Spectrum Sensing Performance of Cognitive Radio Optimized by Soft Decision Fusion Threshold

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Abstract. The study aims to obtain higher spectrum efficiency of the cognitive radio system, effectively solve the hidden terminal problem caused by single user spectrum sensing, and improve the spectrum sensing performance of cognitive radio. Based on the analysis of the hard decision and soft decision fusion threshold, the linear weighted cooperative sensing algorithm is used. The purpose is to optimize the soft decision fusion cooperative spectrum sensing threshold from the two perspectives of minimizing the error probability and maximizing the average throughput of the cognitive network. The mathematical function model of error probability and throughput sensing threshold is established, the expression of the optimal threshold is derived, and the influence of various spectrum sensing parameters on the optimal decision threshold is analyzed. It is found that: when the appropriate sensing threshold is selected, compared with other algorithm models of radio spectrum sensing, the performance of the optimized soft decision fusion model proposed is better. It can reduce the error probability and improve the detection accuracy. When the throughput capacity of the cognitive network reaches the maximum, the optimal threshold obtained by the soft decision algorithm makes the detection probability higher up to 93.83%, and the overall performance of the cognitive system is better. The results have specific practical significance and practical value for the research of cognitive radio spectrum sensing.

Keywords: Cognitive radio · Soft decision fusion · Spectrum sensing · Threshold optimization · Linear weighting algorithm

1 Introduction

With the rapid development of the economy and society, radio communication technology has developed rapidly, and the number of users of wireless networks has also increased sharply. However, due to technical limitations, radiofrequency spectrum resources have been severely restricted [1]. Therefore, on the one hand, continuously investigating new technologies is necessary to develop new technologically advanced spectrums. On the other hand, it is also necessary to fully improve the utilization rate of the currently limited spectrum [2]. At present, ways to improve the utilization rate of the spectrum are very common. The most commonly used method is using the most advanced modulation encoder to increase the use efficiency of the spectrum and

H. Jin et al. (Eds.): CROWNCOM 2021/WiCON 2021, LNICST 427, pp. 3–23, 2022.
https://doi.org/10.1007/978-3-030-98002-3_1

improve the orthogonal performance of the spectrum through three angles: time, space, and frequency domain [3]. These technologies are adopted by many companies and individuals; however, affected by the quantitative limit of Shannon's capacity, these technologies have limitations in improving the efficiency of spectrum utilization [4]. However, this is far from satisfying users' demands for spectrum. Therefore, intelligent radio frequency spectrum technology has been developed rapidly. The radio technology is not restricted by time and space in propagation. It uses radio waves as the major medium and utilizes frequency to transmit and receive signals [5]. Currently, radio technology has become an inseparable component of life, which has been widely accepted in many fields and has achieved good results [6]. The prerequisite and basis for achieving the cognitive radio function are to quickly and accurately detect the valid signals of authorized users in the target frequency band, learn and reason about the information obtained by spectrum sensing, and make configuration decisions to ensure that cognitive users can access the target frequency band without conflictions [7]. Therefore, studying the cognitive radio frequency spectrum is of great value for promoting social development.

The radio spectrum solves the problem of low spectrum utilization caused by the current static spectrum allocation strategy and greatly improves the utilization rate of existing spectrum resources. Thus, spectrum sensing determines the overall performance of cognitive radio [8]. On the one hand, the performance of spectrum sensing reflects the ability of the cognitive radio to find a free spectrum. The higher the performance of spectrum sensing, the freer spectrum recognized by the cognitive radio. The more opportunities for the cognitive radio to access the free spectrum, the higher the utilization rate of the spectrum [9]. On the other hand, the performance of spectrum sensing reflects the ability of cognitive users to detect authorized users. The higher the perception performance, the weaker the signals of authorized users that can be recognized by the cognitive radio. In this way, interference with authorized users can be avoided [10]. Some unlicensed frequency bands can be used by cognitive users; however, the premise is that they do not cause interference to other users, causing a waste of spectrum resources in the time and space domains. Therefore, the purpose is to obtain higher spectrum utilization efficiency of the cognitive radio system, solve the hidden terminal problem caused by single-user spectrum sensing, and improve the performance of cognitive radio spectrum sensing [11]. As an important foundation and prerequisite for the cognitive radio to access the authorized frequency band, spectrum sensing is the core technology to ensure the normal operation of the cognitive radio, which plays an important role in the cognitive radio system [12]. Therefore, the focus is on the spectrum sensing technology of the cognitive radio, emphasizing the joint spectrum sensing algorithm of the cognitive radio.

Currently, soft decision fusion and hard decision fusion are common methods for collaborative spectrum sensing. However, these two fusion criteria are less used to study and analyze the performance of perception threshold optimization from the aspects of minimum error probability and maximum throughput. Based on the analysis of the hard decision and soft decision fusion thresholds, the linear weighted collaborative sensing algorithm is used to minimize the error probability and maximize the average throughput of the cognitive network. The soft decision fusion collaborative spectrum sensing threshold is optimized, the mathematical function model of error probability and throughput sensing threshold is established, and the optimal threshold expression is deduced. The obtained results can provide research ideas for cognitive radio spectrum sensing.

2 Related work

2.1 Cognitive Radio Model

The access method of cognitive radio technology is opportunistic spectrum access. Cognitive users perceive the dynamic spectrum environment through spectrum sensing technology and get the opportunity to share authorized frequency bands with authorized users, that is, primary users. Therefore, the improvement of spectrum sensing performance is crucial in cognitive radio [13]. In this regard, different scholars have established corresponding cognitive radio models. Wang et al. (2017) adopted a practical nonlinear energy harvesting model to maximize the total throughput of secondary users and optimize parameters such as energy harvesting time, channel allocation, and transmit power [14]. They gave the closed-form expressions of the optimal transmit power and channel allocation. The simulation results showed a trade-off between harvesting energy and the total throughput of secondary users. To improve energy efficiency and spectrum efficiency, Wang et al. (2017) examined a non-orthogonal multiple access cognitive radio network with wireless information and power transmission under the actual nonlinear energy harvesting model. They proposed a multi-target resource and optimized the problem to maximize the harvesting power of each energy harvesting receiver [15]. Li et al. (2018) proposed a new machine learning-based collaborative spectrum sensing model, which appropriately grouped cognitive radio users before using energy data samples and support vector models for collaborative sensing. They used the user grouping method to reduce collaboration overhead and improve detection performance [16]. Based on the Deep Neural Network (DNN) detection framework, Liu et al. (2019) used the sample covariance matrix as the input of the Convolutional Neural Network (CNN) and proposed a spectrum sensing algorithm based on the covariance matrix, which further improved the radio perception performance [17]. Vimal et al. (2020) proposed a modern data communication security scheme that used private key encryption and had sensing results. They introduced the eclat algorithm and used the Advanced Encryption Standard (AES) algorithm to protect data communication security in the Change Request (CR) network. Results found that this model could effectively save resources and improve the security of the system [18].

