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Fusion Rule Based on Dynamic Grouping for Cooperative Spectrum Sensing in Cognitive Radio

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ABSTRACT In this paper, we study the distributed cooperative spectrum sensing in heterogeneous cognitive radio networks, where each secondary user (SU) adopts a different spectrum sensing algorithm and experience a different channel environment. To solve the spectrum sensing problem, we propose a fusion rule based on dynamic grouping, which can be used in the mobility of the primary user and SUs. By introducing a grouping parameter, the proposed algorithm can realize the dynamic grouping of SUs. The SUs in group-1 will not be able to participate in the cooperation, and the SUs in groups-2 and groups-3 have different weighting factors. The proposed fusion rule is only required to process the independent decision result of each SU, which significantly reduces the data transmission overhead and processing delay. The simulation results show that the proposed fusion rule can effectively improve the dynamic grouping of SUs and fuse detection information, and outperform the or rule, and rule, equal gain combining, and maximum signal-to-noise ratio under the same conditions.

INDEX TERMS Cognitive radio networks, cooperative spectrum sensing, dynamic grouping, weighting factors.

I. INTRODUCTION

With the rapid development of mobile internet, cloud computing, internet of things (IoT), and the rapid popularization of video surveillance, smart terminals, and application stores, the amount of mobile data is growing exponentially [1], [2]. This means that higher transmission rate and more transmission bandwidth are required to achieve real-time interaction of communication data. Due to the ever-increasing demand of spectrum and unreasonable allocation of frequency resources, the shortage of frequency resources has become a key factor restricting the implementation of many services and technologies. Cognitive radio (CR) is considered to be an effective solution which can overcome the scarcity of frequency resources and improve spectrum utilization [3].

In heterogeneous cognitive radio networks (CRNs), secondary users (SUs) continuously monitor the licensed frequency bands and search for frequency bands that are not used by the primary users (PUs). SUs can opportunistically access the licensed but unused spectrum to realize communication and data transmission [4]. When PUs re-access the licensed frequency bands, SUs must relinquish the frequency bands within the specified time or reduce their own transmitting power to avoid interference to PUs. Spectrum sensing can realize real-time monitoring of spectrum usage status and provide idle spectrum related information for SUs, which is the key and prerequisite for implementing CR. The biggest challenge in spectrum sensing is to achieve reliable spectrum detection under low signal-to-noise ratio (SNR) and high dynamic background noise with acceptable complexity and detection time [5], [6]. Most of the detection algorithms have been proposed for spectrum sensing, which is based

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on covariance matrix, radio identification, cyclostationarity, match filtering, and energy detection [7], [8]. Cyclostationarity detection can achieve reliable spectrum sensing, but it has high complexity and requires quite a long time for detection [9]. Match filtering detection is known as an optimal detection algorithm, but it is not easy to obtain the prior information of signals emitted by PUs in practical applications [10]. Energy detection is the most widely used, because it has low computational complexity, low detection delay, and easy implementation. More importantly, it is a blind detection algorithm that does not require prior information. However, the energy detection cannot guarantee the reliability of spectrum sensing under high intensity dynamic background noise [11], [12]. The limitations of local single-node spectrum sensing make it difficult to detect signals of PUs for desired performance under low SNR condition. Consequently, cooperative spectrum sensing (CSS) is proposed as a potential solution, which can effectively address issues that arise in spectrum sensing due to noise, fading, shadowing and hidden terminals [13]–[15].

In CSS, data fusion and final decision can be executed in two different modes, namely, centralized CSS or decentralized CSS. In the centralized mode, each SU senses the specific spectrum separately and reports local detection information to fusion center (FC) via reporting channel. FC analyzes the detection information received from all SUs to acquire a global decision and related information is fed back to all SUs. On the other hand, in the decentralized mode, there is no FC to collect detection information from each local SU and SUs exchange their detection information with other neighboring SUs. The final decision is made by each SU independently. Considering the limited communication resources between SUs and FC, in this paper, we focus on the problem of CSS in centralized mode. Meanwhile, hard decision fusion (HDF) and soft decision fusion (SDF) are the most commonly used fusion rules in CSS. Normally, OR, AND and K-out-of-M rules are widely used in HDF, and each SU is required to send its own decision result to FC. Equal gain combining (EGC), selection combining (SC) and maximum ratio combining (MRC) are widely used in SDF. To the best of our knowledge, SDF performs better than HDF in the same conditions [13]. Nevertheless, each SU needs to send its local test statistics to FC in SDF. That means more bandwidth and longer time are required to transmit and process detection information [15]. The tradeoff between transmission bandwidth, detection time, and detection performance has being a research focus in CSS field.

A. RELATED WORK

A practical combining rule with low complexity and small performance degradation for CSS in block-fading channel has been designed in [5]. The rule is based on the generalized gauss-laguerre formula solution of the average likelihood ratio detector, which is implemented by linear functions and a comparator. The authors in [6] proposed a cooperative sequential fuzzy hypothesis testing detector to cope with the influence of noise uncertainty as well as to reduce the complexity. Each SU takes a sample in each step and sends it to FC to decide the presence or absence of PU. Accordingly, the algorithm not only improves the detection performance but also increases the transmission overhead and detection time. A simple quantization-based multibit data soft fusion rule has been presented in [16]. Each SU equips an energy detector for local spectrum sensing and sends quantized multibit data which includes detection information, instead of decision results or primary test statistics to FC. In [17], a novel clustering scheme which consists pruning, selecting, and clustering has been proposed to minimize extra detection overhead and achieve better detection performance at low SNR. The work of [18] proposed a linear combination rule which provides nearly optimal performance at affordable computational cost. Moreover, a general and effective method to optimize the weighting factors has been given for three typical scenarios, including the slow fading, the block fading, and the fast fading. According to [19], channel conditions for each SU will be different in a real situation. That is, each SU may undergo independent fading and shadowing. Considering this, a new fusion rule in a realistic scenario where SUs are randomly distributed has been proposed in [19]. In [20], the efficiency of SDF in inhomogeneous background has been studied from the perspective of quantization theory. And two novel quantization schemes with two optimization methods have been presented to obtain the quantizer and decision threshold of SDF.

