Artificial Intelligence Based Traffic Control for Edge Computing Assisted Vehicle Networks

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Abstract

Edge computing supported vehicle networks have attracted considerable attention in recent years both from industry and academia due to their extensive applications in urban traffic control systems. We present a general overview of Artificial Intelligence (AI)-based traffic control approaches which focuses mainly on dynamic traffic control via edge computing devices. A collaborative edge computing network embedded in the AI-based traffic control system is proposed to process the massive data from roadside sensors to shorten the real-time response time, which supports efficient traffic control and maximizes the utilization of computing resources in terms of incident levels associated with different rescue schemes. Furthermore, several open research issues and indicated future directions are discussed.

Keywords: Vehicle networks, Edge computing, Traffic control, Artificial intelligence (AI), Real-time responses

1 Introduction

With the ever-growing of city transportation, traffic congestion in smart cities has become a serious concern. Most of the existing traffic control policies (such as adding extra infrastructures, using traffic signals, and so forth) are not adequate to deal with the increasingly congested traffic conditions arising from the explosive transportation growth. Currently, most of the traffic control systems for cities leverage predetermined timing to operate traffic signals, which are not very efficient. Since green traffic signals will not be adjusted dynamically according to the real-time traffic conditions. In other words, it is non-intelligent, that is, not able to learn from past events and renew the traffic signal control scheme. For example, vehicles have to wait at a road crossing even though there is no traffic while the traffic congestion is heavy on the other adjacent roads [1]. Recently artificial intelligence (AI) technologies have attracted a lot of research attention from both academia and industry [2-4]. Traffic analysis and forecasting using AI and big data analysis, the internet of things (IoT), vehicles to vehicles (V2X), are becoming emerging research areas of intelligent transportation [5-8]. Moreover, the introduction of AI-based traffic control systems not only can dynamically coordinate the urban traffic network operation and equalize the traffic flow at each intersection, thereby improving the road traffic capacity but also reasonably optimizing and configuring the signal phase and timing of each intersection in traffic signal control systems. A vehicle network is composed of the nodes equipped on the mobile vehicles and fixed road- side infrastructure components. Through the vehicle radio communication equipment, the vehicle sensor equipment can sense road conditions, and detect traffic accidents, dangerous driving, and other important events. The vehicle sensor nodes sense different regions, different times of the data that are shared and perceived by a large number of applications to provide more valuable data for supporting traffic control. Meanwhile, AI-based traffic control systems make full use of such a large amount of data together with an AI-based analysis approach to restrict the traffic flow. However, some AI approaches such as deep learning algorithms are highly complex and require a lot of computing resources. The cloud-based equipment cannot guarantee real-time responses due to the unpredictable latency and bandwidth wastage as well as increasing risks of privacy violations [9].

In order to overcome those limitations, Tran et al. [9] and Bowen et al. [10] illustrated cases studies of edge computing which is a new technology for building the relationship between cloud and IoT devices and significantly reduces the volume of data flows, network bandwidth consumptions, and immediate demand response in traffic systems. However, Tran et al. [9] merely focused on setting up a communication framework from the edge computing layer to the cloud computing layer, and Bowen Du et al. [10] put forward data-derived edge computing service. Both of them did not consider the typical application analysis for AI-based traffic control. To this end, in this article, we present a collaborative edge computing network based on the paradigm proposed by Bowen Du et al. [10] for accomplishing an AI-based traffic control strategy. Furthermore, a collaborative edge computing network is capable of achieving several traffic services such as active vehicle location tracking, traffic video analytics, augmented reality (AR) for accident judgment, and connected vehicle service. The advantages of our proposed paradigm include two aspects. On the one hand, when a local traffic accident occurs, the local edge computing device will send information to the driver in time and autonomously control the traffic signal under the jurisdiction to make real-time and decision-making responses without uploading data to the cloud computing control center. On the other hand, in the event of a major traffic accident, the local edge computing device cannot handle the situation locally due to the absence

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of comprehensive control. For this reason, the edge devices will assign to the cloud center and seek cooperation through the collaborative edge computing network, thus generating a global awareness for solving urban traffic control. In summary, the combination of an AI-based traffic control system with collaborative edge computing is capable of providing real-time responsible servers according to incident levels.