2.2 Research Status of Spectrum Sensing

In the actual cognitive radio network, the cognitive radio spectrum sensing technology must be able to avoid interference between control systems, adapt to complex and changeable wireless environments, and meet the efficiency requirements of the system itself to improve the speed and accuracy of spectrum sensing and optimize network performance. Spectrum sensing is the core of the cognitive radio network, and the research on spectrum sensing often focuses on local sensing and collaborative sensing

[19]. Single-node energy-sensing is simple to implement. The first proposed local sensing algorithm includes energy detection, matched filtering, and cyclostationary feature detection [20]. Abbadi et al. (2018) proposed a method for sensing unknown signals in the literature, acquiring signals according to Shannon's sampling theorem, giving the probability density distribution with signal energy as a statistic, and deriving the expressions of false alarm probability and detection probability [21]. Due to the limited perception of a single cognitive user, the detection performance is low due to the influence of shadow fading and hidden terminals. To effectively compensate for the impact of the shadow effect, people have studied the spectrum sensing technology of multi-user collaboration [22]. Under the condition that the sum of false alarm probability and missed detection probability was the smallest, Best et al. (2018) found that the optimal K value under K criteria and derived the optimal decision threshold for single node perception under this optimal K value. The optimal number of cooperative users was obtained when the effective throughput of the cognitive network reached the maximum, and the number of cooperative users was optimized [23]. The spectrum sensing performance in the Additive White Gaussian Noise (AWGN) channel and the fading channel was analyzed using relevant criteria. At present, the optimization problem of cooperative detection has also become a research hotspot [24]. Ni et al. (2019) proposed the optimization problem of cooperative detection and studied the optimization problem of the number of user nodes of cooperative spectrum sensing based on hard decisions and criteria [25]. Muhammad et al. (2019) introduced linear weighted fusion criteria based on detection statistics and gave several methods for selecting weighting coefficients under the optimal criteria. The hard decision fusion and soft decision fusion algorithms were simulated and analyzed, and the detection performance of several algorithms was compared. Results suggested that both fusion algorithms could improve the detection performance of a single sensor node. As the number of sensor nodes increased, the detection performance got improved, and the soft decision fusion algorithm had better detection performance than the hard decision fusion algorithm [26].

3 Research Methodology

3.1 Spectrum Sensing Technology and Algorithm

According to the number of cognitive users participating in perception, many researchers have classified spectrum sensing technology, which is divided into single-user spectrum sensing and multi-user collaborative spectrum sensing, as shown in Fig. 1. In single-user spectrum sensing, cognitive users do not need to coordinate and exchange information. The advantage is that it is easier to design, more mature in technology, and easier to implement. Multi-user cooperative sensing performs information fusion of the detection results of multiple users and makes a comprehensive decision, which can improve the detection probability of cognitive users and reduce the probability of false alarms. At the same time, it can reduce the perception time and enhance the flexibility of the communication network itself. In cooperative spectrum sensing, the same channel is monitored by multiple cognitive users; then, the sensing information is sent to the fusion center for decision [27].

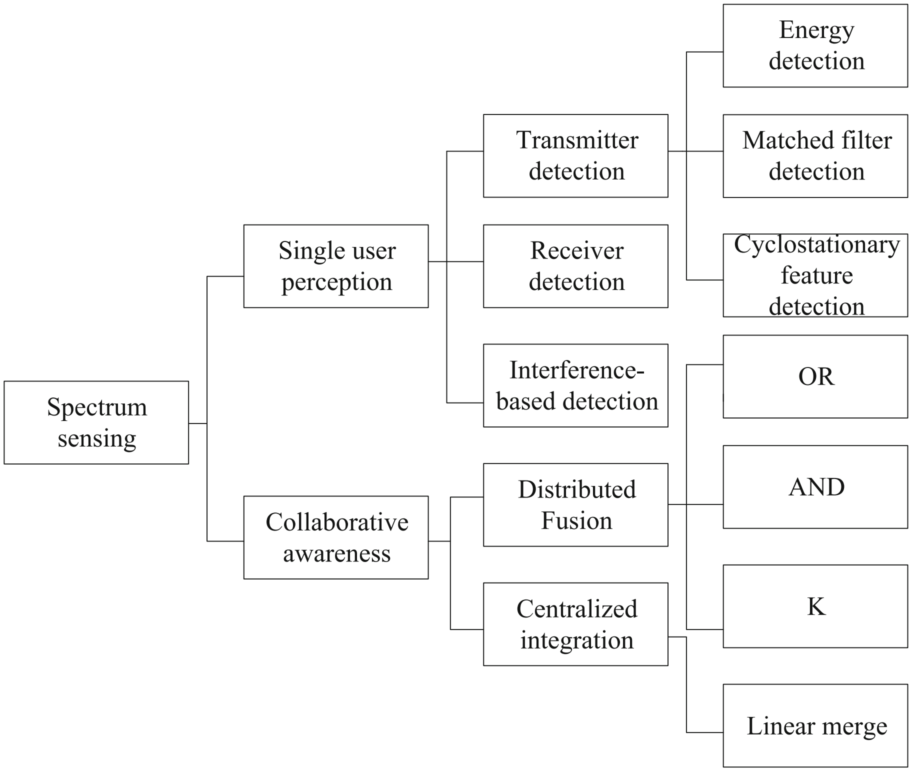

Fig. 1. Classification of spectrum sensing technologies

The focus is on the distributed and integrated spectrum sensing system. Distributed collaborative spectrum sensing is to interact with the messages sensed by each cognitive user independently with other cognitive users. The networking mode of each cognitive user is equal. In this way, each cognitive user makes a fusion decision, and finally, arrives at the decision result. Compared with centralized collaborative spectrum sensing, this sensing method improves the detection performance of the system. Because the detection sensitivity of a single sensing device is reduced, the cost of the device and the difficulty of implementation are also decreased. However, correspondingly, this is all at the cost of increasing network burden and system overhead, and the real-time performance of the system is poor [28]. Figure 2 shows the distributed collaborative spectrum sensing model.

