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Research on an Evaluation Algorithm of Sensing Node Reliability in Cognitive Networks

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ABSTRACT In multi-node cooperative sensing of cognitive networks, as the number of nodes increases, and the energy consumption must increase, but the sensing performance does not necessarily improve. The nodes with less information are not helpful for the sensing performance but will increase the unnecessary energy consumption. To improve the sensing performance and reduce the energy consumption of nodes, a dynamic node selection algorithm based on reinforcement learning is proposed in this paper. The algorithm can evaluate the reliability of sensing nodes in real-time, select the nodes with the highest reliability to participate in cooperative sensing, and update the reliability of nodes in real-time through the method of combining feedback energy consumption and sensing performance. In a real-time environment, nodes with high reliability are selected to participate in cooperative sensing, and the optimal balance between sensing performance and energy consumption is achieved. The experimental results show that the proposed algorithm can reduce energy consumption and improve the perception performance at the same time. Under the same conditions, the detection probability is 5% higher than that of the traditional method, while the energy consumption is only 16.7% of that of the traditional method.

INDEX TERMS Cognitive radio networks, energy efficiency, spectrum sensing, reliability, node selection.

I. INTRODUCTION

In cognitive radio networks, it is necessary for sensing nodes to perform spectrum sensing quickly and accurately while making efficient use of idle frequency bands without interfering with the primary users. However, due to the influence of path loss, shadow fading and hidden terminals, it is difficult for a single sensing node to accurately detect the state of the primary user, and false detection can easily interfere with the primary user [1]. Cooperative sensing fusion of node detection information in different geographical locations can effectively overcome the effects of path loss, shadow fading and hidden terminals [2]. However, with the increase of nodes and energy consumption, it is necessary to make a compromise between sensing overhead and performance gain through node selection [3]. The selection of cooperative nodes is an important factor in determining the sensing performance and energy efficiency. The selection of different cooperative nodes will yield different sensing overhead and cooperation gain. Therefore, reasonable selection of cooperative nodes is an effective method to reduce energy consumption and improve sensing performance.

Green communication is the current research topic, and energy efficiency is an important indicator of cognitive networks. There are relevant research materials in this field. For example, in reference [4], an energy-efficient cognitive radio system design is proposed, which meets the constraints of spectrum sensing reliability and data transmission rate simultaneously. The design adopts the method of relay amplification and forwarding and adopts the power control strategy for the relay node, which can reducing the energy consumption of a single node and does not reduce the energy consumption of the total network. In reference [5], the Karush-Kuhn-Tucker (KKT) condition is used to find the optimal sensing node, which reduces the number of cooperative nodes and the total energy consumption of the cognitive network. Once the node is selected, it is fixed, and the node is not replaced with the change of environment. In reference [6], two technologies for selecting a sensing node and setting the energy detection threshold are combined to realize energy savings.

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The selection of a joint sensing node, detection threshold and decision node is analyzed. The convex optimization method is used to obtain the optimal solution, which can significantly reduce the energy consumption of the cognitive network. In reference [7], a clustering combined loop data acquisition scheme based on compression sensing is used to improve the energy efficiency of wireless sensor networks. The method combines compression sensing technology, and the experimental results show that the method can significantly improve the energy efficiency. These methods can improve the energy consumption and prolong the working life of the network, but the energy consumption is only an indicator of the cognitive network. In the above methods, the health status of nodes is not evaluated, the anti-attack behavior of the network is not considered, and the real-time update mechanism is not established, which will have a negative impact on the security and sensing performance of the cognitive network.

