the overall sensing

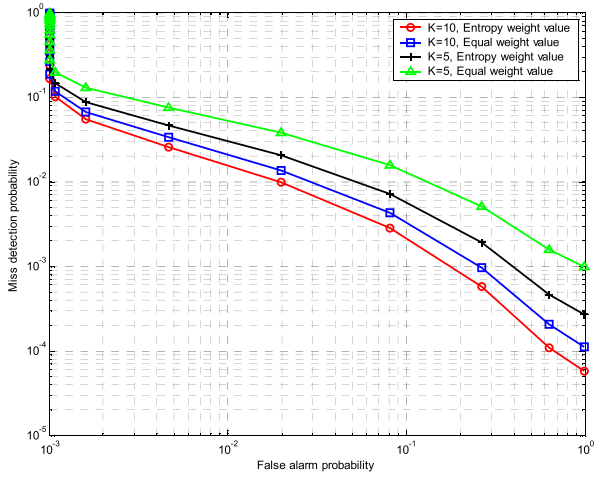


FIGURE 4. The missed detection probability versus the false alarm probability (average SNR=-8dB).

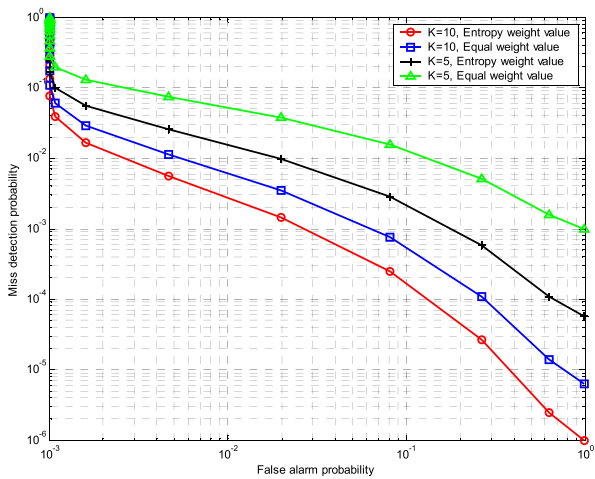


FIGURE 5. The missed detection probability versus the false alarm probability (average SNR=-15dB).

performance will be seriously reduced. Moreover, even if the number of clusters increases, the system performance will not be significantly improved. However, by employing the weight optimization method, our proposed method can well ensure that the detection performance increases with the number of cooperative sensing nodes.

Furthermore, we have simulated the ROC curves in a Rayleigh fading channel and compare the proposed method with the typical algorithms of MCMG [37] and Fuzzy C-means clustering method [38]. Figure 6 shows the performance analysis of the detection probability for various sensing channel's SNRs. It can be observed that the detection probability of all algorithms increases as the value of SNR increases. Moreover, higher quality of sensing channels improves the probability of detection in each cluster, and it results in the rise of the sensing performance further after member nodes' cooperation. At the SNR=-8 dB, the detection probability of our proposed method can be obtained

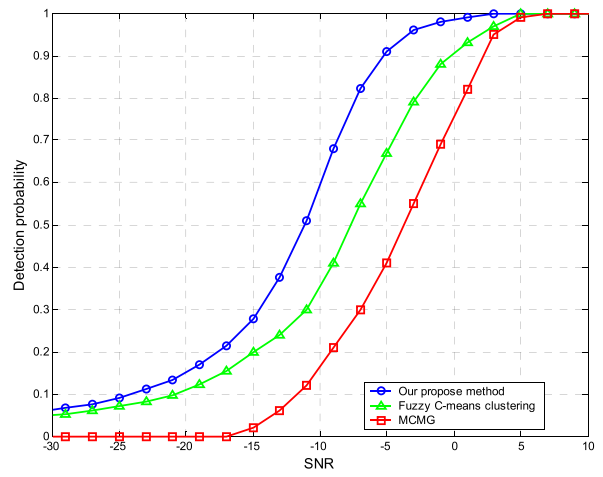


FIGURE 6. The detection probability at different SNR values.

