A Distributed Data Collection System for Traffic Images

Wen Bo[1,2], Hongju Yang[1], Jiaojiao Xiao[2], Liangyan Li[2], and Changyou Zhang[2](✉)

[1] School of Computer and Information Technology, Shanxi University, Taiyuan, Shanxi, People's Republic of China
[2] Laboratory of Parallel Software and Computational Science, Institute of Software, Chinese Academy of Sciences, Beijing, People's Republic of China
changyou@iscas.ac.cn

Abstract. With the development of intelligent traffic system, high-definition cameras are spread along the urban roads. These devices transmit real-time captured images to data center for multi-purpose usability, but these bring higher requirements on network and storage capacity of the traffic images collection system. To address these problems, we proposed a compressed representation method for traffic images and collection system architecture. Firstly, the method proposed in this paper designed a distributed data collection system for traffic images based on edge computing mode. Secondly, we studied on the image feature representation methods for vehicle type/version retrieval, and formed a compressed representation method based on structural relationships selections. In this method, the retrieval precision reaches to 97.78% with the recall ratio of 90%, which proved the usability in this image collection system. Finally, we set up an analysis model based on Petri-net to observe the system requirements on storage, computing and transmission with different setting parameters. This model is powerful on finding bottlenecks of system in early stage and keeping balance in multi-aspects. The simulation experiments show that the data volume needs to be transported and preserved was compressed to 1/2250 comparing to the method of original images and the system transport delay was reduced more than 1/9 of original method. The experimental result showed that compared with the original collection method, the amount of data to be transmitted and stored was compressed by 1/2250, and the system transmission delay of the system was reduced to 1/9.15. This distributed data collection method and system proposed in this paper provided a novel referable revolution for traffic images processing system in intelligent traffics.

Keywords: Traffic images · Data collection · Vehicle type retrieval · Edge computing · Petri-net

1 Introduction

In the dynamic environment of photographing traffic images, a large number of real-time, high-speed and uninterrupted data flows are generated at traffic checkpoints. As a result, the opportunities and problems are caused by data. According to Cai, scalable

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storage, filtering and compression schemes are essential for efficient data processing [1]. If all data is dumped into the storage space, it will cause "data swamp" [2]. Liu Zilong and others explained a big data storage platform called "data Lake". Its main idea is to uniformly store different types of original data in different fields, including structured data, semi-structured data and binary data, so as to form a centralized data storage set containing all forms of data [3].

Edge computing, which is on the side near the source of the object or data source, adopts an open platform integrating network, computing, storage and application core capabilities, which can provide services nearby [4]. For the Internet of things, multiple computing nodes distributed on the network can unload the computing pressure from the centralized data center, and can significantly decrease the waiting time in message exchange [5]. Each traffic image usually contains multiple vehicle targets. Target detection based on deep learning is mainly divided into target detection algorithm based on candidate region and target detection algorithm based on regression [6]. In 2014, Girshick proposed region CNN [7] target detection algorithm. In 2015, Girshick proposed Fast R-CNN [8] and Faster R-CNN [9]. In 2017, He Kaiming proposed Mask R-CNN [10] target detection algorithm based on Faster R-CNN framework. In 2018, the YOLO-V3 [11] algorithm improved the problem of poor detection accuracy of small targets detection through multi-level prediction. The data transmission process between devices uses the network for communication. In the scenario of industrial Internet, the realization of high-efficiency automation needs to complete real-time operation control. If some steps are delayed due to not receiving instructions in time, the service quality will be reduced and even the system will crash. Therefore, higher requirements are put forward for the delay, which needs to be between 1 and 10 ms [12–14]. Petri net model is used to simulate the branches of interaction in the system. It has rich system description means and system behavior analysis technology. The concept of net was first proposed in the dissertation of Dr. Petri [15, 16], which is the cornerstone of the development of Petri net theory.

Distributed data collection system for traffic images method is the basic requirement of improving data storage, data transmission and making full use of the computing power of edge nodes. This paper proposed a distributed data collection system for traffic images. The features of vehicle structure relationship are extracted by intelligent traffic checkpoint and are expressed as lossy compression. This method realizes the vehicle model retrieval under the specific scene-traffic image. It also realizes efficient the transmission of relevant data to all levels of communication information center storage. Finally, the rationality of traffic image distributed data collection method and the functionality of the system are verified by experiments.

2 The Framework of Traffic Images Collection System Based on Edge Computing

To reduce the load pressure of storage, transmission and computing brought by massive traffic data, a traffic image collection system based on edge computing was designed. By using Internet and intelligent devices deployed in traffic junctions to finish images collection, edge computing and data transmission functions, and further achieve typical applications like vehicle model retrieval based on traffic images.