In fact, there are many forms of security problems in cognitive networks, such as node denial of service or data misrepresentation, or node performance degradation due to environmental changes and terminal mobility, and nodes with performance degradation will have a destructive effect on cooperative sensing, so cognitive networks should have the ability to resist abnormal nodes and have strong robustness. At present, some literature entries have studied the robustness of cognitive networks. For example, in reference [8], a simple external sensing method is proposed to prefilter the extreme data in the perceptual data. The average value of the received signal is calculated as the trust factor to measure the availability of cognitive users. The nodes whose reported results are close to the fusion results give higher trust factors to make the perceptual results more reliable. In reference [9], the abnormal factor is set for malicious nodes. The anomaly factor can be calculated according to the weighted sample mean and the standard deviation of the output of the energy detector. The anomaly factor can be adjusted according to the dynamic primary user behavior and the observation value of the nearest neighbor node to improve the detection of malicious users. In reference [10], a consensus-based cooperative sensing mechanism is proposed to deal with the problem of data forgery in cognitive networks. When selecting cooperative neighbor nodes, each reliable node checks the received perceptual data by comparing with the local mean. The neighbor nodes with the maximum deviation between the perceived data and the local mean will be rejected as cooperative nodes, and the reliability of cooperative perception will be improved by isolating malicious neighbor nodes. In reference [11], an evaluation and selection scheme of cooperative nodes based on reinforcement learning is proposed, and it is pointed out that enhanced learning is a candidate technology with strong dynamic control and applicability in cognitive network technology. It is pointed out in reference [12] that the false information of some nodes will also be learned, so the learned information should not be permanent, and the confidence of learning needs to be updated after a certain period. In reference [13], a node selection algorithm based on statistical learning is proposed. Through statistical learning, nodes with strong selection perception ability and good stability form a cooperative perception network. In reference [14], a node selection method based on reinforcement learning is proposed, which enhances the perceptual performance obtained by selecting different nodes several times. In reference [15], a reinforcement learning algorithm is proposed to learn the behavior of nodes and track the fitness value of cooperative nodes in real-time. If the fitness value of a node changes abruptly, the sensing operation will be recorded and stopped. In reference [16], a method of node selection based on BP learning is proposed. The behavior of node selection is classified by BP training, and its reward value is observed. The behavior of node selection with the highest reward value is adopted. In reference [17], it is proposed to select nodes by machine learning to reduce communication overhead. Nodes that consume less energy for learning nodes to perform sensing operations and transmit local decisions to fusion centers are selected as cooperative nodes. In reference [18], an algorithm for selecting redundant nodes is proposed. The perceptual credibility of cognitive users is estimated by an iterative algorithm, and the relationship between the detection performance of the algorithm and the number of cooperative users and perceptual credibility is deduced. On the premise of satisfying the detection performance, as many redundant nodes as possible are deleted. It takes a long time to evaluate the reliability of intermediate nodes, and the evaluation mechanism is not perfect; sometimes, nodes with good performance will be deleted by mistake. The above methods mainly study the possible dangers of various abnormal nodes, without taking into account the important index of energy consumption. High energy consumption can reduce sensing efficiency, in order to improve the sensing efficiency, a weighted cooperative spectrum sensing algorithm based on reliability is used in reference [19], but the algorithm does not choose the optimal number of nodes to participate in cooperative spectrum sensing according to the change of environment. In order to adapt to the change of environment, the algorithm proposed in this paper can interact with the external environment with the fusion center, and can improve the sensing efficiency and have good sensing performance at the same time.

The evaluation indexes of cognitive networks include the anti-attack capability, working life, energy consumption, detection probability and false alarm probability. At present, the methods in the literature have failed to take into account the two indexes of energy consumption and sensing performance. Therefore, the algorithm in this paper selects healthy nodes to participate in collaborative sensing under the condition of considering both energy consumption and sensing performance constraints. The health degree of nodes is measured by the reliability index, and a machine learning method based on real-time interaction information of the sensing environment and fusion center is proposed to improve the robustness of the cognitive network and enhance its anti-attack capability. The nodes selected based on the

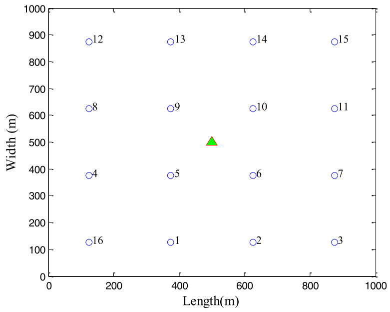


FIGURE 1. Node distribution map of cooperative sensing.

reliability principle can satisfy both the energy consumption and the sensing performance constraints. The experimental results show that the method in this paper can effectively reduce the energy consumption and significantly improve the perception performance.