In all these cases, they consider all SUs located under the coverage area of the PU should participate in the CSS, and the final decision is established based on the detection information of all SUs. In fact, it is unwise for all SUs located under the coverage area of the PU to participate in CSS. In many scenarios, such as the presence of malicious SUs, not only increases the overhead of cooperation and information fusion, but also fails to improve detection accuracy and reliability. Besides, the above algorithms assume that SUs are equipped with the same detector types and do not address more realistic cases where SUs use different detection schemes (known as heterogeneous CRNs).

B. CONTRIBUTIONS

In this paper, we investigate CSS in heterogeneous CRNs which only allows some qualified SUs to participate. We consider channel conditions for each SU are different, and the PU and SUs may move within a certain range. The main contributions of this paper are as follows.

- We consider a more realistic channel model in which the signals sent by PU experience different channels to each SU. This means that the received SNR of each SU is different. In addition, we assume that the noise in the electromagnetic environment is dynamic, that is, there is noise uncertainty.
- We assume that not all SUs located under the coverage area of the PU need to participate in CSS, and some SUs may increase the cost of cooperation and fail to

improve the detection performance. At the same time, in the process of detection information fusion, the SUs should assign different weighting factors.

- We propose a fusion rule based on dynamic grouping, which is grouped according to the distance between the PU and SUs. In our scheme, SUs in different groups are assigned different weighting factors, the FC only needs to collect the decision result of each SU. Therefore, the proposed algorithm is applicable to any heterogeneous network due to FC does not need to know the spectrum sensing algorithm performed by each SU.

The remainder of the paper is constructed as follows. The system model and detection problem is formulated in Section II. After that, the fusion rule based on dynamic grouping for CSS is presented in Section III. And then, we analyze the effects of different grouping parameter and weighting factors on the algorithm performance, and compare the performance among OR rule, AND rule, EGC rule, maximum signal-to-noise ratio algorithm (in short, SNR rule), and the proposed rule. The corresponding simulation results are given in Section IV. Finally, Section V draws the conclusion.

TABLE 1. List of major symbols.

Symbol	Description
$r_m(t)$	Received signal of SU_m
$n_m(t)$	Received noise signal of SU_m
$s_m(t)$	Received PU signal of SU_m
H_0	Absence of PU
H_1	Presence of PU
σ_m^2	Variance of AGWN of SU_m
σ_{sm}^2	Variance of PU signal of SU_m
P_m	Average power of PU signal of SU_m
d_m	Distance between PU and the SU_m
α	Pass-loss exponent
γ	SNR of PU transmission signal
σ_n^2	Nominal noise power
u_m	Noise uncertainty of SU_m
N	Number of samples
T_m	Test statistic of SU_m
R_m	Decision result of SU_m
P_{fm}	False alarm probability of SU_m
P_{dm}	Detection probability of SU_m
λ_m	decision threshold of SU_m
q_m	Transmitted information of SU_m
P_{dOR}	Detection probability of OR rule
P_{fOR}	False alarm probability of OR rule
P_{dAND}	Detection probability of AND rule
P_{fAND}	False alarm probability of AND rule
T_{SDF}	Global test statistic
P_{fSDF}	Detection probability of SDF
P_{dSDF}	False alarm probability of SDF
θ	Grouping parameter
R_{DGF}	Decision result of DGF
L	Numbers of SUs participating in CSS
P_L	Probability of L SUs participating in CSS
τ_{HDF}	Total detection time of HDF
τ_{SDF}	Total detection time of SDF
τ_{DGF}	Total detection time of DGF
$\bar{\tau}_{GDF}$	Average detection time of DGF

For the sake of the convenience, we present a list of the major symbols that are used in Table 1 with their definitions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SIGNAL AND CHANNEL MODEL

We consider a scenario where a heterogeneous CRN consisting of a PU, multiple SUs, and an FC. We assume that all SUs are located under the coverage area of the PU. The PU, SUs, and FC are all distributed independently throughout the region. Specifically, the mobility of PU and SUs should be considered. To improve the detection performance at low SNR condition, many SUs participate in spectrum sensing and collaborate to make a detection decision. The selection of fusion rule should consider that each SU may use different algorithms to implement local SS. As Fig. 1 shows, each SU sends independent detection information to FC, assuming that there are no burst errors in reporting channel. FC fuses all detection information through certain rule to obtain a final detection decision and share it with each SU. In CSS, data transmission and information fusion lead to an increase in bandwidth burden, meanwhile, also increase energy consumption and detection delay. Taking the system overhead and the performance of spectrum sensing into account to optimize fusion rule utility is an urgent issue in CSS.

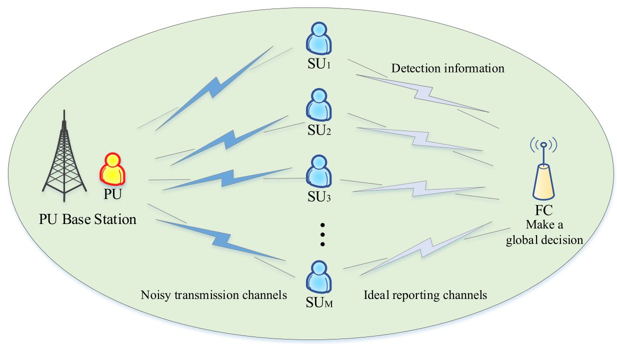

FIGURE 1. CSS model with one PU, M SUs, and one FC.