2.1 The Design of System Structure

The edge computing based on distributed data collection system for traffic images consists of image collection point, traffic communication center, data processing server and storage server, as shown in Fig. 1.

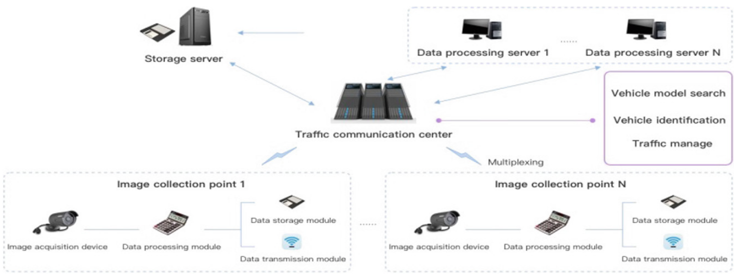

Fig. 1. Edge computing based on traffic images collection system

The deep learning neural network is embedded into the distributed image collection devices to improve the learning ability and reduce network traffic. The image collection point is the resource of traffic images, including data processing module, data storage module and data transmission module. Firstly, the HD camera can collect original traffic images, then use data processing module to achieve efficient object extraction and detection. The data processing module can transform the structural feature information into a lossy compressed representation text. Data transmission module uses network technologies like 5G and Ethernet to transport compressed representation text to network transmission data center in multiplex transmission. At the same time, the data storage module completed the storage function of text and images, and transmitted traffic images to the network transmission center for storage at idle time.

The platform of data transmission center has massive data computing servers and large data storage space. Data processing servers in network transmission center are used to compute, optimize and analyze the lossy compressed representation text; Data storage servers are used to storage traffic images and text information. By this platform, the recognition and retrieval of vehicle model can achieved, traffic scheduling and other typical applications.

2.2 System Features

The compressed representation method based on traffic images enabled the system to store more traffic images information in a same data storage size. With the emergence of the compressed representation method, the information transmitted can be greatly increased when the data transmission traffic is the same, and also greatly improved the real-time transmission. The data collection of edge nodes is also based on the compressed representation method. Data is computed on edge nodes and transferred the processed data to the traffic communication center. Compare transferred original data to the cloud computing center and centralized processing, this method greatly saved network bandwidth and made sure edge computing capabilities are fully utilized.

The system is based on a hierarchical network structure, and data is transferred from the distributed storage nodes to the upper layer according to the tree structure to ensure the correctness of the data and improve the storage efficiency, as shown in Fig. 2.

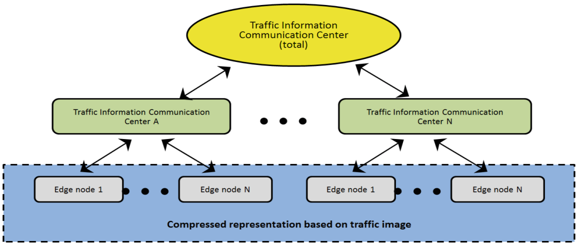

Fig. 2. The hierarchical network structure of system

The system has the distributed feature in both data collection and storage process. When the network bandwidth is poor, the edge nodes can still collect data and store in its data storage space to reduce the time wasted in data transmission process.

3 Compressed Representation of Traffic Images

The compressed representation of traffic images firstly extracts multiple vehicles from the original traffic images according to the edge node target. Then extract the effective structure information of multiple components from the target vehicle. Finally, it is represented as a text with vehicle structure information.

3.1 Data Format

The original traffic data collected by the edge node is a ".png" image with a size of about 2 M. After edge calculation, the target vehicle is a ".png" image with a size of about 500 KB. Finally, the image is represented as ".txt" text with size of about 200 bytes by traffic image compression representation.

3.2 Image Sub-target Extraction

Deep learning is applicable to edge computing environment and intelligent transportation [17]. Yolo-v3 neural network algorithm has the advantages of high precision and fast speed for small target detection, which is used as the function of target extraction in the traffic images in this paper.

Due to the complex background of the image taken by the intelligent traffic junctions, it may contain many kinds of objects. In order to extract the structural vehicle features to get the lossy compressed representation text, the single vehicle in the first step should be extracted. Firstly, use the original traffic images to train the YOLO-V3 neural network model to detect and extract vehicles quickly. As shown in Fig. 3, the target vehicle image extracted by the YOLO-V3 model throws away complex backgrounds and duplicate targets, reducing the storage space by about 75%.

