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Dual Threshold Cooperative Sensing Based Dynamic Spectrum Sharing Algorithm for Integrated Satellite and Terrestrial System

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Abstract: In this paper, cognitive technology is introduced into the integrated satellite terrestrial system to realize the dynamic spectrum sharing of the system and improve the utilization rate of spectrum resources. To overcome the effects of low signal-to-noise ratio (SNR) and noise uncertainty in the channel, a dual-threshold cooperative sensing strategy based on energy detection is introduced. Spectrum sensing is considered as a binary hypothesis problem, but the uncertainty of noise interference in the integrated satellite terrestrial cognitive system will cause the perception to appear ambiguous. Moreover, the noise power varies with time and relative position within a certain range. In the fuzzy state, the perception technology adopts the equal-gain merging algorithm, and derives the voting optimization algorithm to improve the accuracy of decision-making. In addition, taking the minimum error probability as the optimization goal, the optimal adjustment of the adaptive double threshold is realized based on the equal-gain combining algorithm. The simulation results show that the spectrum detection accuracy under low SNR is improved, and the opportunity for terrestrial networks to share spectrum resources is increased.

Keywords: integrated satellite terrestrial system; spectrum sharing; equal-gain merging algorithm; dual threshold cooperative sensing

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1. Introduction

The research into and widespread application of 1G to 5G technologies demonstrate the great potential of terrestrial cellular networks [1]. However, in sparsely populated areas, terrestrial cellular networks will lose profitability due to economic costs [2]. Conversely, mobile satellite systems can provide large-area network coverage at a lower cost. However, due to the shadow effect, satellite networks cannot provide coverage in dense places such as urban areas [3]. Therefore, integrated satellite terrestrial systems can achieve global coverage at an optimal cost by combining a terrestrial network that provides cellular coverage with a satellite network [4]. However, the implementation of an integrated satellite and terrestrial system will be a complex process. The user cost and user experience of satellite communications should be as close as possible to terrestrial networks [5]. If the spectrum resources of the satellite network can be reused, not only can the spectrum be used free of charge, but also the spectrum utilization rate can be further improved and the problem of spectrum scarcity can be alleviated [6,7].

Cognitive technology is an effective way to realize spectrum sharing of integrated satellite and terrestrial systems which can not only realize dynamic and flexible spectrum sharing, but also effectively improve spectrum utilization [8]. The basic principle of cognitive radio is to allow unlicensed spectrum users to access parts of the licensed frequency band in an opportunistic and interference-free manner. However, in the energy detection algorithm of spectrum sensing, the detection threshold is mainly affected by the noise of the detection band [9]. Therefore, cognitive radio technology can achieve minimal dependence on the primary user (PU) [10]. However, in a practical satellite cognitive environment, the energy received by the secondary user (SU) from the Geostationary Orbit (GEO) satellite is very small due to the large signal path loss. In addition, the shadow effect makes the signal energy received by the terrestrial SU very small, resulting in a significant decrease in the detection performance of the energy detection algorithm [11]. Multi-threshold energy detection is an upgrade of single-threshold energy detection, which can improve detection probability and reduce conflicts between cognitive users and authorized users [12].

Spectrum sensing is an important task for which great care must be taken when selecting a solution. Reference [13] connects, manages and helps intelligently allocate resources among secondary users at a central hub through cooperative spectrum sensing. Adding and implementing appropriate machine learning algorithms can help in intelligently predicting spectrum allocation methods. Spectrum detection methods, cyclostationary methods (for high-noise environments) and energy-detection methods (for low-noise environments) are implemented in this work. Machine learning classification techniques, namely decision tree classification and random forest classification, have been implemented for predicting spectrum sensing methods by taking the energy level (dB) and noise level (dB) of the received signal as features. Reference [14] proposes an intelligent machine learning (ML) model to identify and cluster malicious Cognitive Radio-based Internet of Things (CR-IoT) users, and a blockchain technology to design a security framework for efficient spectrum usage and sharing. Each cognitive user acts as a perception node and a mining node in the blockchain-enabled CR-IoT network. Cognitive users will be properly organized before the collaborative spectrum sensing (CSS) and mining process. In short, the CSS approach and secure spectrum access are only motivated by an optimized cognitive user group. Extensive experiments demonstrate the effectiveness of the proposed ML model in blockchain-enabled CR-IoT.

Recently, academia has focused on cognitive-based dual-threshold decision-making mechanisms. Reference [15] designed a two-step cooperative sensing scheme. First, cognitive users use single-threshold energy detection to detect the presence of authorized users. Based on the spectrum sensing results of all cooperative nodes in the fusion center (FC), the cognitive user performs dual-threshold energy detection and makes fusion decisions. However, the judgment process of fusion strategy is not explained in detail in the literature. Reference [16] designed a dual-threshold spectrum sensing algorithm based on energy detection and cyclostationarity. First, a dual-threshold energy detection algorithm is used to determine whether a PU exists. The fuzzy signal between two thresholds is judged using a cyclostationary feature detection algorithm. However, the design complexity of the cyclostationary feature detection algorithm is relatively high.

Reference [17] studies a new cognitive satellite scheme for GEO and Low Earth Orbit (LEO) broadband systems, and proposes the concept of Cognitive Satellite Positioning (CSP) to describe the motion of LEO satellites relative to the ground. Then, due to the uncertainty of spatial noise and lack of prior knowledge, an optimized algorithm for double-threshold energy detection is selected. Reference [18] uses an adaptive dual-threshold detection algorithm (ADE) to improve detection performance, but does not consider the detection of the fuzzy state. The algorithm is able to increase the number of samples at low signal-to-noise ratio (SNR) and complexity. Reference [19] proposes a dynamic dual-threshold spectrum sensing algorithm based on the Markov model (DDEMM). The algorithm uses historical state information to assist decision-making, thereby improving the accuracy of decision-making. Therefore, the cognitive integrated satellite terrestrial network based on double-threshold detection can solve the problem of low detection accuracy in fuzzy states caused by severe channel fading and low SNR. Moreover, the integrated satellite terrestrial network based on cognitive radio can make full use of spectrum resources, and has gradually become a research hotspot in academia.

