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A new IoT resource addressing method based on rough set neural network

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Abstract: In order to overcome the problems of low precision and long time in traditional resource addressing methods of Internet of Things (IoT), this paper proposes a new resource addressing method based on rough set neural network, which enhances the information processing ability of rough set neural network and establishes a new decision system modelling method. The resource names are refined into original resource names and transformed resource names through the model. At the same time, the resource addresses are expanded into resource address information with standard hierarchical structure information and expanded hierarchical structure information, which provides important information for the transformation of resource names and realises the IoT resources addressing. The experimental results show that the proposed method can effectively improve the addressing accuracy and reduce the average search time, and the node failure problem is significantly improved.

Keywords: rough set neural network; IoT; Internet of Things; resource addressing; simulation; standard hierarchical structure information; expanded hierarchical structure information.

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1 Introduction

With the rapid development of science and technology and Internet technology, the application of computers and mobile phones is becoming more and more popular, and people's lives are increasingly inseparable from the network. With the rapid development of network technology, it effectively promotes the development of e-commerce and logistics industry. As the current IoT technology has been unable to meet the needs of human development, the IoT technology was born (Zhu, 2018; Liu and Cai, 2016). Essentially, the Internet of Things (IoT) is an extension and expansion on the basis of the Internet, which is still in its infancy. Because perception data is ubiquitous in the IoT, the client will extend to any device and item. How to connect any article or device to the IoT in a certain coding way and how to realise the addressing of any article or device in the IoT to establish communication connection are the problems that must be solved in the construction of the IoT. As one of the core technologies of the IoT, IoT addressing technology realises accurate, efficient and secure addressing of any terminal in the IoT on the basis that items and devices are connected to the Internet in a specific way. The research and practice on it will build an interconnected ubiquitous network in a true sense. Just like the addressing system in the Internet, the IoT addressing platform will play a core role in the IoT. Devices in the IoT are not only passive transmitters, they can also accept messages and be controlled remotely, but the current information exchange of the IoT is still within the scope of the LAN (Tang and Wang, 2017). The emergence of the IoT addressing system will break the limitations of the IoT, connect numerous islands of information of the IoT, and truly realise global connectivity. At the same time, the IoT will connect various objects in the objective world to the virtual network world, and the number of these objects will be quite large. A large number of objects will exchange information in the IoT at any time, and the addressing system will become an important hub of information exchange in the IoT.

In view of the above analysis, relevant scholars have given some good research results, Kumar and Tomar (2018) proposes the IoT resource addressing method based on IPv6 technology. DNS server is used to resolve the node names of the IoT, IPv6 technology is introduced, different device coding methods in the IoT are analysed, the concepts of direct addressing and indirect addressing are proposed, and indirect addressing method is designed for RFID network. However, due to the strong uncertainty of the IoT resources, the addressing accuracy of this method is low. Nourian (2018) puts forward the challenge of new resource addressing methods for IoT. Based on the identification technology of things in the IoT, combined with the uniqueness of IoT resources and addressing, UDC coding structure is designed, RDDA algorithm is introduced, the key technology of information service discovery in the IoT is analysed, and the addressing of IoT resources is completed. Although the application effect of this method is good, it takes a long time. In Hussain et al. (2017), a resource addressing method of IoT based on machine learning and cellular network is proposed. This paper focuses on the research of the addressing characteristics of the IoT resources, mainly analyses the relevant elements such as resource name and resource address through machine learning, summarises the addressing characteristics of the IoT, and solves the problem of the addressing of the IoT resources. However, the node failure probability of this method is high, which makes this method not widely used.

In order to solve the defect of the above methods, a new resource addressing method based on rough set neural network is proposed. A new rough set neural network decision system is established to effectively solve the uncertainty of IoT resources, enhance the information processing effect and improve the accuracy of the method. A general hierarchical model of IoT addressing is built to reduce addressing time. The resource address is expanded with standard hierarchical structure and extended hierarchical structure information to address the resource and eliminate node failure. Experimental results show that the proposed method can effectively reduce the average searching time and improve the addressing accuracy. In the meantime, the node failure problem is effectively improved.

2 Resource addressing method of IoT based on rough set neural network

The global nature of the IoT obviously has the problem of cross domain communication, so the IoT also needs the support of a set of perfect resource addressing technology to meet its resource addressing needs and promote the interconnection of the IoT. However, due to the uncertainty of the IoT resources, the relevant research results cannot be better applied. To solve this problem, rough set neural network is introduced to obtain the mapping behaviour among entities in the IoT, so as to better address the resources in the IoT.