II. MULTI-NODE COOPERATIVE SPECTRUM SENSING MODEL IN COGNITIVE NETWORKS

Suppose the cognitive network coverage area is a square area, in which there is a primary user, the primary user is in the center of the square area (shown in the triangle in Figure 1), and multiple sensing nodes (shown in the circle in Figure 1) are centered around the primary user and distributed evenly around the primary user. Each node collects the signals of the primary user to determine whether the primary user is working or not and then provide data support for the next decision of the cognitive network. The node distribution of cooperative sensing is shown in Figure 1.

In Figure 1, a number of sensing nodes are uniformly distributed around the primary user, and each node collects the signal energy of the primary user independently to determine whether the primary user is working or not [20]. As you can see, the layouts of each node in Figure 1 and the distances from the main users are not exactly the same. In the square area, the left node is close to the primary user, while the right node is relatively far from the primary user. According to the path loss theory of radio signals, each node in the same condition received the primary user's signal energy difference [21]. According to the energy detection theory [22], nodes receiving less energy are prone to producing incorrect decisions. The node sends the sensing result to the fusion center, which judges whether the primary user signal exists or not according to the fusion rules [23], most of which are shown in equation (1).

$$T = \sum_{j=1}^{M} R_j \begin{cases} > 0, & L_1 \\ < 0, & L_0 \\ = 0, & L_{No} \end{cases} \tag{1}$$

In formula (1), T represents the calculation result of the fusion center, and it is compared with 0. When $T > 0$, the judgment is that the primary user is working, using the L_1 expression; when $T < 0$, the judgment is that the primary user is not working, using the L_0 expression; when $T = 0$, no judgment is made, using the L_{No} expression, and additional sensing time is needed before judgment. M represents the total number of nodes, and j represents the sequence number of sensing nodes. R_j represents the sensing result of the j-th node, and the value is 1 or – 1; when $R_j = 1$, it means that the node decides that the primary user is working, and when $R_j = -1$, it means that the node decides that the primary user is not working [24].

From the fusion rule of formula (1), it can be seen that, when there is a node decision error and the result of the error is sent to the fusion center, it will have a negative impact on the global decision of the fusion center, especially when the number of nodes deciding the error exceeds the number of nodes judging correctly, and the fusion center will make the opposite error judgment according to the fusion rule of form (1), which will seriously interfere with the work of the primary user or lose good access. Therefore, in cooperative spectrum sensing, the collection of the primary user's signal energy is not only not helpful to the global sensing results but will increase the additional energy consumption. To improve the sensing efficiency and reduce the energy consumption, it is necessary to evaluate the reliability of the nodes. In the process of cooperative sensing, selecting the nodes with high reliability to participate in the cooperative perception can effectively improve the perceptual performance, and excluding the nodes with low reliability can significantly reduce the energy consumption.

III. EVALUATION MODEL OF NODE RELIABILITY

In cooperative sensing, each node receives a different signal energy and plays a different role in cooperative sensing. Nodes that collect less energy will interfere with the global decision, which is destructive to the global decision. Therefore, it is necessary to evaluate the nodes when choosing the cooperative node. Because the radio environment and its performance change at any time in the actual sensing process, the signal energy collected by the same node at different times is different, and the contribution to cooperative sensing is also different, that is, the former is the node that contributes greatly, and it may become a destructive node at the next time. Similarly, the former moment is not a trusted node, but due to its own reasons or environmental changes, in the next moment, it may become a contributing node. Therefore, to improve the stability of cooperative sensing, it is necessary to establish a reliable evaluation mechanism to evaluate the nodes in real-time, to exclude the nodes with declining credibility in time, and to add the nodes with enhanced credibility to participate in the cooperation.

