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A Double-Threshold Cooperative Spectrum Sensing Algorithm in the Internet of Vehicles

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Abstract: To address the shortage of wireless spectrum resources caused by the rapid development of the Internet of Vehicles, spectrum sensing technology in cognitive radio is employed to tackle this issue. In pursuit of superior outcomes, a double-threshold cooperative spectrum sensing algorithm is introduced. This algorithm enhances traditional energy detection technology to mitigate the high sensitivity to noise interference in the Internet of Vehicles environment. A double-threshold judgment mechanism can be established based on the uncertainty of noise. Varying fusion rules are implemented in the collaborative spectrum sensing scheme according to the density of vehicles and the spectrum resource demand. Simulation results demonstrate that the performance of the double-threshold cooperative spectrum sensing algorithm surpasses that of the traditional single-threshold energy detection scheme, particularly evident under lower Signal-to-Noise Ratio (SNR) conditions. Moreover, the proposed algorithm exhibits superior sensing performance in environments characterized by higher noise uncertainty.

Keywords: Internet of Vehicles; cognitive radio; cooperative spectrum sensing; energy detection; double threshold

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1. Introduction

With the advancement of the Internet of Vehicles (IoVs), it has emerged as a crucial technology within the Intelligent Transportation System (ITS). However, the Internet of Vehicles requires ample spectrum resources to facilitate data transmission and ensure communication quality [1]. Insufficient spectrum resources can lead to unstable or delayed communication. Nevertheless, wireless spectrum resources are a national asset and represent an exceedingly vital, scarce resource. The dedicated spectrum resources allocated to the Internet of Vehicles are limited. For instance, the United States Federal Communications Commission has designated only 75 MHz (5.850~5.925 GHz) for the Internet of Vehicles, while in China, only a 20 MHz (5.905~5.925 GHz) frequency band is utilized as the operational frequency band for the Internet of Vehicles [2,3]. Furthermore, as the number of vehicles increases and people's demand for entertainment communication within the Internet of Vehicles grows, the existing technology cannot adequately meet these spectrum requirements. Hence, the challenge at hand is how to allocate, manage, and effectively utilize the limited spectrum of resources in the Internet of Vehicles.

The advancement of technology in the Internet of Vehicles holds significant importance for travel and traffic management. However, due to limited spectrum resources and complex channel environments, the development of the Internet of Vehicles has presented substantial challenges [4–7]. Internet of Vehicles technology offers extensive application prospects in public safety communication, secure business communication, and non-secure business communication among vehicles. Safety service communication between vehicles primarily encompasses vehicle collision warnings, road condition information, etc. These safety service communications need to ensure real-time reliability [8,9]. Non-secure service communications include in-vehicle entertainment systems, navigation systems, etc., which require greater bandwidth and quality of service to enhance user experiences. Public safety communication refers to communication between police on duty, fire engines, etc., necessitating significant spectrum resources during emergencies. Therefore, cognitive radio technology will increasingly play a pivotal role in the Internet of Vehicles, steering vehicles toward a more intelligent and digital future.

Spectrum sensing is pivotal in enabling cognitive radio technology for the next generation of wireless communication systems [10]. Despite advancements, current methods such as energy detection, cyclostationary features, and matched filters have inherent limitations, leaving the reliability of spectrum sensing an ongoing concern in wireless communication research. Recently, machine learning techniques have been explored for cooperative spectrum sensing [11]. In [12], a spectrum sensing method rooted in machine learning theory for cognitive radio networks is proposed, rigorously modeled, and validated using a large-scale dataset. The models undergo extensive testing and evaluation, considering metrics such as detection probability, false alarm probability, miss-detection probability, and classification accuracy. Moreover, a novel spectrum sensing algorithm based on support vector machines is introduced in [13]. This approach involves mapping received signals into a multi-dimensional feature space derived from well-established spectrum sensing statistics and their higher-order combinations. Notably, the receiver operating characteristic (ROC) curve of the proposed detector outperforms classical spectrum sensing methods, obviating the need for knowledge of noise variance.

The application of spectrum sensing technology in cognitive radio is extensive. It can be applied not only to the Internet of Things (IoT) [14–16], but also to the Internet of Vehicles to enhance the security and confidentiality of communications. The application of cognitive radio (CR) technology in the context of the Internet of Vehicles facilitates spectrum sharing by detecting idle spectrum, thereby improving spectrum utilization rates and alleviating spectrum resource shortages [17]. In [18], the authors analyze how dynamic access spectrum in cognitive radio can enhance spectrum resource opportunities in IoV communications for unlicensed users by mitigating detrimental interferences for primary users (PUs). In [19], the authors propose a novel spectrum sensing technique wherein CR-assisted vehicles utilize backoff duration for sensing the CR network. Through cooperative spectrum sensing, the information sensed is shared among vehicles, facilitating data transmission through the available spectrum. In [20], a system model is proposed for cooperative centralized and distributed spectrum sensing in vehicular networks. The proposed architecture aims to mitigate both spectral scarcity and high-mobility issues.