For the SU_m, according to Neyman-Pearson criteria, the spectrum sensing problem can be modeled as a binary hypothesis test [15]

$$r_m(n) = \begin{cases} n_m(n), & H_0 \\ n_m(n) + s_m(n), & H_1 \end{cases}, \tag{1}$$

where $m = 1, \ldots, M$, $r_m(t)$ is the signal received by SU_m, and $n_m(t)$ is additive white Gaussian noise (AWGN) with zero mean and variance σ_m^2. Meanwhile, $s_m(t)$ is supposed to be the transmitted signal of PU with zero mean and variance σ_{sm}^2. Average power P_m can incorporate the effects of fading and shadowing, and $P_m = \sigma_{sm}^2$. Consistent with [21], we define $P_m = \mu P/d_m^{\alpha}$, where P is the PU transmitted signal power, d_m is the distance between PU and SU_m. Moreover, μ is a unitless constant that depends on the antenna characteristics, and α is a path-loss exponent, respectively. Furthermore, assume that $n_m(t)$ and $s_m(t)$ are independent to each other. Now, consider the case with uncertainty in the noise. Similar to [22], the distributional uncertainty of noise can be defined as a single interval $\sigma_m^2 \sim U\left(\sigma_n^2/u_m, u_m\sigma_n^2\right)$, where σ_n^2 is the nominal noise power and $u_m > 1$ indicates the quantifies of uncertainty of SU_m. We define the SNR of PU's transmission signal as $\gamma = P/\sigma_n^2$. Furthermore, H_0 and H_1 indicate the absence and presence of PU, respectively.

B. PROBLEM FORMULATION

For the sake of simplicity, we investigate a centralized CRN which all SUs are equipped with energy detectors. This is helpful to analyze the performance of different fusion rule with mathematical expressions. Besides, it is also helpful to compare the proposed algorithm with EGC rule and SNR rule in simulation, so as to better highlight the superiority of the proposed algorithm.

1) LOCAL SPECTRUM SENSING

Energy detectors are widely used to estimate the energy of received signals due to its low complexity and lack of prior information requirements [23]. Assuming that all SUs use a fixed number of samples denoted by N, the test statistic of SU_m is given as

$$T_m = \sum_{n=1}^{N} |r_m(n)|^2. \tag{2}$$

According to the central limit theorem (CLT), when N tends to infinite, T_m follows an asymptotically normal distribution

$$T_m \sim \begin{cases} \mathcal{N}(N\sigma_m^2, 2N\sigma_m^4), & H_0 \\ \mathcal{N}(N(\sigma_m^2 + P_m), 2N(\sigma_m^2 + P_m)^2), & H_1 \end{cases}. \tag{3}$$

Proof: The proof is given in the Appendix A.

Each SU completes spectrum sensing with different preset decision threshold λ_m according to its own channel conditions [24], as follows

$$R_m = \begin{cases} H_0, & T_m < \lambda_m \\ H_1, & T_m \geq \lambda_m \end{cases}. \tag{4}$$

To the best of our knowledge, detection performance is usually measured by detection speed and detection accuracy [25]. The detection speed is mainly affected by N. The detection accuracy is usually described by false alarm probability P_{fm} and detection probability P_{dm}. According to [16], we have

$$P_{fm} = Prob\left(T_m < \lambda_m | H_0\right) = Q\left(\frac{\lambda_m - \sigma_m^2}{\sqrt{2\sigma_m^4/N}}\right), \tag{5}$$

$$P_{dm} = Prob\left(T_m \geq \lambda_m | H_1\right) = Q\left(\frac{\lambda_m - (\sigma_m^2 + P_m)}{\sqrt{2(\sigma_m^2 + P_m)^2/N}}\right), \tag{6}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{t^2}{2}\right)dt$.

In practical application, we can fix the false alarm probability and make the decision threshold adaptively adjust with the channel environment to improve the utilization rate of idle spectrum. According to (5), we can obtain

$$\lambda_m = \sqrt{2\sigma_m^4/N} Q^{-1}\left(P_{fm}\right) + \sigma_m^2. \tag{7}$$

Obviously, by substituting (7) into (6), we can obtain the final expression of the detection probability

$$P_{dm} = Q\left(\frac{\sqrt{2\sigma_m^4/N} Q^{-1}\left(P_{fm}\right) - P_m}{\sqrt{2(\sigma_m^2 + P_m)^2/N}}\right). \tag{8}$$

2) HARD DECISION FUSION

For HDF, the SUs involved in CSS send the independent decision result to FC via reporting channel, and FC obtains the final decision by fusing the received detection information. Usually, each SU only needs to transmit one-bit decision to FC, and the transmitted information q_m can be defined as

$$q_m = \begin{cases} 0, & R_m = H_0 \\ 1, & R_m = H_1 \end{cases}. \tag{9}$$

The FC combines all decision result and makes a global decision, the general form of K-out-of-M rule can be described as

$$\begin{cases} \sum_{m=1}^{M} q_m < K, & H_0 \\ \sum_{m=1}^{M} q_m \geq K, & H_1 \end{cases}. \tag{10}$$

