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# Collaborative channel state perception with classification-based correction for heterogeneous networks

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**Abstract:** Accurately sensing the channel state of heterogeneous networks is key to matching users' diverse service communication demands with the channel state, and is an effective way to improve the utilization efficiency of network resource. However, existing channel state perception methods are not suitable for heterogeneous network, and their perception performance is easily affected by interference uncertainty. In order to achieve channel state perception of heterogeneous networks, this paper adopts a centralized collaborative perception model, where each node obtains local channel state perception results based on statistical pulse parameters at the physical layer. In order to reduce the impact of interference on perception performance, this paper uses the Jousselme distance to quantify the degree of difference among nodes caused by interference. Using the average credibility as a threshold, nodes in the sensing area are classified. On this basis, the local perception results of each node are performed classification-based correction to improve the accuracy and reliability of channel state perception. Simulation results indicate that the proposed method has good adaptability for channel state perception in complex electromagnetic environments. The perception results can accurately reflect the actual channel state, which is conducive to improving the network throughput.

**Keywords:** collaborative perception, heterogeneous networks, classification-based correction, channel state.

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## 1. Introduction

Heterogeneous networks, based on multiple radio access technologies and multi-layer coverage, have effectively enhanced the network capacity and range. They generally satisfy users' diverse service communication demands. Though, the explosive growth of smart terminals has enhanced higher requirements on network connection density. The limited connection capacity of network can easily lead to user access failures or access overload. The demand for high-bandwidth transmission easily conflicts with the limited spectrum resources. Meanwhile, low-latency and high-reliability transmission requires the networks to support precise service matching capabilities. Currently, faced with the acute contradiction between users' high-capacity and varied service communication requirements and severely constrained available resources, the key to achieving technological breakthrough lies in improving the spectrum efficiency. Accurate sensing of channel states in heterogeneous networks serves as an effective solution to this challenge. It can achieve dynamic alignment between the diverse service demand and channel state [1–4].

The channel state perception can be regarded as an important research branch of the cognitive radio spectrum perception. It employs energy detection to obtain the using state of frequency resources. The channel state perception provides a decision-making basis for data access. It is one of the key technologies for improving the efficiency of network resources [5–8]. The results of channel state perception can be presented in two ways: qualitative description and quantitative description.

The channel state is divided into two conditions: busy and idle by qualitative description. It usually accomplishes through local perception by a single node. The carrier sensing technology used in the carrier sense multiple access (CSMA) protocol is a typical representative of qualitative description. This method is simple and easy to implement. But it heavily relies on the reliability of the local perception device. Additionally, its perception performance is susceptible to the hidden terminal. As a result, this method has substantial limitation.

The channel state is quantified and analyzed by quantitative description. It represents the congestion level of the current channel with specific numerical values by counting traffic pulses across dimensions such as time, frequency, space, and polarization. Through local perception method, [9] calculated the channel load statistics by

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counting the number of traffic pulses in the time-frequency domain. This method achieved channel state quantification with low reliability. It heavily depended on the perception capability of local devices and was affected by the noise uncertainty. Through cooperative perception method, [10] computed the final quantitative value of the channel state by data fusion. In this method, multiple nodes separately counted traffic pulses and uploaded the data to a fusion center. The fusion weights were assigned based on the distance between nodes and the fusion center. This method overcame the dependence on a single node device and addressed the problem of hidden terminal. Though, it assumed that all node devices were homogeneous. As a result, the impact of differences in node devices' spectrum perception capabilities did not consider. Consequently, the calculation results failed to reflect the true state of the channel. In [11], through evidence theory, the spectrum perception capability of node devices was evaluated based on multiple characteristic parameters. It reasonably assigned fusion weights to nodes based on their spectrum perception capabilities. It could be improved the accuracy of channel load statistics. This method assumed that all communication networks in the sensing area were homogeneous and shared the same waveform system. As a result, the application of this method was limited.

On the basis of accurate channel state perception, how to achieve a precise match between users' diverse service transmission requirements and the channel state is key to improving the spectrum efficiency in heterogeneous networks. In the enhanced distributed channel access (EDCA) protocol [12], service data was categorized into four types which assigned different channel access weights, in order to enhance service quality. During the backoff process, different service types had different contention windows and waiting times to achieve differentiated services. But in this method, the weights were static and no matching relationship was established between channel access weights and channel state. In the statistical priority-based media access (SPMA) protocol [13,14], service data was divided into multiple priority levels to improve the network throughput and the channel utilization. The matching relationship was established between the service data transmission requirements and the channel state, which could dynamically adjusted nodes' channel access behavior. It effectively met the demands for low-latency and high-reliability of service data transmission. The channel state perception method used in this protocol was only applicable to homogeneous network scenarios and was susceptible to noise or malicious interference. As a result, it was difficult to adapt to channel state perception in complex electromagnetic environments.

To enhance the accuracy and reliability of channel state perception in heterogeneous networks, a collaborative channel state perception method with classification-based correction is proposed. Through the energy detection, it calculates the local perception results based on physical-layer statistics of the number of traffic pulses and pulse durations from neighboring nodes. Subsequently, to achieve a quantized channel state perception result， a multi-objective decision-making method is applied to perform weighted fusion of the perception data from each node. On this basis, the difference among nodes caused by interference is quantified by measuring the Jousselme distance between each node. The distance serves as the basis for calculating the credibility of perception nodes. Nodes within the sensing area are classified by applying the average credibility threshold. On this basis, using with classification-based correction, the perception data from all nodes are fused at the fusion center by weighted method. As a result, the impact of interference signals on channel state perception results is reduced and the channel perception ability is improved. The method proposed in this paper, provides a solid foundation for achieving precise alignment between the users' diverse service transmission requirements and the channel states, ultimately enhancing the efficiency of network resource utilization. As a result, this method accomplishes the purpose of the increasing the network resource utilization efficiency.