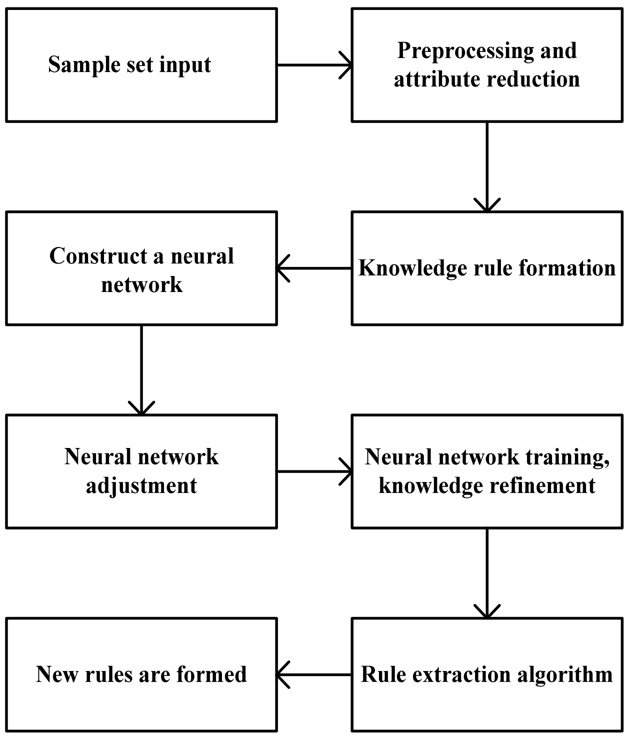
2.1 Rough set neural network modelling

Rough set theory is another mathematical tool to deal with uncertainty after probability theory, fuzzy set theory and evidence theory. As a new soft computing method, rough set has been paid more and more attention in recent years. Its effectiveness has been proved in many successful applications in the field of science and engineering, and it is one of the research hotspots in the field of artificial intelligence theory and application in the world. Rough set theory is based on the classification mechanism, which understands classification as equivalence relation in specific space, and equivalence relation constitutes the division of the space. Rough set theory understands knowledge as the division of data, and each divided set is called concept. The main idea of rough set theory is to use the known knowledge base to describe the imprecise or uncertain knowledge with the known knowledge base. Artificial neural networks (ANNs), also known as

Neural Networks (NNs) or Connection Model, is a mathematical Model of algorithm that simulates the behavioural characteristics of animal Neural Networks for distributed parallel information processing. This kind of network depends on the complexity of the system and achieves the purpose of processing information by adjusting the inter-connected relations among a large number of nodes.

The resources of IoT are mixed and uncertain. Rough set is a promising method to deal with uncertainty. The rough set and neural network are integrated to give full play to their respective advantages, obtain the mapping behaviour between entities in the IoT, and realise the resource addressing of the IoT. Both fuzzy sets and rough sets are used to deal with the problem of uncertainty and imprecision. The structure of rough set neural network is shown in Figure 1.

Figure 1 Specific structure of rough set neural network



Given that the information system is S = (U, A), the information system assumes that it can be expressed in the form of a relational table, then the rows correspond to the required application research objects (Zhang et al., 2019; Bai et al., 2019). When attribute set A is mainly composed of condition attribute set C and decision attribute set D, in addition, the relational table corresponding to information system is called decision table. Rough logic is a theory based on rough set theory, which uses the tools of logic to analyse and process the decision table. The specific basic changes and related theories are given below:

Based on rough set theory, rough logic is a theory uses logic tools to analyse and process the decision table. The specific basic changes and related theory are given below:

Language is mainly composed of language symbol set, mainly including attribute constant set A, attribute value constant set V, then:

$$V = \bigcup V_{\alpha} \tag{1}$$

Given that the information system is S = (U, A), the attribute set is:

$$P = \{a_1, \cdots, a_n\} \tag{2}$$

Because there is a lot of redundant information in the knowledge base (Hu et al., 2016), and all the knowledge is necessary, it can lead to the concept of knowledge reduction. For the rough logic decision algorithm corresponding to the knowledge system, knowledge reduction means the reduction of the whole algorithm.