In fact, (10) represents OR rule when $K = 1$, and when $K = M$ denotes AND rule, respectively. The global detection probability and global false alarm probability for OR rule and AND rule are given as follows

$$P_{dOR} = 1 - \prod_{m=1}^{M}\left(1 - P_{dm}\right), \tag{11}$$

$$P_{fOR} = 1 - \prod_{m=1}^{M}\left(1 - P_{fm}\right), \tag{12}$$

$$P_{dAND} = \prod_{m=1}^{M} P_{dm}, \tag{13}$$

$$P_{fAND} = \prod_{m=1}^{M} P_{fm}. \tag{14}$$

3) SOFT DECISION FUSION

In SDF, each SU is required to send its own test statistic to FC. Assuming that ζ_m denotes the weighting factor of each

SU, the global test statistic T_{SDF} is

$$T_{SDF} = \sum_{m=1}^{M} \zeta_m T_m \sim \begin{cases} \mathcal{N}\left(N \sum_{m=1}^{M} \zeta_m \sigma_m^2, 2N \sum_{m=1}^{M} \zeta_m \sigma_m^2\right), & H_0 \\ \mathcal{N}\left(N \sum_{m=1}^{M} \zeta_m (\sigma_m^2 + P_m), 2N \sum_{m=1}^{M} \zeta_m (\sigma_m^2 + P_m)^2\right), & H_1. \end{cases} \tag{15}$$

Proof: The proof is given in the Appendix B.

The FC compares the global test statistic with a preset decision threshold λ_{FC} to determine whether the PU exists. The global detection probability and global false alarm probability for SDF are given as follows

$$P_{fSDF} = Q\left(\frac{\lambda_{FC} - \sum_{m=1}^{M} \zeta_m \sigma_m^2}{\sqrt{2 \sum_{m=1}^{M} \zeta_m^2 \sigma_m^4 / N}}\right), \tag{16}$$

$$P_{dSDF} = Q\left(\frac{\lambda_{FC} - \sum_{m=1}^{M} \zeta_m \left(\sigma_m^2 + P_m\right)}{\sqrt{2 \sum_{m=1}^{M} \zeta_m^2 \left(\sigma_m^2 + P_m\right)^2 / N}}\right). \tag{17}$$

The weighting factors of different SDF rules are different. For example, the weighting factors of EGC satisfies $\zeta_m = 1$, and the weighting factors of MRC based on SNR are defined as $\zeta_m = P_m/\sigma_m^2$. According to (16) and (17), it is obvious that the weighting factors will directly affect the performance of SDF.

Under the same conditions, SDF can achieve better performance than HDF, but requires more bandwidth and longer time to complete data transmission [26]–[28]. When each SU uses different algorithms for SS, it is not appropriate to use SDF as the fusion rule. While minimizing the cooperative overhead, optimizing the detection performance is the focus of fusion rule research.

III. FUSION RULE BASED ON DYNAMIC GROUPING FOR COOPERATIVE SPECTRUM SENSING

In a real scenario, the signal sent by the PU goes through different channel environments to the receiver of SUs, this means the received SNR of each SU is not equal [29]. At the same time, SUs in future CRNs are likely to adopt completely different spectrum sensing algorithms, and the fusion rule should be appropriate for the information fusion in heterogeneous network [30], [31]. Considering the mobility of PU and SUs, the strategy of fixed clustering for CSS is also inappropriate. In order to solve the above problems, we proposed a fusion rule based on dynamic grouping (in short, DGF) to make a tradeoff between system overhead and detection performance. Based on the distance between each SU and PU, the proposed algorithm selects suitable SUs by dynamic grouping to participate in cooperation. More importantly, we assign different weighting factors to SUs in different groups, and adopt a fusion rule similar to HDF to achieve information fusion.

A. DYNAMIC GROUPING

Dynamic grouping has been applied to intelligently select some SUs to participate in CSS in order to minimize cooperation overhead without degrading detection performance. In fact, we can set a certain time interval for dynamic grouping according to the specific channel environments and actual requirements. The time interval of dynamic grouping is related to the moving speed of the PU and SUs. The advantage of this is that the grouping information can be updated according to the location changes of the PU and SUs. The flexibility of dynamic grouping can better cope with the challenges brought by the mobility of the PU and SUs. We assume that each SU knows its own location, as well as the location of PU. It is also assumed that both PU and SUs are willing to share their location information to the FC. If the location about PU or SU is not available, FC can infer a reasonable estimate of the location of the PU or SU, based on the prior data it collects from the corresponding PU or SU. Location inference is not dealt in this paper. As shown in Fig. 2, the PU, SUs, and FC are randomly distributed within a certain area. Based on the distance between the SU_m and PU, and introducing grouping parameter θ to improve flexibility and accuracy, grouping rule can be represented by

$$\begin{cases} D \le d_m, & SU_m \in G_1 \\ \theta \cdot D \le d_m < D, & SU_m \in G_2 \\ d_m < \theta \cdot D, & SU_m \in G_3 \end{cases}, \tag{18}$$

where D is a default value for dynamic grouping, G_j denotes the group-j. It is assumed that $G_1 = \{SU_i, i = 1, \ldots, \eta_1\}$, $G_2 = \{SU_i, i = 1, \ldots, \eta_2\}$, $G_3 = \{SU_i, i = 1, \ldots, \eta_3\}$, and $\eta_1 + \eta_2 + \eta_3 = M$. We think the SUs in group-1 are too far away from PU, so the received PU signal is weaker than that received by SUs in group-2 or group-3. Different from traditional CSS algorithms, the proposed algorithm will refuse SUs in group-1 to participate in CSS. That is to say, use d_m as a main factor to eliminate SUs with unsatisfactory detection performance, so as to reduce cooperation overhead without the loss of performance. Therefore, only the SUs in group-2 or group-3 are eligible to participate in CSS, and the FC only needs to collect the detection information of SUs in the two groups.