## 2. Cooperative perception method for heterogeneous network channel state

This section first briefly introduces the model of cooperative channel state perception in heterogeneous networks and the problems to be addressed. It then theoretically analyzes the method for quantifying local channel state perception under heterogeneous network conditions. Subsequently, the method for the fusion center to process the perception data from each node is analyzed. Finally, the operational mechanism of the heterogeneous network is described.

### 2.1 Perception model

Accurately sensing the channel state of wireless communication networks, is key to achieving precise matching between users' diverse service data transmission requirements and the channel state based on. It is closely related to the utilization efficiency of the network spectrum resources [15–18]. Cooperative channel state perception has three topological structure types: centralized, distributed, and relay-forwarding [19–21]. The centralized topological structure offers advantages such as fast operation speed, strong real-time performance, and strong adaptability to complex electromagnetic environments. Hence, this paper adopts the centralized topological structure. It can be seen in Fig. 1.

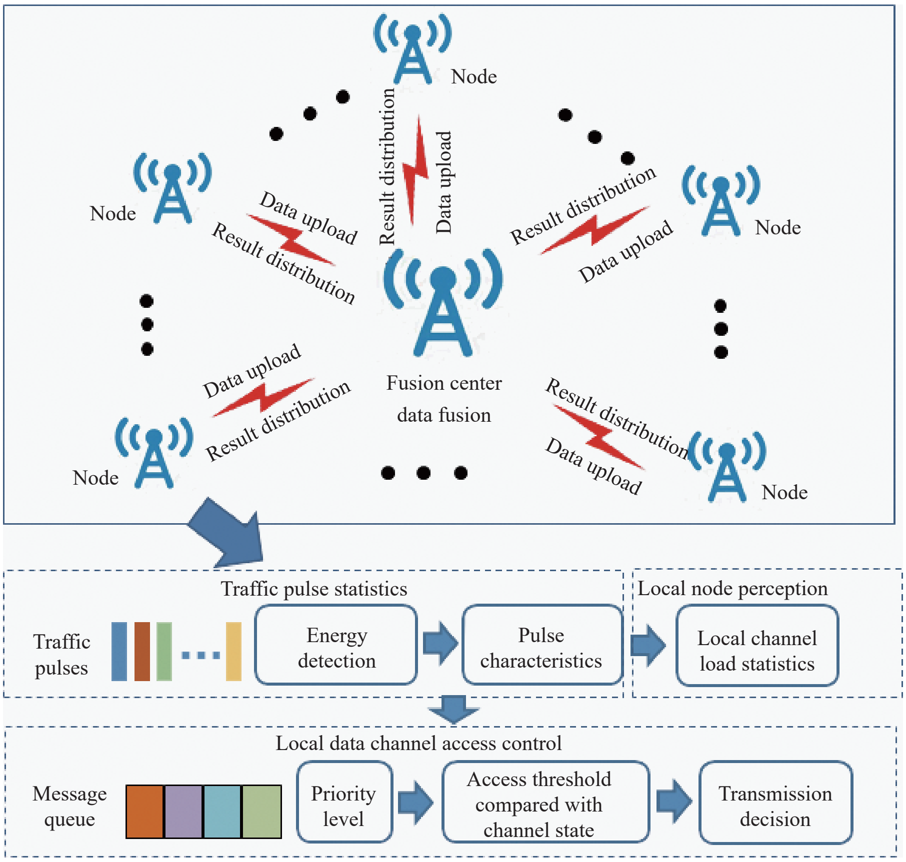


**Fig. 1 Centralized channel state perception model**

Fig. 1 shows that, channel state perception with the centralized topological structure mainly includes four stages: traffic pulse statistics, local node perception, data fusion, and result distribution and sharing. These are explained in detail as follows.

(i) Stage 1: traffic pulse statistics

During the statistical time window, each node in the sensing area counts the number of traffic pulses of user service data based on the physical layer. Through the energy detection method, the perception nodes detect whether an energy signal exists in the channel. The energy detection value is compared with the preset threshold to judge whether the pulse signals of user service data are present in the current channel. The perception nodes employ a counting method to obtain the traffic pulse statistics result.

(ii) Stage 2: local node perception

During the statistical time window, each node in the sensing area calculates the channel load statistic value in the two-dimensional time-frequency domain by counting the number of traffic pulses from its one-hop neighbors. This value represents the quantized result of channel state perception for local node. It is then reported to the fusion center.

(iii) Stage 3: data fusion

The fusion center receives the local perception results from each node. Using a fusion rule, it rationally allocates data fusion weights to each node and computes the final channel load statistic result by weighted fusion, which is quantified the current channel state.

(iv) Stage 4: result distribution and sharing

The fusion center shares the quantified channel state result obtained during the current statistical time window to other nodes in the network. Based on the matching relationship between diverse service data transmission requirements and the channel state, each node determines whether the service data can access the channel.

## 2.2 Problem description

In the cooperative channel state perception method, the perception network generally adopts the centralized topology structure. Each node within the network senses the channel state separately. The local perception result is uploaded to the fusion center. The fusion center calculates the final channel state perception result by the fusion rule. This method reduces the dependency on the perception capability of individual node devices and eliminates the impact of the hidden terminal on perception performance. It is helpful to improve the accuracy and reliability of the perception results. Yet, there are still shortcomings in both node local perception and data fusion for existing perception methods.