Note: the license plate information is hidden

Fig. 3. Vehicle target extraction from original traffic image

Then extract the structural features of the vehicle images. After the edge calculation, the single vehicle target images realize the multi-component target detection by the YOLO-V3 neural network model, extracts the component structure information, and represents the traffic images information as text information, as shown in Fig. 4.

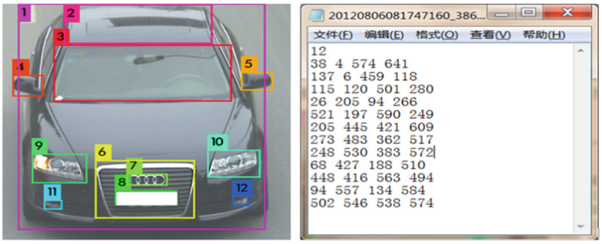

Fig. 4. Compressed representation of multi-part target extraction

Compressed representation text occupies about 200 bytes of storage space. Compared with the original images, the compressed representation of the image greatly reduces the storage space, providing new possibilities for data storage mode and fast data transmission in the future.

3.3 Deployment Requirements for Extraction Methods

Put forward the deployment requirements of validity and accuracy for the extraction method, so carry out validation experiments on the typical scenario of vehicle model retrieval. First of all, using the component pixels in the text to construct the structural features of vehicle components, establish a vehicle structural feature model. Then, in order to improve the computational efficiency, filter out the invalid features by voting, and optimize the vehicle structural feature model. Finally, analyze the weight of the remaining features, establish the vehicle structure weighted feature model. The vehicle retrieval experiment results are shown in Fig. 5.

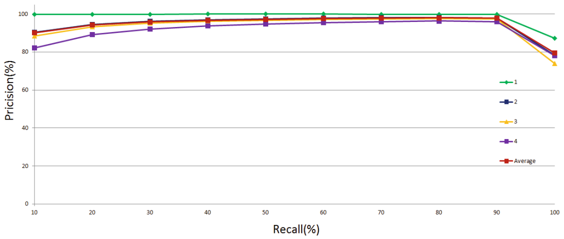

Fig. 5. Vehicle type retrieve P-R diagram

The 4 types of vehicle samples for vehicle type were used retrieve experiments. Among the several types of vehicles, the best results are the first type of vehicles, achieving an optimal precision rate of 99.83% when the recall rate is 90%. The fourth type of vehicle achieved an optimal precision rate of 95.89% when the recall rate was 90%. The average precision of the sample of the four types of vehicles is up to 97.78%. The experiment fully proves the validity and accuracy of the method.

4 Deployment of Traffic Images Compression Method

Based on big data and edge computing, our distributed data collection method for traffic images embedded deep learning neural networks in distributed collection image intelligent devices to improve learning performance and reduce network flow. With the migration of data in the system, the data transmission center is also changing. Therefore, a deployment way based on the traffic images compression method was established, as shown in Fig. 6.

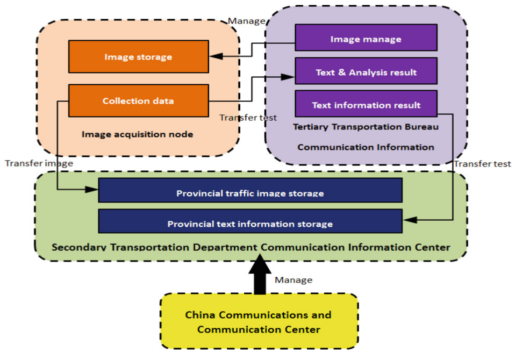

Fig. 6. Deployment way based on traffic images compression method

Firstly, extract the target images from the original traffic images obtained from the image collection node. Then, calculate the text data and transmitted the text data to the Tertiary Transportation Bureau Communication Information Center for calculation and storage. As well as the text data and analysis results were transferred to the Secondary Transportation Department Communication Information Center for preservation. After that, the target image data was transmitted directly from the edge node to the secondary unit. Finally, China Communications and Communication Center (level 1) can call all secondary storage. In this process, the tertiary traffic units do not save the image data, and the image data can be directly called from the collection point storage module, which will save the storage load pressure of the three-level unit.

5 System Simulation Verification Based on Colored Petri-Net

In order to verify the rationality and functionality of the distributed data collection method for traffic images, a colored Petri-net model for the whole system based on the data storage and transmission was established.

5.1 Petri-Net

Petri-net is suitable for describing asynchronous and concurrent computer system models. Petri nets have both strict mathematical expressions and intuitive graphical expressions. It has rich system description methods and system behavior analysis techniques [18, 19]. The definition of the Oriented Net in it is defined as 1.