The rough logic language is mainly composed of symbol set, which mainly includes attribute constant set and attribute value constant set. All the formulas in the rough logic language have certain meanings and can be expressed as the sets of different objects in different domains.

The main advantage of rough logic reasoning is that it can reduce the role algorithm through the relevant rough logic theory, and find a concise and efficient method to effectively solve the actual problem (Li et al., 2017; Kumar and Tomar, 2018). The following are the specific implementation steps, as shown in Figure 2:

(1) Knowledge code in the attribute domain:

Appropriate condition attributes and decision attributes are selected, meanwhile, the attribute domain is discretised and coded.

(2) Knowledge acquisition:

A decision table is formed to describe the relationship between conditions and decision attributes (Nourian, 2018; Hussain et al., 2017). The decision table is mainly formed by actual measurement, test data or expert experience knowledge. The incompatibility of the data in the decision table means that there are too few condition attributes or too many knowledge particles in the equivalent class division. It can be improved by the actual situation. If the distribution of knowledge points is reasonable, the initial decision table can be formed.

(3) Decision algorithm simplification:

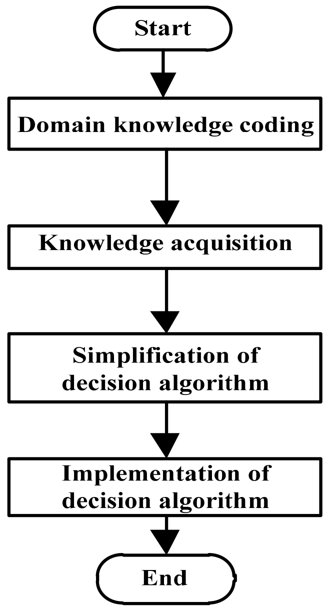
It mainly includes the following:

- attribute simplification
- decision rules simplification
- minimisation of decision algorithm.

(4) Implementation of decision algorithm:

The corresponding decision rules are extracted from the decision table, and the corresponding rough logic neural network is constructed at the same time. On the basis of the above, the practical problems are effectively solved.

Figure 2 Operation flow of the algorithm



On the basis of the above operations, combined with relevant theories, a rough logic neural network is established. The whole network is mainly composed of four parts (Hu, 2016; Jiang, 2016), namely:

(1) Input layer, where the representation of input vector is:

$$x = (x_1, x_2, \cdots, x_N)^T \tag{3}$$

(2) Blur layer:

Through any discretisation method, different input variables x_i are discretised to form r_i different values (Liu and Chen, 2016). Then the fuzzy neuron is used to complete the fuzzification of the discrete interval. Therefore, the neuron excitation function of the fuzzification layer can select the Gauss type membership function. The specific expression is as follow:

$$\mu_i^j = \exp\left(\frac{x_i - c_{ij}}{\delta_{ij}}\right)^2 \tag{4}$$

(3) Regular layer:

Each node in the conventional layer represents different rules. According to the rough logic theory (Sun et al., 2016; Zhang and Zhao, 2016), the acquisition of corresponding rules and the description of related theories are determined. The connection between the neurons in the rule layer and other layers is determined by the pre and post conditions of the rules. The neurons in this layer complete the calculation of rule adaptability. Then the output of the kth neuron R_k can be expressed as follows:

$$O_k^3 = \mu_1^{j1}, \mu_2^{j2} \cdots \mu_n^{jn} \tag{5}$$

(4) Output layer:

This layer is also called the decision layer with output as follows:

$$y_c = O_k^4 = f_4\left(\sum_{l=1}^{p} O_k^3\right) \tag{6}$$

The weight parameters of the network to be adjusted are w_{1k}, the class centre c_{ij} and variance δ_{ij} of equivalent type stratification, which can be trained iteratively by back propagation BP algorithm. In the process of model building, the following two problems need to be solved:

- In the design process, most of the parameters are set in advance. In order to solve the above problems, it is necessary to take the dynamic adaptive algorithm into consideration to learn and achieve division of equivalent classes;
- During the design process of the whole model, incompatible decision rules are obtained, which is caused by too few condition attributes (Chen et al., 2020; Song et al., 2017). The most effective solution is to add condition attributes to get the corresponding decision table, but this is not necessarily feasible, and the attributes to be added may be unknown.