(i) Shortcomings in node local perception

Current wireless communication networks exhibit complex forms. Ultra high frequency (UHF)/very high frequency (VHF)/L/S/Ku/Ka and other frequency bands are all used. Multiple access technologies such as time division multiple access (TDMA), code division multiple access (CDMA), and frequency division multiple access (FDMA) coexist. Multiple waveform schemes such as minimum shift keying (MSK), *M*-ary quadrature amplitude modulation (MQAM), and orthogonal frequency division multiplexing (OFDM) are all adopted. While heterogeneous networks effectively improve the network coverage and communication capacity, they also bring new challenging problems for channel state perception. Existing channel state perception methods usually assume that the communication networks within the sensing area are homogeneous and employ identical waveform schemes. This is obviously inconsistent with practical application scenarios.

(ii) Shortcomings in data fusion

In cooperative channel state perception methods, the fusion center receives perception results from other nodes within the network and compute the final channel state perception result with a fusion rule. Fusion rules typically use either equal-gain combining or weighted combining. In the weighted combining, weights are assigned based on the distance between nodes or according to the nodes' spectrum perception capabilities. When the perception environment is a complex electromagnetic environment or there is malicious interference, the perception results of the interfered node differ substantially from those of other nodes. When the perception environment involves complex electromagnetic conditions or the presence of malicious interference, the perception results of affected nodes exhibit considerable discrepancies compared to others. As a result, the perception results between nodes show more obvious conflict characteristics. Though, existing fusion rules fail to characterize this disparity. Consequently, the final channel state perception result from the fusion centers deviates considerably from the actual channel state. It is unable to reflect the true channel state.

## 2.3 Local channel state perception quantification method

When qualitative description is used for the channel state perception results, the channel state can only be categorized into either busy or idle states. It is suitable for wireless communication networks with single-carrier fixed-frequency. Currently, multi-carrier communication system, represented by OFDM, has become the waveform standard for mobile communications. It effectively improves the system frequency efficiency [22–24]. Frequency hopping (FH), as a typical anti-interference technology, has been widely adopted in various data communication networks [25]. It substantially enhanced the transmission reliability of service data in complex electromagnetic environments [26,27]. Hence, the qualitative description is no longer applicable to current wireless communication network.

The current wireless communication networks exhibit diverse forms. The coverage of high-frequency and low-frequency networks overlaps with each other. Multiple access technologies and waveform schemes coexist. The intra-pulse and inter-pulse characteristics of service data transmitted in channel exhibit substantial differences. To achieve channel state perception in heterogeneous networks, it is necessary to count not only the number of traffic pulses for service data transmission in the channel, but also their duration. During the statistical time window, to count the number of traffic pulses, each node in the network counts the number of transmitted and received pulses from its one-hop neighbors based on the physical layer. The node adopts the energy detection method to gain the detected signal value and compares with a preset threshold. Based on the comparison result, the node judges the presence of pulse signals in the channel. To count the duration of traffic pulses, it is necessary to preset a pulse rising-edge detection threshold. If the detected signal value exceeds this threshold, the pulse duration timer starts; otherwise, it stops. The pulse duration is obtained. The local node periodically distributes and shares the number of traffic pulses and their durations with all nodes within its one-hop range by a broadcast message.

During the statistical time window, each node in the network obtains the number of traffic pulse and pulse durations by receiving broadcast messages reported by other nodes. The channel load statistics value can be obtained by calculating the occupancy ratio of user service data transmission in the time-frequency two-dimensional space. The quantified local channel state can be represented. The calculation formula for the channel load statistics value $\mathrm{Cos}_k$ of the node $k$ is expressed as

$$\mathrm{Cos}_k = \sum_{j=1}^{N}\left\{\sum_{i=1}^{M}\left(\mathrm{Rn}_{f_i}^{j}\cdot\alpha_{f_i}^{j}+\mathrm{Sn}_{f_i}^{j}\cdot\beta_{f_i}^{j}\right)\right\}\Big/\mathrm{MT}_w+ \sum_{i=1}^{M}\left(\mathrm{Rn}_{f_i}^{k}\cdot\gamma_{f_i}^{k}+\mathrm{Sn}_{f_i}^{k}\cdot\delta_{f_i}^{k}\right)/\mathrm{MT}_w \tag{1}$$

where $M$ denotes the number of frequency hopping points in the heterogeneous network. $N$ represents the number of neighbor nodes within one-hop range of the current node. $\mathrm{Rn}_{f_i}^{j}$ and $\mathrm{Sn}_{f_i}^{j}$ denote, respectively, the number of traffic pulses received and transmitted by neighbor node $j$ on the frequency hopping point $f_i$. $\alpha_{f_i}^{j}$ and $\beta_{f_i}^{j}$ represent, respectively, the pulse durations of the traffic pulses received and transmitted by neighbor node $j$ on the frequency hopping point $f_i$. $\mathrm{Rn}_{f_i}^{k}$ and $\mathrm{Sn}_{f_i}^{k}$ denote, respectively, the number of traffic pulses received and transmitted by the node $k$ on the frequency hopping point $f_i$. $\gamma_{f_i}^{k}$ and $\delta_{f_i}^{k}$ represent, respectively, the pulse durations of the traffic pulses received and transmitted by the node $k$ on the frequency hopping point $f_i$. $T_w$ represents the duration of the statistical time window.

