Fast Detection Method for Local Search Target of Community Structure Under Big Data

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Abstract. The traditional detection method has the problems of complicated operation and slow search speed, which brings great impact to the efficient operation of the local search system of community structure. To this end, it studies the rapid detection method of local search target of community structure under big data. Analyze the key technologies for constructing detection methods, use quantitative algorithms to achieve rapid target location, perform resource entry on targets, and calculate data convolution kernel size. The convolution data is statistically analyzed, and the detection result is subjected to parsing and storage, thereby realizing the extraction of the target and completing the rapid detection of the local search target of the community structure. It is proved by experiments that the fast detection method of local search target of community structure has obvious advantages in search time consumption and has a good development prospect.

Keywords: Big data · Community structure · Local search · Target · Rapid detection method

1 Introduction

In the era of big data, the rapid detection method of local search targets in community structure is very important. The reason is that the reconnaissance system can automatically switch the data model to achieve further accurate segmentation of the target, extract the essential features of the target of interest, and lay the foundation for rapid feature matching and automatic determination of the target type. The current local search target detection methods mainly include: a template matching based detection method, which is simple and mature, but requires a target template and is only suitable for target instance detection. The second is based on the detection method of key points, which is invariant to image noise, rotation, scale and illumination changes, but requires a target template and cannot obtain the target area. The third method is based on the segmentation detection method. The method is less affected by noise and the segmentation region is accurate, which is beneficial to the intelligent target recognition, but the segmentation result is unreliable and the calculation amount is large. The fourth method is based on the sliding window detection method. This method is simple and real-time, but the target area cannot be obtained. The classifier needs more supervision information when training. The fifth type is based on the partial detection method. This

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type has good detection effect on the deformed target and the occluded target, but the target representation is complex and computationally intensive, and high-resolution images are needed, which is not suitable for detecting small targets. In this chapter, aiming at the detection speed of traditional detection models, a fast detection method for local search targets of social structures is proposed. By redesigning the social structure, the network depth and network performance are weighed. This paper first introduces the design principle of the target fast detection method, and proposes the design form of various methods according to the principle, and gives the design scheme of the final detection method of the local social structure local search target. Then quantitative analysis of each structure is carried out to judge the rationality of the detection method in advance. Then the local search target fast detection method is merged into the Faster R-CNN model to obtain the target fast detection network, and the self-built data set is used for parameter training to obtain the final detection model. Finally, the validity of the network is verified by experiments.

2 Analysis of Rapid Detection Method for Local Search Target of Community Structure Under Big Data

2.1 Key Technology Analysis of Target Rapid Detection Method

Community structure local search target rapid detection method construction involves many aspects, and each content is closely related. For example, the ontology classification and the attribute description of the ontology class determine the construction of the judgment matrix between the organizations, and also affect the design of the storage table of the device component instance. The judgment matrix affects the selection of the device component type. The design of the storage table of the device component instance will affect the efficiency and quality of the instance query [1]. Therefore, based on the analysis of relevant research, combined with the current status of detection methods, the key technical analysis of the rapid detection method of local search target of community structure is as follows: The first detection equipment component modular analysis and modeling technology, the detection equipment can be regarded as a mechatronics equipment. Different from general mechanical equipment, electromechanical equipment has higher accuracy requirements, faster response speed, better stability and better rigidity. It also has to have good reliability, light weight, small volume, long life and other requirements. In order to meet these requirements, the testing equipment shall classify the components that constitute the non-standard testing equipment in detail, and describe the performance attributes of each component in detail. How to use effective modeling methods to divide non-standard components and describe their attributes will be the focus of this paper. The second detection device component instance storage technology, and the instance storage of the detection device component is the basis and premise for implementing the selection query. It is also one of the research points to effectively store non-standard equipment components with strong heterogeneity to ensure the efficiency of query matching. The third device component selection and instance detection technology, after the device resource library is constructed, realizes the classification and storage of the device resource library, and constructs the premise of device component selection and instance retrieval. How to select the fast equipment components when the new testing equipment requirements come, and to find and match the existing resources in the resource library is also one of the focuses of this paper.

2.2 Overall Model Framework

The overall architecture of the local search target fast detection method is shown in Fig. 1.

