



## Optimization Strategy for Spectrum Sensing in Cognitive Radio Networks Using Deep Learning Algorithms

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**SUMMARY:** As communication technology advances quickly, spectrum resources are becoming more and more limited, and cognitive radio (CR) network spectrum sensing technology has problems in balancing perception performance, perception effect, and complexity. Therefore, this article used deep learning algorithms to study the spectrum sensing of CR networks. Firstly, a Convolutional Neural Network (CNN) was used to construct a spectrum sensing model, which learned and extracted useful features from various spectrum data to better understand and predict the state of spectrum sensing. Then, the Q-learning algorithm was used to study the collaborative spectrum sensing strategy, determine the weight factors of each indicator in the spectrum fusion process, and help the spectrum sensing model run better. Experiments have shown that when the signal-to-noise ratio was between -15dB and -10dB, the detection probability of CNN can already reach over 80%. Moreover, as the number of statistics increases, the overall blocking probability of the perception strategy studied in this paper can ultimately be reduced to around 15.5%, which was much lower than the spectrum sensing strategies constructed by other methods. Deep learning algorithms can be used to study the spectrum sensing strategy of CR networks. By leveraging the powerful capabilities of deep learning models, comprehensive utilization of spectrum resources can be achieved, effectively improving spectrum utilization efficiency.

**KEYWORDS:** Cognitive Radio Networks, Spectrum Perception, Optimization Strategies, Deep Learning Algorithms, Convolutional Neural Networks

## 1 Introduction

Radio spectrum resources are getting harder to come by as wireless communication technology advances quickly and intelligent gadgets become more commonplace. There is a significant loss of spectrum resources as a result of the outdated techniques of allocating spectrum. Therefore, how to efficiently utilize spectrum resources has become a current research hotspot. Cognitive radio (CR), as an intelligent radio technology, can select and use idle spectrum by sensing the wireless network environment. Due to the poor performance, complex operation process, and high operating cost of traditional spectrum sensing methods, this paper can use deep learning algorithms to study the spectrum sensing strategy of CR network. Deep learning algorithms can learn from a large amount of data and complete complex tasks by constructing deep neural network models, providing good results. Applying them to spectrum sensing research can effectively improve the accuracy and efficiency of spectrum sensing.

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The spectrum sensing strategy of CR network mainly focuses on more accurate identification and utilization of idle spectrum resources. Its goal is to provide users with the best knowledge of spectrum access through intelligent decision-making processes in complex wireless networks, improving the spectrum utilization efficiency and communication performance of the entire network [1, 2]. Ansere, James Adu believed that sensor nodes consume a large amount of energy to support dynamic spectrum sensing and switching of CR operations. Therefore, he proposed an energy-saving optimal transmission power allocation technology to improve dynamic spectrum sensing and data throughput [3]. Wu Cheng believed that the CR network was an intelligent network that dynamically changes its characteristics and adapts to its environment through the process of spectrum sensing [4]. Kaur, Amandeep believed that CR was a technology that solves the problem of spectrum scarcity by utilizing various unused frequency bands. He has carried out an exhaustive categorization and studied different machine learning methods that support intelligent spectrum management, together with associated CR network optimization methodologies [5]. Kim Junhee proposed a cooperative spectrum sensing scheme based on machine learning, introducing how to place social networks to ensure the performance of machine learning-based social networks. He verified that hiding the main user problem can lead to overlapping data distribution, thereby reducing spectrum sensing ability [6]. Spectrum sensing, according to Saad Mohammed Ayad, was one of the most significant and difficult problems in CR. Strong and effective spectrum sensors were needed to design a dynamic spectrum access technique. Therefore, a new detection method based on machine learning was proposed, which used cyclostationary features to achieve detection [7]. Liu Xiaoying developed an optimal cooperative spectrum sensing strategy based on the final decision threshold  $k$ , which maximizes the expected throughput of the mobile energy harvesting CR network and is subject to conflict and energy causal constraints [8]. In summary, in-depth research has been conducted on the spectrum sensing of CR networks, and some research results have been obtained. However, these studies still have shortcomings in terms of perception performance and perception effect.

Deep learning algorithms play an important role in spectrum sensing in CR networks. By using deep learning, it is possible to understand and analyze complex radio signals, optimize the efficiency of spectrum resource utilization, and achieve intelligent perception and analysis of complex radio signals [9, 10]. Spectrum sensing, according to Zheng Shilian, is a classification challenge. To mitigate the effects of noise power uncertainty, he suggested a deep learning-based perception method that normalizes the received signal power [11]. Xie Jiandong believed that for most existing spectrum sensing detectors, their testing design relies on certain signal noise model assumptions. Therefore, he proposed a Convolutional Neural Network (CNN) and Long Short-Term Memory Network detector that extracts energy related features from the covariance matrix generated from sensing data using CNN [12]. Lees W. Max collected more than 14,000 bands using measurement activity, proving that machine learning algorithms are significantly superior to classical signal detection methods [13]. Liu Chang developed a spectrum sensing system based on covariance matrix perception CNN and employed deep neural networks to intelligently examine data-driven test results. The experiment found that the performance of this method is close to that of the optimal detector and significantly better than traditional methods [14]. In order to improve the quality of local spectrum sensing results, Sarikhani, Rahil applied cooperative spectrum sensing to combine local sensing results. He proposed a cooperative spectrum sensing algorithm based on deep reinforcement learning to reduce signaling in the network, and through simulation, it was found that the proposed method is superior to state-of-the-art methods [15]. Xie Jiandong brought forward a spectrum sensing method that is based on non-supervised deep learning.