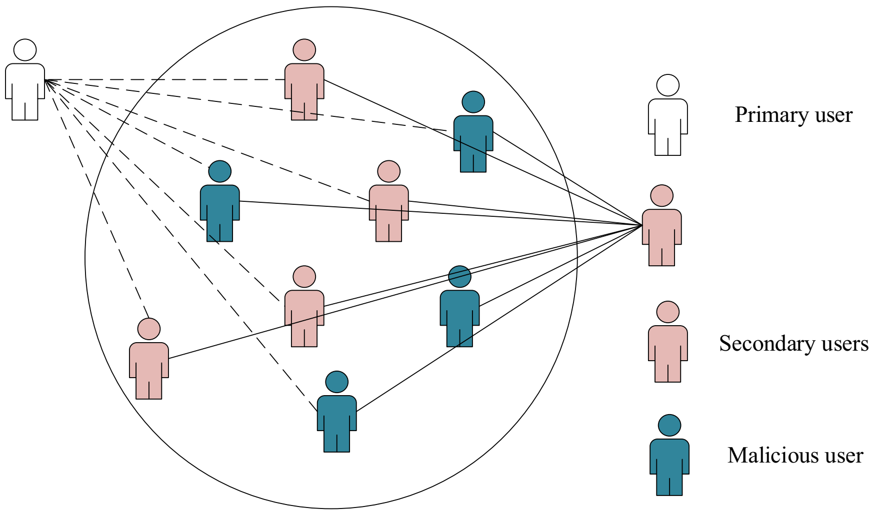

Fig. 2. Distributed collaborative spectrum sensing model

(1) AND criteria: in the cognitive radio cooperative spectrum sensing system, when all cognitive users' decision results are H_1, the system will make the final decision of H_1; otherwise, it will make the decision of H_0. If one of the users' decisions is false, the system's decision is false [29]. Assuming that M cognitive users participate in the collaboration, in a system using AND criteria, the calculation equations for the detection probability, false alarm probability, and missed detection probability of the combined spectrum sensing are:

$$Q_d = \prod_{i=1}^{M} p_{d,i} \tag{1}$$

$$Q_f = \prod_{i=1}^{M} p_{f,i} \tag{2}$$

$$Q_m = 1 - Q_d = 1 - \prod_{i=1}^{M} p_{m,i} \tag{3}$$

In (1)–(3), $p_{d,i}$ refers to the detection probability, $p_{f,i}$ refers to the false alarm probability, and $p_{m,i}$ refers to the missed detection probability. If the detection performance of any cognitive user is very low, the final decision result is very likely to incorrectly determine that there is a spectrum hole, indicating that while increasing the spectrum utilization rate, a greater probability of conflict is needed between the primary user and the cognitive user. Therefore, AND criteria are rarely used as the decision criteria for spectrum sensing in actual radio systems.

(2) OR criteria: if the perception result reported by a cognitive user is H_1, the system will make the final decision of H_1; otherwise, it will make the decision of H_0. When any cognitive user decides the main user signal, the final decision is the main user; otherwise, it decides that the main user does not exist [30]. The OR criteria detection probability, false alarm probability, and missed detection probability are expressed as:

$$Q_d = 1 - \prod_{i=1}^{M} (1 - p_{d,i}) \tag{4}$$

$$Q_f = 1 - \prod_{i=1}^{M} (1 - p_{f,i}) \tag{5}$$

$$Q_m = 1 - Q_d = \prod_{i=1}^{M} (1 - p_{m,i}) \tag{6}$$

(3) K-rank criteria: for a system with M cooperative perception of cognitive users, when the perception result reported by no less than K cognitive users is H_1, the fusion decision center will make the final decision of H_1; otherwise, the decision is H_0. The obtained value is compared with the set threshold. If at least K user decisions are true, the final decision of the fusion center is true [31]. Assuming that the decision result reported by the i-th user is D_i, the decision rule can be expressed as:

$$\begin{cases} \sum_{i=1}^{M} D_i \geq \lambda, H_1 \\ \sum_{i=1}^{M} D_i \leq \lambda, H_0 \end{cases} \tag{7}$$

Assuming that there are independent decisions of M users, using the K rank criteria fusion decision algorithm can get:

$$Q_d = \sum_{j=K}^{M} C_M^i \prod_{i=1}^{M} p_{d,i} \prod_{i=j+1}^{M} (1 - p_{d,i}) \tag{8}$$

$$Q_f = \sum_{j=K}^{M} C_M^i \prod_{i=1}^{M} p_{f,i} \prod_{i=j+1}^{M} (1 - p_{f,i}) \tag{9}$$

$$Q_m = 1 - Q_d = 1 - \sum_{j=K}^{M} C_M^i \prod_{i=1}^{M} p_{d,i} \prod_{i=j+1}^{M} (1 - p_{d,i}) \tag{10}$$

3.2 Soft Decision Fusion Threshold Optimization

In the cognitive network, multiple cognitive users and the fusion center system form a unity. In the system, M cognitive users participate in cooperative spectrum sensing. Each cognitive user i uses an energy detection algorithm to sample the received signal and obtain the energy statistics. After passing through the Gaussian channel and adding channel noise, the energy statistics are sent to the system. The system weights and accumulates the received energy statistics according to the weight distribution criteria, sets a decision threshold in advance, and compares it with the accumulated energy value to make the final decision [32]. The model of the weighted cooperative spectrum sensing system is shown in Fig. 3.