A. REAL-TIME EVALUATION MECHANISM OF NODES

To improve the stability of cooperative sensing, it is necessary to evaluate the nodes in real-time. For this reason, this paper establishes an online node evaluation mechanism based on reinforcement learning to enhance the intelligence of the cognitive network and enhance the interaction capability between the fusion center and radio environment. The mechanism evaluates the reliability of each node. The fusion

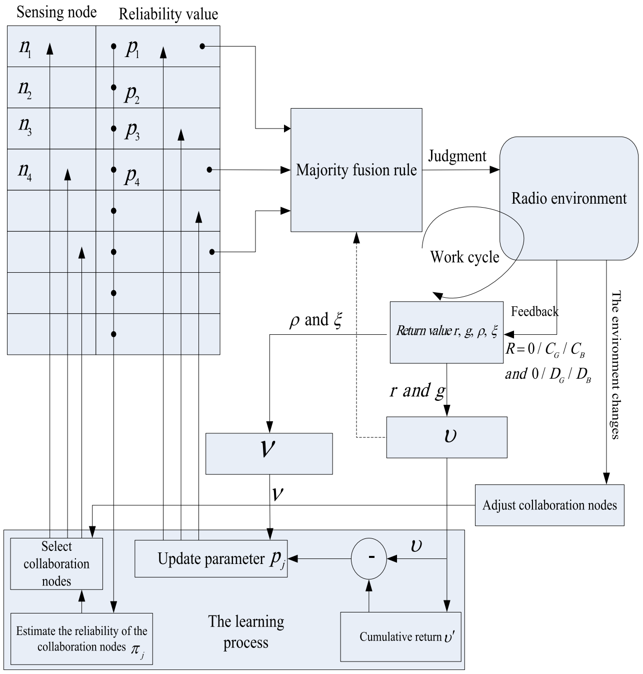


FIGURE 2. Dynamic node selection process based on reinforcement learning.

center establishes a reliability numerical list based on the evaluation results and selects the nodes with high reliability to participate in the collaboration. Figure 2 shows the dynamic process of real-time selection of trusted nodes in the fusion center based on the reinforcement learning mechanism.

In Figure 2, the reliability of the j-th collaboration node is q_j, and the definition of q_j is as shown in (2):

$$q_j = \frac{\sum_{i=1}^{k} |R_{j,i}| \cdot r_{j,i}}{\sum_{i=1}^{k} |R_{j,i}|} \tag{2}$$

In Formula (2), k represents the maximum number of sensing, $|R_{j,i}|$ represents the sensing result of the j-th sensing node at the i-th sensing cycle, and the value of $R_{j,i}$ is described in Formula (1). $r_{j,i}$ denotes a prize value acquired by the j-th sensing node at the time of the i-th sense; when the fusion center judges that the primary user is working at the i-th time, that is, the decision value is "1," at the same time, if the weight of the j-th node is 1 at the i-th time, the reward value of the j-th node is $r_{j,i} = 1$, and otherwise it is $r_{j,i} = 0$. Similarly, when the fusion center decides that the primary user is not working, the decision value is "0," and while the weight of the jth node is - 1, the reward value of the node is $r_{j,i} = 1$, and otherwise $r_{j,i} = 0$.

The initial reliability value of each node is calculated by formula (2), the initial value is stored in the reliability list, and the reliability values are ordered from high to low. Then, the value of q_j is updated by the learning parameter p_j, which is updated every other perceptual cycle. When a new sensing period starts, the fusion center selects N nodes with high reliability values from the reliability list in Figure 2 to participate in the collaborative sensing (a total of M nodes, $N \leq M$). During a perception period, the cooperative nodes report their perception results to the fusion center, which makes a global decision and compares the global results with the results reported by each node and then calculates the feedback values of the corresponding nodes. The feedback value consists of two parts: the return values: r, g and υ; and the correction coefficients: ρ, ξ and ν.