This method does not need earlier information, and it only requires the collection of a small quantity of samples which do not have the main user signal. [16]. Research has shown that studying deep learning algorithms can optimize spectrum sensing strategies and help improve spectrum sensing performance.

Traditional spectrum allocation methods cannot meet this growing demand, resulting in a mismatch between supply and demand of spectrum resources. In order to solve this problem, wireless technology has emerged, providing wireless devices with the ability to perceive and understand the wireless environment, enabling them to selectively use idle spectrum resources, thereby improving the overall utilization of spectrum resources. This article mainly studies spectrum sensing methods by utilizing convolutional neural networks (CNN) in deep learning algorithms to learn and extract important features from a large amount of wireless data, thereby achieving accurate and efficient spectrum sensing. This can boost the CR network's security and communication quality in addition to increasing spectrum consumption.

## 2 Build a CR Network Spectrum Sensing Model

### 2.1 Data Preprocessing

This article collects a large amount of radio signal data and constructs a dataset. In the constructed dataset, each modulated signal has multiple signal-to-noise ratios, and each signal-to-noise ratio has 1000 samples. The dataset contains tens of thousands of pieces of data, and the selected data is divided into a test set and a training set. Firstly, the main data can be sliced, with each data signal sliced at 100 sampling intervals. After processing, 30 signal samples can be set, meaning that each signal can be divided into multiple test signals. In addition, each group has a different number of samples for training the network, thus solving the problem of inconsistent samples. The time-domain and frequency-domain diagrams of the collected OFDM (Orthogonal Frequency Division Multiplexing) modulated signal are shown in Figure 1.

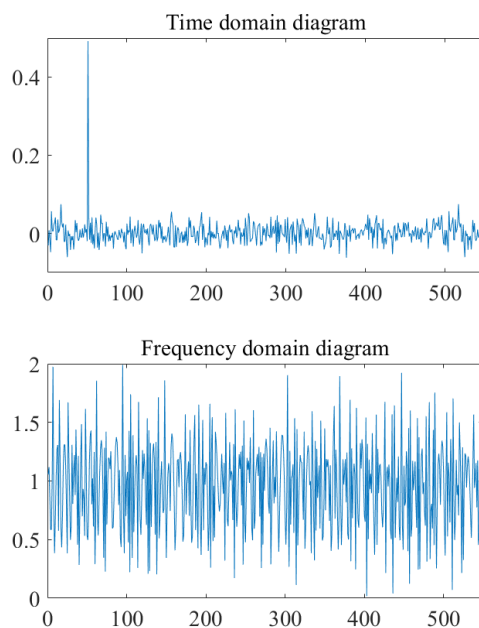


Figure 1: Time and frequency domain plots of collected signals

## 2.2 Construction of Spectrum Perception Model

The key point of CR network is to use sensitive idle frequency bands to meet the information needs sent to secondary users based on the wireless environment information obtained from the spectrum. It has low requirements for network control models and can be used in both centralized and distributed models [17, 18]. As a new branch of machine learning, deep learning has developed rapidly in the past decade and has received increasing attention from researchers. Compared with shallow learning, deep learning can directly cross the design process, utilize multi-layer processes for learning, and directly improve classification accuracy from raw data. Convolutional neural networks have the same structure as neural networks and are the main models of deep learning [19, 20]. In the CR network, multiple SU (Secondary User) spectrum access is used as a means of supporting system research, mainly including cooperative and non cooperative types. Collaborative methods allow for the exchange of information between multiple SUs, better understanding of the external environment, and then making all decisions.

Starting from the process of spectrum sensing, perception algorithms and models are only used to analyze and process data acquisition signals, and the specific expression is as follows:

$$\begin{cases} F_0 : a(t) = m(t) \\ F_1 : a(t) = h(t) + m(t) \end{cases} \quad (1)$$

Among them,  $a(t)$  represents the received signal,  $h(t)$  represents whether there is a main user signal in the channel, and  $m(t)$  represents the noise signal in the channel.

For signal models with secondary users, a good data block  $d(n) = [d_{n,0}, d_{n,1}, \dots, d_{n,M-1}]^T$  with a mean of 0 and variance of  $\delta_s^2$  can be sent. This data block mainly refers to the serial parallel conversion process in OFDM signals. It can be seen that the modulation signal is:

$$a(n) = [a_{n,0}, a_{n,1}, \dots, a_{n,M-1}]^T = Hd(n) \quad (2)$$

Among them,  $H$  is the transformation matrix of  $M * M$ , and the signal received at the receiving end is:

$$q_{n,m} = \sum_{k=0}^K f_k a_{n,m-k} + v_{n,m} \quad (3)$$

Among them,  $K$  represents the number of secondary users, and  $v_{n,m}$  represents additive Gaussian white noise with a mean of 0 and a variance of  $\delta_s^2$ . In actual channels, a more accurate representation of the received signal is:

$$b_{n,m} = e^{-j(2\pi\epsilon m/M+\theta)} q_{n,m} + v_{n,m} \quad (4)$$

When service users need to change, the objective function of the cognitive engine should also be changed accordingly, and the weight scales of each objective function should be reset accordingly. Error rate is an important indicator for evaluating communication quality:

$$P(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp\left(-\frac{z^2}{2}\right) dz \quad (5)$$

The value of  $H_y$  depends on the received signal power  $F$ , symbol rate  $E_r$ , and modulation base  $N$ :

$$H_y = \frac{F}{E_r * \log_2 N} \quad (6)$$

$$F = Q_w - Q_l \quad (7)$$

In the formula,  $Q_w$  represents the transmission power and  $Q_l$  represents the path loss.