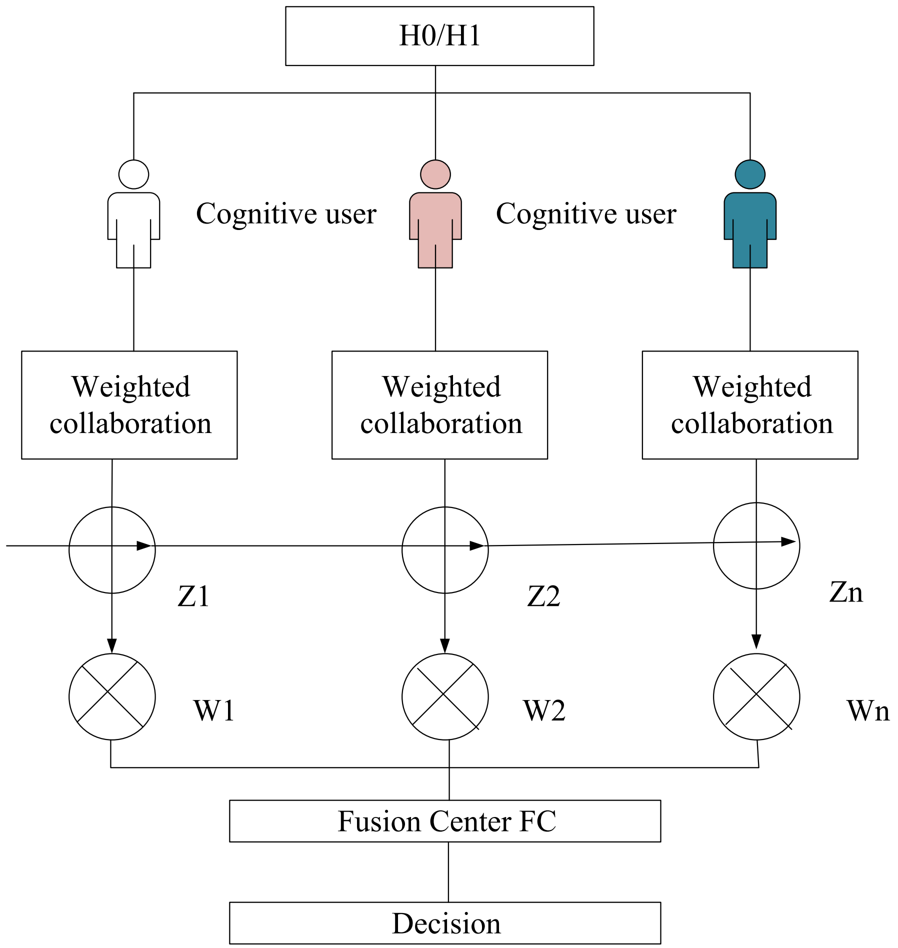

Fig. 3. Weighted collaborative spectrum sensing model

The system collects the energy statistics of M cognitive users, adopts the Signal-to-Noise Ratio (SNR) method of weighted distribution weights, and linearly accumulates these energy statistics to obtain the final decision statistics:

$$Z_c = \sum_{i=1}^{M} \omega_i Z_i = \omega^T z \tag{11}$$

$$\omega^T = \frac{SNR_i}{\sqrt{\sum\limits_{i=1}^{N} SNR_i}} \tag{12}$$

In (11) and (12), ω^T represents the weight assigned by the fusion center to user i based on SNR weighting, and Z_i signifies a normal random variable whose linear combination is also a normal random variable; thus, the mean of Z_i is:

$$E(Z_c) = \begin{cases} \mu_0^T \omega, H_0 \\ \mu_1^T \omega, H_1 \end{cases} \tag{13}$$

In (13), μ_0^T and μ_1^T represent the mean vectors in the case of 0 H and 1 H. There are uncorrelated Gaussian variables in the space, and the mean variance is:

$$Var(Z_c) = \begin{cases} \sum\limits_{i=1}^{N} (\sigma_{0,i}^2 + \delta_i^2)\omega_i^T = \omega^T \sum\limits_{0} \omega, H_0 \\ \sum\limits_{j=1}^{N} (\sigma_{0,j}^2 + \delta_j^2)\omega_j^T = \omega^T \sum\limits_{1} \omega, H_1 \end{cases} \tag{14}$$

In (14), $\sum_0 \omega, H_0$ and $\sum_1 \omega, H_1$ are diagonal matrices.

3.3 Model Performance Testing

(1) Minimum error probability: the detection probability, false alarm probability, and missed detection probability based on weighted soft decision cooperative spectrum sensing can be expressed as [33]:

$$Q_d = Q\left(\frac{\lambda - \mu_1^T \omega}{\sqrt{\omega^T \sum_1 \omega}}\right) \tag{15}$$

$$Q_f = Q\left(\frac{\lambda - \mu_0^T \omega}{\sqrt{\omega^T \sum_0 \omega}}\right) \tag{16}$$

$$Q_m = 1 - Q\left(\frac{\lambda - \mu_1^T \omega}{\sqrt{\omega^T \sum_1 \omega}}\right) \tag{17}$$

The overall error probability is:

$$Q_e = P(H_0)Q(\frac{\lambda - \mu_0^T \omega}{\sqrt{\omega^T \sum_0 \omega}}) + P(H_1)\left[1 - Q(\frac{\lambda - \mu_1^T \omega}{\sqrt{\omega^T \sum_1 \omega}})\right] \tag{18}$$

The goal of perception threshold optimization aims to minimize Q_e by finding the optimal threshold. The optimized function can be expressed as:

$$\lambda = \arg\min Q_e(\lambda) \tag{19}$$

The conversion of the mean and variance equations under the two assumptions shows that the optimal detection threshold can be expressed as:

$$\lambda_{out} = \frac{\mu_0}{2} + \mu_0 \sqrt{\frac{\sigma_1^2}{4\sigma_0^2} + \frac{\sigma_1^2}{2\mu_0(\mu_1 - \mu_0)} \ln(\frac{P(H_0)}{P(H_0)} \times \frac{\sigma_1}{\sigma_0})} \tag{20}$$

(2) Average throughput: the optimization goal of the perception threshold aims to find the optimal threshold to maximize the average throughput of the cognitive radio system. After optimization, the objective function [34] can be expressed as:

$$\lambda = \arg\min R(\lambda) \tag{21}$$

Since the Gaussian function is a monotonically decreasing function, the constraint condition can be converted into a linear constraint condition:

$$\lambda \leq \lambda_{\max} \tag{22}$$

$$\lambda_{\max} = \mu_1^T \omega + \sqrt{\omega^T \sum\nolimits_1 \omega} Q^{-1}(1 - \varepsilon) \tag{23}$$