B. INFORMATION FUSION

Considering that the SUs in a heterogeneous CRN are equipped with different detectors, and to avoid a large number of transmission requirements brought by CSS, we adopt a fusion scheme similar to HDF and only process the independent decision information from each SU. Within the allocated detection time interval, the SUs in group-2 or group-3 are allowed to use an different detection algorithm to make a decision. In the next time slot, each SU sends the decision result q_m to FC. The fusion rule can be described as follows

$$Q = \beta_2 \sum_{i=1}^{\eta_2} Q_i + \beta_3 \sum_{i=1}^{\eta_3} Q_i, \tag{19}$$

$$Q_i = \begin{cases} -1, & q_i = 0 \\ 0, & q_i = 1 \end{cases}, \tag{20}$$

$$R_{DGF} = \begin{cases} H_0, & Q < 0 \\ H_1, & Q \geq 0 \end{cases}, \tag{21}$$

where β_2 and β_3 are the weighting factors of SUs in groups-2 and groups-3, respectively. The algorithm proposed in this paper is not affected by the type of detection algorithm adopted by SUs, because the FC only cares about the final decision result of each SU. Therefore, DGF can be well applied to heterogeneous CRNs.

C. EVALUATION OF THE PROPOSED ALGORITHM

Assume the probability that the distance between the SU$_m$ and PU is not greater than D is ρ_m, i.e $Prob\{d_m \leq D\} = \rho_m$, then the probability of L SUs participating in CSS is

$$P_L = Prob\{\eta_2 + \eta_3 = L\} = \binom{M}{L} \rho_m^L (1 - \rho_m)^{M-L}, \tag{22}$$

where $L \leq M$. For any SU, we assume the sampling frequency is f_s and the time required to transmit unit bit data is t_b. The FC cannot communicate with multiple SUs at the same time. Assuming that the data processing delay is small enough to be negligible, so the total detection time of HDF, SDF (Y-bit quantization), and DGF can be described as

$$\tau_{HDF} = M \cdot N \cdot (1/f_s) + M \cdot t_b, \tag{23}$$

$$\tau_{SDF} = M \cdot N \cdot (1/f_s) + M \cdot Y \cdot t_b, \tag{24}$$

$$\tau_{DGF} = L \cdot N \cdot (1/f_s) + L \cdot t_b. \tag{25}$$

In fact, the average detection time required by DGF algorithm should be

$$\bar{\tau}_{GDF} = \sum_{L=1}^{M} P_L \cdot (L \cdot N \cdot (1/f_s) + L \cdot t_b). \tag{26}$$

Obviously, the DGF algorithm requires the shortest detection time and the least bandwidth for data transmission.

Since the SUs participating in CSS are dynamically screened according to d_m, and the SUs under different groups have different weighting factors, it is not easy to derive the closed expression of detection probability and false alarm probability of DGF. Therefore, we use MATLAB® to realize the simulation of algorithm performance in section IV.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, we provide numerical results through Monte-Carlo simulation to verify the superiority of the DGF algorithm. Considering the random distribution of M SUs and one PU in a specific region, it is assumed that each SU adopts the traditional energy detection algorithm and all the signals are transmitted on an ideal channel with no burst errors. We consider a binary phase-shift keying (BPSK) modulated signal is transmitted by PU. The system parameters are summarized in Table 2.

TABLE 2. Basic parameters of system simulation.

Parameters	Values
M	15
Radius of dynamic grouping D	150 m
Sampling frequency f_s	4000 Hz
Nominal noise power σ_n^2	1
Quantifies of uncertainty u_m	2 dB
Simulation time	3000
Scalar μ	1
Path-loss exponent α	3

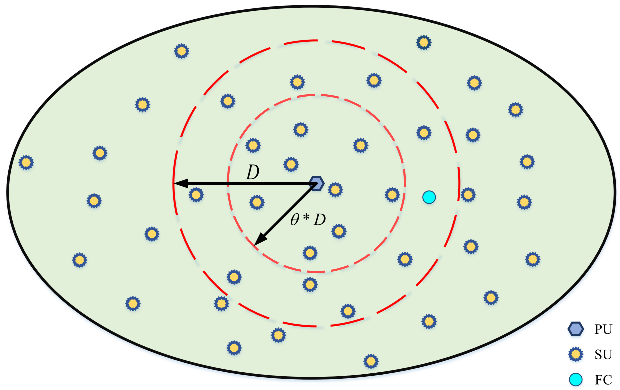

FIGURE 2. Dynamic grouping model with one PU, M SUs, and one FC.

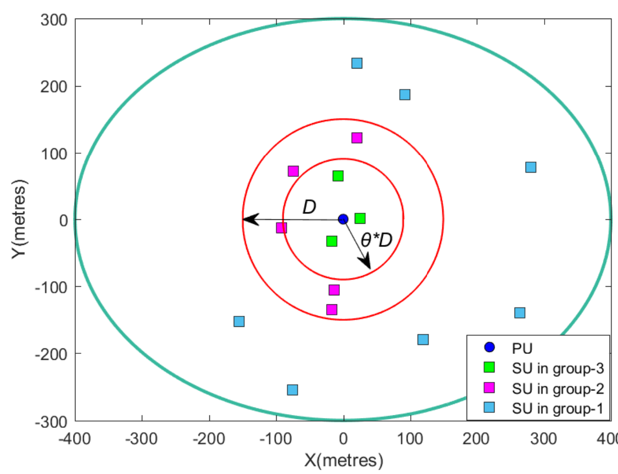

FIGURE 3. Simulation of dynamic grouping when $\theta = 0.6$.