When defining the action space, considering the situation where SU has not sent data at the current time, it can be assumed that the task receives  $SINR = 0$  at this time, and the reward obtained by  $SU_1$  executing the action  $x_1$  can be written as:

$$f_1(s_1, x_1) = \begin{cases} -1 \\ -\log_2(1 + SINR_1) \\ \log_2(1 + SINR_1) \end{cases} \quad (8)$$

### 2.3 Model Experiment

Different spectrum sensing methods have different effects and are suitable for different situations. In this study, the CNN algorithm-constructed spectrum sensing method's performance is compared to alternative approaches. Table 1 displays the specific comparative results.

Table 1: Performance of various spectrum detection algorithms

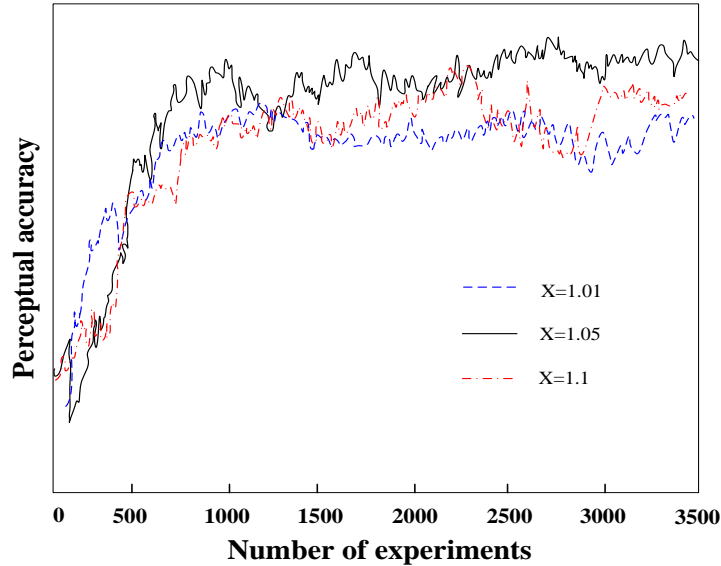
Detection algorithm	Scope of adaptation	Advantages	Disadvantages
Energy detection (ED)[21]	Unknown a priori information of the main user	No prior experience is required, and the operation is simple.	It is sensitive to noise and has a long detection time.
Matched filter detector (MFD)[22]	Predict the a priori information of the main user	The operation is simple and the maximum signal-to-noise ratio can be achieved.	A priori information and synchronization are required.
Cyclostationary feature detection (CFD)	The main user signal is unstable	It can distinguish noise categories and has high detection sensitivity.	The calculation is complicated.
Interference temperature detection (ITD)	Known master user information	No prior information of the main user is required.	Cognitive users have small work and complex operations.
Detection method of this article	Predict the a priori information of the main user	The cost is low, the detection time is short, and the restricted range is small.	None

As shown in Table 1, CNN can learn and extract effective features from signals, avoiding self-designed complex processes. The spectrum sensing method constructed by CNN can control more signal types and expand the usage range, and exhibits good generalization ability. By training a wide range of data, CNN-based spectrum sensing methods can achieve better spectrum sensing results at a low cost. Next, this article continues to study the spectrum sensing method based on CNN algorithm. Based on its non correlation with noise signals, experimental parameters need to be designed. The specific parameter designs are shown in Table 2.

Table 2: Simulation parameter settings for CNN-based perceptual spectrum algorithm

Serial number	Parameter name	Parameter values
1	Number of channels	4-10
2	Training batch size	128
3	Algorithm learning rate	0.01
4	Weight attenuation	0.001
5	Optimizer	Adam
6	Number of training times	3000

Due to the fact that the driving frequency of signals is a very important factor affecting signal detection in CR networks, it is discussed whether the classification performance of spectrum sensing algorithms based on CNN has undergone significant changes under different pilot modes. On the simulation platform, the same data can be sent and set according to the parameter indicators in Table 2. The learning value can be set to 0.01 to study the impact of different values of  $x$  on the perception accuracy of CNN-based spectrum sensing methods. The specific impact results are shown in Figure 2.

Figure 2: The impact of different  $x$  values on the accuracy of spectrum sensing

As shown in Figure 2, it can be seen that in the CR network, the perceptual accuracy of the spectrum sensing method constructed using CNN also varies when the value of  $x$  is different. When the value of  $x$  is 1.05, the algorithm has the best performance and can achieve the best perceptual accuracy. When the value of  $x$  is too large, due to the characteristics of exponential functions, the algorithm tends to only use it in the initial stage of training, resulting in a decrease in accuracy.

Four spectrum sensing construction algorithms can be selected from Table 1 to compare their advantages and disadvantages with the algorithms studied in this paper. Next, further research can be conducted on the performance of the sensing spectrum algorithms constructed using these methods. This article mainly studies the perception and detection probabilities of these 5 spectrum sensing methods under different Signal-to-Noise Ratio (SNR) conditions. The specific research results are shown in Figure 3.