When the false alarm probability and the missed detection probability are both low, it can be converted to a tractable convex optimization problem. The Lagrangian algorithm [35] is used to solve this convex optimization problem, and the Lagrangian function is established:

$$L(\lambda, \mu) = R(\lambda) - \mu[Q_m(\lambda) - \varepsilon] \tag{24}$$

In (24), μ represents the Lagrangian multiplier factor, and the one-variant quadratic equation can be obtained:

$$\lambda^2 - A\lambda + B = 0 \tag{25}$$

3.4 Model Parameter Settings

The number of sampling points N is = 512, the SNR of the main user transmitter is = 20 dB, the SNRs of all cognitive users are = 6 dB, the noise variance is both 21, and the number of cognitive users participating in the collaboration is $M = 5$. The probability of H_0 is $P(H_0) = 0.7$, and the probability of H_0 is $P(H_0) = 0.3$, where K in the "K rank" fusion criteria is = 3.

4 Results and Analysis

4.1 Spectrum Sensing Performance Analysis

Figure 4A shows the detection performance analysis results of the three fusion criteria. When the false alarm probability is less than 0.1, the detection probability using AND criteria is relatively high. When the false alarm probability is greater than 0.1, the detection probability using OR criteria for the fusion decision is relatively high. Under the same false alarm probability, the detection probability of K criteria among the three fusion criteria is slightly lower. Figure 4B reveals the variation of the error probability with the perception threshold in energy detection. The error probability is a downward convex curve, and there is an optimal λ value. With the increase in SNR, the error probability has a downward trend, which suggests that SNR can reduce the error rate of spectrum sensing, thereby increasing the perception performance. Figure 4C demonstrates how the throughput of a single user changes with the sensing threshold. As the sensing threshold increases, the throughput is also increasing. When the sensing threshold increases to 1.3, the throughput of the system no longer changes, which explains that the threshold cannot be too large; otherwise, the detection probability will be reduced.

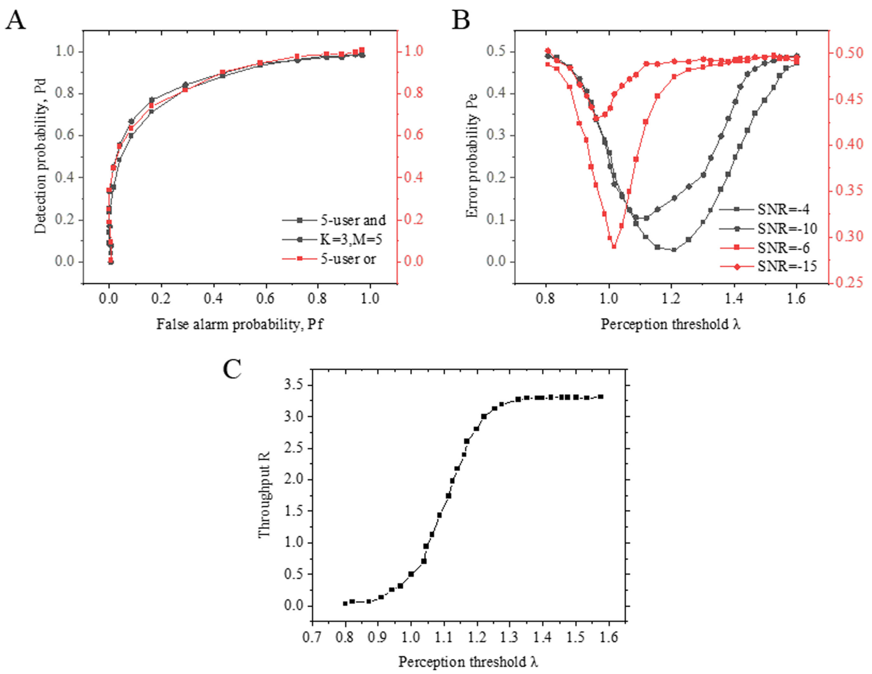

Fig. 4. Spectrum sensing performance analysis

4.2 Model Performance Analysis Under Different Criteria

Figures 5A–5C present the relations among the error probability, the number of users, and the perception threshold under AND, OR, and K criteria, respectively. As the number of perceived users increases, the minimum overall error probability of the three fusion criteria decreases. Therefore, multi-user collaborative sensing can effectively improve the detection performance of spectrum sensing. In K criteria, when $K = M/2$, spectrum sensing performance is the best.

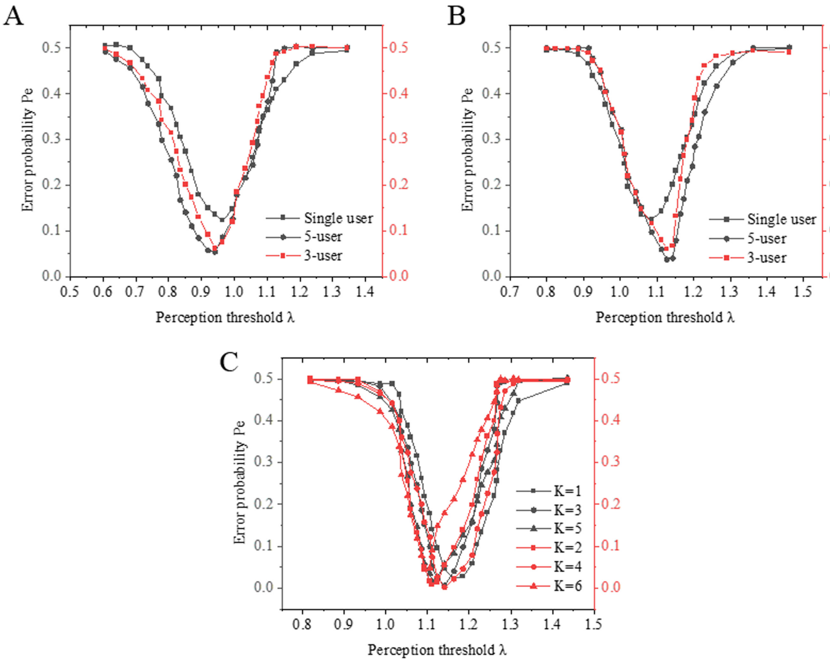

Fig. 5. Relationship between error probability and perception threshold under different criteria

Figure 6A displays the trend of the error detection probability of the three fusion criteria with the threshold. Under the same simulation conditions, the minimum value of the overall error probability of the three fusion criteria is smaller than the error probability perceived by a single user. Using K fusion criteria minimizes the overall error probability of spectrum sensing. Figure 6B demonstrates the relationship between the average achievable throughput of the system and the perception threshold under the three decision fusion criteria. Compared with single-user detection, the perception threshold when the average throughput of the cognitive network reaches the maximum is smaller under AND criteria and K criteria but larger under OR criteria.