Definition 1. Oriented Net.
N = (S, T, F) is called oriented net, if and only if:

(1) $S \cup T \neq \emptyset . S \cap U = \emptyset$;
(2) $F \cap (S \times T) \cup (T \times S)$;
(3) $dom(F) \cup cod(F) = S \cup T, where, dom(F) = \{x | \exists y : (x, y) \in F\}, cod(F) = \{y | \exists x : (x, y) \in F\}$ are the domain and value range of F respectively.

S is place set of N, T is transition set of N, F is flow relationship.

5.2 System Modeling Based on Colored Petri-Nets

In the model of distributed data collection, data transmission analysis needs to consider various factors. For example, image information and text information have different transmission timeliness. As well as, there are differences in the data storage space of information communication centers at all levels. Therefore there are differences in the types of storage data and the timeliness of calling storage data at different levels of information and communication centers.

The colored network system is a type of advanced Petri net that defines the token color to distinguish the types of resources which enhances its ability to describe the system [19, 20]. In the system, the storage nodes are mapped to places and the related parameters are mapped to places tokens in place. The different information communication centers correspond to the different colors of tokens and the parameter information corresponds to the value of token, which are both important elements in traffic images based distributed data collection system.

The corresponding relationship of elements is shown in Table 1.

Table 1. The corresponding relationship of elements

Service value chain element	Petri-net element
Data transmission	Transition
Storage node in the system	Place
Related parameters	Token
Transmission control	Connection
Information and communication center	Token color
Parameter information	Token value

On the basis of the colored Petri-net, the control unit is added to represent the data storage, transmission control, information communication center scheduling, etc. The distributed data collection net system for traffic images is defined as 2.

Definition 2. Traffic images based distributed data collection system.
The necessary and sufficient condition for $\Pi = (P, T; F, C, K, D,)$ to be called a distributed data collection net system is:

(1) $\sum = (P, T; F, C,)$ is colored network system
(2) $t \in C$, $D(t)$ is the control function of Transition t
(3) $p \in P$, $K(p)$ is the resource limit function of the Place p.

5.3 Construction of System Petri-Net Model

First, use CPN-tools to build the traditional traffic data collection system model, as shown in Fig. 7. The original image is usually transmitted by using the traditional model. Data are kept in traffic information centers at all levels. Although access time is not required, the transmission time is greatly increased.

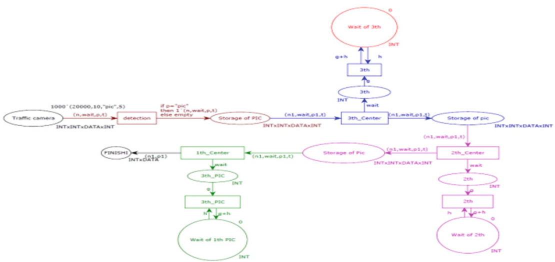

Fig. 7. Petri-net model of the traditional traffic data collection network system

The traffic cameras capture the original images and save them in the data storage node. Then, transfer the original data to the Tertiary traffic information and communication center for preservation and processing. After that, the data and results are transmitted to the Secondary traffic information and communication center for storage and use. If the primary center wants to use the data, data transmission will be required again. This method transmission not only wastes the data storage space and computing power of the intelligent traffic junctions, but also increases the data transmission duration and load, which causes the unnecessary expenses of establishing and maintaining data space of the traffic communication centers.

The storage and scheduling of data has been mentioned in the previous chapter. The Petri-net model of the distributed data collection system for traffic images Petri-net model of is shown in Fig. 8.

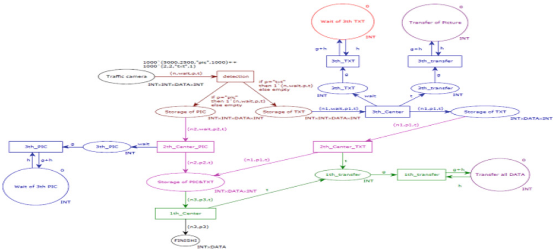

Fig. 8. The Petri-net model of the distributed data collection system for traffic images

The Petri-net model of the distributed data collection system for traffic images solves the problem of information island between multi-level traffic communication centers reduces the maintenance cost of the large-capacity data space in transportation units, and avoids the repeated establishment of storage space. As well as, the method solves the wastage of computing resources in the edge nodes and ensures that the centers at all levels make full use of the optimal data space to complete the tasks of upstream and downstream collaboration.