The remainder of the article is organized as follows. An overview of AI-based traffic control is provided in section 2. In section 3, the typical application of AI-based traffic flow perception system and intelligent traffic signal control system is illustrated. A collaborative edge computing network for AI-based traffic control is given and the edge computing reliability analysis in AI-based traffic control systems for typical scenarios has been taken into consideration. In section 4, we highlight the opportunities and challenges of AI-based traffic control. Finally, the ending part is the conclusion of the article in section 5.

2 Overview of AI-based Traffic Control

2.1 Overview of AI

Artificial intelligence is a kind of intelligence demonstrated by machines, in contrast to the natural intelligence (NI) demonstrated by humans and other animals. In computer science, AI is defined as "intelligent agents". Any device with AI is to maximize its chance of successfully achieving goals by perceiving its environment and taking proper actions. In recent years, the field of AI is flourishing from speech recognition to driver-less smart cars. In particular, intelligent traffic control has become remarkable for its development. Recently, an AI-based traffic control system for realizing intelligent transportation has been receiving a lot of attention from researchers.

As depicted in Figure 1, the AI-based traffic control system is mainly applied in two typical scenarios: the route guidance and the traffic signal control system. These systems make full use of such a large amount of data collected by the vehicle and roadside sensor equipment which can sense environments and traffic conditions, and are combined with AI approaches to provide an optimal route for drivers and adjust the traffic signal dynamically. The automatic guidance to the vehicle can be implemented effectively, through the rational application of AI algorithms such as recurrent neural networks (RNN), deep convolutional neural networks (CNN), long short-term memory (LSTM), K-nearest neighbor (KNN), SVR, and so forth. This brings hope for cities to mitigate traffic congestion. Next, we provide typical scenarios for existing research results.

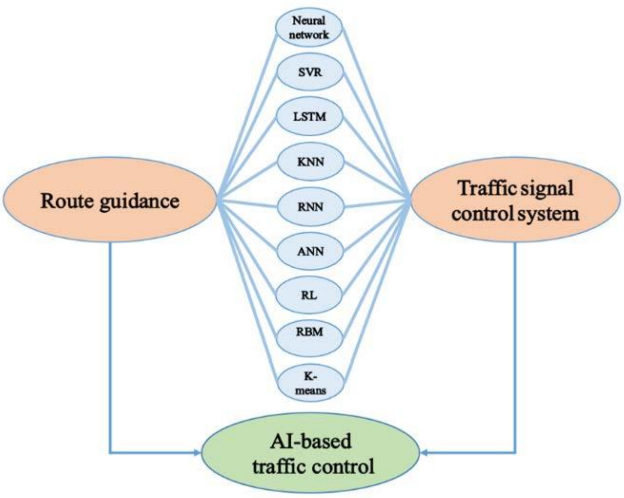


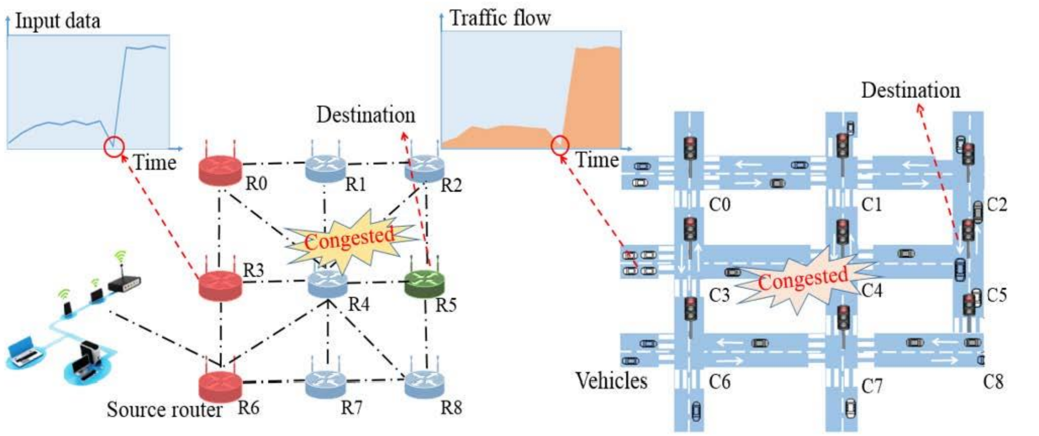
Figure 1. Various AI algorithm for solving traffic control problems