B. PERFORMANCE RETURN VALUE

The performance return value is expressed as r, and its definition is shown in formula (3):

$$r = \frac{1}{k}\sum_{i=1}^{k}[(1 - X_i)(\alpha_i \cdot C_G + (1 - \alpha_t)C_B) + X_i\,(\beta_i \cdot C_G + (1 - \beta_i) \cdot C_B)] \tag{3}$$

In formula (3), X_i represents the decision result of the fusion center of the first sensing cycle; if the primary user is working, the value is 1, and otherwise the value is 0. k represents the total perceptual cycle (number of decisions) in a working period, C_G is the weighted factor of correct judgment, reflecting the intensity of reward, and C_B is the weighted factor of incorrect judgment, which reflects the intensity of punishment. The values of α_i and β_i are shown in formula (4):

$$\alpha_i = \begin{cases} 1, & X_i = 0|H_0 \\ 0, & X_i = 0|H_1 \end{cases}, \quad \beta_i = \begin{cases} 1, & X_i = 1|H_1 \\ 0, & X_i = 1|H_0 \end{cases} \tag{4}$$

C. ENERGY CONSUMPTION RETURN VALUE

g represents the energy consumption return value for each perception cycle, and its formula is as shown in formula (5):

$$g = \frac{1}{k}\sum_{i=1}^{k}[D_G Y_i + D_B(1 - Y_i)] \tag{5}$$

In formula (5), D_G represents the weighted factor whose energy consumption is less than the threshold, and D_B represents the penalty factor whose energy consumption is greater than the threshold. The value of Y_i is shown in formula (6):

$$Y_i = \begin{cases} 1, & \lambda - \sum_{j=1}^{M} e_{i,j} \geq 0 \\ 0, & \lambda - \sum_{j=1}^{M} e_{i,j} < 0 \end{cases} \tag{6}$$

In formula (6), λ is the preset energy consumption threshold, which represents the maximum energy consumption allowed by all cooperative nodes in a sensing cycle.

D. COMPREHENSIVE RETURN VALUE

υ represents the comprehensive return value of each cycle, which is the sum of weights, such as the performance return value and energy consumption return value, that is to say, perceptual performance and energy consumption are considered to be equally important and given the same reward. The formula for calculating υ is shown in (7):

$$\upsilon = \frac{1}{2}r + \frac{1}{2}g \tag{7}$$

E. PERFORMANCE CORRECTION COEFFICIENT

ρ represents the performance correction coefficient, which is used to punish the average number of false reports of a single node in a sensing cycle when the fusion center decides that the primary user does not exist. The calculation formula is shown in Formula (8):

$$\rho_j = \frac{1}{k}\sum_{i=1}^{k}[x_i(j)\cdot(1-X_i)+(1-x_i(j))\cdot X_i] \tag{8}$$

In formula (8), $x_i(j)$ represents the report result of the j-th node, and X_i is the decision result of the fusion center of each sensing cycle.

F. ENERGY CONSUMPTION CORRECTION COEFFICIENT

ξ represents the energy consumption correction coefficient, which is used to punish the node whose energy consumption exceeds the average, that is, the average number of times that the energy consumption of the node exceeds the average in each sensing cycle. The formula is as shown in (9):

$$Y_i(j) = \begin{cases} 1, & \mathrm{e}_i(j) - \dfrac{\sum_{j=1}^{M} e_{i,j}}{M} \geq 0 \\ 0, & \mathrm{e}_i(j) - \dfrac{\sum_{j=1}^{M} e_{i,j}}{M} < 0 \end{cases} \tag{9}$$

where $\mathrm{e}_i(j)$ represents the energy consumed by the j-th node and $\sum_{j=1}^{M} e_{i,j}/M$ represents the average energy consumed by each node.

G. COMPREHENSIVE CORRECTION COEFFICIENT

ν is the comprehensive correction coefficient, which is obtained by the weight summation of the performance correction coefficient and the energy consumption correction coefficient, that is, it is considered that reporting errors and consuming more energy will be equally punished. The formula for ν is shown in formula (10):

$$\nu_j = \frac{1}{2}\rho_j + \frac{1}{2}\xi_j \tag{10}$$

IV. NODE RELIABILITY UPDATING PROCESS

Based on the iterative formula of the Instantaneous Differential (ID) algorithm in enhanced learning [25], the update method of the learning parameters in each application cycle can be obtained as shown in equation (11):

$$p_j^{n+1} = p_j^n + \beta_1\left(\upsilon + \upsilon^{\cdot} - \beta_2\cdot\nu_j^n\right)\cdot\pi_j^n \tag{11}$$

where p_j^n is the learning parameter of the current work cycle; β_1 and β_2 are normal numbers, the value of β_1 represents the influence of current reinforcement learning decision-making on future reinforcement decision-making, and the greater the value of β_1 is, the greater the impact is. β_2 determines the intensity of punishment for single node deviation, and the greater the punishment is, the stronger the punishment is. υ represents the comprehensive return value of each work cycle; ν_j^n represents the comprehensive punishment; π_j^n represents the reliability of the j-th node in the current working cycle, and its formula is shown in (12).