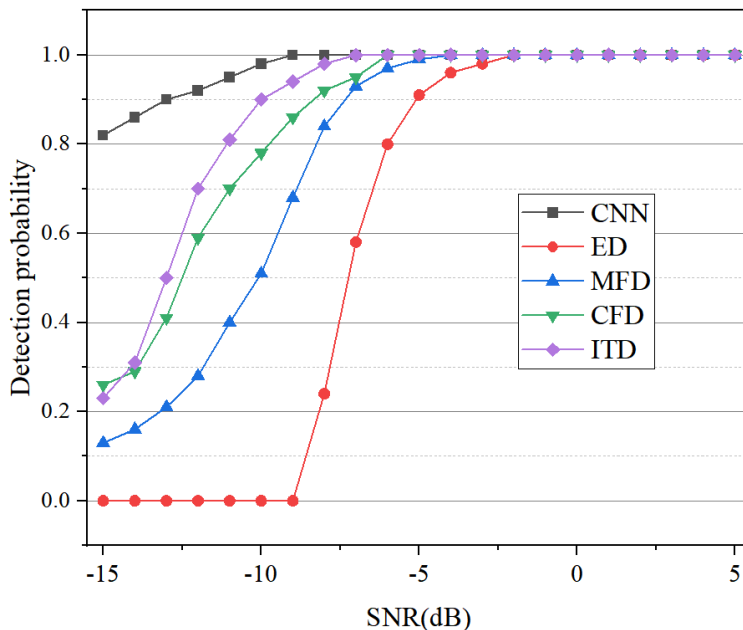


Figure 3: Comparison of detection probabilities of different spectrum sensing construction methods under different signal-to-noise ratios

As shown in Figure 3, it can be observed that the spectrum sensing method constructed using CNN in this paper has a much higher correct detection probability under different signal-to-noise ratio conditions than other spectrum sensing methods. This also indicates that the CNN algorithm is more suitable for the field of spectrum sensing than other algorithms. Due to using the same training and testing samples in different signal-to-noise ratio environments, the 5 extracted methods are less affected by noise. Among them, when the signal-to-noise ratio is between -15dB and -10dB, the detection probability of CNN can already reach over 80%, which is much higher than other spectrum sensing methods. Meanwhile, the spectrum sensing method based on CNN achieved a detection probability of 100% at a signal-to-noise ratio of -9dB, while the methods based on ED, MFD, CFD, and ITD achieved 100% at -2dB, -4dB, -6dB, and -7dB, respectively. The research method is less affected by noise and has good detection performance.

### 3 Spectrum Perception Strategies

#### 3.1 Spectral Perception Fusion

Spectrum sensing technology considers the time-allowed spectrum as the main function of CR, which is the key to distinguishing whether network systems are feasible [23, 24]. Due to the fact that intelligent users can access authorized channels, channel information related to the authorized spectrum must be collected before sending data to avoid interference with authorized users, which requires spectrum sensing function. The specific classification diagram of spectrum sensing technology is shown in Figure 4.

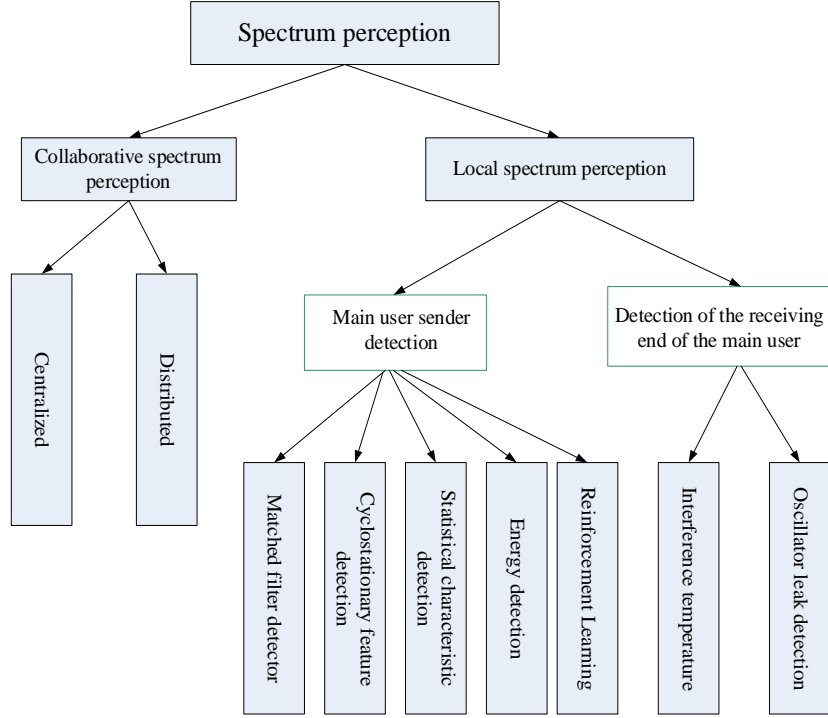


Figure 4: Schematic diagram of spectrum sensing technology classification

Spectrum detection technology, as the most important technology in CR networks, can be divided into authorized user receiver detection and authorized user sender detection based on the characteristics of the discovery [25, 26]. During the process of signal generation, many factors can cause differences in reaction sensitivity. The sensitivity of the reaction can change with the distance between the sensor and the user authorized sensing node, and the shorter the distance, the better the sensing effect. The decisions of perception nodes with positive channel states are more reliable, while those with negative channel states are more reliable. Therefore, if the fusion center treats the reported data from the perception node equally during the actual perception process, it can have an impact on the perception effect. Therefore, this article is based on the Q-learning algorithm in deep learning algorithms to study the weights of perception nodes, helping to better fuse segment data [27, 28]. It mainly allocates weights to perception nodes with different perception effects. Nodes with good perception effects can receive higher weights, while those with poor perception effects have lower weights. In the fusion process, the weights of perception nodes are considered, and when making the final decision, ensuring lower communication traffic during the perception process can effectively improve the overall perception performance.

The fusion center can fuse the decision results published by each perception node into data [29]. Among them,  $D_{j,i}$  represents the result obtained by the perception node  $M_j$  in the  $i$ th perception process, and  $HD_i$  represents the fusion order of the fusion center in the  $i$ th perception process. The specific expression is as follows:

$$HD_i = \begin{cases} 0 & \sum D_{j,i} \leq \frac{N}{2} \quad M_j \in W \\ 1 & \sum D_{j,i} > \frac{N}{2} \quad M_j \in W \end{cases} \quad (9)$$

From the above model, it can be seen that in the traditional fusion process, the differences in channels between nodes have not been taken into account.