According to the channel environment and actual requirements, we select an appropriate D to select the SUs participating in CSS, and use grouping parameter θ to achieve dynamic grouping. Fig. 3 draws a dynamic grouping simulation of the proposed algorithm when $\theta = 0.6$. Obviously, the values of D and θ will directly affect the grouping result, and the appropriate values will be conducive to achieving a good performance of DGF algorithm.

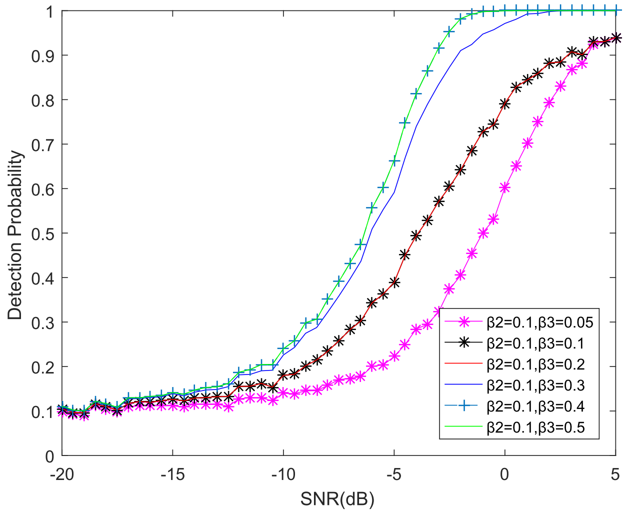

FIGURE 4. The detection probability versus γ with different weighting factors, and $\theta = 0.6$.

When $\theta = 0.6$, $N = 4000$, and $P_{fm} = 0.1$, the curves of detection probability versus γ with different weighting factors are shown in Fig. 4. It is evident that the weighting factors of group-2 and group-3 will directly affect the detection probability of the proposed algorithm. Consequently, assigning reasonable weighting factors according to the location of the SU is a prerequisite for guaranteeing the performance of algorithm.

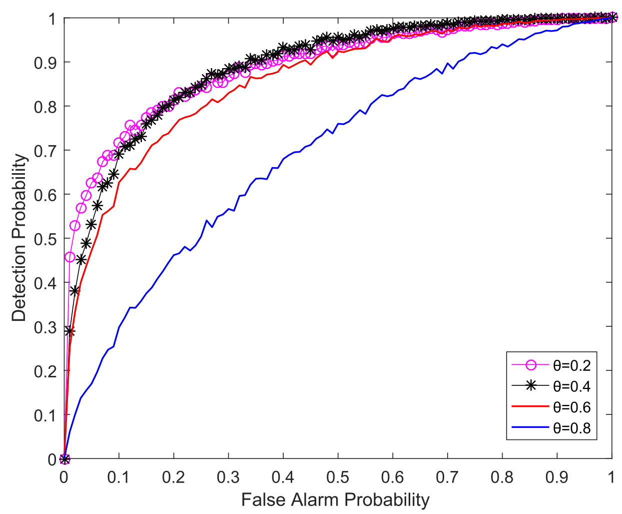

FIGURE 5. The ROC curves of DGF algorithm with different grouping parameter, $N = 4000$ and $\gamma = -5$ dB.

In the following simulation, we uniformly set $\beta_2 = 0.1$, and $\beta_3 = 0.4$. Fig. 5 plots the receiver operator characteristic (ROC) curves of DGF algorithm with different grouping parameter θ under $\gamma = -5$ dB. From the result, it is readily observed that grouping parameter will affect the detection performance of DGF algorithm. Setting an appropriate grouping parameter is a key to achieving a better performance. When other conditions remain unchanged, increasing the false alarm probability can improve the detection probability. However, a large false alarm probability leads to the undetectable idle spectrum, resulting in the waste of spectrum resources.

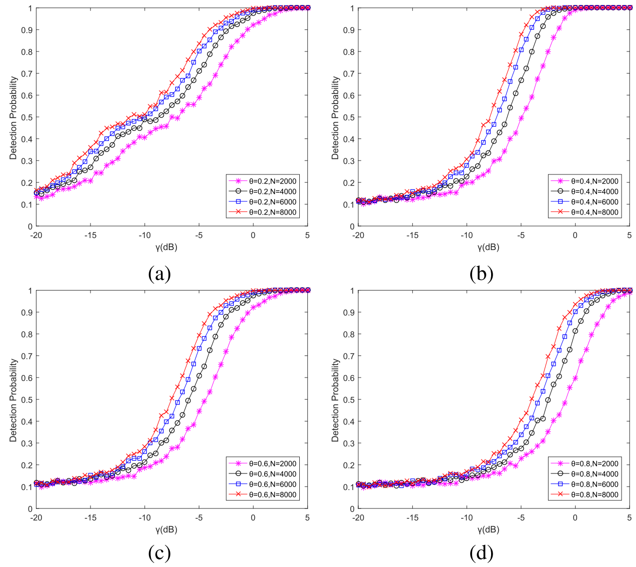

FIGURE 6. The detection probability versus γ with different number of samples and grouping parameter. ($D = 150$ m).

The curves of the detection probability versus γ with different number of samples (e.g. 2000, 4000, 6000, and 8000) are shown in Fig. 6, $P_{fm} = 0.1$, and the grouping parameter is 0.2, 0.4, 0.6, and 0.8 respectively. According to the result described by Fig. 6, we can find that the DGF algorithm performs even better with the increase of the SNR and sampling number. However, when sampling number increases from 6000 to 8000, the gain of the algorithm performance is not obvious, especially when the SNR is relatively high. This means the sampling number is no longer a major factor limiting the improvement in detection performance. Therefore, increasing sampling number can obtain a better performance before the sampling number reaches a certain value. Besides, comparing the results of different grouping parameter, it can be concluded that the DGF algorithm based on dynamic grouping can improve the detection performance effectively if grouping parameter θ is reasonably selected.