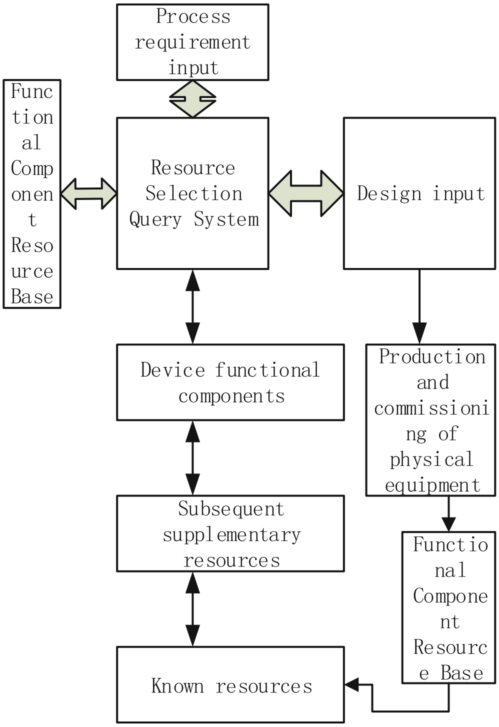

Fig. 1. Overall architecture of the rapid detection method

First, under the guidance of industry experts, build a library of device feature resources that contain existing knowledge and open interfaces for future entry of new resources. The resource in the resource library contains two parts, one of which is the description of the device component, including the device component class description, the device component attribute description, and the judgment matrix between the attributes; the second is the instance storage of the device component [2]. After the resource library is built, when the detection device requires input, the query matching is performed through the selection query system, the selection of the device components is completed, and the available device functional components are output. The designer uses the functional component as a guide to design the equipment. After the design is completed, the virtual prototype model of the non-standard equipment key components is constructed. The simulation software is used to simulate the key components, and the software design is used to analyze the existing design scheme. If the design scheme is satisfied, the production and debugging of the physical equipment can be performed. If it is not satisfied, the design will be modified according to the generated problem [3].

2.3 Web Search Model

The parameters in the convolutional neural network are derived from the number of convolution kernels in each convolutional layer, and the structure of the single-layer convolutional layer is more complicated [4]. When a feature map with a channel number of M passes through the convolutional layer, a convolution operation is performed separately with each convolution kernel. And forming, by the activation function, one channel information corresponding to the output feature map, the plurality of convolution kernels such that the output feature map remains multi-channel. In order to obtain more complete feature information, this requires a deeper level of network, with more convolution kernels per layer. This leads to a huge computational overhead of the network, affecting its extraction speed. Therefore, the design direction of optimization and improvement for convolutional neural networks is to achieve good feature extraction performance when the number of network layers is shallow. In addition, according to the parameter source analysis, the number of channels between layers has a direct impact on the number of parameters and computational overhead. Therefore, the main design principle of the optimization and improvement of the convolutional network is to reduce the number of channels between the convolutional layers, reduce the parameter size and reduce the computational cost by the low channel number [5]. In order to reduce the number of channels, the number of points convolution channels must be selected to be smaller than the input feature map and the number of channels in the convolutional layer. The number of channels in the convolutional layer is positively correlated with the number of its parameters. By reducing the number of channels in the input to output process, the parameter size of the convolutional layer can be reduced. Therefore, the CR-mlpconv structure can effectively reduce the scale of convolution parameters of the convolutional layer and reduce the complicated computational cost caused by the number of parameters, while maintaining its feature extraction performance. Combined with the above structure, this paper proposes a hybrid structure CNN model [6]. The model adopts a full convolution structure design. Only 6 layers of convolutional layers are used in the network for concatenation, which reduces the information loss caused by the pooling layer and the excessive parameter size brought by the full connection layer [7]. In addition, in order to further reduce the parameter size of the network, according to the main design principles of structural optimization, the CR-mlpconv convolutional layer structure proposed in this paper replaces the original convolutional layer and uses the C.ReLU strategy for synergy. Therefore, in the hybrid structure convolutional neural network structure designed in this chapter, the first layer is still the standard convolutional layer, and the other five layers are all CR-mlpconv convolutional layer structure. At the same time, in the first three layers of the network, the C.ReLU strategy is adopted, that is, the second and third layers are further mixed of the CR-mlpconv structure and the C.ReLU policy.