In addition, authors in [21] propose a cognitive vehicle assistance network that adopts a cooperative spectrum sensing and allocation model. This model enables cognitive vehicles to detect current and future frequency spectrum usage on the highway, achieving opportunistic access to authorized idle frequency bands. This improves the efficiency of vehicle communication and accommodates different communication needs. Authors in [22] propose a distributed collaborative spectrum sensing method for the Internet of Vehicles, optimizing the threshold value based on single-threshold collaborative spectrum sensing to enhance the success rate of spectrum sensing. However, this method still does not completely resolve the issue of single-threshold energy detection's over-dependence on signal-to-noise ratio (SNR). Building upon the single threshold value in [22], authors in [23] enhance the algorithm to utilize a double-threshold value, resulting in improved spectrum sensing performance. This addresses the problem of the single-threshold value's excessive dependence on signal-to-noise ratio to some extent. Nevertheless, a drawback is the simplicity of setting the thresholds; relying solely on the number of vehicles may compromise the accuracy of simulation results.

Different from the single-threshold energy detection used in radar, the advantages of the proposed double-threshold cooperative spectrum sensing algorithm in the Internet of Vehicles are mainly reflected in the following aspects: (1) Improved detection probability and reduced false alarm probability: Compared with the traditional single-threshold energy detection algorithm, under the same conditions, the double-threshold collaborative detection algorithm is more likely to accurately identify the target signal while reducing false alarms caused by misjudgment. (2) Adaptation to low-SNR environments: In relatively low-SNR environments, the double-threshold collaborative detection algorithm exhibits excellent performance. This is because the double-threshold design can better handle noise interference, achieving more stable detection results in complex Internet of Vehicles environments. (3) Reduction in the impact of error noise estimation: In real Internet of Vehicles environments, the original signal may be mixed with ever-changing noise, affecting detection accuracy and false alarm probability. The double-threshold collaborative detection algorithm can better handle noise interference by setting two threshold values, thus reducing the influence of error noise estimation on detection performance.

The major contributions of this article are as follows:

A system model of the cognitive Internet of Vehicles is constructed, which combines the double-threshold decision criterion and collaborative spectrum sensing technology to enhance spectrum sensing performance and significantly increase the utilization of spectrum resources in vehicles within the Internet of Vehicles.

The proposed algorithm dynamically adjusts the threshold value according to noise uncertainty, broadening the range of confusion interval in high-noise environments, thereby improving detection probability even under conditions of low SNR in the Internet of Vehicles.

The paper is organized as follows: Section 2 discusses the system model of the proposed scheme in the Internet of Vehicles. Section 3 presents a double-threshold cooperative spectrum sensing algorithm. Simulation results are discussed in Section 4. Section 5 discusses the findings, validation of the method and shortcomings of this study. We conclude the paper in Section 6.

2. System Model

The system model of the cognitive Internet of Vehicles is depicted in Figure 1. It comprises the Primary Base Station (PBS), the Fusion Center (FC), and several cognitive vehicle nodes capable of facilitating communication between vehicles and the FC, along with communication among vehicles. In this scenario, in the event of a significant traffic accident or congestion, numerous vehicle nodes may simultaneously initiate vehicle service communication requests, potentially leading to a shortage of spectrum resources. In such instances, the cognitive Internet of Vehicles must promptly activate cognitive functions to conduct spectrum sensing, identify the available idle spectrum, enhance spectrum utilization, and ensure the efficiency and reliability of vehicle communication.

The PBS transmits signals within the authorized frequency band to cognitive vehicles within its coverage range, typically operating within the television frequency band. The yellow region illustrated in Figure 1 delineates the coverage area of the PBS. In the absence of the PU's signal transmission, certain cognitive vehicles can utilize these idle frequency bands for data transmission, effectively alleviating pressure on the frequency band.

The cognitive vehicle user primarily obtains the vehicle's position, speed, and driving route through onboard sensors and Global Positioning System (GPS) positioning. On one hand, the cognitive vehicle user can employ spectrum sensing to detect idle spectrum within the frequency band authorized by the PU, as depicted by the red arrow in Figure 1. On the other hand, vehicles outside the coverage range of the PBS can communicate with covered vehicles to exchange data and obtain information, such as the driving status and road conditions faced by the other vehicle, as illustrated by the blue arrow in Figure 1.

The role of the fusion center in collaborative spectrum sensing is to communicate with cognitive vehicles within its range. Since the coverage area of the PBS is limited, multiple cognitive vehicle users collect vehicle data within their respective ranges and then upload the data to the fusion center, as indicated by the yellow arrow in Figure 1. The fusion center collects spectrum sensing judgment results uploaded by cognitive vehicles, selects appropriate fusion rules based on different situations to make the final judgment, and then transmits the judgment results to each cognitive vehicle user. This allows for them to dynamically access idle frequency bands for communication.