In order to verify the superiority of DGF algorithm, we choose OR rule, AND rule [32], EGC rule [33], and SNR rule [34] as the comparison algorithm, and the performance comparison is given in Fig. 7. Besides, we set $N = 4000$, $\theta = 0.4$, and the false alarm probability of each SU is 0.1, i.e. $P_{fm} = 0.1$. Obviously, OR rule and AND rule have the worst detection performance. Although the former has a high detection probability, it also has a high false alarm probability. Although the latter has a very low false alarm probability, the detection probability is also very low.

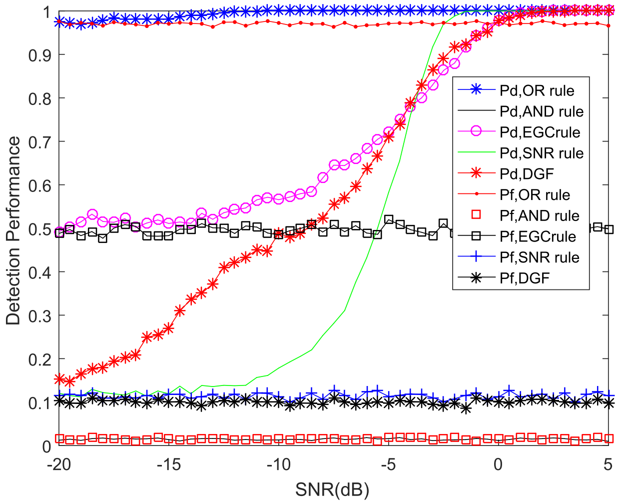

FIGURE 7. **Comparison of detection performance among OR rule, AND rule, EGC rule, SNR rule, and DGF.**

The simulation results are consistent with the theoretical analysis in (11) to (14). Moreover, EGC rule has a higher detection probability than DGF when $\gamma < -4.7$ dB. It is also a pity that EGC rule will bring a relatively high false alarm probability, which will lead to a decrease in the utilization of idle spectrum. Although the SNR rule has a low global false alarm probability, the detection probability is much lower than the DGF rule when $\gamma < -3.6$ dB due to the noise uncertainty.

To sum up, the DGF algorithm is simple to implement, has a small system overhead, and has a relatively ideal performance when the system parameters are selected reasonably.

V. CONCLUSION

This paper studied a complex heterogeneous CRN with full consideration of various factors, which is different from the traditional CSS model. We introduced path-loss factor and noise uncertainty to simulate the different fading and shadow experienced by each SU. Besides, we investigated a fusion rule based on dynamic grouping under the assumption that each SU undergoes different channel conditions. Considering the mobility of PU and SUs, a dynamic grouping scheme based on location information of PU and SUs has been proposed. Dynamic grouping greatly improves the flexibility and compatibility of fusion rule. Moreover, SUs in different groups will be assigned different weighting factors to finish information fusion. The DGF only requires the FC to collect the decision result of each cooperative SU, which reduces the amount of data transmission and data processing. Simulation results show that the proposed algorithm can obtain a better performance while reducing the cooperation cost compared with the existing methods.

APPENDIX A
PROOF OF (3)

Supposed that random variables $X_1, \ldots, X_N$ are an independent and identically distributed samples, whose elements follow normal distribution with zero mean and variance σ^2, then the joint probability density function (PDF) of $(X_1, \ldots, X_N)$ is

$$\begin{aligned} f(X_1, \ldots, X_n) &= \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{X_1^2}{2\sigma^2}\right)\cdots\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{X_N^2}{2\sigma^2}\right) \\ &= \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\exp\left(-\frac{X_1^2+\cdots+X_N^2}{2\sigma^2}\right). \end{aligned} \tag{27}$$

Define $Z = X_1^2 + \cdots + X_N^2$, the cumulative distribution function (CDF) can be expressed as

$$\begin{aligned} F_Z(z) &= Prob\,(Z < z)\,(z > 0) \\ &= \int_{X_1^2+\cdots+X_N^2<z} f\left(X_1^2+\cdots+X_N^2\right)dX_1\cdots dX_N \\ &= \int_{X_1^2+\cdots+X_N^2<z} \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \\ &\quad \times \exp\left(-\frac{X_1^2+\cdots+X_N^2}{2\sigma^2}\right)dX_1\cdots dX_N \\ &= \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\int_0^{\sqrt{z}}\int_{S^{N-1}}\exp\left(-\frac{r^2}{2\sigma^2}\right)d\Omega\left(S^{N-1}\right)dr \\ &= \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\int_0^{\sqrt{z}}\exp\left(-\frac{r^2}{2\sigma^2}\right)\frac{2\pi^{\frac{N}{2}}r^{N-1}}{\Gamma\left(\frac{N}{2}\right)}dr \\ &= \frac{2}{(2\sigma^2)^{\frac{N}{2}}\Gamma\left(\frac{N}{2}\right)}\int_0^{\sqrt{z}} r^{N-1}\exp\left(-\frac{r^2}{2\sigma^2}\right)dr, \end{aligned} \tag{28}$$

where S_{N-1} denotes the surface area of an N-dimensional ball with radius $r = \sqrt{X_1^2+\cdots+X_N^2}$. And $\Gamma(x)$ is the gamma function, $\Gamma(x) = \int_0^{\infty} t^{x-1}\exp(-t)dt$. Then, assume $z > 0$, the PDF of Z can be derived as

$$\begin{aligned} f(z) &= \frac{dF_Z(z)}{dz} \\ &= \frac{2}{(2\sigma^2)^{\frac{N}{2}}\Gamma\left(\frac{N}{2}\right)} z^{\frac{N-1}{2}}\exp\left(-\frac{z}{2\sigma^2}\right)\frac{d\left(\sqrt{z}\right)}{dz} \\ &= \frac{1}{(2\sigma^2)^{\frac{N}{2}}\Gamma\left(\frac{N}{2}\right)} z^{\frac{N}{2}-1}\exp\left(-\frac{z}{2\sigma^2}\right). \end{aligned} \tag{29}$$