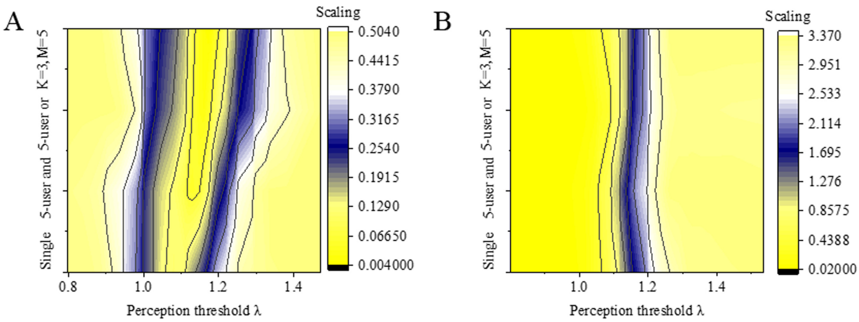

Fig. 6. Error detection probability and throughput results under different OR criteria

Figure 7 shows the relationship between the throughput of the cognitive radio system and the perception threshold under AND, OR, and K criteria. When the average throughput of the cognitive network reaches its maximum value, different fusion criteria have different perception thresholds. In AND criteria, as the number of users participating in collaboration increases, the perception threshold that maximizes throughput decreases, and a smaller perception threshold can increase the detection probability. Moreover, before the throughput reaches the maximum value, when the threshold is perceived, the throughput increases with the increase in the number of

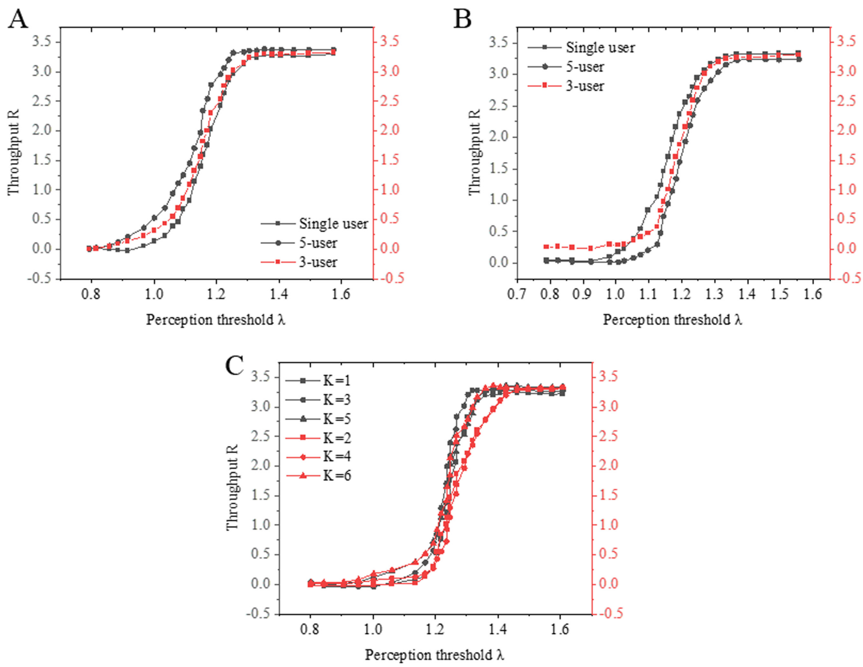

Fig. 7. Relationship between radio system throughput and perception threshold under different criteria

users, and the OR criteria is the opposite. In K criteria, as the value of K increases, the perception threshold that maximizes the throughput gradually decreases. Besides, before the throughput reaches the maximum, under the same perception threshold, the greater the value of K, the greater the throughput.

4.3 Minimum Error Probability in Different Scenarios

Figure 8 shows the relationship between detection probability and false alarm probability under hard decision and soft decision fusion criteria. When the false alarm probability is small, the detection probability of the soft decision fusion algorithm is higher than that of the three hard decision algorithms. Compared with the hard decision algorithm, the soft decision collaborative spectrum sensing collects a large amount of information from authorized users, and the detection performance is relatively high.

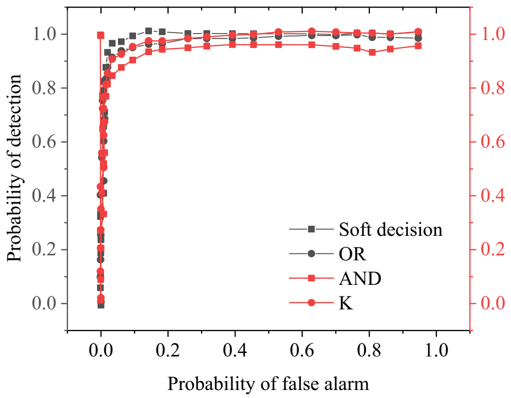

Fig. 8. Relationship between detection probability and false alarm probability under hard decision and soft decision fusion criteria

Figures 9A and 9B show the comparative analysis of soft decision threshold optimization and three hard decisions when the SNR and variance of each cognitive user are the same under the conditions of scenario 1. When the cognitive user's SNR and noise variance are the same, the error probability corresponding to the optimal threshold of the weighted soft decision is 0.002, which is smaller than the error probability of the three hard decisions. At this time, the probability of correctly detecting the primary user is 0.996, the detection probability is higher, and the detection performance is better. Figures 9C and 9D compare and analyze the soft decision threshold optimization and three hard decisions under the condition of scenario 2. When the noise variance is the same, and the cognitive user's SNR is different, the optimal perception threshold of the weighted soft decision algorithm is 2.156, and the detection probability at this time is 0.848, which is significantly higher than the detection probability of the three hard decisions. Therefore, selecting this optimal threshold can improve detection performance.