Through simplest decision table which is known as the simplification result of decision algorithm, the corresponding rough logic neural network is established. The input layer consists of three neurons, which contains data of 3 bands. The fuzzy layer contains 10 neurons, which correspond to the discrete interval division of each band. And the rule layer contains 10 neurons, which correspond to 10 simplest decision rules.

By enhancing the information processing ability of rough set neural network, a new decision model is established.

2.2 Implementation of IoT resource addressing

According to the decision model of rough set neural network, the mapping behaviour among entities in the IoT is obtained to form the resource addressing behaviour. The conversion between resource names and resource addresses can be made by the behaviour. Using the addressing function, the specific forms of relevant definition is given as follow:

If the resource name of the IoT is set to R and the resource address is D, then the namespace of the resource name and the resource address can be expressed in the following forms respectively:

$$\text{NameSpace}^{\text{R}} = \left\{R_1, R_2, \cdots, R_j, \cdots, R_k\right\} \tag{7}$$

$$\text{NameSpace}^{\text{D}} = \left\{D_1, D_2, \cdots, D_j, \cdots, D_k\right\} \tag{8}$$

Where, the unary function AS needs to meet the following constraints:

$$\text{NameSpace}^{\text{D}} = \text{AS}\left(\text{NameSpace}^{\text{R}}\right) \tag{9}$$

Where

$$R_i = R_j \Rightarrow \mathrm{AS}(R_i) = AS(R_j) \tag{10}$$

In the process of addressing IoT resources, the IoT resource web address belongs to the relative concept (Lou and Shen, 2016; Nie et al., 2016). If it is impossible to obtain the resource address directly, then it is saved as the basis for addressing other resources, and then continued to search for resources.

If the initial resource name of the IoT is set to Y, the conversion resource name is Z, and the resource address information is D, the spatial names of the three can be expressed in the following forms:

$$\mathrm{NameSpace}^{\mathrm{Y}} = \{Y_1, Y_2, \cdots, Y_j, \cdots, Y_k\} \tag{11}$$

$$\mathrm{NameSpace}^{\mathrm{Z}} = \{Z_1, Z_2, \cdots, Z_j, \cdots, Z_k\} \tag{12}$$

$$\mathrm{NameSpace}^{\mathrm{D}} = \{D_1, D_2, \cdots, D_j, \cdots, D_k\} \tag{13}$$

If the IoT resource conversion function is set as a binary function TS, the following constraints need to be met:

$$\mathrm{NameSpace}^{\mathrm{Z}} = \mathrm{TS}\left(\mathrm{NameSpace}^{\mathrm{Y}}, \mathrm{NameSpace}^{\mathrm{D}}\right) \tag{14}$$

$$Y_i = Y_j \Rightarrow \mathrm{TS}(Y_i, D) = TS(Y_j, D) \tag{15}$$

To ensure the quality of resource addressing system (Han et al., 2016; Lv et al., 2017), it is necessary to cache it and provide a new update mechanism.

The update of cache content mainly involves the issue of update efficiency, which is mainly to improve the addressing efficiency of resource addressing system. However, with the update, the network service problem becomes more and more important.

The security mechanism of resource addressing refers to the security mechanism given in the process of resource addressing, which enables the corresponding relationship between resource name and resource address to be queried for the searcher who meets the authority requirements. However, in the process of operation, the sensitive names contained in the system can only be accessed by users with specific permissions and a specific range (Wang et al., 2017), and in the process of addressing, the above data cannot be monitored and forged by others, so the security of the system needs to be guaranteed.

The relationship between different resource name hierarchy types and addressing mechanisms is detailed in Table 1.

Table 1 Relationship between resource name hierarchy type and addressing mechanism

Hierarchy	*Flat*	*Hierarchical*
WF	Convert	Convert
WT	Direct	Convert
KF	Convert	Convert
KT	Direct	Direct

In Table 1, ‘direct’ means that the resource names belonging to the hierarchy do not need to be converted, and can be used as system input directly; ‘conversion’ means that the resource names in the hierarchy need to be converted, and the converted resource names are used as system input.

On the basis of the analysis in Section 2.1, the IoT resource addressing model is established (Meng et al., 2016). This model is also a theoretical model aiming at the essence of IoT resources and the relationship between addressing systems. The IoT addressing model further divides it into two different sub models, which are divided into:

- hierarchical iterative model
- applied structure model.

Figure 3 shows the hierarchical iterative model of IoT resource addressing.