In the study of node weights in the perception process based on Q-learning algorithm, the fusion center fuses data based on the perception node weight factor two of the uploaded decision results. The expression is as follows:

$$HD_i = \begin{cases} 0 & \sum Q_j, D_{j,i} \leq \frac{1}{2} \quad M_j \in W \\ 1 & \sum Q_j, D_{j,i} > \frac{1}{2} \quad M_j \in W \end{cases} \quad (10)$$

When conducting data fusion, the fusion center not only considers the decision results  $D_{j,i}$  uploaded by each perception node, but also adds the weight factor  $Q_j$  of each perception node to the fusion decision process. In this way, nodes with good channel quality or high reputation have a greater chance of making correct decisions, and the fusion center can give them greater weight in the final fusion perception. The final result obtained can have a relatively large proportion in the entire fusion process, making its proportion in the final perceptual fusion larger, and vice versa. After such processing, the probability of the fusion center making the correct decision can be greatly increased. Figure 5 depicts the general structural framework of deep learning-based spectrum sensing.

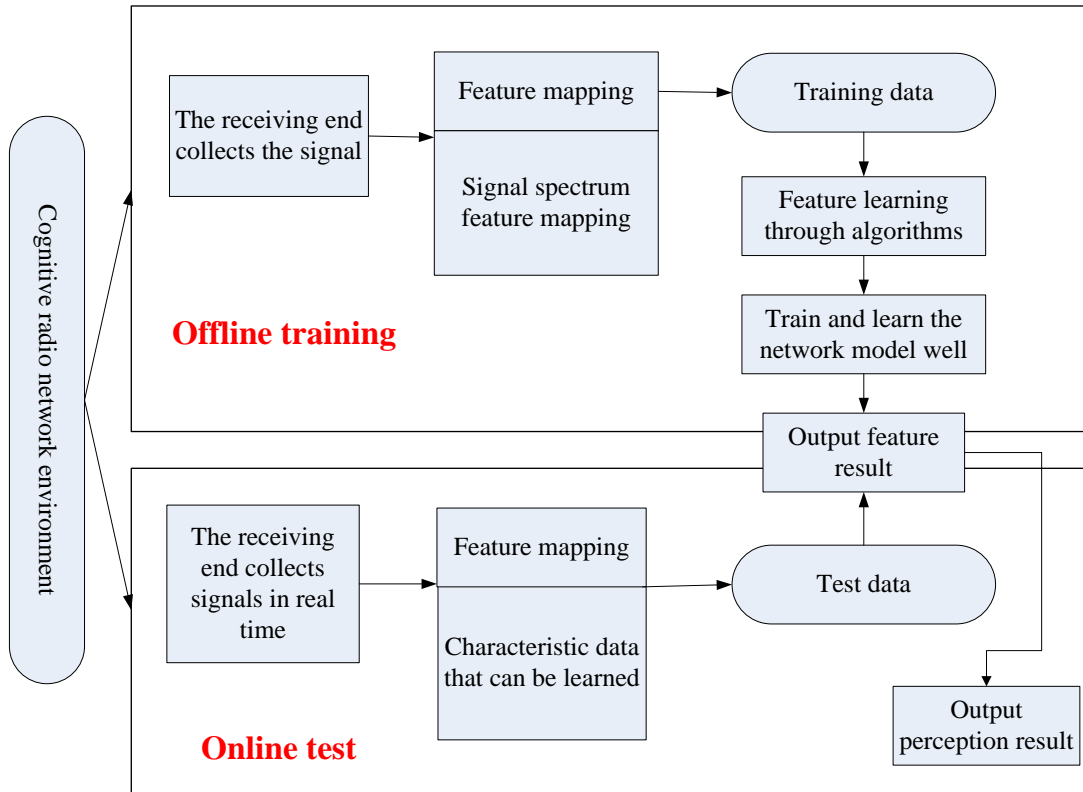


Figure 5: Overall structural framework for spectrum sensing based on deep learning

It is vital to enhance SU's usage of spectrum resources in order to accomplish information exchange while protecting user privacy. Specifically, the fusion center first initializes the model and publishes the initial model within SU. After receiving the model, SU uses local data to train the model. After training for a period of time, the user uploads the local model parameters to the fusion center. The fusion center fuses the received local SU patterns and further broadcasts the aggregated global model parameters to the SU. The above process can be repeated repeatedly until the expected goal is achieved.

### 3.2 Spectrum Sensing Strategy Based on Q-learning Algorithm

Deep learning models may be utilized by us for the sensing of spectrum in CR networks. Through the real-time receiving and processing of radio signals, the occupation and usable condition of spectrum resources can be ascertained by us. According to these circumstances, the parameters and strategies of CR network running can be dynamically changed to reach effective use of frequency spectrum resources. Cooperative spectrum perception is a method that multiple CR networks work mutually to sense the spectrum, which therefore can promote the accuracy and reliability of spectrum sensing. Because a great number of nodes are able to share information and carry out its fusion, when we compare it with individual spectrum sensing, collaborative spectrum sensing therefore not only obtains collaborative advantages but also hence promotes energy efficiency [30, 31]. This article has incorporated a collaborative spectrum sensing method which is based on Q-learning algorithm into the selection work of secondary users that is based on location information, therefore, in order to lower the location correlation of secondary users which participate in collaborative sensing. This can promote the detection outcomes of the system, hence raise its detection probability for making users to have understanding.