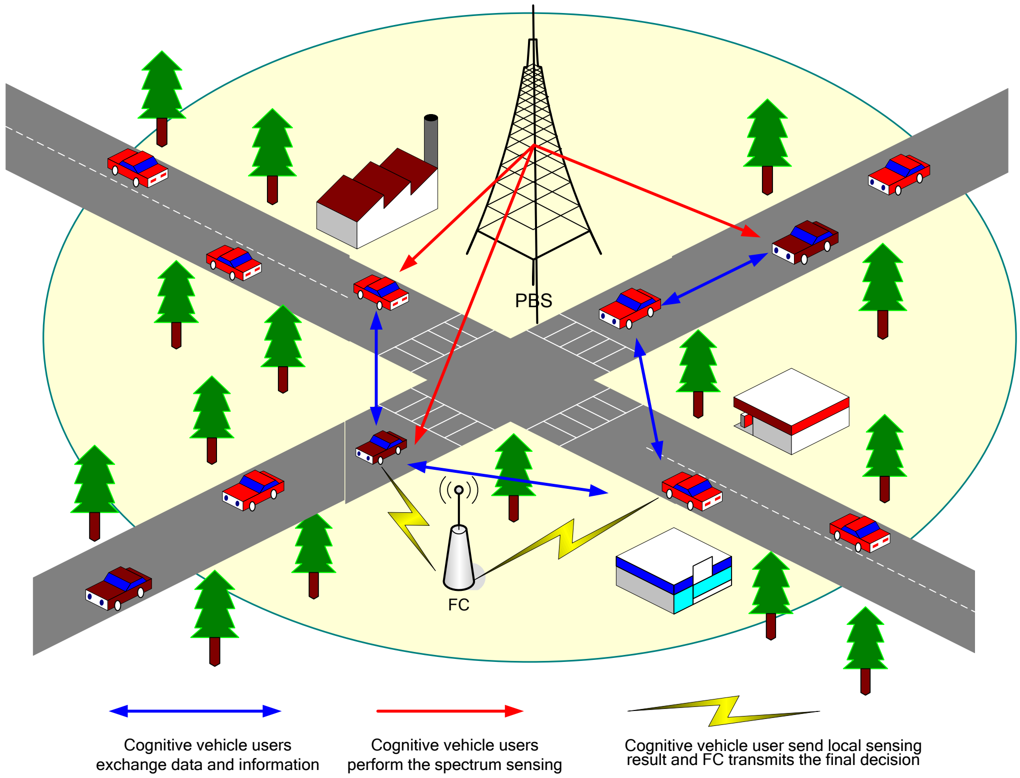

Figure 1. System model of cognitive Internet of Vehicles.

Given the high velocity of vehicles and the intricacies of the continuously evolving communication landscape, the conventional single-threshold spectrum sensing algorithm frequently encounters difficulties to achieve high detection probability in low-SNR environment. In response to this challenge, the double-threshold collaborative spectrum sensing algorithm endeavors to enhance detection probability effectively in a low-SNR environment.

3. The Proposed Double-Threshold Cooperative Spectrum Sensing Algorithm

The energy detection technology is simple, can be implemented on low-cost hardware, and has a wide range of applications with good real-time performance. However, it also possesses a notable disadvantage: susceptibility to interference from noise. When energy detection is impacted by noise, improving the accuracy of spectrum sensing becomes challenging, making the threshold setting particularly crucial. To address the issue of noise interference in energy detection, this paper proposes a double-threshold cooperative spectrum sensing algorithm. The threshold setting can be flexibly adjusted according to changes in noise uncertainty within the environment.

3.1. *Energy Detection Technology*

It is assumed that $y(t)$ represents the signal received by the cognitive vehicle user, while $n(t)$ denotes the Additive Gaussian White Noise (AWGN) with a mean value of zero and variance σ_n^2, where N is the number of samples. Detection statistic T for the cognitive vehicle user is

$$T = \frac{1}{N}\sum_{k=1}^{N}|y(t)|^2 \tag{1}$$

Detection statistic T can approximate Gaussian distribution

$$\begin{cases} H_0 \ T \sim N(\sigma_n^2, 2\sigma_n^4/N) \\ H_1 \ T \sim N((1+\gamma)\sigma_n^2, 2(1+\gamma)^2\sigma_n^2/N) \end{cases} \tag{2}$$

where σ_s^2 is the average power of the received signal, $\gamma = \frac{\sigma_s^2}{\sigma_n^2}$ represents the signal-to-noise ratio received by the cognitive vehicle user, and detection probability P_d and false alarm probability P_f of energy detection can be obtained, respectively.

$$P_f = P(T > \lambda|H_0) = Q\left(\frac{\lambda - N\sigma_n^2}{\sqrt{2N}\sigma_n^2}\right) \tag{3}$$

$$P_d = P(T > \lambda|H_1) = Q\left(\frac{\lambda - N(1+\gamma)\sigma_n^2}{\sqrt{2N}(1+\gamma)\sigma_n^2}\right) \tag{4}$$

In Equation (3), P refers to the probability that detection statistic T of cognitive vehicle users exceeds decision threshold λ when the authorized spectrum resources are idle (H_0), representing false alarm probability. In Equation (4), P denotes the probability that detection statistic T of cognitive vehicle users exceeds decision threshold λ when the authorized spectrum resource is occupied (H_1), representing detection probability. $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-\frac{t^2}{2}} dt$ is the complementary cumulative distribution function of the Standard Normal Distribution, and λ represents the threshold value. Since false alarm probability is predetermined, the threshold value can be derived from Equation (3).

$$\lambda = \sigma_n^2(\sqrt{2N}Q^{-1}(P_f) + N) \tag{5}$$

3.2. A Double-Threshold Cooperative Spectrum Sensing Scheme

The threshold value of traditional energy detection technology is fixed, making it suitable for low-speed and stable communication environments. However, it proves inadequate for complex and dynamic Internet of Vehicles scenarios featuring high-speed moving vehicles. In real vehicular road environments, adopting traditional energy detection technology leads to the underutilization of spectrum resources. The implementation of a double-threshold spectrum sensing algorithm enhances the flexibility and adaptability of spectrum sensing.