5.4 Experimental Environment and Parameter Settings

The experiment simulates the runtime system model on CPN Tools 4. 0. 1. CPN Tools support the standard ML language and provide basic data type definitions, data operation descriptions, etc., so as to build a concise parametric mathematical model. In the experiment, defined the range of values of data, detected the duration of the transmission and call of each Token record, and verified the effectiveness of the distributed data collection method for traffic images. The descriptions, types and abbreviations of the main parameters defined in this paper are shown in Table 2.

Table 2. Descriptions of the main parameters

Description	Type	Abbreviation
data size	int	n
data transmission duration	int	wait
data type	string	p
data call duration	int	t
traffic communication center time	int	g
iteration time	int	h
data file type	string	pic,txt

5.5 Experimental Data

The traditional model of traffic data collection net system and our model of the distributed traffic data collection net system are tested in the 20 M Ethernet network environment. Experiment tested 1000 original traffic images data with a size of 2 MB by using the traditional system model, and obtained the results of transmission duration and storage space. As a contrast, 1000 targets extraction vehicle images with a size of 450 KB and 1000 compressed representation texts of images with a size of 200 bytes were tested, and obtained the experimental results of transmission duration, scheduling time and the size of storage space.

5.6 Result Analysis

In the experiment of verifying the rationality of the traffic images distributed data collection method and the function of the system, implemented node functions through different methods of data transmission, storage and scheduling. Expected results are mainly in three aspects as follows. From the perspective of data storage, the data collection methods proposed can greatly reduce storage space and waste of resources. From the perspective of the total time of traffic communication center, the traditional method data scheduling transmission takes much longer than the method designed. From the perspective of cost, the data collection methods proposed can save a lot of cost in data space establishment and maintenance. The results are shown in Fig. 9 below.

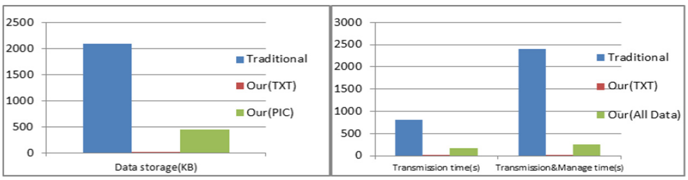

Fig. 9. Comparison of experimental results

Experiment took 1000 images from the camera in the intelligent transportation checkpoint, and transmitted and dispatched them in the 20 M Ethernet network environment. There are some main network parameter settings. Because there is no decimal definition in CPN-Tools, set the parameter n1 representing the original data size to 20970, the parameter n2 representing the storage size of the target extraction vehicle image is 4500, and the parameter n3 representing the size of the compressed description of traffic image is 2. Again, set wait: wait1 = 800, wait2 = 175, wait3- = 78. And set t: t1 = 0, t2 = 87, t3 = 39. It should be noted that wait3 and t3 are both in microseconds, and the other parameters are in milliseconds.

Compared with the traditional method, this method proposed reduces the storage space of the original image by 10485 times and the storage space of the target extracted by the vehicle image by 2250 times. The node transmits compressed text about 78 ms long, which is 10256 times shorter than the original image transmission time. And compared with the total time of three-level traffic communication center is 2400S in the traditional method, the total time of single vehicle image transmission and data scheduling is about 262.2 s in our method, which is about 9.15 times shorter. Compared with the traditional method, the distributed data collection method for traffic image greatly decreases the size of data storage space, reduces the transmission time of data scheduling and the pressure of communication load, and saves the cost of establishing and maintaining the data space. The rationality of the distributed data collection method and the functionality of the system are proved by simulation experiments.

6 Conclusions and Prospects

This paper verified the rationality of the distributed data collection method and the functionality of the system from the perspective of data form, storage and transmission, designed the data storage and transmission collaboration scheme of traffic communication center, optimized the traffic data collection method. And we simulated the process of data storage and transmission, and then analyzed the experimental results. The experimental results show that collection method for traffic images greatly save the data communication bandwidth, and the computing power of the edge node is fully utilized. Moreover, the size of data storage space is greatly reduced while we can effectively retrieve the vehicle models. And the data transmission duration and the communication load pressure are also reduced. Based on this method, in the future this method can be used for the detection of image structure similarity, image recognition and retrieve, urban planning, smart transportation and other big data storage and application from Internet of Things in distributed scenarios. However, there are still some shortcomings that need to be further improved. For example, there are few types of vehicle retrieval in data sets, and few network parameters designed in the system. The multi-classes vehicle retrieval and network parameter expansion is the next research direction of this paper.

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