### 2.4 Data fusion method at the fusion center

At each node in the network, the local sensing result is uploaded to the fusion center. The fusion center calculates the final channel state sensing result based on fusion rules. Fusion weights are the key to ensuring the accuracy and reliability of the final sensing result, which are appropriately assigned to the nodes based on the contribution of the local sensing result to the channel state sensing result. In some scenarios, the nodes will be used to deploy in complex electromagnetic environments or subjected to malicious interference. Compared to other nodes, the interfered nodes will be exhibited more substantial conflicting characteristics. When its sensing results are uploaded to the fusion center, as a result, the credibility of the final channel state sensing result will be inevitably decreased. The true state of the channel is difficultly reflected. It is believed that reasonable establishment of fusion rules for the fusion center becomes particularly important. The impact of local sensing results from interfered nodes on the final channel state sensing result can be removed through rationally allocating fusion weights among the network nodes.

At the sensing node level, there are two factors which affect channel state sensing performance. Namely the local sensing capability and the sensing environment. In the traditional fusion rules, each node in the sensing area is regarded to be homogeneous. That is, all nodes are with same sensing capability. The sensing capabilities of each node is extremely different. The capability is related to its transceiver performance. Receiving sensitivity, antenna voltage standing wave ratio (VSWR), operating months, and mean time between failures (MTBF), et al, are all the important factors to its transceiver performance. Nodes in the sensing area are not homogeneous.

One should comprehensively evaluate the impact of these factors on the node's sensing capability, and take it into account in the fusion rules. The sensing environment exhibits important impact to the sensing result. It is mainly manifested as the disturbance on energy detection by the noise or interference signal. The false alarm probability of node detection will be increased and the reliability of traffic pulse number will be decreased by such disturbance. It is considered that the impact of sensing environment should also be reflected in the fusion rule. The radiation of the noise or interference signal has strong directionality. The interference intensity gradually decreases with increasing interference distance. Well, this characteristic results in substantial differences in the degree of interference experienced by each node.

The network nodes should be categorized according to their interference degree. The nodes can be classified into three types: non-interfered nodes, moderately interfered nodes, and severely interfered nodes. As the node type varies, so does the data fusion weigh. When setting the fusion rules, in addition to the local sensing capability and the sensing environment, we also need to consider the consistency of historical local sensing results. It is used to evaluate the actual sensing ability of the node. The consistency factor of historical local sensing results for the node $i$ in the previous statistical time window can be expressed as

$$\mathrm{Un}_i = 1-\frac{|\mathrm{Cos}_i-\mathrm{Res}|}{\mathrm{Res}} \tag{2}$$

where $\mathrm{Cos}_i$ represents the channel load statistics of node $i$ in the previous statistical time window, and Res represents the final channel state perception result in the previous statistical time window.

It is considered that the better the consistency of historical local sensing results, the higher the reliability of the node's sensing capability, well, such a node should be assigned a higher weight during data fusion. Conversely, node should be assigned a lower fusion weight.

Through the above analysis, it can be concluded that the channel state sensing results are closely related to the local sensing capability, the sensing environment, and the consistency of historical local sensing results. How can we quantitatively describe the impact of the above factors on the final channel state sensing results? It is a critical question. We can employ the analytic hierarchy process (AHP) to address this question [28–30]. The final channel state sensing result calculated by the fusion center can be expressed as

$$\text{Res} = \sum_{i=1}^{K} \text{Cos}_i \left[\rho \cdot f_i(\xi_i, z_i, \text{num}_i, \text{gz}_i) + \sigma \cdot \text{ac}_i + \vartheta \cdot \text{Un}_i\right] \tag{3}$$

where $K$ represents the number of nodes participating in data fusion. $\text{Cos}_i$ represents the channel load statistics of node $i$. $f_i(\cdot)$ represents the perception ability factor of node $i$, which is a function of its receiver sensitivity $\xi_i$, antenna VSWR $z_i$, operational months $\text{num}_i$, and mean time between failures $\text{gz}_i$. Reference [11] disclosed a calculation method for comprehensively evaluating node perception ability based on multiple factors, which will not be reiterated here. $\text{ac}_i$ denotes the classification correction factor for node $i$, determined by the interference level. As for how to classify the network nodes, we will explain in detail in the next section. In the above formula, $\text{Un}_i$ represents the consistency factor of historical local sensing results for node $i$, $\rho$, $\sigma$, and $\vartheta$ respectively represent the weights for the node sensing ability factor, node classification correction factor, and the consistency factor of historical local sensing results, satisfying $\rho + \sigma + \vartheta = 1$. In this paper, the AHP method is used to determine their values. Reference [30,31] disclosed a weight allocation method based on AHP, which is not reiterated here.

### 2.5 Network operation mechanism

Before the network starts, it is necessary to preset the types of user service data. Through comprehensively considering factors such as the real-time requirements, reliability, and source platform types for the various service data types, the priority levels for different service data types are ranked. The channel access thresholds are set for the service data of each priority level separately. The higher the priority of the service data, the larger its corresponding the channel access threshold.

After the network starts, each node in the sensing area calculates its local channel state perception results based on physical layer statistics and uploads it to the fusion center. The fusion center employs a fusion rule with weighted calculation to obtain the quantified channel state perception results for the current statistical time window and distributes them to other nodes in the network. User service data of each node is queued according to its priority order. When transmitting a specific priority service data, its channel access threshold is compared against the current channel state results. The service data is allowed to access the channel only when its channel access threshold is greater than the channel state perception result.

## 3. Node classification and correction method based on Dempster-Shafer theory

When some nodes in the sensing area are subjected to interference, their sensing results bring about uncertainty on the final fusion results. The more diverse interference on nodes is, the more varied the uncertainty on the sensing results becomes. In this paper, the evidence distance is used to quantify the differences between nodes caused by interference. Based on the differences, the network nodes are classified. We separately correct the fusion data according to their classifications, reducing the impact of interference on the channel sensing results.