2.2 AI-based Perception System for Guiding Traffic Flow

The conventional traffic control system, using a fixed time of traffic light, was originally designed for the static adjustment of the traffic flow. Obviously, this method cannot be adapted to efficiently solve traffic congestions since its inability to dynamically guide traffic flow may lead to urban traffic congestions in large areas. This problem may also appear in heterogeneous network traffic control, such as network traffic delay, packet loss rate, and heavy congestion. The survey conducted in [11-13] demonstrated that there exist AI architectures, such as deep learning and machine learning, to be exploited for heterogeneous network traffic control systems.

Two cases of traffic control are shown in Figure 2, which consists of (a) routers traffic control, and (b) traffic control in the urban vehicle network. Real-time deep learning based heterogeneous network traffic control system considers several routers as depicted in Figure 2(a). As shown in Figure 2(a), the author in [12] raised a simple wireless network backbone consisting of 9 routers, denoted by R0, R2, ... R8, respectively. In order to ensure an efficient network, it is necessary to make the shortest route planning for each routing path. Nevertheless, the traditional traffic control approaches are likely to cause network congestions since they cannot dynamically adjust traffic control according to the real-time traffic conditions. For example, it can be seen from Figure 2(a) that the edge routers R0, R3, and R6 receive input packets and then send them to the destination router R5. In general, the capacity of router R4 is limited. Before the appearance of burst traffic at the source routers (R0, R3, R6), the traditional routing strategy will choose R4 to forward the packets to R5. However, when the burst traffic occurs suddenly at the source routers (R0, R3, R6), the strategy source routers remain the same. As a result, the throughput of router R4 will increase dramatically, leading to congestion at R4. In order to deal with such network congestion, the packets should be forwarded via alternative paths (such as through R1 and/or R7) which can be dynamically chosen to relieve the burden at R4 [12]. Therefore, the article [12] proposed a novel real-time deep learning based intelligent routing strategy which collects past "errors", such as an ineffective routing decision leading to network congestion, then predicts and avoids the same errors when similar situations recur. Extensive simulation results have shown that real-time deep learning based intelligent network traffic techniques could achieve fewer packet loss rates and lower average latency in contrast with the traditional routing strategies. In addition, such kind of path planning problems also exists in urban traffic control networks.

Figure 2(b) shows that all the traffic flow at the intersection (C0, C3, C6) is bound for C5 and the majority of vehicles have to pass through C4. The vehicle capacity of the C4 is, however, limited. If the vehicle traffic flow rate increases dramatically at C0, C3, and C6, meanwhile the chosen paths remain the same, it is likely to cause congestion at C4. This situation seems similar to the heterogeneous network traffic control problems mentioned above, which may help us propose new approaches to intelligent network traffic control. Deep learning algorithms may be used to construct real-time dynamic traffic control systems, offering more flexible path selection strategies for urban vehicle networks. Although this strategy can alleviate traffic congestion, the control center has to deliver relevant guide commands to drivers in real-time, which requires sophisticated service equipment with low latency and massive throughput of data in vehicle networks. In Section 3, we propose a collaborative edging computing equipment network to effectively ensure the real-time implementation of deep learning algorithm based traffic control strategy.