In this paper, an equal-gain combining algorithm is introduced to improve the detection accuracy of fuzzy states. Through the dynamic management of spectrum resources, the detection parameters are adjusted and the spectrum is used opportunistically to improve the utilization rate of spectrum resources. In the architecture of this paper, Section 2 introduces the system model, and Section 3 introduces the dual-threshold cooperative spectrum sensing technique based on equal-gain combination. The adaptive dual-threshold cooperative sensing technology is introduced in Section 4, and simulation analysis is carried out in Section 5.

2. System Model

2.1. Integrated Satellite Terrestrial Cognitive System

The spectrum sharing frequency band in this paper is 2 GHz, in which the GEO satellite network is the licensed frequency band and the terrestrial network is the cognitive system. Therefore, the priority of spectrum usage belongs to the primary satellite users, while the ground-based cognitive users share the satellite frequency band through spectrum sensing technology. For the downlink of the integrated satellite terrestrial cognitive scenario, the terrestrial SU uses cognitive technology to share the frequency band of the satellite downlink. There are two interfering links in the scenario: (1) interference of satellite signals on cognitive base stations or terminals. (2) interference of signals transmitted by cognitive base stations or cognitive users on satellite terminals. Figure 1 shows the integrated satellite terrestrial network spectrum sharing system considered in this paper.

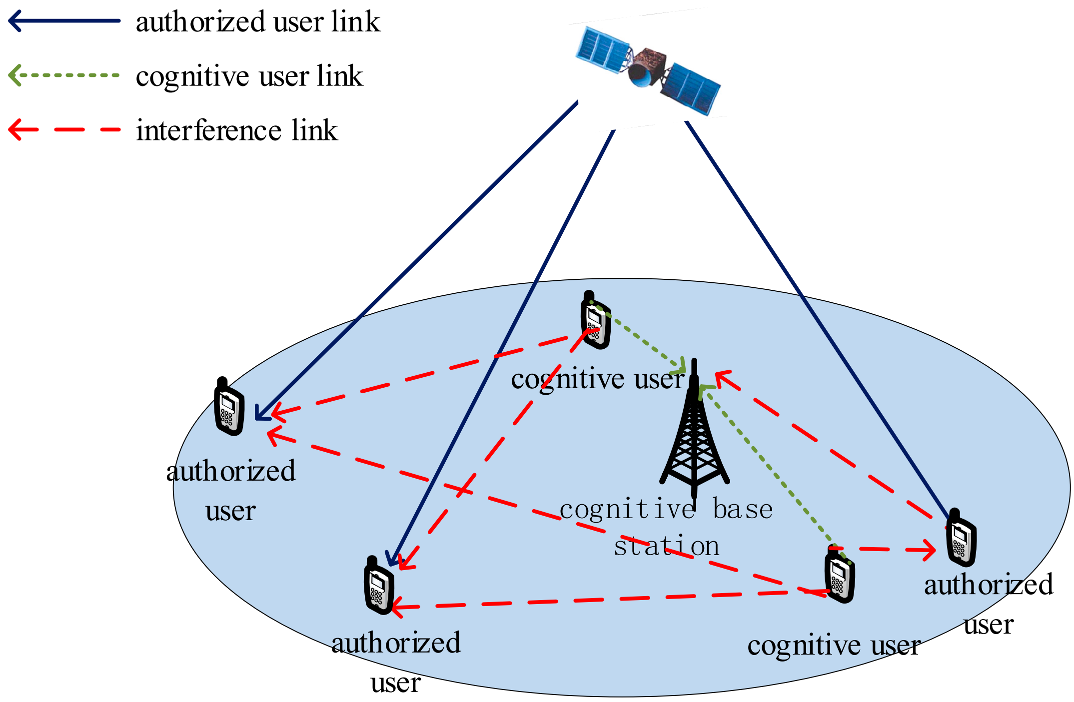

Figure 1. Spectrum sharing for integrated satellite terrestrial networks.

2.2. Dual Threshold Energy Detection Model

Generally, spectrum sensing can be considered as a binary hypothesis problem. The null hypothesis, H_0, is that PU does not exist, that is, the band is not occupied. The alternative assumption, H_1, is that PU exists, that is, the frequency band is occupied.

$$r(m) = \begin{cases} w(m) & m = 1, 2, \cdots, M \quad H_0 \\ s(m)h(m) + w(m) & m = 1, 2, \cdots, M \quad H_1 \end{cases}, \tag{1}$$

where $r(m)$ is the signal received by terrestrial SU, $s(m)$ is the signal of the satellite PU. $h(m)$ is the spectrum sensing channel gain between satellite PU and SU, $w(m)$ is the noise signal, and M is the number of sampled signals during the observation time. The statistics of energy detection algorithm can be expressed as:

$$R_i(r_i) = \sum_{m=1}^{M} |r_i(m)|^2, \tag{2}$$

where $r_i = (r_i(1), r_i(2), \cdots r_i(M))$ is the i-th sensed signal energy, $R_i(i)$ is the detection statistics, and M is the number of sampling points. In the case of additive white Gaussian noise, the detection probability P_d and false alarm probability P_f are respectively expressed as:

$$P_d = P(R_i(r_i) > \lambda | H_1) = Q\left(\frac{\lambda - M(\sigma_x^2 + \sigma_w^2)}{\sqrt{2M(\sigma_x^2 + \sigma_w^2)^2}}\right), \tag{3}$$

$$P_f = P(R_i(r_i) > \lambda | H_0) = Q\left(\frac{\lambda - M\sigma_w^2}{\sqrt{2M\sigma_w^4}}\right), \tag{4}$$

When the noise power σ_w^2 is known, the error threshold λ can be calculated by the false alarm probability P_f:

$$\lambda = (Q^{-1}(P_f)\sqrt{2M} + M)\sigma_w^2, \tag{5}$$

However, the noise in the integrated satellite terrestrial cognitive system includes not only Gaussian white noise, but also other types of interference. At the same time, the noise power varies with time and relative position within a certain range, and this noise instability is the noise uncertainty. The increase of noise uncertainty will make the spectrum sensing performance worse, that is, the detection probability will decrease and the false alarm probability will increase. In order to reduce the influence of noise, double-threshold energy detection can be used to improve the accuracy of spectrum sensing. Assume that the noise uncertainty of the wireless channel is:

$$\rho = \frac{\hat{\sigma}_w^2}{\sigma_w^2} \in [10^{-A/10}, 10^{A/10}], A \geq 0, \tag{6}$$

where $\hat{\sigma}_w^2$ is the noise variance.A is the upper bound of 10lgρ, which is the largest noise uncertainty. Then the lower bound λ_1 and upper bound λ_2 of the algorithm are:

$$\lambda_1 = \left(\sqrt{\frac{2}{N}}Q^{-1}(P_f) + 1)\right)\frac{1}{\rho}\sigma_w^2. \tag{7}$$

$$\lambda_2 = \left(\sqrt{\frac{2}{N}}Q^{-1}(P_f) + 1)\right)\rho\sigma_w^2 \,. \tag{8}$$