Different wireless environments may require varying threshold values for energy detection, rendering a single threshold method inadequate in adapting to changes across environments. Through employing the double-threshold spectrum sensing algorithm, distinct threshold values can be established corresponding to different environments, enhancing the flexibility and adaptability of spectrum sensing. Moreover, the double-threshold spectrum sensing algorithm can effectively mitigate the energy consumption associated with spectrum sensing. In contrast, the single threshold method necessitates substantial computing and communication resources due to the requirement for all-band signal energy detection. Using the double-threshold spectrum sensing algorithm, energy detection can be confined to a specific frequency band, thus reducing energy consumption and computational complexity. Therefore, the adoption of the double-threshold method introduces only an uncertain interval between the decision interval and the non-decision period when compared to the single-threshold approach.

In the double-threshold spectrum sensing algorithm, if the energy value received by the cognitive vehicle user is less than threshold value λ_1, the local judgment result is H_0. If the energy value received by the cognitive vehicle user is greater than threshold value λ_2, the local judgment result is H_1. If the energy value received by the cognitive vehicle user is greater than λ_1 but lesser than λ_2, the local judgment result is inconclusive.

The double-threshold value can be derived from the single-threshold value. This double-threshold value can be determined based on noise uncertainty, as outlined in [24]. Noise uncertainty refers to the fluctuation in the size of the noise signal within a certain range due to randomness during noise measurement. Assuming u (in dB) represents noise uncertainty, we let $\tau = 10^{\frac{u}{10}}$. The greater the instability of noise in the communication environment, the higher the value of τ. Consequently, the power of the noise is evenly distributed within interval $[\sigma_n^2/\tau, \tau\sigma_n^2]$. Based on noise uncertainty u, the double threshold can be set as

$$\lambda_1 = \frac{\lambda}{\tau}, \lambda_2 = \tau\lambda \tag{6}$$

Detection probability Q_d and false alarm probability Q_f under the double-threshold spectrum sensing algorithm can be derived from Equation (6) as follows:

$$Q_d = P(T > \lambda_2 | H_1) = Q\left(\frac{\lambda_2 - N(\sigma_s^2 + \sigma_n^2)}{\sqrt{2N}(\sigma_s^2 + \sigma_n^2)}\right) \tag{7}$$

$$Q_f = P(T > \lambda_2 | H_0) = Q\left(\frac{\lambda_2 - N\sigma_n^2}{\sqrt{2N}\sigma_n^2}\right) \tag{8}$$

When the cognitive vehicle user conducts spectrum sensing, it calculates the energy and threshold values based on the received signal. Subsequently, the energy value is compared with the threshold value. If the energy value is less than the smaller threshold value λ_1, the local judgment indicates that the PU does not exist. Conversely, if the energy value exceeds the larger threshold value λ_2, the local judgment indicates the presence of the primary user. If the energy value falls between the two threshold values, then the local decision is inconclusive.

When multiple cognitive vehicle users perform collaborative spectrum sensing, the OR fusion rule and the AND fusion rule are adopted, and then the fusion center chooses the fusion rule to use according to the actual traffic environment.

The concept behind the AND rule is that the fusion center employs a logical "AND" method to determine the judgment results submitted by each cognitive vehicle user. In essence, the final decision infers the existence of the primary user's (PU) signal within a specific frequency band only when all cognitive vehicle users conclude that the PU's signal is present. The advantage of the AND rule lies in its ability to reduce false alarm probability and prevent the wastage of idle spectrum when the PU's signal is absent but mistakenly detected as present. However, its drawback is a reduction in detection probability, potentially leading to excessive occupation of the primary user's frequency band by the secondary user, thus impacting the primary user's operation. In the context of the IoVs, the AND rule can be applied in scenarios characterized by high vehicle density and less urgent PU information. This allows for more vehicle users to utilize the idle frequency band of the primary user, thereby alleviating pressure on spectrum resources. The fusion detection probability and false alarm probability are illustrated in Equation (9):

$$\begin{cases} Q_{d,AND} = \prod_{k=1}^{M} Q_{d,k} \\ Q_{f,AND} = \prod_{k=1}^{M} Q_{f,k} \end{cases} \tag{9}$$

The concept behind the OR rule is that the fusion center utilizes a logical "OR" method to determine the judgment results provided by each cognitive vehicle user. The final decision indicates the presence of a PU signal if any vehicle user detects its existence. The advantage of this rule is its potential to enhance the overall detection probability to a certain extent and diminish the impact of secondary user signals on PU communication. However, this may result in reduced spectrum utilization. In the context of the Internet of Vehicles, this rule can be applied in scenarios characterized by low vehicle density and minimal interference with PU information. Its fusion detection probability and false alarm probability are depicted in Equation (10):

$$\begin{cases} Q_{d,OR} = 1 - \prod_{k=1}^{M} (1 - Q_{d,k}) \\ Q_{f,OR} = 1 - \prod_{k=1}^{M} (1 - Q_{f,k}) \end{cases} \tag{10}$$

The flowchart of the double-threshold cooperative spectrum sensing algorithm is presented in Figure 2. When multiple cognitive vehicle users participate in collaborative spectrum sensing, each cognitive vehicle user initially transmits its local decision results to the fusion center, which then consolidates these decisions. Subsequently, the fusion center chooses the appropriate fusion rule based on the prevailing road traffic conditions. If the number of cognitive vehicle users is small and the PU information requires urgent communication, the fusion center selects the OR rule for collaborative spectrum sensing. Conversely, if there is a high number of vehicle users and the PU's information is not urgent, the fusion center opts for the AND rule for collaborative spectrum sensing.