2.4 Convolution Nuclear Quantitative Analysis

In a typical convolutional neural network, assume that the k-th layer convolutional layer input feature map size is $D_M \times D_M \times M$, where M is the number of input image channels. After the convolution operation, the output feature map size is $D_M \times D_M \times N$, where N is the number of output channels, it can be clarified that the convolution layer is composed of N convolution kernels. Assuming the size of each convolution kernel is, there are:

$$D_N = \frac{D_M - D_K + 2P}{S} + 1 \tag{1}$$

Where P represents the width of the edge fill and S represents the sliding step size of the convolution kernel [8]. This paper assumes that the input length and width of a typical convolutional neural network are equal and there is no bias term. The parameter number Pk and computational cost Ck of the k-th layer convolutional layer are as follows:

$$P_K = M \times N \times D_K \times D_K \tag{2}$$

The above formula can be seen that the number of channels is positively correlated with the number of parameters and the computational cost, which indicates that reducing the number of channels can reduce the parameter size of the network model [9]. For the CR-mlpconv structure, the selection criterion of the number of channels N' of the dot convolution is that the number of input channels M and the number of output channels N are about three times N'. Then the number of parameters of the kth layer convolution layer becomes $p'_k = M \times N' \times 1 \times 1 + N' \times N \times D_K \times D_K$. The computational overhead becomes $C'_K = p'_k \times D_N \times D_N$, compared to the original convolution structure:

$$\frac{p'_k}{P_K} = \frac{C'_K}{C_K} = \frac{N'}{N \times D_K \times D_K} + \frac{N'}{M} \tag{3}$$

According to the appropriate choice of N', the CR-mlpconv layer structure can reduce the number of parameters and computational cost of about 45% to 80%.

3 Realize the Rapid Detection of Local Search Target of Community Structure Under Big Data

3.1 Extraction of Local Search Targets

The user can use the Client to perform resource entry and process requirement submission of the resource library, and present the selection result to the designer for guiding design after Sever performs device component selection feedback. So the Client operation is simple and the results are intuitive. C#.Net is an object-oriented programming language released by Microsoft [10]. Its Windows Forms program development module is suitable for writing interface software under Windows platform. Therefore, based on the VS2013 development platform, this article uses the Windows Forms application module under C#.Net to write the client software. The Client may be logged in by multiple people at the same time, so the user name and password are required for user differentiation. After logging in to the page, first confirm the IP and port number of the data center Sever, which is used to establish Socket communication with Sever. The IP and port numbers are the default under normal circumstances, and can be modified without modification. Only after the Sever address changes will be modified. Enter the username and password. Different user name suffixes represent different permissions. “usemame_Add” means the user who adds data to the server. “usemame_Submit” indicates the submitting user of the process requirement [11]. There is a click interface “Sever connection and user login test button”, the verification pass shows “Severe connection Sever and verify user information through”, if there is no pass, there will be corresponding prompt information. For example, “User name and password are incorrect”, “Server connection error”, etc. After the verification is passed, click OK to display the next level application interface [12, 13].

Simulating the community structure is the basis and premise of the local search target detection method. Simulating the community structure can reduce the delay of local search target detection. At present, there are two community structure simulation methods, one is based on the physical model, and the other is based on the mathematical model. Firstly, the local search target status of clock synchronization is analyzed through the simulation calculation of the community structure, and then the local search target detection node is set on the community structure, and the local search target detection method is analyzed through calculation.

The relationship between the background position q_{i-leak} of the community structure node and the local search target position is as follows:

$$q_{i-leak} = aQ_i^{red} H^{avl} \tag{4}$$

In the formula, Q_i^{red} represents the location of the local search target node i of the community structure; a represents the local search target node simulation parameter; H^{avl} is the node background location coefficient.

The relationship between the position of the local search target node and the positioning coefficient is shown in Eq. (5):

$$Q^{val} = \begin{cases} Q^{red}, H^{red} \geq H^{des} \\ Q^{red}\left(\frac{H^{avl}-H^{\min}}{H^{des}-H^{\min}}\right)^{\frac{1}{a}}, H^{\min} \leq H^{avl} \leq H^{des} \\ q_{i-leak}, H^{avl} \leq H^{\min} \end{cases} \tag{5}$$

In the formula, Q^{val} represents the actual position of the local search target node; Q^{red} represents the detection position of the local search target node; H^{des} represents the critical positioning coefficient of the local search target node; $H^{\min}$ represents the minimum positioning coefficient of the local search target node.

The addition of instance data is divided into transmission mechanism attribute entry, detection sensor mechanism attribute entry, guidance mechanism attribute entry, and actuator attribute entry. It also adds an interface to quickly check that the matrix is consistent, as shown in Fig. 2.