In practice, there may be fuzzy states where binary assumptions cannot make accurate decisions.

$$R_c = \begin{cases} 1 & R > \lambda_2 & H_1 \\ x & \lambda_1 \leq R \leq \lambda_2 & H \\ 0 & R < \lambda_1 & H_0 \end{cases} . \tag{9}$$

where R_c is the sub-channel state. The detection result R is compared with the threshold value to determine whether the PU exists. In the sub-channel state, "1" indicates that the PU exists, "0" indicates that the PU does not exist, and "x" indicates that the PU is in a fuzzy state. Figure 2 shows the above three states, and the range between the two thresholds is the blurred area, that is, the blurred state. Moreover, in the fuzzy state, it is difficult to use a single threshold to judge the existence of a PU.

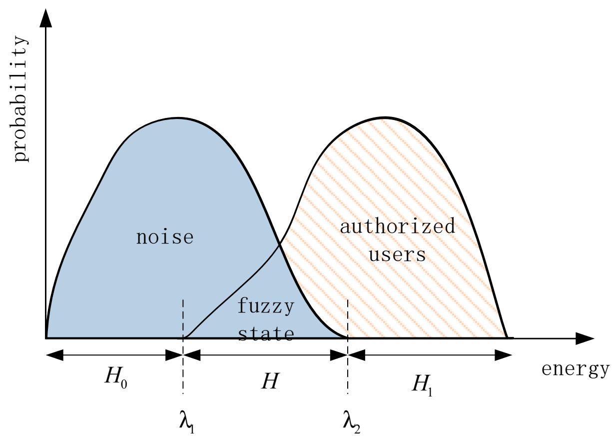

Figure 2. Energy distribution of noise and signal.

In state H_0, the probability P_a, false alarm probability P_f and hole uncertainty Δ_0 are defined as:

$$P_f = P(R_i(r_i) > \lambda_2 | H_0) = Q\left(\frac{\lambda_2 - M\sigma_w^2}{\sqrt{2M\sigma_w^4}}\right) \tag{10}$$

$$P_a = P(R_i(r_i) < \lambda_1 | H_0) = 1 - Q\left(\frac{\lambda_1 - M\sigma_w^2}{\sqrt{2M\sigma_w^4}}\right) \tag{11}$$

$$\Delta_0 = P(\lambda_1 \le R_i(r_i) \le \lambda_2 \Big| H_0) = 1 - P_f - P_a \,. \tag{12}$$

In state H_1, the detection probability P_d, miss detection probability P_m and occupancy uncertainty Δ_1 are defined as:

$$P_d = P(R_i(r_i) > \lambda_2 | H_1) = Q\left(\sqrt{\frac{2K\overline{\gamma}}{K+1+\overline{\gamma}}}, \sqrt{\frac{\lambda_2(K+1)}{K+1+\overline{\gamma}}}\right) \tag{13}$$

$$P_m = P(R_i(r_i) < \lambda_1 | H_1) = 1 - Q\left(\sqrt{\frac{2K\overline{\gamma}}{K+1+\overline{\gamma}}}, \sqrt{\frac{\lambda_1(K+1)}{K+1+\overline{\gamma}}}\right) \tag{14}$$

$$\Delta_1 = P(\lambda_1 \le R_i(r_i) \le \lambda_2 | H_1) = 1 - P_d - P_m \,. \tag{15}$$

where $Q(\cdot)$ is the standard Gaussian complementary distribution function. The channel model uses a Rician channel, where K is the Rician factor.

3. Dual Threshold Cooperative Spectrum Sensing Based on Equal Gain Combination

3.1. Integration Strategy

In the cooperative sensing strategy used in spectrum sensing, each SU needs to transmit the local decision data of each node to the FC for mutual cooperation. In cooperative spectrum sensing, a key technology is to efficiently process the data transmitted by each cooperative node and make effective decisions. At present, the decision-making strategies of collaborative spectrum sensing mainly include: (1) Decision fusion, that is, hard decision-making, and decision fusion is carried out through the decision results transmitted by cooperative nodes. (2) Data fusion, that is, soft decision-making, requiring full use of sensors and data. Collaborative spectrum sensing generates a deterministic description of the observed samples through a comprehensive analysis of the observed information.

The hard fusion criterion of cooperative awareness requires each SU participating in the cooperation to submit a local detection result, that is, the node determines that the existence of the detected PU is “1”, otherwise it is “0”. Then, each cognitive user submits the detection result of each node to FC. Typically, cooperative sensing includes “AND”, “OR" and “K-out-of-N” algorithms. Assuming that there are N sensing nodes for cooperative spectrum sensing, the "AND" algorithm requires N sensing nodes to detect the presence of a PU. The perceptual result means that the FC can only determine the existence of the PU when it receives N "1"s. The "OR" algorithm is that only one sensing node detects the existence of PU, and FC can make the result of PU. The "K-out-of-N" algorithm first needs to determine the voting threshold K. When fewer than K sensing nodes give a decision, the FC decides that the PU does not exist. Moreover, the size of K can be fixed or adjusted according to the accumulation of test results. Therefore, collaborative sensing can improve the detection performance, and different fusion strategies will have different effects on the detection results.