### 3.1 Credibility calculation of node data

The spectrum sensing process is the detection of licensed signals in essence. This process intrinsically involves uncertainty. Evidence theory can be used to spectrum sensing. This helps reduce the impact of uncertain factors on sensing performance. In this paper, the evidence theory is integrated with the binary hypothesis model of spectrum sensing. This integration establishes a frame of discernment with two elements: $\text{H}_0$ and $\text{H}_1$. $\text{H}_0$ represents the proposition that pulse signals are present in the channel. $\text{H}_1$ represents the proposition that pulse signals are not present in the channel.

The energy detection method is employed to determine whether there are user service data pulse signals in the channel. When the number of sampling points $N$ is sufficiently large, the energy detection value of the node, $x_{E_i}$, approximately follows a normal distribution, expressed as

$$\begin{cases} \text{H}_0:\ x_{\text{E}_i} \sim N(\mu_{0i}, \sigma_{0i}), & \text{existence} \\ \text{H}_1:\ x_{\text{E}_i} \sim N(\mu_{1i}, \sigma_{1i}), & \text{non-existence} \end{cases} \tag{4}$$

where $\mu_{0i} = N$, $\mu_{1i} = N(1+\text{snr}_i)$, $\sigma_{0i} = 2N$, $\sigma_{1i} = 2N(1+2\text{snr}_i)$. $\text{snr}_i$ denotes the signal-to-noise ratio of node $i$.

The sensing information from each node can be converted into evidence values. A normal distribution function is then applied to extract evidence from each sensing node. We can construct the basic probability assignment function for each node. That of the node $i$ can be expressed as

$$m_i(\text{H}_0) = \int_{x_{E_i}}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_{0i}} \exp\left[-\frac{(x-\mu_{0i})^2}{\sigma_{0i}^2}\right] \mathrm{d}x, \tag{5}$$

$$m_i(\text{H}_1) = \int_{-\infty}^{x_{E_i}} \frac{1}{\sqrt{2\pi}\sigma_{1i}} \exp\left[-\frac{(x-\mu_{1i})^2}{\sigma_{1i}^2}\right] \mathrm{d}x. \tag{6}$$

The radiation of the noise or interference signal has strong directionality. The interference intensity gradually decreases with increasing interference distance. Compared to other nodes, the sensing results of the nodes deployed in interference areas show considerable conflicting characteristics. In order to quantify the differences between nodes caused by interference, we use the

Jousselme distance [32]. The distance between node $i$ and node $j$ is expressed as

$$d(\boldsymbol{m}_i, \boldsymbol{m}_j) = \sqrt{\frac{1}{2}\left(\|\boldsymbol{m}_i\|^2 + \left\|\boldsymbol{m}_j\right\|^2 - 2\langle \boldsymbol{m}_i, \boldsymbol{m}_j\rangle\right)} \tag{7}$$

where $\boldsymbol{m}_i = (m_i(\mathrm{H}_0), m_i(\mathrm{H}_1))$, $\|\boldsymbol{m}_i\|^2 = \langle \boldsymbol{m}_i, \boldsymbol{m}_i\rangle$, $\langle \boldsymbol{m}_i, \boldsymbol{m}_j\rangle$ represent the inner product of two vectors, and its calculation is given by

$$\langle \boldsymbol{m}_i, \boldsymbol{m}_j\rangle = \sum_{k=1}^{2}\sum_{l=1}^{2} m_i(A_k) m_j(A_l) \frac{|A_k \cap A_l|}{|A_k \cup A_l|} \tag{8}$$

where $A_k, A_l \in \{\mathrm{H}_0, \mathrm{H}_1\}$. The greater the Jousselme distance, the greater the conflict between nodes and the lower their similarity; conversely, the smaller the conflict, the greater the similarity.

Based on the Jousselme distance between nodes, a similarity matrix $\boldsymbol{S}$ is constructed between the nodes, which can be expressed as

$$\boldsymbol{S} = \begin{vmatrix} 1 & s_{12} & \cdots & s_{1j} & \cdots & s_{1K} \\ s_{21} & 1 & \cdots & s_{2j} & \cdots & s_{2K} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{i1} & s_{i2} & \cdots & s_{ij} & \cdots & s_{iK} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{K1} & s_{K2} & \cdots & s_{Kj} & \cdots & 1 \end{vmatrix} \tag{9}$$

where $s_{ij}$ represents the similarity between the perception nodes, expressed as

$$s_{ij} = 1 - d(\boldsymbol{m}_i, \boldsymbol{m}_j),\ i, j = 1, 2, \cdots, K. \tag{10}$$

The support level between nodes is closely related to their similarity. The greater their similarity, the greater the support level. The support level of a node can be calculated from its similarity matrix of the nodes. The support level of node $i$ can be expressed as

$$\mathrm{Sup}_i = \sum_{j=1, j\neq i}^{K} s_{ij}. \tag{11}$$

The credibility of a node can be calculated from its support level. Specifically, the credibility of node $i$ can be expressed as

$$\mathrm{Crd}_i = \frac{\mathrm{Sup}_i}{\sum_{j=1}^{K} \mathrm{Sup}_j}. \tag{12}$$

From the above equation, it can be known that the credibility of a node is proportional to its support level. When some nodes in the sensing area are interfered with noise, the distance between the interfered nodes and other nodes will increase, and the reliability will decrease. This will reduce its contribution to the final channel state sensing results. Similarly, the distance will decrease between nodes not interfered with noise, and their credibility will increase. Well, this will increase their contribution to the final channel state sensing result.