The specific algorithm flow is as follows:

Firstly, the double-threshold collaborative spectrum sensing algorithm determines the received signal energy by setting two distinct threshold values: the upper and the lower threshold. These thresholds are usually determined based on the uncertainty of noise in the Internet of Vehicles communication environment to ensure an effective distinction between authorized user signals and noise signals.

In the Internet of Vehicles environment, every vehicle is outfitted with a cognitive radio device dedicated to spectrum sensing and communication. Each vehicle autonomously conducts local spectrum sensing, employing a radio-frequency receiver to capture the signal and compute its energy value. Subsequently, each vehicle compares the derived energy value with predetermined upper and lower thresholds.

Based on the comparison results, a local decision is generated for each vehicle. If the received signal energy value is higher than the upper threshold, it is judged that an authorized user exists. If the energy value is lower than the lower threshold, it is determined that the authorized user does not exist. If the energy value falls between the two threshold values, it enters an uncertain region and requires further processing.

Subsequently, each vehicle sends its own local decision to the fusion center. The fusion center is responsible for collecting the decision results of all vehicles and selecting a fusion rule for global decision-making according to the spectrum resource requirements of the vehicles. The final decision is based on either the AND or the OR rule.

Finally, the fusion center assesses whether the current frequency band is occupied by authorized users based on the global decision results and disseminates these findings to all vehicles. Each vehicle then adapts its communication strategy under the received results to prevent interference with authorized users.

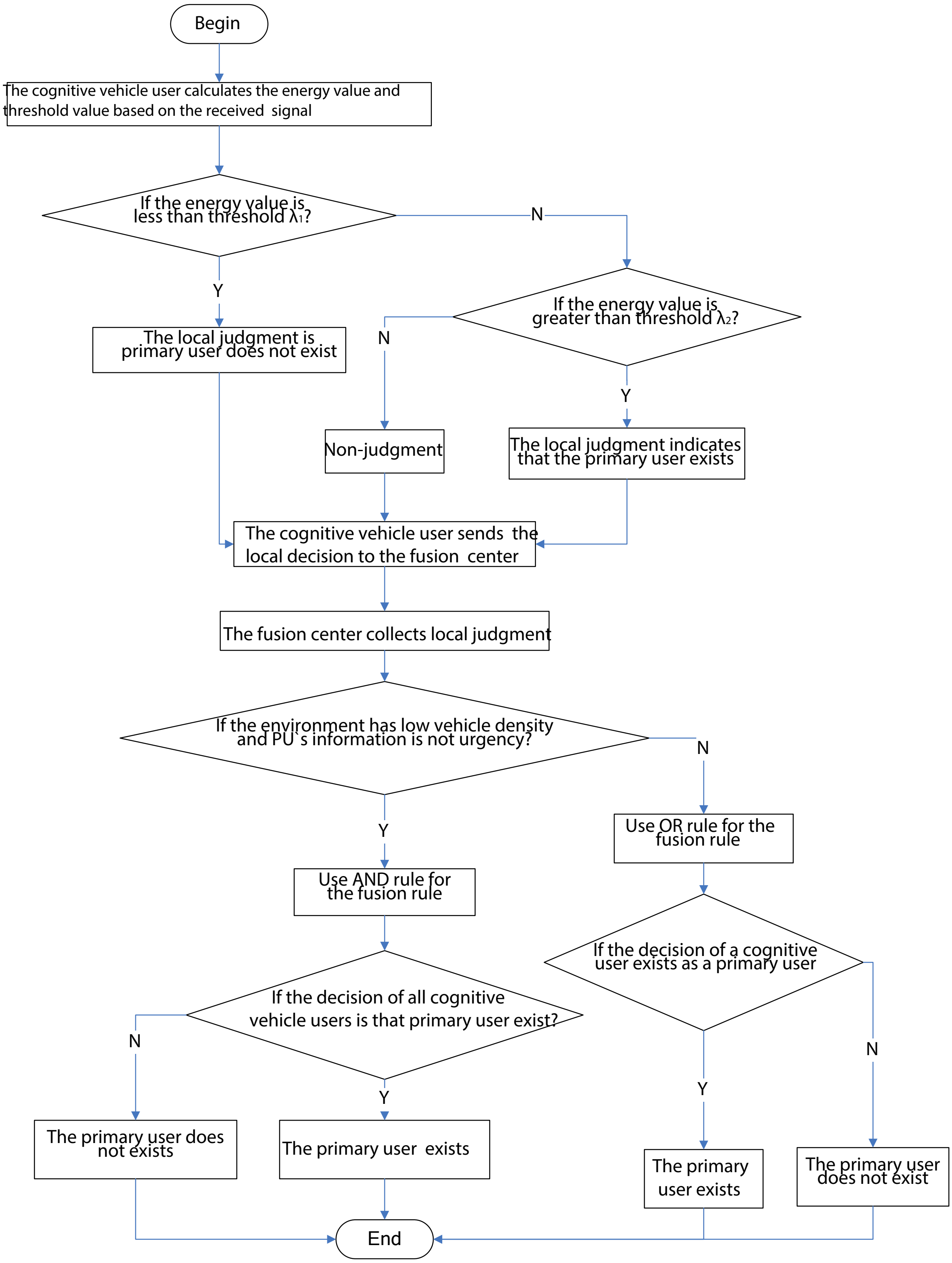

Figure 2. Flow chart of double threshold in cooperative spectrum sensing algorithm.