$$\pi_j = \frac{e^{p_j}}{\sum_{j=1}^{N} e^{p_j}} \tag{12}$$

In formula (11), $\upsilon^{\cdot}$ represents the cumulative global return, and its updated iterative formula is shown in formula (13):

$$\upsilon' = \gamma\cdot\upsilon + (1-\gamma)\cdot\upsilon', \quad 0 < \gamma \leq 1 \tag{13}$$

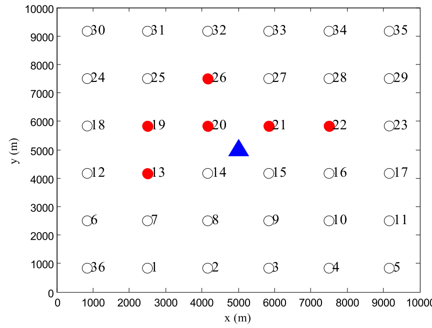
where γ is a constant, the υ' on the right of the equation is the current cumulative return value, and the υ' on the left of the equation is the cumulative return value at the next moment (after iteration).

The fusion center selects the top M nodes in the top value of π_j to carry out the cooperative perception in the next work cycle to improve the sensing performance and reduce the energy consumption at the same time.

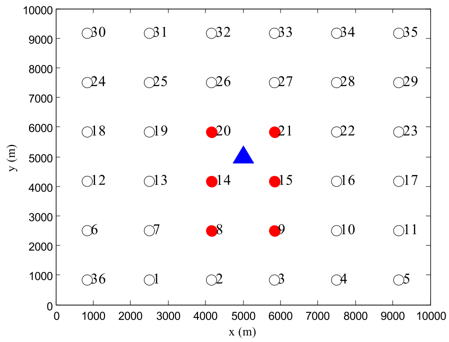
V. ANALYSIS OF THE SIMULATION EXPERIMENT

To evaluate the performance of the node reliability evaluation mechanism in this paper, four groups of experiments are designed. The first group of experiments shows that the nodes participating in cooperative sensing are selected according to the reliability requirements, and the differences between the nodes selected according to the principle of spatial location are compared. The second group of experiments is to compare the sensing performance of the three node selection schemes, and the three methods are: the sensing performance of the node selection method based on the reliability principle; the sensing performance of all equal-gain combination schemes; and the sensing performance of the node selection method based on the spatial location. The third group is a comprehensive comparison among the three node selection schemes, including the number of nodes, sensing performance and energy consumption. The fourth group of experiments is to compare the sensing performance of the primary user under different working probability, so as to understand the influence of the primary user's working probability on the sensing performance. Monte Carlo simulation is performed in the case of path loss, fading and additive white Gauss noise.

In the simulation experiments, we assume that the PU signal is a BPSK (Binary Phase Shift Keying) signal, the bandwidth is 10 kHz, the sensing time is 0.1 s. The first to the third group of experiments assume that the working probability of the primary user is $\beta = P(H_1) = 0.5$. The transmission



(a) **Node selection results based on reliability requirements**



(b) **Node selection results based on the spatial location principle**

FIGURE 3. Comparison of Node differences between the Reliability principle and Spatial position principle.

power of the PU is 0.01 W, and the noise power fluctuation is modeled by changing the SNR. Moreover, there are 36 nodes uniformly distributed in a normal area with a side length of 10,000 meters. The path simulation model is shown in formula (14).

$$P_{r,i} = P_t \cdot K \cdot [\frac{d_o}{d_i}]^r \quad i = 1, 2, \cdots, 36 \tag{14}$$

In formula (14), assume that the path loss exponent is $r = 3$, the channel attenuation coefficient is $K = 0.027$, $P_{r,i}$ is the signal power received by the ith node, $P_t = 0.1W$ is the transmitted signal power of the primary use, $d_o = 1$m is the reference distance, and d_i is the distance between the ith node and the primary user. The standard deviation of the shadow is 6 dB, and the mean of the multipath Rayleigh fading is 1 [22].