(a) Routers traffic control

(b) Traffic control in urban vehicle network

Figure 2. Two cases traffic control

2.3 AI-based Adaptive System for Intelligent Traffic Signal Control

Unlike the conventional traffic signal control in which the periodicity is fixed and pre-defined, the periodicity in intelligent traffic signal control is self-organized to adapt to the real-time environment. These data, including the number of vehicles or the license plate number obtained by observation from the real-time environment, will be collected by the roadside sensors, such as radars, radio frequency identification readers (RFID), and cameras, which can transmit these data to the control center. The control center will attain an optimal control schedule, such as the optimal length of the periodicity of the traffic signal, to adjust automatically the traffic situation via utilizing AI algorithms. In practice, transmitting the data from the sensor to the control center directly requires a high bandwidth, which increases the burden of the communication network. As a result, the delay of system responses would affect the quality of service (QoS).

D. K. Prasad et al. [14] presented the architecture of a local video-based traffic signal control system with a deep learning algorithm to mitigate the congestion by controlling the traffic light time automatically. The authors assumed that the intelligent surveillance camera is connected with the traffic light through a micro-controller, and the video stream is transmitted to the control center for real-time processing. The data-flow process is illustrated in Figure 3.

There are various image processing blocks in the micro-controller, such as image enhancement, background extraction, shadow removal, and so forth. After carrying out the pre-processing and feature extraction for the video frame, the system obtains the optima schedule via machine-learning receiving the optimized data set from the optimizer. Especially, different features are endowed with corresponding priority in terms of the importance in the optimizer. The machine learning module, as the knowledge base for the whole system, utilizes various deep neural network algorithms concerning the historical and current traffic data to enhance the ability of adaptive learning. In order to deal with the occasional events, a feedback process is added to the decision-making module.

By the above processing, the optimal traffic signal control schedule is generated. The scenario where the control schedule can be decided via the cooperation of several intersections has not been considered in [14].

Based on this consideration, N. Nathalia Moraes Do et al. [15] presented an extended architecture, taking the cooperation among intersections into account, in which cloud computing servers analyze and arrange the data set derived from sensors installed in the environment sensing layer via using Recurrent Neural Network (RNN) to achieve traffic signal control adaptively. The two-layer architecture for urban traffic control is shown in Figure 4, which consists of the environment sensing layer and the cloud computing layer. The environment sensing layer involves a number of typical elements. For a traffic scenario, these typical elements contain traffic lights, vehicles, road segments, and intersections. A segment refers to a section of a road, whereas intersections link more than two segments. Each road segment is equipped with a micro-controller connected to the cloud server to record the number of vehicles passing through all road segments per time period. Then the collected data by the cloud server will help to make a collaborative decision to control the traffic light in every segment. Moreover, the cloud computing layer connected with all micro-controllers executes the data analysis based on deep learning algorithms and then transmits the control schedule for adaptive traffic signal control. For instance, the RNN is leveraged to analyze data uploaded from the micro-controllers, in which the output of a segment's traffic light color influences its next network input, so that the traffic lights will be recorded to optimize the current routine automatically. Meanwhile, using a genetic algorithm, the cloud computing layer analyzes the congestion area and the changes of traffic lights of the whole region in a period of time to make a weight allocation among road segments which can gain priority access for RNN with higher weight, finally updating the decision for each micro-controller. The architecture can control traffic light sequences in one area and relieve the traffic congestion of the whole road network more accurately. However, the procession of unexpected emergencies has not been taken into account. The problem of high latency, large bandwidth demand and security in terms of data processed in cloud servers has also not been solved.