For the fusion criterion, the joint detection probability Q_d and joint false alarm probability Q_f can be obtained as:

$$\begin{cases} Q_{d\_K} = \mathrm{P}\left(\sum\limits_{i=1}^{N} d_i \geq k|H_1\right) = \sum\limits_{i=k}^{N} C_N^i P_d (1-P_d)^{N-i} \\ Q_{f\_K} = \mathrm{P}\left(\sum\limits_{i=1}^{N} d_i \geq k|H_0\right) = \sum\limits_{i=k}^{N} C_N^i P_f \left(1-P_f\right)^{N-i} \end{cases}. \tag{16}$$

where the dual threshold of spectrum sensing technology adopts λ_0 and λ_1. If SU uses dual-threshold energy detection for local decision-making, and does not deal with fuzzy states at this time, the following formula is obtained:

$$\begin{aligned} Q_{d\_K\_dou} &= P\{G=1|H_1\} = \sum_{K=1}^{N} C_N^K \prod_{i=1}^{K} P(O_i \leq \lambda_0 \cup O_i \geq \lambda_1 |H_1) \\ &* \prod_{i=K+1}^{N} P(\lambda_0 < O_i < \lambda_1 |H_1) \sum_{i=k}^{K} C_K^i P_d^i P_m^{K-i} \\ &= \sum_{K=1}^{N} C_N^K (1-\Delta_1)^K {\Delta_1}^{N-K} \sum_{i=k}^{K} C_K^i P_d^i P_m^{K-i} \end{aligned} \tag{17}$$

$$\begin{aligned} Q_{f\_K\_dou} &= 1 - P\{G=1|H_0\} = \sum_{K=1}^{N} C_N^K \prod_{i=1}^{K} P(O_i \leq \lambda_0 \cup O_i \geq \lambda_1 |H_1) \\ &* \prod_{i=K+1}^{N} P(\lambda_0 < O_i < \lambda_1 |H_1) \sum_{i=k}^{K} C_K^i P_f^i P_a^{K-i} \\ &= \sum_{K=1}^{N} C_N^K (1-\Delta_0)^K {\Delta_0}^{N-K} \sum_{i=k}^{K} C_K^i P_f^i P_a^{K-i} \end{aligned}. \tag{18}$$

The voting threshold of the traditional K-rank criterion is $k = \lceil N/2 \rceil$, and $\lceil \cdot \rceil$ is the ceiling function. In addition, the voting threshold can be adjusted automatically.

At present, the commonly used soft decision algorithms include weight combination, likelihood ratio algorithm, and so on. Compared with other soft fusion standards, the weighted gain combining algorithm (WGC) is widely used due to its low complexity and easy implementation. Therefore, this paper mainly introduces the weighted gain combination algorithm. The process of the WGC algorithm is that the cooperative cognitive nodes send the detected energy value directly to the FC, and then set a weight w_i as a multiplication factor according to the contribution of the cognitive nodes. FC compares the result calculated by the formula (19) with the threshold η to obtain the decision result.

$$S = \sum_{i=1}^{n} X_i w_i. \tag{19}$$

When the weight coefficient is $w_i = 1$, WGC is equivalent to the equal gain combining (EGC) algorithm. When the FC uses the EGC criterion to make data decisions, the cooperative cognitive nodes need to pass the local measurement value $X_i, i = 1, 2, \cdots, N$ to the FC. The EGC algorithm is modeled as follows:

$$G_{EGC} = \begin{cases} 0 & S_{EGC} = \sum_{i=1}^{N} \frac{X_i}{N\delta_n^2} < \lambda_{EGC} \quad H_0 \\ 1 & S_{EGC} = \sum_{i=1}^{N} \frac{X_i}{N\delta_n^2} \geq \lambda_{EGC} \quad H_1 \end{cases}. \tag{20}$$

where λ_{EGC} is the threshold of the EGC algorithm, and δ_n^2 is the noise variance. This paper assumes that each cognitive node is independent and identically distributed. Therefore, when the measured value is in a fuzzy state, the equal-gain combination algorithm is used, and the distribution of S_{EGC} in H_0 and H_1 obeys the following formulas:

$$S_{ECG} \sim \begin{cases} \chi_{2uN}^2 & H_0 \\ \chi_{2uN}^2(2\mu N\gamma) & H_1 \end{cases}. \tag{21}$$

The joint detection probability and false alarm probability of the algorithm are as follows:

$$\begin{cases} Q_{f\_EGC} = \frac{\Gamma\left(Nu, \lambda_{EGC}/2\delta_n^2\right)}{\Gamma(Nu)} \\ Q_{d\_EGC} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda_{EGC}}\right) \end{cases}. \tag{22}$$

where $\gamma = \sum_{i=1}^{N} \gamma_i$ is the instantaneous SNR of FC, and γ_i is the SNR of the i-th cognitive user. In order to improve the accuracy of decision-making, the EGC algorithm is used to judge the received signal samples in a fuzzy state.

3.2. Algorithm Analysis and Optimization

Most of the dual-threshold cooperative spectrum sensing algorithms are based on the K-rank fusion strategy, which directly ignores the decision-making of the fuzzy state. Therefore, the optimal voting threshold is derived by using EGC judgment to improve the decision-making accuracy of fuzzy state. In fact, EGC-based dual-threshold cooperative spectrum sensing is an algorithm that combines software and hardware. First, cooperative cognitive nodes detect dual-threshold energy. Second, the detection result Y_i is sent to the FC. For nodes in the fuzzy state, the sensing signal is sent directly to the FC.

$$Y_i = \begin{cases} 0 & X_i \leq \lambda_1 \\ X & \lambda_1 < X_i < \lambda_2 \\ 1 & X_i \geq \lambda_2 \end{cases}. \tag{23}$$

where X_i is the local detection energy value, and λ_1 and λ_2 are preset double thresholds. The FC will classify the received Y_i, and use a soft decision for the submitted local detection energy value X_i. The judgment result S is obtained by using the EGC judgment mentioned above, and then a hard judgment is made in the FC together with Y_i whose local detection results are 0 and 1, and finally whether the PU exists can be judged.

In order to improve the sensing accuracy of the integrated satellite terrestrial system, the voting optimization algorithm of the double-threshold cooperative spectrum sensing algorithm based on EGC is deduced. The joint probability of the algorithm is as follows:

$$\begin{aligned} Q_d &= 1 - (1 - P_{\mathrm{d\_EGC}})(1 - Q_{d\_K\_double}) \\ &= 1 - P_{m\_EGC} + P_{m\_EGC} \sum_{M=1}^{N} C_N^M (1 - \Delta_1)^M \Delta_1{}^{N-M} \sum_{i=k}^{M} C_M^i P_d^i P_m^{M-i} \end{aligned} \tag{24}$$

$$Q_m = 1 - Q_d \tag{25}$$

$$\begin{aligned} Q_f &= 1-\left(1-P_{f\_EGC}\right)\left(1-Q_{f\_K\_double}\right) \\ &= 1-P_{a\_EGC}+P_{a\_EGC}\sum_{M=1}^{N} C_N^M(1-\Delta_0)^M{\Delta_0}^{N-M}\sum_{i=k}^{M} C_M^i P_f^i P_a^{M-i}. \end{aligned} \tag{26}$$