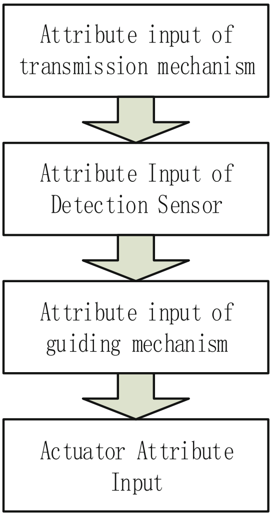

Fig. 2. Addition of instance data

The addition of each instance data includes four parts, one is the addition of public attributes, that is, the information attributes mentioned in Chapter 3, and the second is the attribute addition of the instance type. Three and four are manually added for the public attribute manual addition and the transmission attribute, respectively, to add unique attributes that are not intersected between the same type of equipment components. After the instance data is added, click the OK button. The Client encapsulates the attribute into an XML file and transfers it to Sever for data storage via Socket. After the data is stored, in order to facilitate the information exchange between the client and the server in the programming, and in order to facilitate the subsequent query, the data needs to be encoded first. The class hierarchy is coded according to the class structure diagram of the ontology design, and each level code is divided into two parts. The first part is the first two acronyms and numbers of the class name, and the class level code 0 number can be in the order of modeling in the ontology. The other class hierarchy codes are below the level code 0, the order in the modeling tool is arranged in lexicographic order, and the layer codes outside the 0 level are numbered according to the acronym and the lexicographic order. The existence of the lexicographic number can make it impossible for the class hierarchy to be the same even if the acronyms are the same.

3.2 Local Search Target Rapid Detection Process

The server is running the Hadoop platform. The development environment is shown in Table 1.

Table 1. Sever development environment

Project	Version specification
Operating system	Ubuntu16.0.43 LTS
Hadoop	2.8.2
HBase	1.3.1
Zkeeper	3.4.11
Eclipse	Jee-oxyen-la
JDK	1.8.0

The task submitted by the client is parsed by DOM4J to determine the task file type. If it is an instance storage file, the API in the table is called for instance storage. If not, the task file type is the organization selection file. First, the hierarchical analysis is performed to generate the selection result. The HBase instance query is performed by the hierarchical analysis result, and finally the result is returned to the package.

4 Experimental Results

The experiment performs target detection tasks for common community structure goals, and the pre-training network is trained by the classification task of 24 categories of targets. The pre-training network training dataset is derived from the SubImageNet dataset, and both the training set and the test set data of the target detection network are derived from the SubVOC dataset. In the experiment, the target rapid detection network is trained. At the same time, the two common network models are trained by using the same data set and the same training mode. The obtained network model is compared with the target rapid detection model of this paper. The experimental results are shown in Table 2.

Table 2. Experimental results

Model	Parameter quantity	Computational overhead	Running memory(MB)	Running time(ms/fps)	MAP
Fast target detection network	1187 K	451.4 M	895	32/31	44.5
Fastr R-CNN (VGG-16)	34 M	13.5G	5525	128/7	56.2
Faster R-CNN (ZFNet)	3725 K	1.2G	1227	47/21	43.5

It can be seen from Table 2 that the detection performance of the target rapid detection method proposed in this paper is 44.5%, which is −11.7% and +1.0% compared with the detection performance of the other two models. However, in terms of parameter quantity and computational cost, the advantage of the target fast detection data presented in this paper is obvious. The model can reduce the number of parameters by 69% and 95%, respectively, and reduce the computational cost by 69% and 95% respectively.

In order to ensure the effectiveness of the rapid detection method of local search target of community structure under the big data proposed in this paper, experimental demonstration is carried out. Compared with the traditional detection method, the search target consumption time is compared, and the experimental results are shown in Table 3.

Table 3. Search target consumption time comparison table

Number of experiments/time	Traditional method/s	Improved method/s	Time ratio
1	2.565	0.621	4.13:1
2	3.192	0.782	4.07:1
3	2.506	0.930	4.03:1
4	3.441	0.622	3.71:1
5	3.494	1.0922	3.02:1

It can be seen from Table 3 that under the same conditions, the traditional method takes about 3 s, while the proposed method takes about 0.9 s; the rapid detection method of community structure local search target has obvious advantages, and this method can greatly improve The operating speed is of great significance.

5 Conclusion

The so-called target detection is to simulate human visual organs and brain systems by combining techniques such as image processing and machine learning algorithms, and to accurately locate and accurately represent the target in an unknown image. It usually includes two subtasks: target location and target recognition. Target location is to search for the target in the image and frame the location of the target. Target recognition is to classify and identify the target of the search location. In the context of the era of big data, the rapid detection method of local search target of community structure is one of the important basic research topics at present, and also the cornerstone of many related research questions. The main deep search model used is convolutional neural network, which is also the research focus of this topic. Through the analysis, optimization and reconstruction of the CNN model, combined with the existing target detection methods, a target rapid detection network is established. Then, according to the impact of purely improving the detection speed on the network detection accuracy, the corresponding optimization strategy is adopted to further weigh the detection speed and detection accuracy of the CNN-based target detection model, which has important research value and significance in application engineering.

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