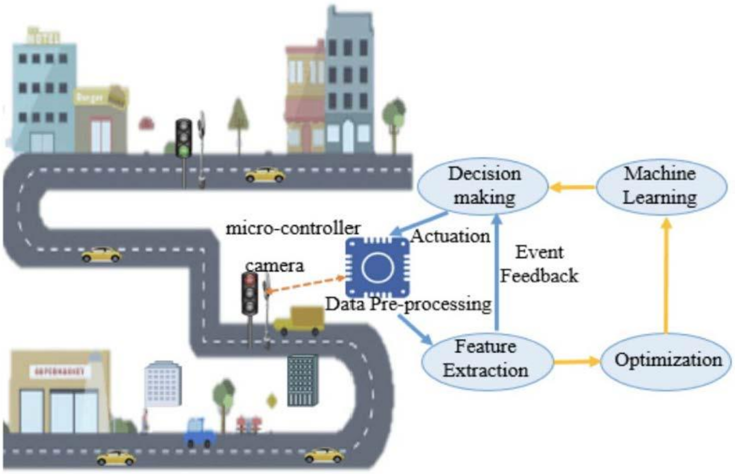


Figure 3. Video-based traffic signal control system

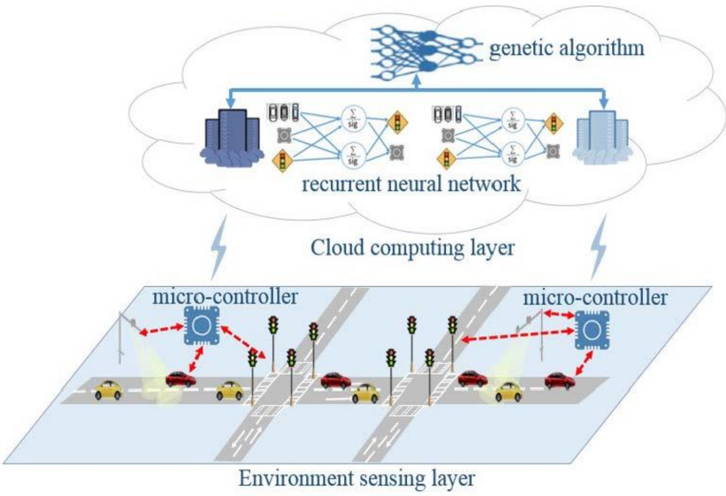


Figure 4. Adaptive traffic signal control system with cloud computing

3 Collaborative Edge Computing Network Analytics in AI-based Traffic Control

In this section, we introduce collaborative edge computing network analytics for AI-based traffic control with ultra-low latency responses and sharing global awareness. We first present the definition of a collaborative edge computing network, and then incorporate it with traditional cloud computing. Lastly, a practical application scene based on the proposed structure is presented to verify the availability of the proposed structure.

3.1 Collaborative Edge Computing Network Analytics in AI-based Traffic Control

The edge computing device consists of an edge computing gateway, edge server, database and agile controller. All these parts play a decisive role in it, and a brief introduction about them will be given as follows. The edge computing gateway provides data interfaces for various sensors and preprocessing. The edge server and database receive heterogeneous data for analysis. The agile controller offers real-time control response from local instructions. Furthermore, multiple implementation options can be used to integrate edge computing devices. Edge computing offers information technology (IT) and cloud-computing capabilities within the radio access network (RAN) in close proximity to mobile subscribers, which accelerates the responsiveness of contents, services and applications. The experiences of consumers can be enriched through efficient network and service operations [16-17]. Recently, edge computing has been applied to enhance the ability of intelligent urban traffic management [18-19]. For example, the authors in [19] utilized edge computing to process the data about intelligent traffic networks in the era of the 5-th generation (5G) wireless communications. Although the problems of the long delays and high demands of communication bandwidths have been somewhat solved, the applications of their model are limited to deal with different incident levels. To this end, we present a novel structure in which edge computing devices can cooperate with each other associated with the AI-based traffic control, which is referred to as collaborative edge computing network analytics in AI-based traffic control in this paper. The collaborative edge computing network schematic is shown in Figure 5, which consists of the environment sensing layer, collaborative edge computing network layer, and cloud computing layer. We will elaborate on the three layers as follows.

A. Environment sensing layer

In the environment sensing layer, various sensors are deployed in the vehicles, traffic lights, surveillance cameras, and streetlights to collect data with respect to velocity, engine speed, destination, lane, as well as the data about the surrounding environment such as temperature, humidity and visibility. The collected data are transmitted by the sensors to an edge computing device connected to it. This layer plays a significant role to collect data in the collaborative edge computing network at the first step.