According to the above formula, the global error probability can be defined as:

$$\begin{aligned} Q_{error} &= Q_m+Q_f \\ &= 1+P_{m\_EGC}-P_{m\_EGC}\sum_{M=1}^{N} C_N^M(1-\Delta_1)^M{\Delta_1}^{N-M}\sum_{i=k}^{M} C_K^i P_d^i P_m^{M-i} \\ &-P_{a\_EGC}+P_{a\_EGC}\sum_{M=1}^{N} C_N^M(1-\Delta_0)^M{\Delta_0}^{N-M}\sum_{i=k}^{M} C_M^i P_f^i P_a^{M-i}. \end{aligned} \tag{27}$$

In order to obtain the optimal voting threshold k_{opt}, i.e., Q_{error} is the minimum. Then the derivation of Formula (28) is as follows:

$$\begin{aligned} \frac{\partial Q_{error}}{\partial k} &= \frac{\partial Q_m}{\partial k}+\frac{\partial Q_f}{\partial k}=\frac{Q_{error}(k+1)-Q_{error}(k)}{(k+1)-k} \\ &= P_{m\_EGC}\sum_{M=1}^{N} C_N^M(1-\Delta_1)^M{\Delta_1}^{N-M}C_M^k P_d^k P_m^{M-k} \\ &-P_{a\_EGC}\sum_{M=1}^{N} C_N^M(1-\Delta_0)^M{\Delta_0}^{N-M}C_M^k P_f^k P_a^{M-k}. \end{aligned} \tag{28}$$

When Q_{error} reaches the minimum, then $\frac{\partial Q_{error}}{\partial k}=0$. The following formula can be obtained:

$$P_{m\_EGC}(1-\Delta_1)^M{\Delta_1}^{N-M}P_d^k P_m^{M-k}=P_{a\_EGC}(1-\Delta_0)^M{\Delta_0}^{N-M}P_f^k P_a^{M-k}. \tag{29}$$

The derivation of both sides of formula (29) is as follows:

$$k_{opt}=\frac{M\ln\left(\frac{P_a}{P_m}\right)+\ln\left(\frac{1-\Delta_0}{1-\Delta_1}\right)^M\left(\frac{\Delta_0}{\Delta_1}\right)^{N-M}\frac{P_{a\_EGC}}{P_{m\_EGC}}}{\ln\left(\frac{P_aP_d}{P_mP_f}\right)}. \tag{30}$$

When k_{opt} satisfies Formula (30), Q_{error} reaches a minimum value, and we obtain:

$$\begin{aligned} \left.\frac{\partial^2 Q_{error}}{\partial k^2}\right|_{k=k_{opt}} &= \frac{\left.\frac{\partial Q_{error}(k+1)}{\partial k}\right|_{k=k_{opt}}-\left.\frac{\partial Q_{error}(k)}{\partial k}\right|_{k=k_{opt}}}{(k+1)-k} \\ &= \sum_{M=1}^{N} C_N^M C_M^{k_{opt}+1}P_{m\_EGC}(1-\Delta_1)^M{\Delta_1}^{N-M}\frac{P_d}{P_m}P_d^{k_{opt}}P_m^{M-k_{opt}} \\ &-\sum_{M=1}^{N} C_N^M C_M^{k_{opt}+1}P_{a\_EGC}(1-\Delta_0)^M{\Delta_0}^{N-M}\frac{P_f}{P_a}P_f^{k_{opt}}P_a^{M-k_{opt}}. \end{aligned} \tag{31}$$

From Formula (10) to Formula (15), theoretically there are $P_a>P_m$ and $P_d>P_f$. The results are as follows:

$$\frac{P_d}{P_m}>\frac{P_f}{P_a} \tag{32}$$

$$\left.\frac{\partial^2 Q_{error}}{\partial k^2}\right|_{k=k_{opt}}>0. \tag{33}$$

The minimum value of the global error probability is obtained when $\frac{\partial Q_{error}}{\partial k}=0$.

$$k_{opt}=\left\lceil\frac{M\ln\left(\frac{P_a}{P_m}\right)+\ln\left(\frac{1-\Delta_0}{1-\Delta_1}\right)^M\left(\frac{\Delta_0}{\Delta_1}\right)^{N-M}\frac{P_{a\_EGC}}{P_{m\_EGC}}}{\ln\left(\frac{P_aP_d}{P_mP_f}\right)}\right\rceil. \tag{34}$$

where P_a,P_m,P_d,P_f,Δ_0 and Δ_1 are functions of the lower limit λ_1 and upper limit λ_2 of double thresholds. The optimal voting threshold can be obtained by substituting the lower bound λ_1 and the upper bound λ_2.

4. Adaptive Dual Threshold Cooperative Sensing

The value of the lower threshold λ_1 and the upper threshold λ_2 of the dual-threshold spectrum sensing algorithm, and the fuzzy state between them, will affect the complexity of the spectrum sensing algorithm. The area of fuzzy state is reduced when the SNR is high, thereby reducing the complexity of spectrum sensing decisions. In addition, the decision-making ability of the system can be further improved by adaptively adjusting the thresholds of the dual thresholds.

The double-threshold algorithm satisfies $\lambda_1 \leq \lambda_2$, and the size of the double-threshold will directly affect the change in decision-making performance. When the threshold value λ_1 decreases, P_m will decrease. When the value of λ_2 increases, P_f will decrease, but P_d may also decrease. As the difference between the two thresholds increases, the probability of a received signal sample in fuzzy state increases. The global error probability is defined in Formula (28), and when solving the adaptive dual-threshold algorithm, the optimization problem is:

$$\begin{array}{c} \min(Q_{error}(\lambda_1, \lambda_2)) \\ \text{s.t.} \quad 0 < \lambda_1 < \lambda_2 < +\infty. \end{array} \tag{35}$$

Find the optimal $\lambda_{1_{opt}}$ and $\lambda_{2_{opt}}$ when $Q_{error}(\lambda_1, \lambda_2)$ is the minimum value. Then $\lambda_{1_{opt}}$ and $\lambda_{2_{opt}}$ are required to meet the following requirements:

$$\begin{cases} \left.\frac{\partial Q_{error}(\lambda_1,\lambda_2)}{\partial \lambda_1}\right|_{\lambda_{1_{opt}}} = 0 \\ \left.\frac{\partial Q_{error}(\lambda_1,\lambda_2)}{\partial \lambda_2}\right|_{\lambda_{2_{opt}}} = 0 \end{cases}. \tag{36}$$