Evidently, the random variable Z is gamma-distributed with shape $N/2$ and scale $2\sigma^2$, i.e. $Z \sim \Gamma\left(N/2, 2\sigma^2\right)$. According to the properties of gamma distribution, we know the mean and the variance of Z are $N\sigma^2$ and $2N\sigma^4$, respectively. When N becomes large enough, according to the central limit theorem (CLT), the gamma distribution is approximated by a normal distribution, that is,

$$Z \sim \mathcal{N}\left(N\sigma^2, 2N\sigma^4\right). \tag{30}$$

For the SU_m, when there is no PU, the signal received by the SU_m can be denoted as

$$r_{m0}(n) = n_m(n) = \sum_{i=1}^{N} n_m(i), \tag{31}$$

$$T_{m0} = \sum_{i=1}^{N} |n_m (i)|^2. \tag{32}$$

Similarly, when the PU exists, we have

$$r_{m1} (n) = (n_m (n) + s_m (n)) = \sum_{i=1}^{N} (n_m (i) + s_m (i)), \tag{33}$$

$$T_{m1} = \sum_{i=1}^{N} |n_m (i) + s_m (i)|^2, \tag{34}$$

where $n_m (i)$ and $s_m (i)$ denote the i-th sample point of noise signal and PU signal, respectively. For all we know, $n_m (n) \sim \mathcal{N} \left(0, \sigma_m^2\right)$ and $s_m (n) \sim \mathcal{N} \left(0, \sigma_{sm}^2\right)$. Obviously, we have $r_{m0} (n) \sim \mathcal{N} \left(0, \sigma_m^2\right)$ and $r_{m1} (n) \sim \mathcal{N} \left(0, \sigma_m^2 + \sigma_{sm}^2\right)$. Accordingly, by substituting $\sigma^2 = \sigma_m^2$ and $\sigma^2 = \sigma_m^2 + \sigma_{sm}^2$ into (30), we can derive as follws

$$\begin{cases} T_{m0} \sim \mathcal{N} \left(N\sigma_m^2, 2N\sigma_m^2\right), & H_0 \\ T_{m1} \sim \mathcal{N} \left(N(\sigma_m^2 + \sigma_{sm}^2), 2N(\sigma_m^2 + \sigma_{sm}^2)^2\right), & H_1 \end{cases}. \tag{35}$$

By substituting $P_m = \sigma_{sm}^2$ into (35), the T_m can be given as (3), which completes the proof.

APPENDIX B
PROOF OF (15)

For simplicity, supposed that $X_m = \zeta_m T_m, m = 1, \ldots, M$. According to (3), for any X_m, we have

$$X_m \sim \begin{cases} \mathcal{N} \left(N\zeta_m\sigma_m^2, 2N\zeta_m^2\sigma_m^2\right), & H_0 \\ \mathcal{N} \left(N\zeta_m(\sigma_m^2 + \sigma_{sm}^2), 2N\zeta_m^2(\sigma_m^2 + \sigma_{sm}^2)^2\right), & H_1 \end{cases}. \tag{36}$$

It is obvious that $X_1, \ldots, X_M$ are independent normally distributed random variables. Without loss of generality, the characteristic function of X_m can be expressed as

$$\varphi_{X_m} (t) = E\left(e^{itX_m}\right), \tag{37}$$

The characteristic function of the normal distribution with expected value μ and variance σ^2 is

$$\varphi (t) = \exp\left(it\mu - \frac{\sigma^2 t^2}{2}\right), \tag{38}$$

The characteristic function of the sum of M independent random variable is just the product of the M separate characteristic functions, i.e.

$$\begin{aligned} &\varphi_{X_1+\cdots+X_M} (t) \\ &= E\left(e^{it(X_1+\cdots+X_M)}\right) = \varphi_{X_1} (t) \cdots \varphi_{X_M} (t) \\ &= \exp\left(it\mu_{X_1} - \frac{\sigma_{X_1}^2 t^2}{2}\right) \cdots \exp\left(it\mu_{X_1} - \frac{\sigma_{X_1}^2 t^2}{2}\right) \\ &= \exp\left(it\left(\mu_{X_1} + \cdots + \mu_{X_M}\right) - \frac{\left(\sigma_{X_1}^2 + \cdots + \sigma_{X_M}^2\right) t^2}{2}\right). \end{aligned} \tag{39}$$

This is the characteristic function of the normal distribution with expected value $\mu_{X_1} + \cdots + \mu_{X_M}$ and variance $\sigma_{X_1}^2 + \cdots + \sigma_{X_M}^2$. Combining (36) and (39), the T_{SDF} can be given as (15), which completes the proof.

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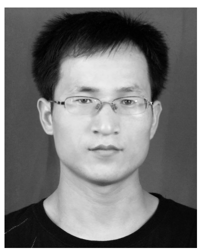

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