Figure 3 Hierarchical iterative model of IoT resource addressing

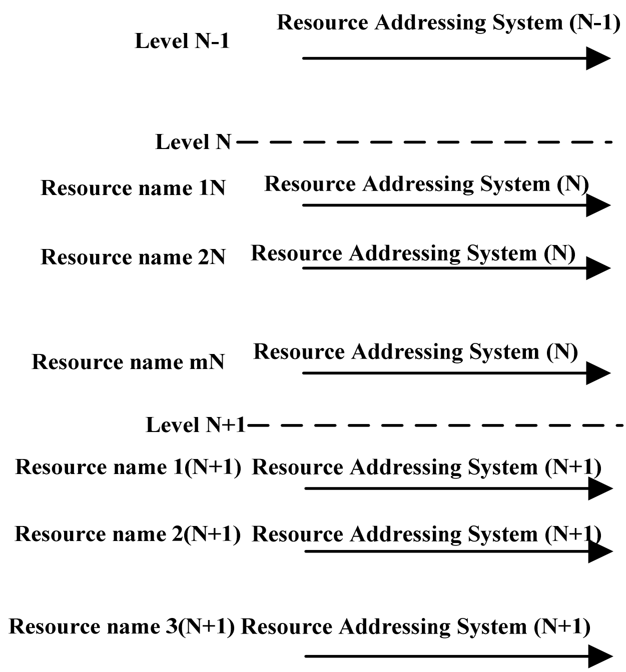
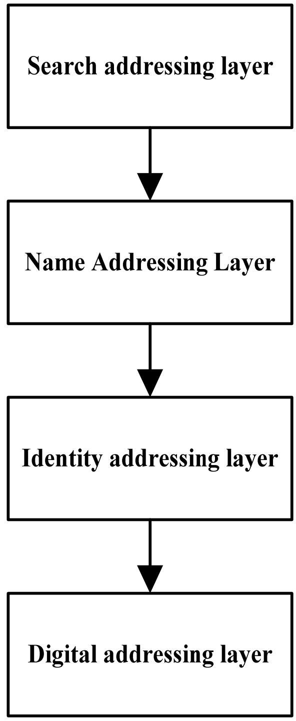


Figure 4 shows the structure model of IoT resource addressing.

Analysis of the above theories shows that the two sub models in the IoT addressing model have laid a solid foundation for the follow-up research. However the support of hierarchical structure for resource addressing is not very perfect which causes the decentralised structure decentralised and unknown. Therefore this method cannot be widely used.

Due to the particularity of the IoT, the original resource names of each level are converted into resource names, and the corresponding addressing information is provided by the previous level output. At the same time, the resource addressing address of current level can also be used as the conversion information for the lower level. Then the resource addressing information is expanded so that the resource addressing is achieved.

Figure 4 Application structure model of IoT resource addressing



3 Simulation experiment

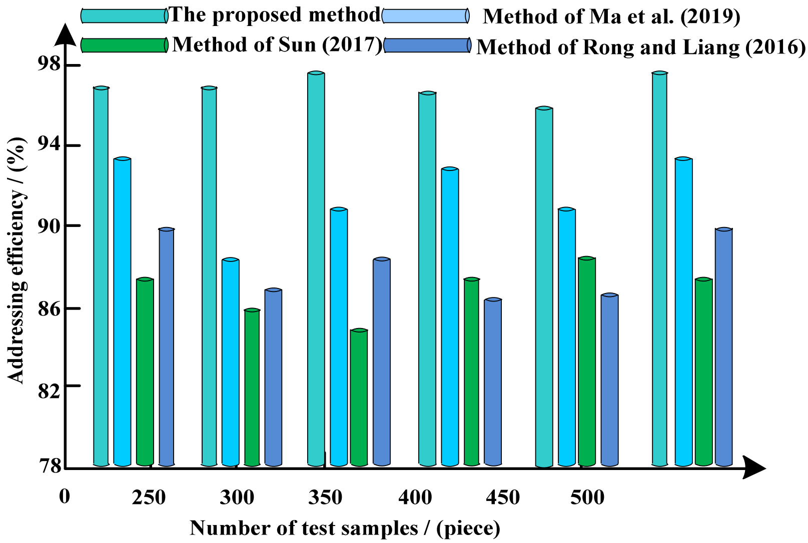
In order to verify the feasibility of the proposed method based on rough set neural network, simulation experiments are needed. The specific environment is: a PC with Windows 10 operating system installed, 16GB memory, 1TB disk, and Intel Core i7-6700hq processor. Taking the methods in Kumar and Tomar (2018), Nourian (2018) and Hussain et al. (2017) as the experimental control group, the test results of the traditional methods are compared with the proposed methods. The experimental indexes include the addressing efficiency, average searching time, failure probability of IoT resources. And the comprehensiveness of experimental indexes can enhance the reliability of experimental results.