A. COMPARISONS OF NODE DIFFERENCES SELECTED ACCORDING TO THE RELIABILITY PRINCIPLE AND SPATIAL LOCATION PRINCIPLE

Six nodes selected according to reliability requirements are shown in Figure 3 (a) as red circles. As seen from Figure 3 (a), the nodes selected according to the reliability requirements are not all the nearest ones to the primary user. This is because the fading effect is taken into account in the simulation model. In the actual environment, different obstacles may exist between the nodes and the primary user, which may lead

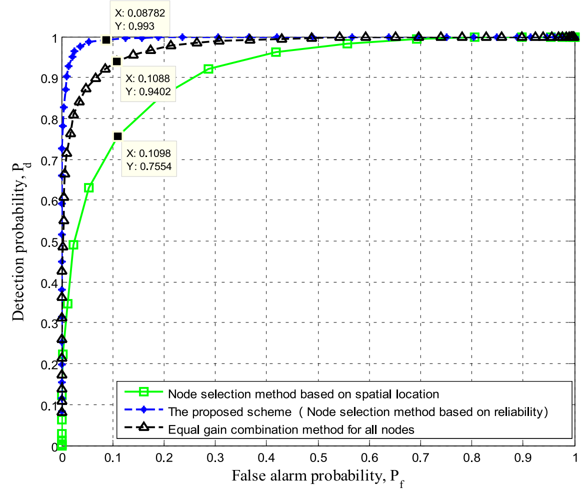


FIGURE 4. Comparison of perceptual performance of different node selection methods.

to different reliability. Figure 3 (b) is based on the principles of space of the recently selected node, as shown in the red circle in the figure, and based on the principles of space, the position of the recently selected six node is closest to the primary user. Compared with Figure 3 (a), there are four different nodes, and this is because, based on the principles of spatial position regardless of the actual environment, the distance of ideal conditions loss, so the nearest main user nodes are selected.

B. COMPARISON OF SENSING PERFORMANCE AMONG THREE NODE SELECTION SCHEMES

In Figure 4, six nodes are selected to participate in cooperative sensing, and the selected nodes are shown in the red circle in Figure 3. Of all the equal-gain combination schemes, 36 nodes participate in cooperative sensing. The perceptual performance is measured by the detection probability (P_d) and false alarm probability (P_f) of the fusion center. Detection probability refers to that the primary user is working, and the fusion center also decides that the primary user is working, that is to say, the decision is correct; false alarm probability refers to that the primary user is not working because of the influence of noise and other factors, but the fusion center decides that the primary user is working, that is, a false alarm. From the meaning of detection probability and false alarm probability, we can see that high detection probability and low false alarm probability are superior performance characteristics. As seen from Figure 4, the detection probability of the reliability-based node selection method is 0.99 when the false alarm probability is 0.1, while under the same false alarm probability, the detection probability of all nodes equal gain combination method and space-based node selection method [26] are 0.94 and 0.75, respectively, which are much lower than those of reliability-based node selection. The detection probability of the method shows that the sensing performance of the node selection method based on reliability is much better than that of the other two methods.

TABLE 1. Comprehensive comparison among the four node selection schemes.

Method	Number of nodes	P_d	Energy consumption
Reliability	6	0.99	6
Spatial location	6	0.75	6
Equal gain combination	36	0.94	36
broadcast based code	5	0.96	5

This is because the method based on node reliability is to select the six nodes with the highest reliability to participate in cooperative perception, in which the probability of error in each node is very low, and the fusion center combines six highly reliable sensing results, the probability of error is even lower, and the results are reflected in the experimental results. However, in the scheme of equal gain combination of all nodes, the sensing results of a few nodes will have a negative impact on the global decision, so the sensing performance of the scheme is not as good as that of the reliability-based method. However, the method based on spatial position is superior to the method based on spatial position because the method based on spatial position produces an incorrect decision because of obstacle blocking, which leads to the decrease of decision accuracy of the fusion center, while the probability of error decision in the fusion center is lower than that based on spatial position because of the large number of nodes.