The paper have conducted in-depth research on how to use Q-learning algorithm to learn perception strategies in CR networks, and the specific research process is shown in Figure 6. Firstly, each cognitive user acts as a separate proxy node, which makes other authorized and cognitive users relevant interference signals. Then, when a new transmission request begins, the cognitive user can determine whether the current cognitive effect is satisfied, further determining whether the network's preferred spectrum access learning has been completed. If satisfied, the node agent can directly enter the implementation phase and select the optimal channel. If not satisfied, the agent can interrupt the request to send data and attempt to record the strength of the radio signal. The learning process is similar to the use of spectrum, so it can not be further explained. In addition, when access is not possible, spectrum access or energy collection is carried out on the selected channel, and cognitive users can interrupt data transmission for a period of time. Therefore, it can be determined that there should be a wireless channel at present. Therefore, the intelligent agent can directly collect energy for the current frequency band and continuously select the channel as the learning strategy until the end.

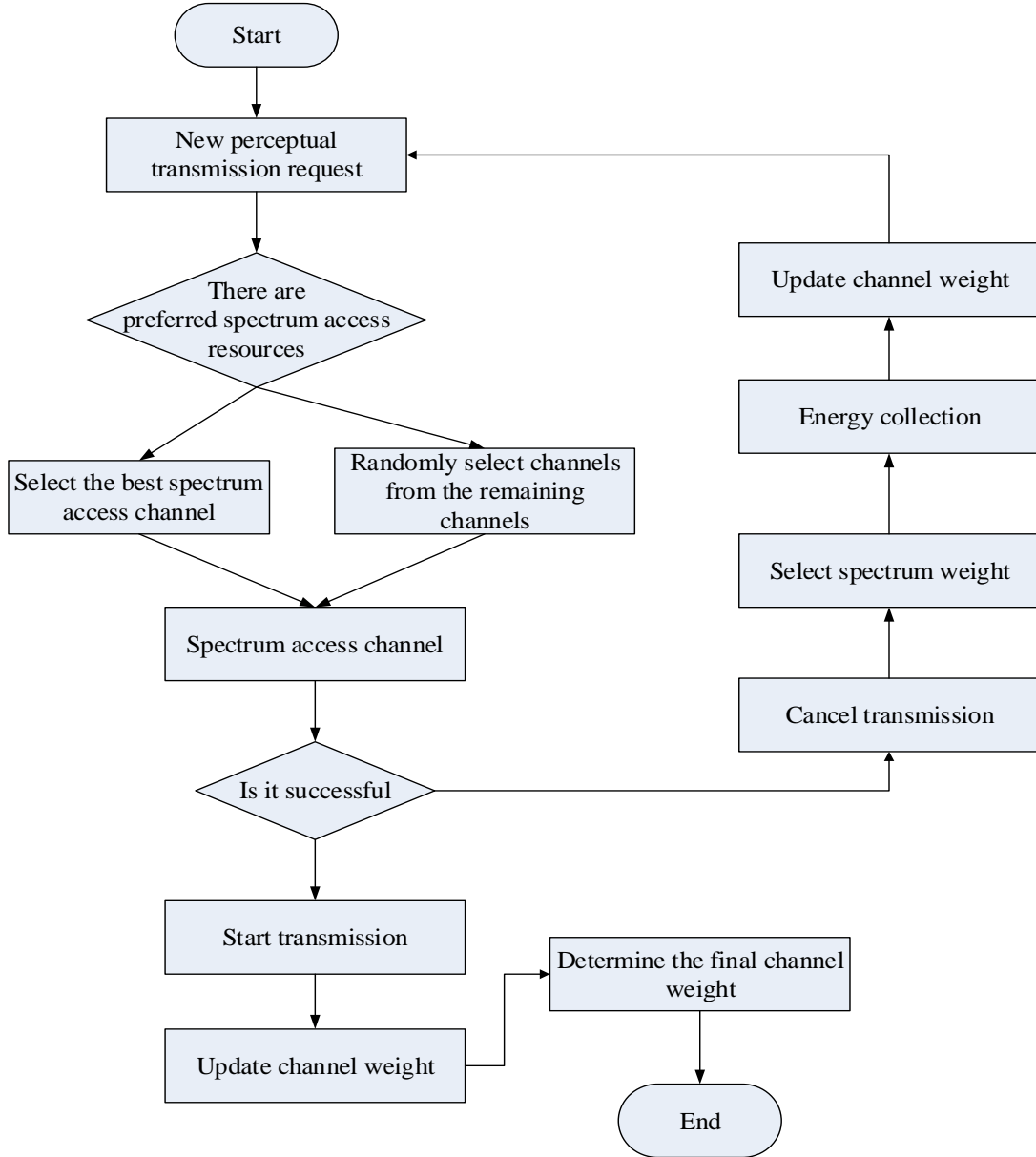


Figure 6: Schematic diagram of perceptual strategy learning process based on Q-learning algorithm

Based on the Q-learning algorithm to select perceptual sub bands and secondary users,  $Q$  (a) represents the Q value after performing action  $a$  at the time step, expressed as follows:

$$x_t^* = \arg \max_x Q_t(x) \quad (11)$$

After taking action  $x$ , the Q value can be updated. The update method for Q value is as follows:

$$Q_{t+1}(x) = (1 - \beta_t)Q_t(x) + \beta_t f_{t+1}(x) \quad (12)$$

Among them,  $(x)$  represents the reward received after taking action  $x$  in  $t + 1$ ,  $\beta_t$  is the step size parameter, and  $0 \leq \beta_t \leq 1$ . To ensure the convergence of the algorithm is in a stable state, the value of  $\beta_t$  meets the conditions as shown in the formula:

$$\sum_{t=1}^{\infty} \beta_t = \infty * \sum_{t=1}^{\infty} \beta_t^2 < \infty \quad (13)$$