Compared with methods such as the Dezert and Smarandache theory (DSmT) and proportion conflict redistribution (PCR), in this paper, the Jousselme distance is employed to handle evidence conflicts. There are substantial differences between them. DSmT, PCR, and similar methods focus primarily on "how to fuse". They address evidence conflicts through designing fusion rules. In contrast, the Jousselme distance focuses on measuring conflicts. Equation (1) shows that it provides an objective basis for weight assignment in the fusion of node sensing data. The Jousselme distance is slightly less accurate than methods such as DSmT and PCR. Though, it is simple, fast, and exhibits low complexity.

### 3.2 Classification-based correction method for node data

The channel state perception observations from interfered nodes can reduce the reliability of the fusion result. In this paper, the nodes in the sensing area is classified based on the average credibility of the nodes as the threshold. The classification correction factor is adopted to express the degree of correction for each type of node. Fig. 2 shows the calculation process of the classification correction factor.

The average credibility of a node can be expressed as

$$\overline{\mathrm{Crd}} = \frac{1}{K}\sum_{i=1}^{K} \mathrm{Crd}_i. \tag{13}$$

Based on the average credibility, nodes in the sensing area are classified into three categories: non-interfered nodes, moderately interfered nodes, and severely interfered nodes.

Non-interfered nodes: The node credibility is greater than the average credibility, that is, it satisfies the following relationship:

$$\mathrm{Crd}_i > \overline{\mathrm{Crd}}. \tag{14}$$

The perception results of this type of node are completely reliable and do not require correction during data fusion.

Moderately interfered nodes: The node credibility is greater than 0.5 times the average credibility but less than or equal to the average credibility, that is, it satisfies the following relationship:

$$0.5\overline{\mathrm{Crd}} \leqslant \mathrm{Crd}_i \leqslant \overline{\mathrm{Crd}}. \tag{15}$$

The perception results of this type of node have a limited impact on the final fusion results but are not entirely trustworthy, appropriate correction is needed during data fusion.

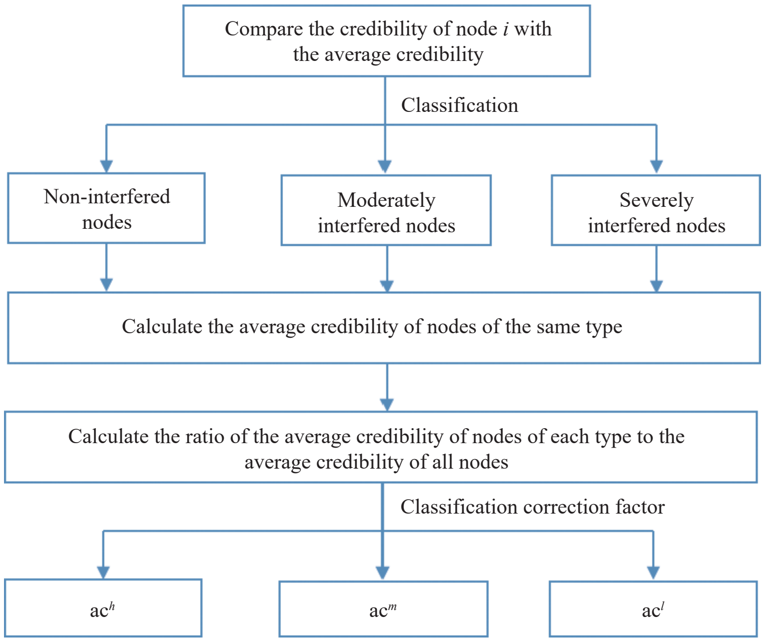


**Fig. 2 A schematic diagram for calculating the classification correction factor**

Severely interfered nodes: The node credibility is less than 0.5 times the average credibility, that is, it satisfies the following relationship:

$$\mathrm{Crd}_i < 0.5\overline{\mathrm{Crd}}. \tag{16}$$

The perception results of this type of node have a substantial impact on the final fusion results, correction to this node's data should be strengthened during data fusion.

After classifying the nodes in the sensing area, it is necessary to correct the perception results of each node according to their category, in order to reduce the disturbance impact of interference signals on the final fusion results. In this paper, the classification correction factors are used to represent the degree of correction for different types node. The perception results of the non-interfered nodes are completely trustworthy data and do not need to be corrected. Their classification correction factor is expressed as $\mathrm{ac}^h = 1$.

The perception results of the moderately interfered nodes are considered partially trustworthy data for the final fusion result, and their classification correction factor is represented as

$$\mathrm{ac}^m = \frac{1/\mathrm{Mid}\sum_{i=1}^{\mathrm{Mid}}\mathrm{Crd}_i^m}{1/K\sum_{i=1}^{K}\mathrm{Crd}_i} \tag{17}$$

where Mid represents the number of the moderately interfered nodes in the perception area, $\mathrm{Crd}_i^m$ represents the credibility of node $i$ among the moderately interfered nodes, and $K$ indicates the total number of nodes in the sensing area.

The perception results of the severely interfered nodes have a considerable impact on the final fusion results, and their classification correction factor is expressed as

$$\mathrm{ac}^l = \frac{1/\mathrm{Low}\sum_{i=1}^{\mathrm{Low}}\mathrm{Crd}_i^l}{1/K\sum_{i=1}^{K}\mathrm{Crd}_i} \tag{18}$$

where Low represents the number of the severely interfered nodes in the sensing area, and $\mathrm{Crd}_i^l$ denotes the credibility of node $i$ among the severely interfered nodes.