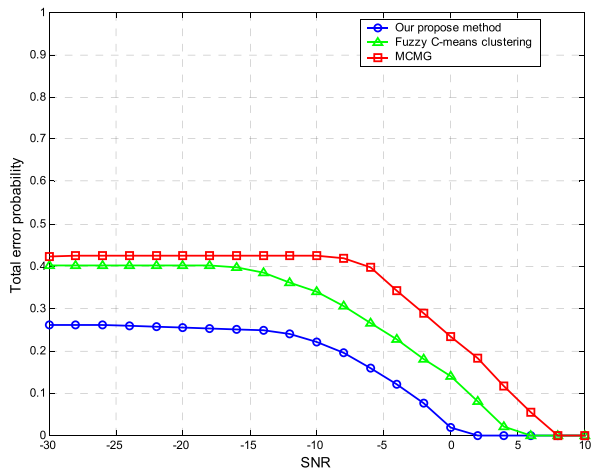


FIGURE 7. The total error probability at different SNR values.

as 0.812, while 0.247 for MCMG and 0.495 for Fuzzy C-means clustering method. It can be concluded that our proposed method can effectively make use of local sensing results of clusters with better channel conditions, so as to improve the performance of CSS.

Figure 7 shows the probability of error at different SNR values. As can be seen from the results, the probability of total error for the proposed scheme is significantly lower than other fusion schemes at any SNR value. In our proposed method, owing to assign reasonable weight value of CHs in final fusion, it can obtain a lower false alarm probability and result in reducing the total error probability. In addition, it is noted that in Figure 6 the detection probability of Fuzzy C-means clustering method is not significant different from our proposed method. However, the total error probability of our proposed method is clearly lower than that of Fuzzy C-means clustering method, especially under low SNR conditions. It illustrates that the detection probability of Fuzzy C-means clustering method can be maintained at a certain level at the expense of false alarm probability.

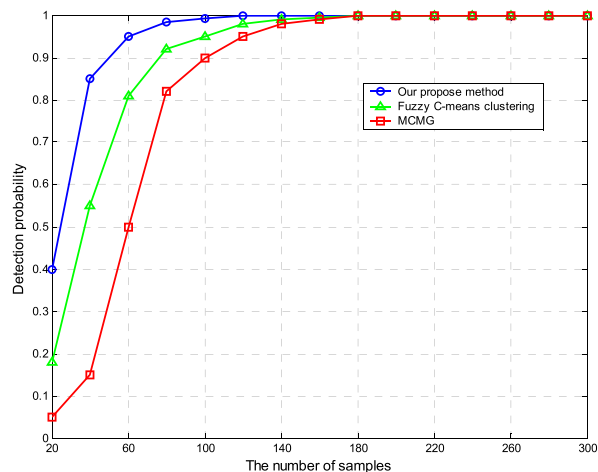


FIGURE 8. The detection probability versus the number of samples.

Figure 8 illustrates the relationship between the detection probability and the number of samples for all algorithms. Simulation experiment is carried out at a SNR of  $-12$  dB. It can be found that when the number of samples is small, the detection probability of our proposed method is significantly higher than that of other methods. When the expected detection probability reaches to 0.9, the number of samples in our proposed method, MCMG and Fuzzy C-means clustering method will approximate to 50, 70, and 100, respectively. It demonstrates that the proposed algorithm can also effectively reduce the sampling overhead and greatly improve the detection performance.

## VI. CONCLUSION

In this paper, we investigate the optimization of CSS schemes based on hierarchical CRSN with soft fusion and propose a soft-data fusion scheme with entropy weight method. Initially, the sensor nodes will be organized into several logical groups to achieve energy efficiency and enhance the sensing accuracy. After gathering the soft sensing data from all member nodes, the cluster heads employs the equal gain soft combination for inter-cluster fusion and then forwards the decision of local cluster to the FC. During the final decision, the entropy weight method is applied to assign optimal weight value to corresponding cluster local decisions. The simulation results illustrates that the proposed scheme outperforms some typical clustering scheme for spectrum sensing in terms of the detection probability and the total error probability.

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