4. Simulation Results and Discussion

To verify whether the spectrum sensing accuracy of the proposed double-threshold collaborative spectrum sensing algorithm is superior to that of a traditional single-threshold energy detection, simulations were conducted using the MATLAB simulation platform [25]. The signal received by the cognitive vehicle user was a Binary Phase Shift Keying signal, with the sampling number N set to 500 and the number of Monte Carlo experiments set to 10,000. Firstly, the proposed double-threshold collaborative spectrum sensing algorithm was compared with traditional single-threshold energy detection to determine whether detection probability improved. We observed the simulation results under different signal-to-noise ratios and noise uncertainty to assess whether they met expectations and analyzed the reasons behind the simulation results. Finally, we compared the detection probabilities under two fusion rules in collaborative spectrum sensing.

Figure 3 compares the detection probabilities of the traditional single-threshold energy detection and the double-threshold collaborative spectrum sensing algorithm. The noise uncertainty is set to 0.5, and the SNRs are set to −5 dB and −20 dB.

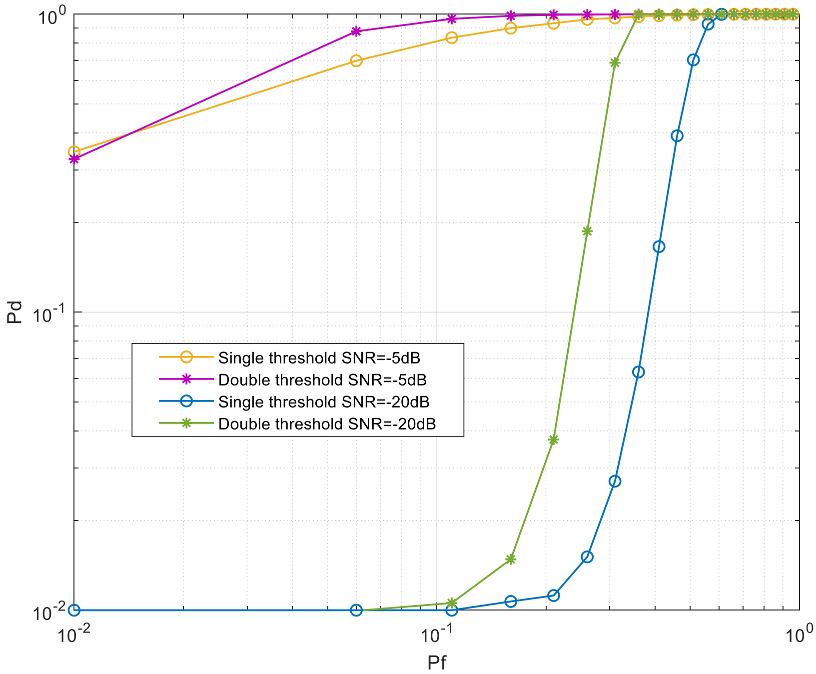

Figure 3. Comparison of detection performance of double−threshold detection algorithm and single−threshold energy detection under different SNRs.

When the SNR is −5 dB and the false alarm probability is 0.1, the detection probability of the double-threshold algorithm is 0.9659, while that of single-threshold energy detection is 0.8388. The detection probability of the double-threshold algorithm increases by only 0.1271 compared to single-threshold energy detection. With a high signal-to-noise ratio, the improvement in sensing performance using the double-threshold algorithm is limited. However, when the SNR is −20 dB and the false alarm probability is 0.36, the detection probability of the double-threshold algorithm is 0.9712, whereas that of single-threshold energy detection is 0.0589. Here, the detection probability of the double-threshold algorithm increases by 0.9123 over single-threshold detection. Obviously, in a low-SNR environment, the performance of single-threshold detection significantly deteriorates due to noise interference. In such scenarios, the double-threshold detection algorithm markedly enhances the performance of single-threshold detection, indicating its effectiveness in mitigating the impact of noise on energy detection.

Figure 4 compares the detection probabilities of the double-threshold detection algorithm with single-threshold energy detection when the noise uncertainty is 0.5 and 0.9, with a signal-to-noise ratio of −15 dB. As shown in Figure 4, the performance of the double-threshold detection algorithm is superior to that of single-threshold energy detection under the same signal-to-noise ratio. Furthermore, the detection probability of the double-threshold algorithm is higher when the noise uncertainty is greater. This indicates that the double-threshold detection method performs better in environments with higher noise instability.