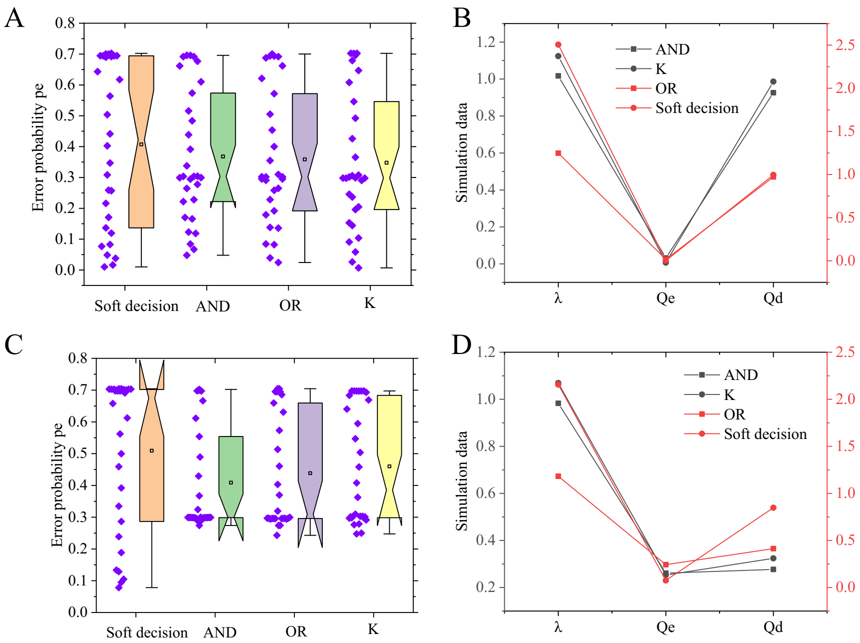

Fig. 9. Comparison and analysis of soft decision threshold optimization and three hard decisions in scenarios 1 and 2

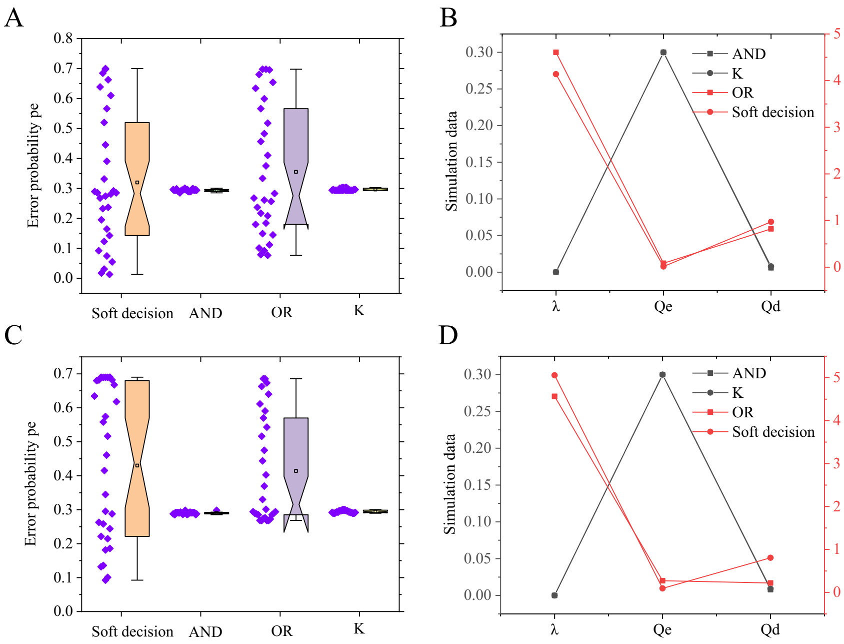

Fig. 10. Comparison and analysis of soft decision threshold optimization and three hard decisions in scenarios 3 and 4

Figures 10A and 10B are the comparative analysis of soft decision threshold optimization and three hard decisions under the condition of scenario 3. When the cognitive user SNR is the same and the noise variance is different, the optimal perception threshold of the weighted soft decision algorithm is 4.138, and the detection probability at this time is 0.9727, which is significantly higher than the detection probability of the three hard decisions, proving the best detection performance. Figures 10C and 10D compare and analyze the soft decision threshold optimization and three hard decisions under the condition of scenario 4. When cognitive users have different SNRs and different noise variances, the optimal perception threshold of the weighted soft decision algorithm is 5.056. The corresponding error probability is 0.0929, which is significantly lower than the error probability of the three hard decisions, and the detection probability is 0.806. Choosing the optimal perception threshold at this time can achieve the best detection performance.

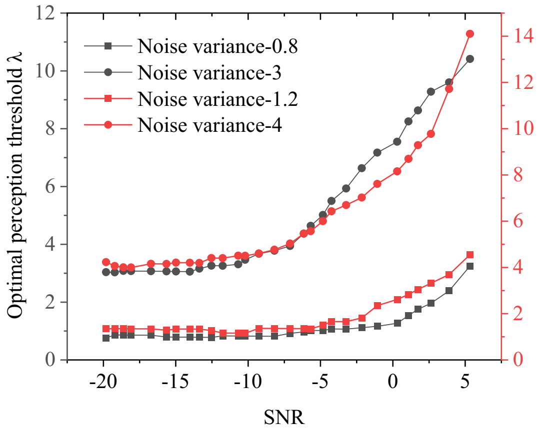

Fig. 11. Changes in the optimal perception threshold in the soft decision algorithm with SNR and noise variance

Figure 11 shows the relations among the optimal perception threshold, noise variance, and SNR. When the noise variance is the same, the greater the SNR, the greater the optimal perception threshold; when the SNR is the same, the optimal perception threshold increases as the noise variance increases.