From the expression of the classification correction factors, it can be seen that the degree of correction is proportional to the credibility of each type of node. Through comparison, it can be seen that, the credibility of the non-interfered nodes is the highest, the credibility of the severely interfered nodes is the lowest, and the credibility of the moderately disturbed nodes is in between. The classification correction factors of the different type nodes satisfy the following relationship:

$$0 < \mathrm{ac}^l < \mathrm{ac}^m < \mathrm{ac}^h = 1. \tag{19}$$

This relationship indicates that for the severely interfered nodes, their impact on the final fusion result is considerable, and the correction intensity should be increased. For the moderately interfered nodes, their impact on the final fusion result is relatively lower, therefore the correction intensity can be appropriately reduced. For the non-interfered nodes, their perception results are completely trustworthy data for the final fusion result and do not need to be corrected.

## 4. Simulation results and analysis

To further analyze the performance of the heterogeneous network channel state perception method proposed in this paper, simulation verification is carried out using simulation software based on the above theoretical analysis. The simulation parameters are listed in Table 1. The characteristics of the heterogeneous network are primarily reflected in parameters such as the number of heterogeneous networks, frequency bands, modulation, and pulse periods.

**Table 1 Simulation parameters**

| Parameter | Setting |
|---|---|
| Channel environment | Multipath fading channel |
| Number of heterogeneous networks | 3 |
| Frequency band | VHF, UHF |
| Modulation | MSK, QPSK |
| Pulse period/μs | 26, 52 |
| Number of nodes within on hop | 5~45 |
| Transmission rate/(Mbit/s) | 1 |
| Packet inter-arrival time | Poisson distribution |
| Statistical time widow size/ms | 100 |
| Packet size/bit | 50 |
| Packet priority | 0～7 |

To better evaluate the performance of the proposed method, the simulation results are compared with several typical methods. Reference [9] presented a typical local sensing approach. But its performance in heterogeneous network sensing heavily depended on the sensing capability of the local devices. Reference [10] introduced a typical cooperative sensing method. It assigned fusion weights based on the distances between nodes and the fusion center. Yet, this method does not account for the impact of device heterogeneity on spectrum sensing performance. Reference [11] also proposed a cooperative sensing method. It assigned fusion weights according to the spectrum sensing capabilities of the nodes. This approach improved spectrum sensing performance to some extent. Both methods in [10] and [11] assumed that the communication networks in the sensing area were homogeneous. This assumption limited their effectiveness in heterogeneous network sensing scenarios.

Channel state perception performance is closely related to network scale, which can be represented by the number of neighbor nodes within one-hop range. This paper simulates and analyzes the impact of the number of neighbor nodes within one-hop range on channel state perception results under homogeneous network conditions. The simulation results are shown in Fig. 3.

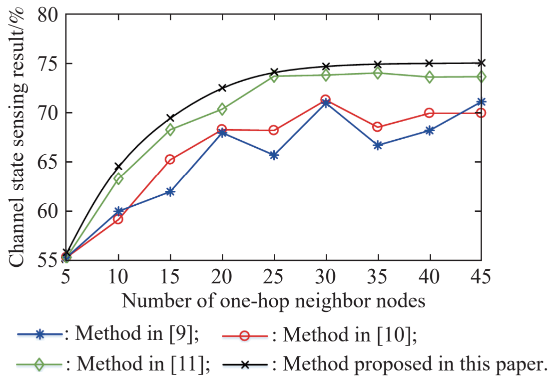


**Fig. 3 Impact of the number of one-hop neighbor nodes on channel state perception result under homogeneous network conditions**

The simulation results in Fig. 3 show that, with the change in the number of neighbor nodes within a one-hop range in the network, the channel state perception results calculated by the local perception method in [9] exhibit the greatest fluctuations, the cooperative perception methods in [10] and [11] show moderate fluctuations, while the trend of the method proposed in this paper tends to be stable. This is mainly because the channel state perception results calculated by the local perception method in [9] are completed by the local node alone, making them highly dependent on the perception ability of the local device. When the node's perception ability and the consistency of historical local perception results fluctuate (simulation parameter: randomly selected within a normalized fluctuation range of 0.70 to 0.95), it can cause considerable variations in the channel state perception results. Both [10] and [11] employ a cooperative perception method to compute the channel state perception results, overcoming the dependency on the perception ability of individual nodes. In the perception method of [10], the fusion rule does not take into account the impact of changes in node perception ability. In the perception method of [11], the fusion rule does not take into account the impact of the consistency of historical local perception results. As a result, the channel state perception results exhibit a certain degree of fluctuation.

This paper simulates and analyzes the impact of the number of neighboring nodes within a one-hop range on channel state perception results under heterogeneous network conditions, and compares it with the local perception method in [9] and the cooperative perception methods in [10] and [11]. Under this simulation condition, the perception environment is set with two network systems, TDMA and CDMA, employing MSK and quadrature phase shift keying (QPSK) waveforms respectively, and having different pulse period times of 26 μs and 52 μs. The simulation results are shown in Fig. 4.

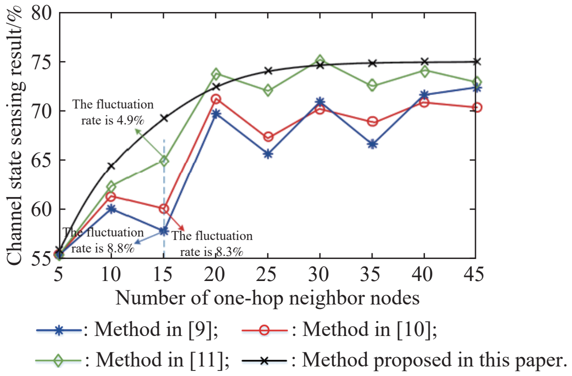


**Fig. 4 Impact of the number of one-hop neighbor nodes on channel state perception result under heterogeneous network conditions**