Through mathematical derivation, we can obtain:

$$\begin{aligned} \left.\frac{\partial Q_{error}(\lambda_1,\lambda_2)}{\partial \lambda_1}\right|_{\lambda_{1_{opt}}} &= \left.\frac{\partial\left(-\sum\limits_{M=1}^{N} C_N^M \sum\limits_{i=k}^{M} C_K^i P_{m\_EGC}(1-\Delta_1)^M {\Delta_1}^{N-M} P_d^i P_m^{M-i}\right)}{\partial \lambda_1}\right|_{\lambda_{1_{opt}}} \\ &+ \left.\frac{\partial\left(\sum\limits_{M=1}^{N} C_N^M \sum\limits_{i=k}^{M} C_K^i P_{a\_EGC}(1-\Delta_0)^M {\Delta_0}^{N-M} P_f^i P_a^{M-i}\right)}{\partial \lambda_1}\right|_{\lambda_{1_{opt}}} \end{aligned} \tag{37}$$

$$\begin{aligned} \left.\frac{\partial Q_{error}(\lambda_1,\lambda_2)}{\partial \lambda_2}\right|_{\lambda_{2_{opt}}} &= \left.\frac{\partial\left(-\sum\limits_{M=1}^{N} C_N^M \sum\limits_{i=k}^{M} C_K^i P_{m\_EGC}(1-\Delta_1)^M {\Delta_1}^{N-M} P_d^i P_m^{M-i}\right)}{\partial \lambda_2}\right|_{\lambda_{2_{opt}}} \\ &+ \left.\frac{\partial\left(\sum\limits_{M=1}^{N} C_N^M \sum\limits_{i=k}^{M} C_K^i P_{a\_EGC}(1-\Delta_0)^M {\Delta_0}^{N-M} P_f^i P_a^{M-i}\right)}{\partial \lambda_2}\right|_{\lambda_{2_{opt}}} \end{aligned}. \tag{38}$$

To make Equations (37) and (38) equal to 0, we assume:

$$\begin{aligned} G(\gamma) &= -\sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC}(1-\Delta_0)^{M-1} {\Delta_0}^{N-M} P_f^i P_a^{M-i} M \\ &+ \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC}(1-\Delta_0)^{M} {\Delta_0}^{N-M-1} P_f^i P_a^{M-i} (N-M) \\ &- \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC}(1-\Delta_0)^{M} {\Delta_0}^{N-M} P_f^i P_a^{M-i-1} (M-i) \end{aligned} \tag{39}$$

$$\begin{aligned} Q(\gamma) &= -\sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M-1} {\Delta_1}^{N-M} P_d^i P_m^{M-i} M \\ &+ \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M} {\Delta_1}^{N-M-1} P_d^i P_m^{M-i} (N-M). \\ &- \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M} {\Delta_1}^{N-M} P_d^i P_m^{M-i-1} (M-i) \end{aligned} \quad (40)$$

The first optimal threshold result can be obtained as follows:

$$\lambda_{1_{opt}} = \sqrt{2M(\gamma+1) \times \ln\left(\sqrt{\gamma+1}\frac{G(\gamma)}{Q(\gamma)}\right)}. \quad (41)$$

Using the same derivation process, we assume:

$$\begin{aligned} Y(\gamma) &= -\sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC} (1-\Delta_0)^{M-1} {\Delta_0}^{N-M} P_f^i P_a^{M-i} M \\ &+ \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC} (1-\Delta_0)^{M} {\Delta_0}^{N-M-1} P_f^i P_a^{M-i} M(N-M) \\ &- \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{a\_EGC} (1-\Delta_0)^{M} {\Delta_0}^{N-M} P_f^{i-1} P_a^{M-i} M \Delta_0 P i \end{aligned} \quad (42)$$

$$\begin{aligned} Z(\gamma) &= -\sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M-1} {\Delta_1}^{N-M} P_d^i P_m^{M-i} M \\ &+ \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M} {\Delta_1}^{N-M-1} P_d^i P_m^{M-i} (N-M)\,. \\ &- \sum_{M=1}^{N} C_N^M \sum_{i=k}^{M} C_K^i P_{m\_EGC} M(1-\Delta_1)^{M} {\Delta_1}^{N-M} P_d^{i-1} P_m^{M-i} i \end{aligned} \quad (43)$$

The second optimal threshold result can be obtained as follows:

$$\lambda_{2_{opt}} = \sqrt{2M(\gamma+1) \times \ln\left(\sqrt{\gamma+1}\frac{Y(\gamma)}{Z(\gamma)}\right)}\,. \quad (44)$$

Therefore, Equations (41) and (44) are the optimal solutions for the threshold and vary with the current SNR.

5. Simulation Results and Analysis

Figures 3 and 4 are the curves of the error probability of the integrated satellite terrestrial system with the change of the SNR in the case of different noise uncertainties of the dual-threshold cooperative energy detection technology. Moreover, a lower error probability means a stronger detection capability of the spectrum sensing system. When $P_f = 0.1$ is set and the number of cognitive nodes is $N = 5$, the simulations are carried out for the cases where the noise uncertainty is $\rho = 1.01$ and $\rho = 2$. As shown in Figure 3, when the noise uncertainty satisfies $\rho = 1.01$, the noise uncertainty is extremely low, and the two thresholds of the dual-threshold detection algorithm are relatively close. At this time, the detection probability of the OR algorithm and the double-threshold cooperative spectrum sensing algorithm based on EGC is obviously better than the performance of other fusion strategies. The OR criterion only needs to have one cooperating node judged as 1, then the system judges that the frequency band is occupied. Therefore, the OR algorithm exchanges a part of P_f for the improvement of P_d, while the double-threshold cooperative spectrum sensing algorithm based on EGC increases the detection probability by increasing the judgment of the fuzzy state.