4.4 Different Spectrum Maximum Throughput

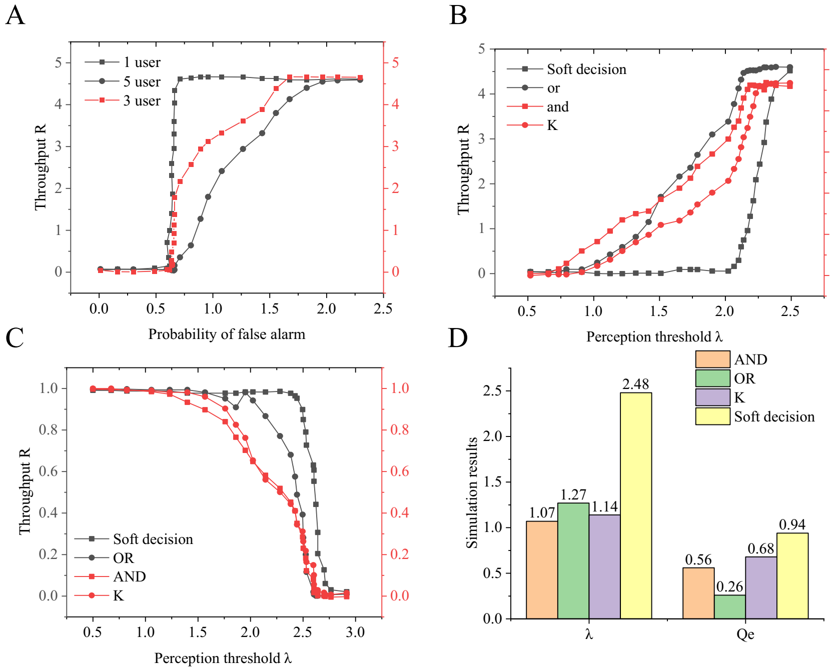

Fig. 12. Relationship between the throughput and the sensing threshold of different cooperative spectrum sensing

Figure 12A demonstrates the relationship between the soft decision fusion algorithm's cooperative spectrum sensing throughput and the sensing threshold. Cooperative spectrum sensing can improve the performance of spectrum sensing. When the throughput of the system reaches the maximum, the perception threshold of different cooperative users is different. Figures 12B–12D illustrate the relations among the cognitive radio system throughput, detection probability, and perception threshold under the four fusion criteria. When the system throughput reaches the maximum, the optimal perception thresholds of the four fusion criteria are different. Among the detection probabilities corresponding to the merit value, the detection probability of soft decision fusion criteria is about 0.938, which is significantly greater than the other three hard decision fusion criteria. Therefore, the optimal perception threshold obtained by soft decision fusion criteria can maximize the throughput and ensure that the detection probability is large enough and the detection accuracy is high. Hence, soft decision fusion criteria is the optimal criteria.

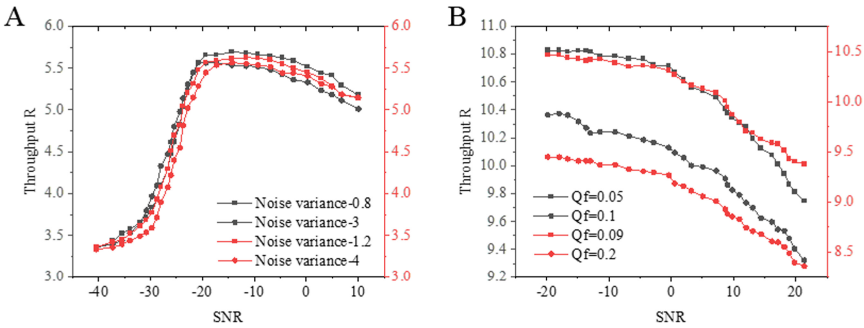

Fig. 13. Relationship between noise variance, false alarm probability, and throughput under different SNR conditions

Figure 13A demonstrates the relations among throughput, cognitive user SNR, and noise variance when using soft decision fusion criteria. When the noise variance is constant, as the SNR increases, the throughput first increases and then decreases to a particular value. When the SNR is the same, the throughput decreases as the noise variance increases. Figure 13B reveals the changing trend of throughput with the false alarm probability Q_f. The smaller the Q_f, the greater the average throughput of the system, and the better the system performance. Moreover, as the SNR increases, the throughput continues to decrease.

5 Significance and Influence

Cognitive radio technology can share spectrum resources with authorized users without interfering and alleviate the contradiction between the scarcity of spectrum resources and the increasing demand for wireless services through cognition and reallocation. To improve the performance of spectrum sensing, people have investigated the spectrum sensing technology of multi-user collaboration from two aspects: error probability and throughput. Moreover, the hard decision fusion and soft decision fusion criteria are used to study the perception threshold optimization, bringing practical significance to the research on cognitive radio spectrum sensing. The contributions are: (1) The spectrum sensing threshold optimization for the three decision fusion algorithms is analyzed in terms of minimum error probability and maximum cognitive network throughput, which not only improves the spectrum sensing performance but also increases the utilization of spectrum resources. (2) Through comparative research with the hard decision algorithm, the accuracy of model detection is improved. When the throughput of the cognitive network reaches the maximum, the optimal threshold obtained by the soft decision algorithm makes the detection probability higher, and the overall performance of the cognitive system is better, which is of great significance to the research on cognitive radio spectrum sensing.

6 Conclusion

The hard decision and soft decision fusion threshold algorithms are studied from the aspects of minimum error probability and maximum cognitive network throughput. By adopting the linear weighted cooperative sensing algorithm, the mathematical function model of the error probability and the throughput sensing threshold is established, the expression of the optimal threshold is deduced, and the influence of various spectrum sensing on the threshold is analyzed. When an appropriate perception threshold is selected, the performance of the soft decision algorithm is better, which can reduce the overall error probability of cognitive radio spectrum sensing and improve the detection accuracy. When the throughput of the cognitive network reaches the maximum, the optimal threshold obtained by the soft decision algorithm makes the detection probability higher; at this time, the overall performance of the cognitive system is better. Although the soft decision fusion threshold algorithm can be optimized, there are several shortcomings. First, the channels of spectrum sensing are ideal Gaussian channels. Whether the algorithm can achieve ideal performance in fading channels, such as the Rayleigh fading channel and the Rice channel, remains to be studied. Second, the involved single user uses energy sensing algorithms and does not include matched filter detection, cyclostationary feature detection, or interference temperature detection. Hence, these two aspects will be researched continuously in the future to improve the optimization algorithm.

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