By analyzing the simulation results shown in Fig. 3, it can be seen that, compared to the perception in homogeneous networks, the channel state perception results of heterogeneous networks exhibit greater fluctuations. Among them, the method in [9] has the largest fluctuations, the method in [10] has moderate fluctuations, the method in [11] has smaller fluctuations, and the fluctuations of the method proposed in this paper are negligible. Comparing the simulation results shown in Fig. 2, when the number of neighboring nodes is 15, the channel state perception result calculated by the method in [9] decreases from 62% to 57%, with a fluctuation rate of 8.8%. The result calculated by the method in [10] decreases from 65% to 60%, with a fluctuation rate of 8.3%. The result calculated by the method in [11] decreases from 68% to 65%, with a fluctuation rate of 4.9%. This is mainly because existing methods are only suitable for homogeneous network scenarios. The pulse parameters they count at the physical layer only include the number of traffic pulses, and they assume that the pulses transmitted in the channel have the same pulse period parameters. This results in a deviation between the calculated channel state perception results and the true values.

We know that throughput is an important metric for evaluating the transmission performance of communication networks. Fig. 5 shows that the impact of channel state perception results on the throughput of heterogeneous networks under interference-free conditions.

Through analyzing the simulation results, we can therefore get a relatively clear conclusion under the same channel state perception conditions. The network throughput performance of the method proposed in this paper is the best. The method in [9] is the worst. The methods proposed in [10] and [11] is intermediate. The method in [9] is easily affected by fluctuations in the perception capabilities of local devices. The fluctuations reduce the reliability of the number of traffic pulses counted at the physical layer, making it difficult to accurately reflect the true state of the channel. As a result, it leads to an increased probability of conflicts in users' service data transmission and a decrease in network throughput. In the methods proposed in [10] and [11], the pulse signals are treated as homogeneous. Only the effect of the number of traffic pulse on channel state perception results is taken into account. The data fusion rule is set unreasonably, resulting in the calculated channel state perception results deviating from the actual values, which leads to a decrease in network throughput.

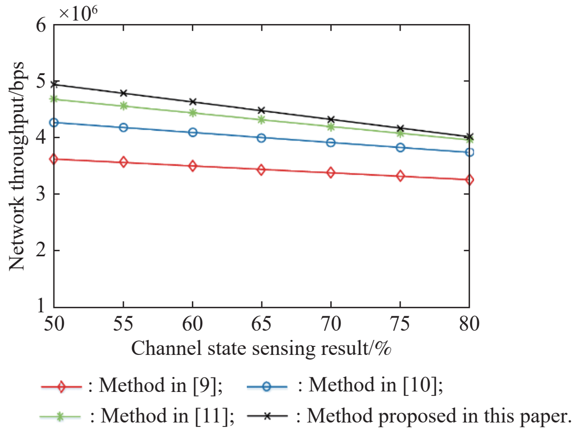


**Fig. 5 Impact of channel state perception result on network throughput under interference-free conditions**

Fig. 6 shows that the impact of channel state perception results on the throughput of heterogeneous networks under interference conditions. In the simulation parameters, the interference signal is comb-spectrum interference, covering 32% of the nodes.

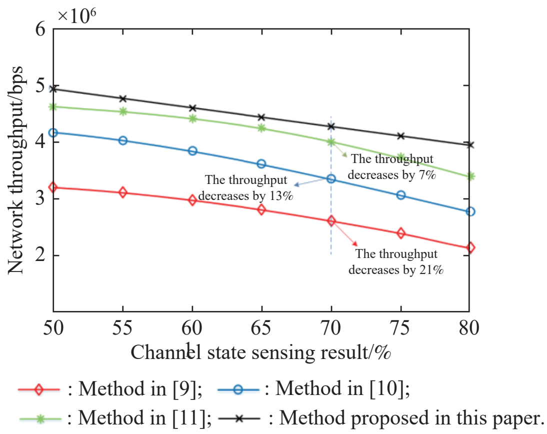


**Fig. 6 Impact of channel state perception result on network throughput under interference conditions**

Through analyzing the simulation results, it leads to the conclusion that, compared to an interference-free environment, the throughput of the heterogeneous network tends to decrease as the channel perception results increase. The method in [9] has the steepest decline, the methods in [10] and [11] have moderate declines, and the decline of the method proposed in this paper is almost negligible. When the channel state perception result is 70%, compared with the simulation results shown in Fig. 4, the throughput of the method in [9] decreases by 21%, the throughput of [10] decreases by 13%, the throughput of [11] decreases by 7%, while the throughput of the method proposed in this paper remains almost unchanged. This shows that the method proposed in this paper has strong adaptability for channel state perception in complex electromagnetic environments.

## 5. Conclusions

Multiple access technologies coexist with waveform schemes. It is the current state of wireless communication networks. Accurately sensing the channel state is key to matching users' diverse service communication requirements with the channel conditions, and also serves as an effective way to improve the utilization efficiency of network resource. The network nodes are classified based on the average credibility. The data fusion rules are optimized by introducing the classification correction factors. It is beneficial for improving the ability to perception channels in complex electromagnetic environments. The simulation results show that the heterogeneous network channel state perception method proposed in this paper can accurately reflect the channel state. It improves the network throughput and provides technical support to meet users' high-capacity and diverse service communication demands.

It is effective for solving the spectrum sensing problem in complex electromagnetic environments with heterogeneous network. When it is used in network with a lot of nodes, the computational complexity increases substantially as the number of evidence increases. This increase in complexity can become an issue. The fusion center may fail to achieve real-time processing. A clustering architecture can be introduced to address this issue. The distributed fusion can optimize the network structure. The high complexity challenges inherent in large-scale network applications can be effectively addressed.

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