C. THE ENERGY CONSUMPTION COMPARISON AMONG FOUR NODE SELECTION SCHEMES

The energy consumption comparison is carried out under the conditions of the previous experiments. The energy consumption of a node performing sensing operations in a sensing cycle is set as one unit of energy consumption, and the energy consumption of each node performing sensing operations in a sensing cycle is equal. The specific comparison data are shown in Table 1. Table 1 shows that the reliability-based method is equivalent to the location-based method in terms of energy consumption, but the reliability-based method is far superior to the location-based method in terms of sensing performance. Compared with the equal-gain combination method for all nodes, both the energy consumption and sensing performance have outstanding advantages, such as broadcast-based code dissemination scheme [27]. The energy consumed by this method is related to the number of participating nodes, and the sensing performance is also related to the number of nodes; when the number of nodes is 5, the optimal balance between energy consumption and sensing performance is obtained. Therefore, the evaluation algorithm based on node reliability in this paper has an obvious effect on selecting highly reliable nodes to participate in cooperative sensing.

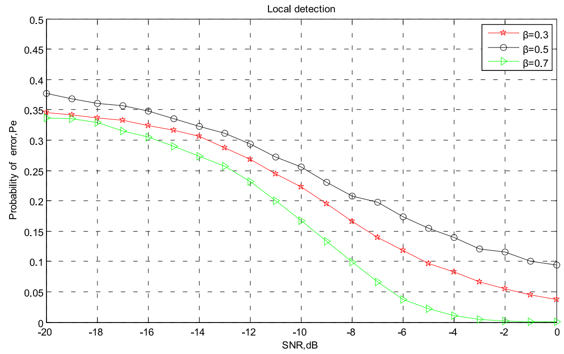


FIGURE 5. Comparison of sensing performance of primary users under different working probabilities.

D. COMPARISON OF SENSING PERFORMANCE OF PRIMARY USERS UNDER DIFFERENT WORKING PROBABILITIES

The fourth group of experiments is to compare the sensing performance of primary user under different working probability. The purpose of this experiment is to verify the error probability when the primary user working probabilities are $\beta = 0.3$, $\beta = 0.5$ and $\beta = 0.7$, respectively. In this paper, the error probability is used as the index of sensing performance, because the error probability combines the detection probability and false alarm probability at the same time, which can better reflect the current sensing performance. It can be seen from Figure 5 that when $\beta = 0.5$, the error probability (P_e) is the largest, because the uncertainty is the largest, it is easy to be affected by noise and signal power attenuation, and it is the most difficult to make a preparation decision. When $\beta = 0.7$, the P_e is obviously less than $\beta = 0.5$, because the signal received by the node will be very strong, it is easy to make a correct decision, but when $\beta = 0.3$, the primary user signal will be weakened, at this time, the sensing results are easily affected by noise, so the error probability is higher than $\beta = 0.7$. This shows that the working time of the primary user has a significant impact on the sensing performance. When the working time and the rest time are similar, it is most difficult to judge the working state of the primary user. In practice, the working time of the primary user is much less than the rest time, so it is easy to determine the working state of the primary user, which also shows the advantages of the algorithm in this paper.

VI. CONCLUSION

In cooperative sensing, a balance between sensing performance and energy consumption needs to be achieved. For this reason, a reliability-based node selection algorithm is proposed, which includes a node reliability evaluation machine. The system can rank the reliability of nodes, and the fusion center chooses the nodes with high reliability to participate in cooperative sensing and updates the health status of nodes through performance feedback and energy feedback to provide reliable data support for the fusion center to select healthy nodes in time. The experimental analysis shows that the proposed method improves the perception performance. Under the same conditions, the detection probability of the proposed method is 5% higher than that of the traditional method, while the energy consumption is only 16.7% of that of the traditional method. Follow-up research must improve the working life of the cognitive radio network, make the working time of each node more balanced, and improve the equal probability of working and resting between nodes.

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