Among them, the first condition can be used to ensure that  $\beta_t$  is large enough to overcome the limitations of the first condition;  $\beta_t$  is small enough to ensure the final convergence of the algorithm, which is equivalent to overcoming the second constraint. When the step size is a constant, that is, satisfies  $\beta_t = \beta$ , the formula can be converted to:

$$Q_{t+1}(x) = (1 - \beta)^{t+1}Q_0(x) + \sum_{j=1}^{t+1} \beta(1 - \beta)^{t+1}f_j(x) \quad (14)$$

Among them, the step size  $\beta$  is a constant, and  $f_j(x)$  represents the return value for each time slot. In actual CR networks, the real channel is non-stationary, so it is necessary to permanently set an appropriate step size.

In the collaborative spectrum sensing system, the data fusion center can adopt the strategy of collaborative spectrum sensing. The collaborative spectrum sensing strategy based on Q-learning algorithm has two main objectives: the first is to select spectra with good states for sensing, that is, to maximize the benefits for the secondary user network. The second is that the perception strategy can select secondary users with richer perception performance for deployment, thereby improving the perception performance of the system. Based on these two objectives, the collaborative perception strategy based on Q-learning algorithm should calculate two types of Q values: one is that each group in the channel has a Q value, and the other is that each secondary user corresponds to the Q value of each sub band.

## 4 Performance Evaluation of CR Network Spectrum Sensing Model

In different CR networks, the number of users varies, and the constructed spectrum sensing methods also have different probabilities for correctly detecting users. The experimental parameters are still using the parameters in Table 2. This article studies the correct detection probability of different spectrum sensing methods under different numbers of users. It mainly compares the correct detection probability of the spectrum sensing method constructed using CNN in this article with the spectrum sensing methods based on ED, MFD, CFD, and ITD. The specific comparison results are shown in Figure 7.

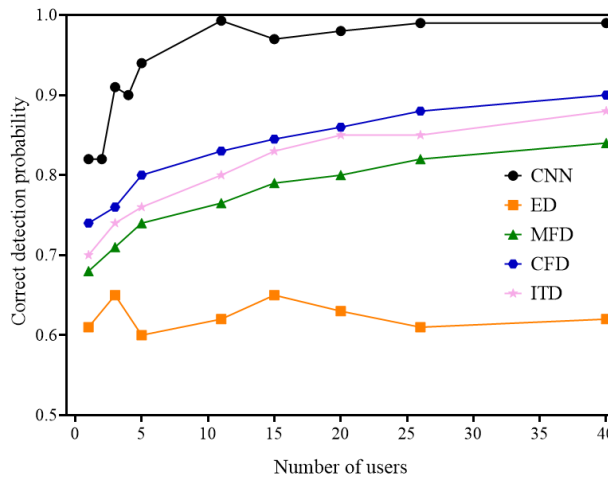


Figure 7: Correct detection probability of different spectrum sensing methods under different numbers of users

The number of users is shown on the x-axis in Figure 7, and the likelihood of a correct detection is shown on the y-axis. Compared to other spectrum sensing techniques, the CNN method’s proper detection probability under varying user counts is significantly greater. Among them, when the number of users is 1, the correct detection probability of the research method in this article is 82%, which is 0.21, 0.14, 0.08, and 0.12 higher than the detection probabilities of the spectrum sensing party constructed based on ED, MFD, CFD, and ITD, respectively. When the number of users is 40, the correct detection probability of the research method in this article is 99%, which is 0.37, 0.15, 0.09, and 0.11 higher than the detection probabilities of the spectrum sensing party constructed based on ED, MFD, CFD, and ITD, respectively. Meanwhile, the method based on ED has the lowest correct detection probability, mainly due to various fading and shadows causing significant errors in the detection results, resulting in a lower detection probability. The method based on CNN construction considers improving both the overall utility value and individual user utility value simultaneously, making it more flexible and stable, resulting in a higher probability of correct detection.

In CR networks, the frequency of sensing by spectrum sensing methods varies, and the required time also varies. The number of sensing times and sensing time of spectrum sensing methods can be studied to determine the speed of the constructed spectrum sensing method and demonstrate the superiority of the method’s performance. This article compares the false alarm probability of spectrum sensing methods based on ED, MFD, CFD, and ITD under varying perception times with the running time of the CNN built method. Figure 8 displays the specific comparative results.