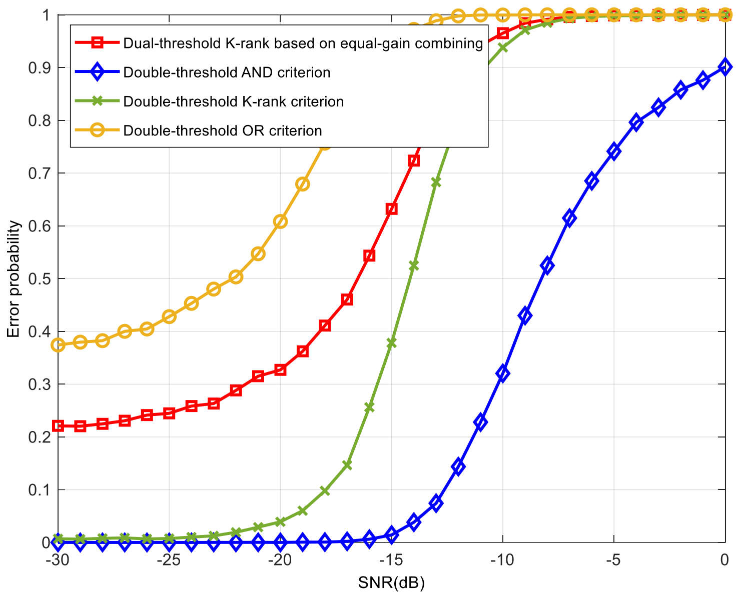

Figure 3. Detection probability of different fusion criteria (Rice factor K = 5 dB, noise uncertainty ρ = 1.01).

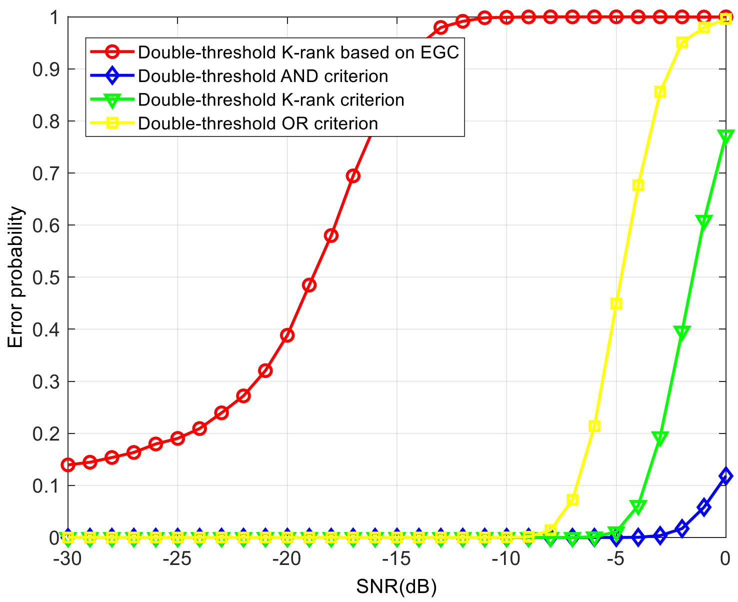

Figure 4. Detection probability of different fusion criteria (Rice factor K = 5 dB, noise uncertainty ρ = 2).

As shown in Figure 4, when the noise uncertainty is $\rho = 2$, the error probability of the EGC-based dual-threshold cooperative spectrum sensing algorithm is significantly higher than the other three fusion criteria in the case of low SNR. This is because when the noise uncertainty is $\rho = 2$, the fuzzy state area increases significantly, and the K-rank, OR and AND criteria all ignore the fuzzy state judgment. When the EGC-based dual-threshold cooperative spectrum sensing algorithm is used for decision, the fuzzy state is decided by EGC, which improves the decision accuracy of the system. By analyzing Figures 3 and 4, the sensing system using the EGC-based dual-threshold cooperative spectrum sensing algorithm has higher stability. Therefore, the simulation results show that the detection probability of the double-threshold cooperative spectrum sensing algorithm based on EGC is better when the noise uncertainty is relatively high. In addition, the increased detection probability indicates that the terrestrial network can use the satellite frequency band more flexibly, which further improves the spectral efficiency.

Figure 5 shows the error probability change of the double threshold K-rank algorithm and optimized K-rank algorithm with SNR under M = 1000, $P_f = 0.1$. The optimization algorithm uses a dynamic voting threshold technique with the goal of minimizing the error probability. Adapting the optimization algorithm to changes in the current environment, the error probability is significantly reduced as shown in Figure 3. In addition, when $\rho = 1.01$, the decision mainly relies on the K-rank cooperation algorithm, and the performance improvement is obvious. However, when $\rho = 2$, most of the signal energy is in fuzzy state, which mainly depends on the EGC algorithm.

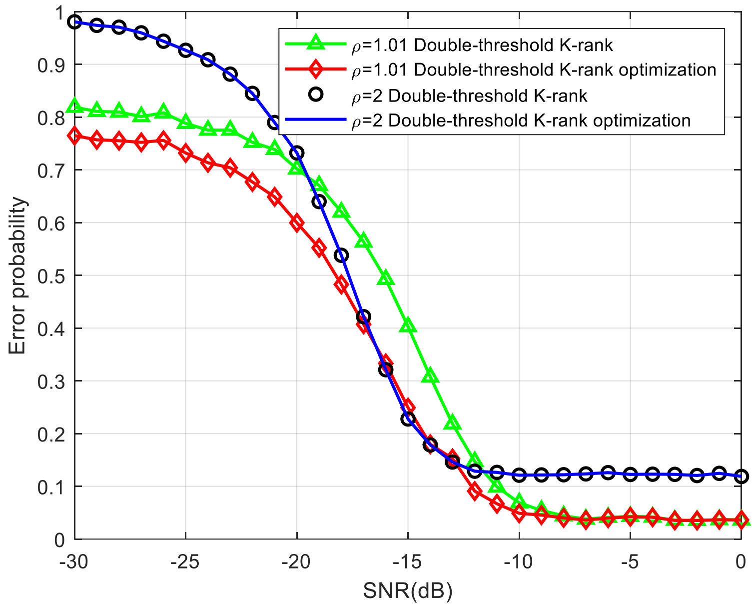

Figure 5. Performance of optimized K-rank algorithm.

Figure 6 shows the performance analysis of the EGC-based adaptive dual-threshold collaborative sensing optimization algorithm. The false alarm probability of GEO satellite is $P_f = 0.1$, and five cooperative sensing nodes are used. The adaptive algorithm dynamically adjusts the threshold through the SNR, and the fuzzy area becomes larger when the SNR is low. Conversely, the fuzzy area becomes smaller when the SNR is high. Moreover, the simulation results also show that the EGC-based algorithm can improve the detection accuracy. In addition, the accuracy of decision-making mainly depends on the collaborative decision-making strategy, and the detection probability is improved by optimizing the voting algorithm.