3.1 Comparison of addressing efficiency of IoT resources by different methods

In the experiment, three traditional IoT resource addressing methods are selected for simulation test. The specific experimental comparison results are shown in Figure 5.

The experimental data in Figure 5 shows that the addressing efficiency of the proposed method is significantly higher than other methods.

Figure 5 Comparison of addressing efficiency with different methods (see online version for colours)



3.2 *Comparison of average searching time of IoT resources with different methods*

In order to further verify the effectiveness of the proposed method, the average searching time of the four methods are compared as follows, and the specific experimental comparison results are shown in Table 2.

Table 2 Average searching time of the proposed method

	Average searching time / (min)			
Searching times	*Proposed method*	*Method in Kumar and Tomar (2018)*	*Method in Nourian (2018)*	*Method in Hussain et al. (2017)*
20	0.45	0.58	0.64	0.81
40	0.47	0.66	0.71	0.87
60	0.50	0.72	0.75	0.94
80	0.52	0.78	0.84	1.05
100	0.55	0.84	0.90	1.17
120	0.58	0.90	0.96	1.24
140	0.61	0.96	1.03	1.29
160	0.64	1.04	1.08	1.36
180	0.67	1.10	1.13	1.45
200	0.70	1.16	1.17	1.53
220	0.74	1.21	1.22	1.64
240	0.78	1.25	1.26	1.67
260	0.81	1.28	1.35	1.72

Comprehensive analysis of the experimental data in the above table shows that with the continuous increase of search times, the average searching time is constantly changing. Compared with the other three methods, the average searching time of the proposed method is significantly lower.

3.3 Comparison of failure probability of IoT nodes with different methods

As the evaluation index, node failure probability with different methods is compared in the experiment. The results are shown in Table 3.

Table 3 Node failure probability with different methods

	Failure probability of nodes / (%)			
Network nodes	*Proposed method*	*Method in Kumar and Tomar (2018)*	*Method in Nourian (2018)*	*Method in Hussain et al. (2017)*
200	0.120	0.140	0.120	0.145
400	0.118	0.145	0.128	0.152
600	0.114	0.148	0.134	0.168
800	0.111	0.151	0.137	0.174
1000	0.098	0.154	0.140	0.180
1200	0.096	0.157	0.145	0.185
1400	0.094	0.160	0.148	0.192
1600	0.090	0.164	0.152	0.198
1800	0.086	0.168	0.156	0.203
2000	0.084	0.172	0.160	0.210
2200	0.080	0.176	0.168	0.215
2400	0.076	0.180	0.174	0.222
2600	0.072	0.184	0.180	0.228
2800	0.068	0.188	0.185	0.234
3000	0.064	0.192	0.190	0.236

Based on the experimental data in the table, it can be seen that the node failure probability of each IoT resource addressing method is constantly occurring, and the node failure probability of the proposed method shows a downward trend, but the node failure probability of the other three methods increases with the increase of the number of network nodes, which fully verifies the effectiveness of the proposed method.

4 Conclusion

- Aiming at a series of problems existing in traditional addressing methods for IoT resource, this paper designs and proposes a new addressing method for IoT based on rough set neural network. The resource addressing model of the IoT is established, and the best resource addressing scheme of the IoT is given based on the rough set neural network.

- In order to verify the application performance of the proposed method, a simulation experiment is designed. The experimental results show that the resource addressing efficiency of the IoT can reach 96~98% by the proposed method, which is proved to be an ideal application efficiency by numerical simulation. Comparing the average searching time of IoT resources with different methods shows that the time of the proposed method is relatively short. When the number of resource searching reaches 260 times, the time is 0.81 min. Finally, the experimental results show that the proposed method has lower node failure probability and better application performance.
- In the future, we will focus on further improving the addressing scheme for IoT resource supporting different item coding standards, and improving the mechanism of item information discovery.

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