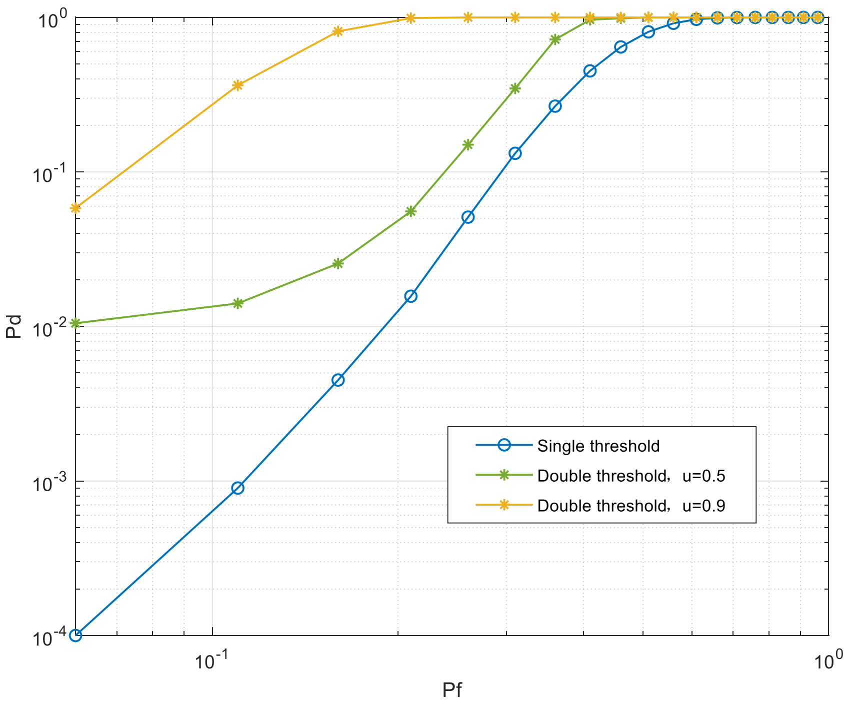

Figure 4. Comparison of single-threshold energy detection scheme and double−threshold spectrum sensing algorithm under different noise uncertainties.

The double-threshold spectrum sensing algorithm is applied to multi-user collaborative spectrum sensing, with the number of cognitive vehicle users participating set to 20. In Figure 5, the signal-to-noise ratio is set to SNR = −15 dB, and the noise uncertainty of the double threshold is set to $u = 0.5$. Figure 5 compares the cooperative detection probabilities of multiple cognitive vehicle users under both OR and AND rules.

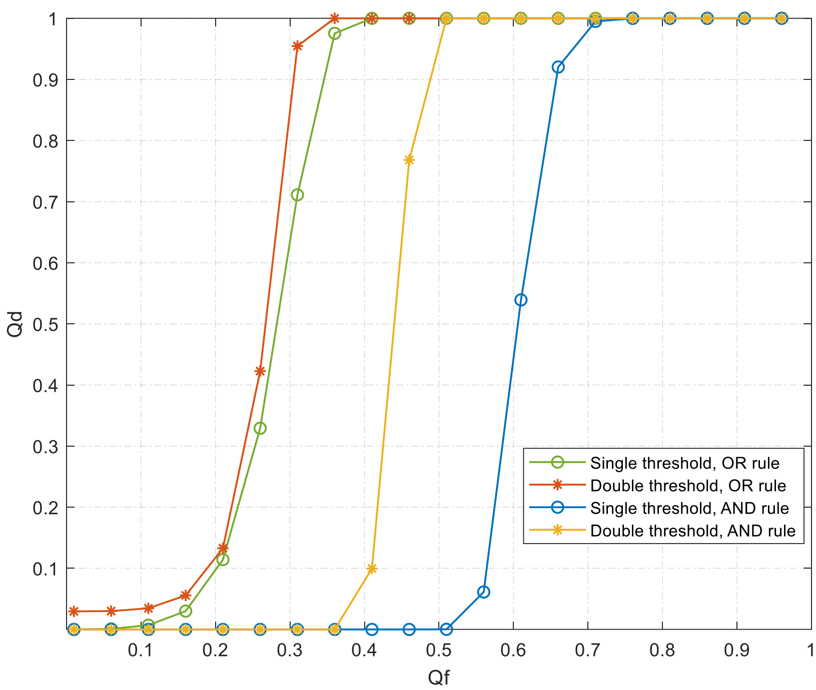

Figure 5. Comparison of detection performance between single−threshold and double−threshold collaborative spectrum sensing algorithm with different fusion rules.

On one hand, the OR rule proves more effective as it enhances detection probability, albeit at the expense of an increased false alarm probability, as depicted in Figure 5. Under this rule, the fusion center confirms the presence of the PU's signal once any cognitive vehicle user detects it. Conversely, the AND rule mandates fusion centers to confirm the PU signal's presence only when all cognitive vehicle users detect it. Consequently, the detection probability of the AND rule is lower compared to that of the OR rule, as it prioritizes lower false alarm probability over detection probability. Furthermore, the double threshold performs notably better under the AND rule. Different fusion rules are suitable for different scenarios; the OR rule is preferable in scenarios with low vehicle density where PU information is crucial, whereas the AND rule is preferred in the opposite scenario.

On the other hand, under the OR rule, the performance improvement of the proposed algorithm compared with the traditional single threshold is not obvious. This is due to the decision criterion of the OR rule itself. However, the proposed algorithm demonstrates that the performance of the double-threshold detection algorithm is significantly better than the single-threshold detection criterion when using the AND rule.

Figure 6 compares the collaborative spectrum sensing performance of cognitive vehicle users using double-threshold collaborative spectrum sensing under the AND fusion rule and the OR fusion rule at SNRs of −5 dB, −10 dB, and −15 dB, respectively. As depicted in the figure, regardless of whether it is the OR rule or the AND rule, a decrease in SNR from −5 dB to −10 dB leads to a significant deterioration in detection performance over a wide range. Moreover, when the SNR decreases from −10 dB to −15 dB, there is a corresponding deterioration in detection performance. Notably, it is observed that when the SNR decreases from −5 dB to −10 dB, despite the same amplitude decrease in signal-to-noise ratio, the detection performance experiences a substantial decline.