In order to analyze the performance of the optimization algorithm of dual threshold cooperative sensing based on EGC, this paper compares it with several other algorithms. Figure 7 shows the performance comparison of the proposed algorithm with other algorithms. The simulation results show that the performance of the adaptive cooperative algorithm based on EGC is higher than the other three algorithms. When the SNR is higher than −8 dB, the detection performances of the adaptive dual-threshold co-sensing algorithms based on the EGC, “ADE” and "DDEMM" algorithms are comparable. The adaptive dual-threshold cooperative perception based on EGC, “DDEMM”, “Cyclostation-DE” and “ADE” algorithms starts to drop sharply at −14 dB, −10 dB, −10 dB and −7 dB, respectively. The adaptive dual-threshold cooperative algorithm based on EGC has better decision-making effect with the decrease of SNR. Compared with the “DDEMM”, “Cyclostation-DE” and “ADE” algorithms, the detection performance of the EGC-based dual-threshold cooperative sensing algorithm at 20 dB is improved by 40.1%, 187% and 195.75%, respectively.

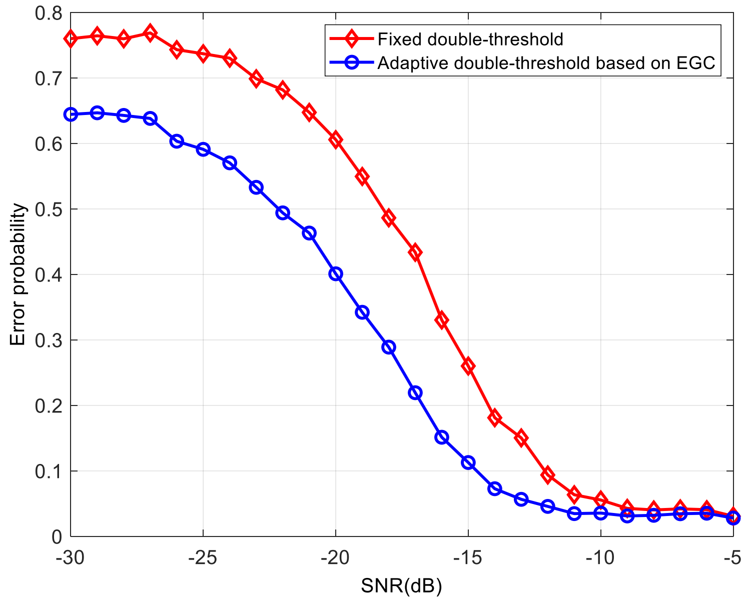

Figure 6. Performance of adaptive double threshold algorithm.

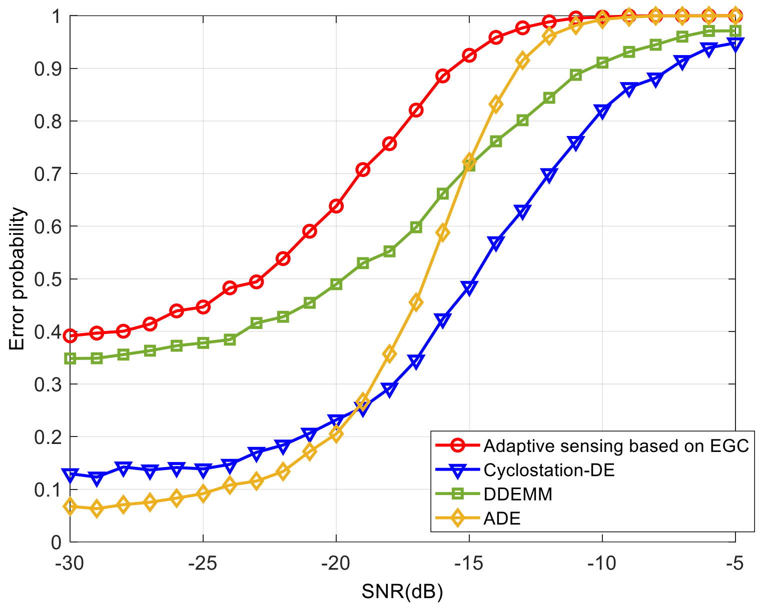

Figure 7. Performance of dual threshold cooperative sensing algorithm based on EGC.

When the detection probability $P_d \geq 0.9$ is satisfied, the minimum SNR of the above four algorithms are -15 dB, -10 dB, -13 dB and -8 dB, respectively. Figure 7 shows that the adaptive dual-threshold cooperative sensing algorithm based on EGC has a significant improvement over other algorithms under the condition of low SNR. In the case of low SNR (-30dB to -20 dB), the adaptive dual-threshold cooperative sensing based on EGC and "DDEMM" algorithm has better detection performance. However, the detection performance of "DDEMM" slowly improves with the increase of the SNR. The traditional self-adaptive double-threshold algorithm lacks the judgment of ambiguous state, and the overall detection performance is not high. However, the cyclostationary feature detection introduced by the "Cyclosure-DE" algorithm can improve the detection performance, but cannot overcome the limitation of fixed thresholds.

6. Conclusions

In this paper, cognitive radio technology is introduced into the integrated satellite terrestrial system to dynamically realize spectrum sharing to increase spectrum utilization. The spectrum sensing scenario of the integrated satellite terrestrial system is studied, and the fading situation of the sensing link is determined. However, the uncertainty of noise interference in the system can lead to a fuzzy state of perception. The traditional double-threshold cooperative sensing technology usually ignores the detected fuzzy state. Therefore, the equal-gain combination algorithm is introduced to improve the decision-making accuracy of the fuzzy state. Furthermore, the optimal value of voting threshold and dual threshold algorithm is derived based on the equal gain combination algorithm to minimize the error probability. The simulation results show that the optimal values of the two thresholds vary with the SNR, which can dynamically adapt to the complex scene of the integrated satellite terrestrial system. The dual-threshold cooperative spectrum sharing algorithm improves the detection accuracy of the integrated satellite terrestrial sensing system. Cognitive technology increases the opportunity for ground systems to share satellite spectrum, reduces the interference of ground systems to satellite systems, and alleviates the current shortage of spectrum resources.

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