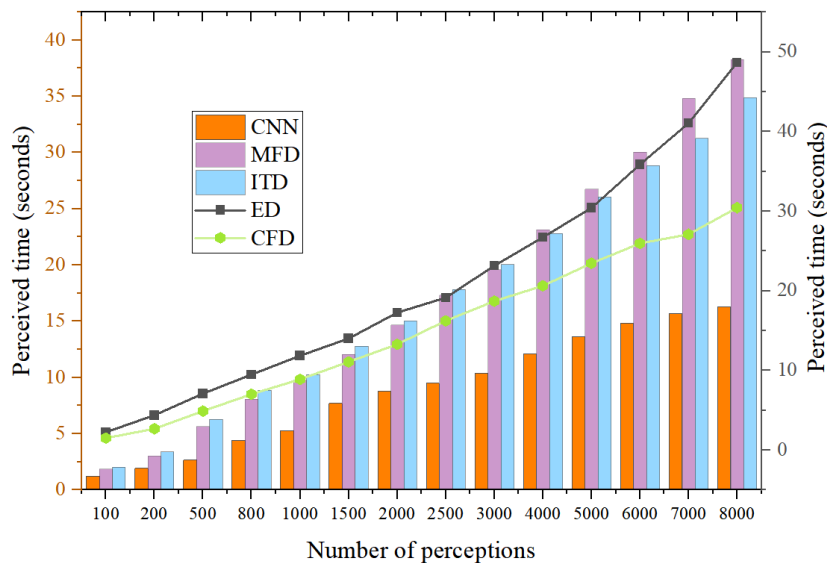


Figure 8: Comparison of application time of different spectrum sensing methods

Figure 8’s left and right y-axes show the perception time (unit: seconds), while the x-axis shows the total number of perception numbers. The spectrum sensing method based on CNN, MFD, and ITD algorithms refers to the left y-axis, while ED and CFD refer to the right y-axis. As shown in Figure 8, it can be observed that the running time of perception using CNN-based methods is much lower than other methods. Among them, when the perception frequency is 100 times, the time required for the perception of the research method in this article is 1.21 seconds, which is 1.05 seconds, 0.67 seconds, 0.31 seconds, and 0.85 seconds less than the spectrum perception methods based on ED, MFD, CFD, and ITD, respectively. The method based on ED requires more time for perception than the method based on CFD.

The method based on MFD requires less time than the spectrum sensing method based on ITD when the sensing frequency is equal to or less than 3000 times. When it is greater than or equal to 4000 times, the required time is higher than ITD. The Q-learning algorithm can be used to study collaborative strategies for spectrum sensing, and the Q-learning algorithm-based spectrum sensing strategy can be used to study blocking probability. Blocking probability refers to the probability of cognitive users failing to transmit data. The lower the blocking probability, the higher the accuracy of the user's transmission data, indicating that the designed strategy is better. The study on blocking probabilities of different spectrum sensing strategies is shown in Figure 9.

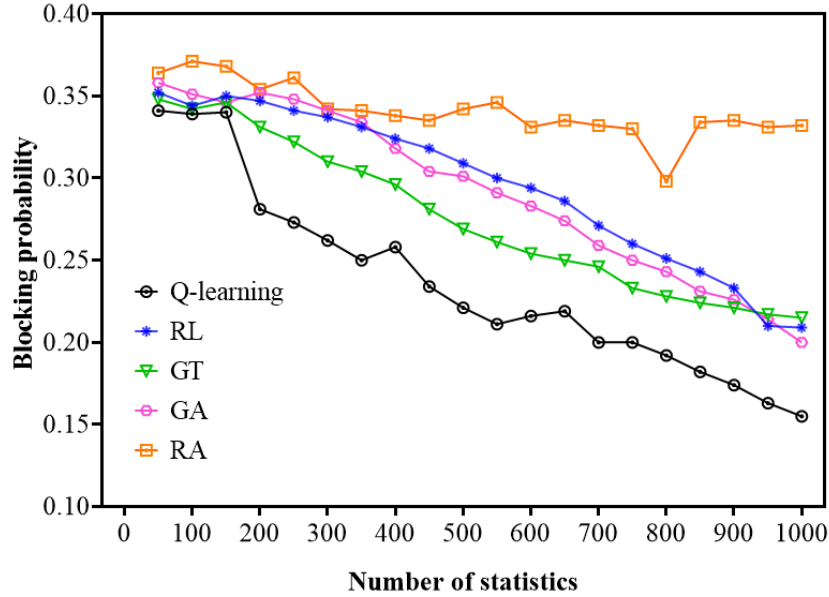


Figure 9: Research on blocking probability of different spectrum sensing strategies

In Figure 9, the x-axis represents the number of statistics, and the y-axis represents the blocking probability. This article uses Q-learning algorithm to study the spectrum sensing strategy, which effectively improves the performance of spectrum sensing. The overall blocking probability is much lower than that of spectrum sensing strategies constructed by other methods. Among them, as the number of statistics increases, the perception strategy studied in this article can ultimately be reduced to about 15.5%, while compared to perception strategies such as RL, GT, GA, and RA, it can ultimately be reduced to about 20.9%, 21.5%, 20%, and 33.2%. It can be found that the method studied in this article has a significant performance improvement on perception strategies. When the number of transmission requests is relatively small, the difference in blocking probability between the Q-learning algorithm-based perception strategy and other strategies is relatively small, because the cognitive user is in the exploration stage at this time. As the number of transmission requests increases, cognitive users gradually learn the optimal spectrum resource pool with high returns, and the corresponding blocking probability gradually decreases. The accuracy of user transmission data also increases, indicating that the designed strategy is also better.

## 5 Conclusions

Depth study has made very big promotion to the development of spectrum examination in CR network systems. Deep learning arithmetic, through automatic study and decision

optimization, help promote the accuracy and detection efficiency of spectrum sensing, promote the performance of wireless networks, therefore, provide one solution for spectrum sensing in CR networks. This article uses the CNN algorithm to study spectrum sensing in CR networks. By training neural networks, intelligent sensing and optimized spectrum allocation can be achieved. The Q-learning algorithm can be used to study spectrum sensing strategies, which can be trained through supervised learning to optimize the network or improve spectrum utilization. The following conclusions can be drawn: 1. The spectrum sensing method based on CNN can obtain the patterns and operating modes of spectrum data through training with a large amount of data. Therefore, it has good robustness and wide applicability, and can maintain stable performance in various locations and situations, with a wide range of applications. 2. The Q-learning algorithm continuously updates the Q-value to learn the optimal spectrum sensing strategy. This learning ability enables the CR network to gradually optimize its spectrum sensing performance, improve its spectrum sensing performance and utilization, and have a certain degree of robustness against uncertain factors such as noise and interference.

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