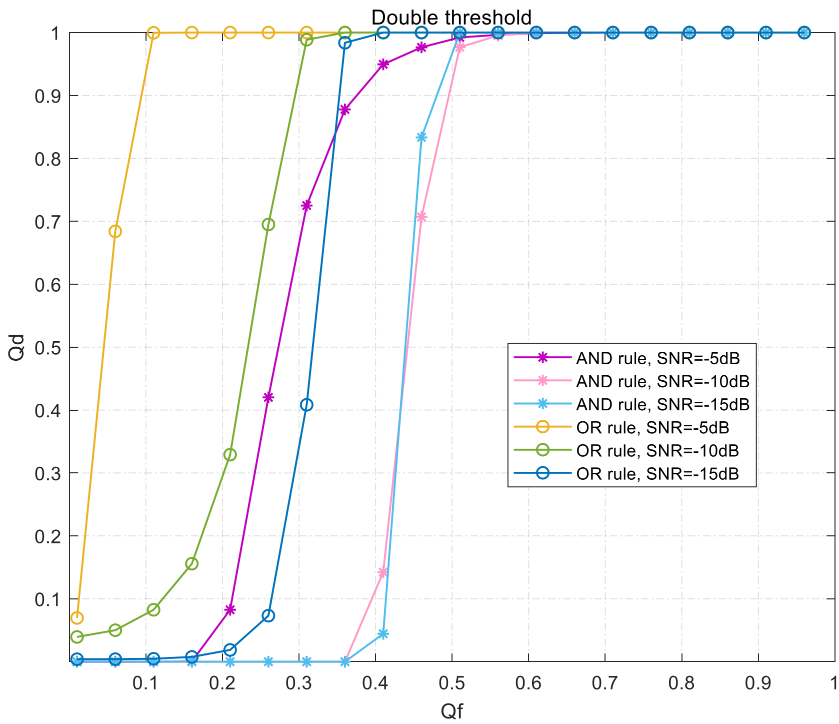

Figure 6. Comparison of different SNRs under the AND and OR rule for the double−threshold collaborative spectrum sensing algorithm.

It can be concluded that although the sensing performance of the double-threshold collaborative spectrum sensing algorithm declines with decreasing SNR in multi-user collaborative spectrum sensing, given that SNR is the primary factor affecting sensing performance in any spectrum sensing, this decline cannot be mitigated at low SNR. However, the proposed double-threshold method mitigates the decline in sensing performance with decreasing SNR. In other words, the double-threshold method is more suitable under low-SNR scenarios.

5. Discussion

To address the impact of low SNR on spectrum sensing performance in IoV environments, this paper proposes a double-threshold collaborative spectrum sensing algorithm. In low SNR environments, the performance of the double-threshold algorithm is superior to that of the single-threshold algorithm. The double-threshold spectrum sensing method performs better in environments with higher noise instability. Additionally, the application scenario of the double-threshold cooperative spectrum sensing algorithm is discussed. The double-threshold algorithm is more suitable for improving spectrum sensing performance among multiple vehicle users using the AND rule.

Indeed, verification at the analog signal level alone is insufficient, especially in scenarios involving complex and demanding real-world applications such as the Internet of Things or Vehicle-to-Vehicle (V2V) communication. Verification in a real environment can directly reflect the algorithm's performance in actual operation, considering various possible disturbances and variables. Nevertheless, due to the complexity and uncontrollable factors in real-world environments, it may be difficult to perform and may involve challenges, potentially high costs and risks. In addition, it is also feasible and practical to simulate traffic systems and virtual vehicles in a virtual environment for verification. Due to current research conditions and resource constraints, it is impossible to build the required virtual environment.

6. Conclusions

This paper first introduced the system model of the cognitive Internet of Vehicles, then derived the threshold value from the detection probability and false alarm probability formulas of energy detection. Subsequently, a double-threshold detection method was proposed based on noise uncertainty, and the flow chart of the proposed method when cognitive vehicle users performed spectrum sensing was analyzed. Following this, a simulation of the double-threshold spectrum sensing algorithm was conducted and compared with single-threshold energy detection, demonstrating the intuitive performance improvement of double-threshold detection over single-threshold detection. Finally, collaborative spectrum sensing was performed under multiple cognitive vehicle users, and the differences in sensing performance between the OR rule and the AND rule were analyzed.

The research results of the proposed algorithm demonstrate that the performance of the double-threshold detection algorithm is significantly better than that of the single-threshold detection criterion when using the AND rule. The value of the proposed spectrum sensing algorithm lies in providing ample spectrum resources for the vehicle users of the Internet of Vehicles. This aids in integrating Internet of Vehicles technology with 5G technology, facilitating efficient interconnection between vehicles and infrastructure, and further enhancing the safety and convenience of intelligent connected vehicles. Simultaneously, it also offers urban traffic control centers more flexible access to spectrum resources for allocation and management.

While this paper enhances the spectrum sensing performance of vehicle networking and increases the utilization rate of spectrum resources, it still faces certain shortcomings and limitations in the context of complex and dynamic vehicle networking environments. With the rapid development of intelligent vehicle networking, the demand for spectrum resources for human–vehicle interaction and vehicle–vehicle interaction is also increasing. Addressing a more unstable noise environment will be the main focus in the later stages of this research. The next step will involve addressing additional challenges encountered in the vehicle networking environment.

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Data Availability Statement: Data can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviation

AWGN	Additive Gaussian White Noise
CR	Cognitive Radio
FC	Fusion Center
IoT	Internet of Things
IoVs	Internet of Vehicles
ITS	Intelligent transportation system
PBS	Primary Base Station
PUs	Primary Users
SNR	Signal-to-noise Ratio
V2V	Vehicle-to-Vehicle

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