B. Collaborative edge computing network layer

Edge computing is devoted to processing data at the edge of the intelligent traffic network, which can reduce the latency of the signal control, ensure highly efficient network operation and service delivery, and offer an improved driver experience. In order to enhance the ability of the intelligent traffic network, we apply the edge computing devices to the middle layer of the collaborative edge computing network. In this layer, there are several edge computing devices for the sensors deployed in the environment sensing layer, where each edge computing device only serves the sensors under its own jurisdiction region. In addition to saving the huge amount of data associated with the sensor for a long term, the edge computing device forwards the data to the cloud server center in the cloud computing layer to update the cloud storage for the centralized processing. It should be noted that the edge computing device also caches the data locally and makes the optimal control schedule itself. The control schedule from the cloud computing or the local edge computing device can be transmitted to the sensor to manage the traffic through the collaborative edge computing network layer. Moreover, the local information associated with the edge computing device can be shared with other edge computing devices via communications among the edge computing devices. In order to enhance the intelligent traffic control, the collaborative edge computing network offers the following four basic services [16-17, 19-20].

Active vehicle location tracking: This service allows a geo-location application hosted on the edge computing devices using the ‘best-in-class’ third-party geo-location algorithms to record the driving routes for vehicles. While the vehicles drive into coverage areas where local edge computing devices are available, active vehicle location tracking services are implemented until the vehicles drive out of this area. Subsequently, the local edge computing device shares the driving trajectory with the adjacent edge computing devices and uploads it to the cloud server. Ultimately, the global vehicle route is demonstrated in the cloud server center.

Active vehicle location tracking aims to support location services for different subscribers. For instance, the information of the real-time driving trajectory can be shared with family and friends to report the safety information of drivers. Meanwhile, the vehicle route analysis is a useful clue to find out the cause of an accident.

Traffic video analytics: This service shows that video streams generated from traffic surveillance cameras on each road segment can be implemented by the video analytics service which is employed on the edge computing devices to support the specific configurable traffic events. This service aims to transcode the video streams and process data to extract valuable information that can intercept the related video clip and is forwarded to the cloud server for storage according to the requirement.

Traffic video analytics is one of the conventional methods for intelligent traffic control. For instance, it can be used for vehicle tracking by police, and offer real-time information to examine the traffic congestion situation at intersections.

AR for accident judgment: augmented reality (AR) applications hosted on edge computing devices can provide local object tracking and local AR content caching based on traffic surveillance cameras. AR application can restore a traffic accident scene via analyzing video clips and setting up virtual reality (VR) scenes. The edge computing device, as a real-time data processing center, can minimize the program round trip time and maximize the throughput for optimum quality of service.

While a traffic accident occurs, the video streams from the driving recorder, roadside sensors and the traffic surveillance cameras are transmitted to the edge computing devices in the accident area. This service can generate the AR video for the traffic accident to help police determine the responsibility of the accident.

Connected vehicles service: This service allows a connected vehicles application run on the edge computing device to supply the roadside functionality. The application can take over local messages directly from the roadside sensors and vehicles, analyze them and then deliver ultra-low latency hazard warnings as well as other latency-sensitive information to other vehicles in the region. Services are housed close to the vehicles, which can reduce the interaction time of data. The advantage is that a nearby vehicle can receive data in a matter of milliseconds, allowing the driver to immediately react.

When a traffic accident occurs, the adjacent edge computing devices are informed immediately by sensors about the event and then propagate hazard warnings to vehicles that are close to the affected area. Finally, the edge computing devices can send local information to the cloud computing center for reporting and further centralized processing.

C. Cloud computing layer

The merits of cloud computing may include its scalability, high availability, easy management and centralized process of massive data, which is reliable for intelligent traffic control. Compared with those of edge computing, the advantages of cloud computing lie in more storage resources and more high-performance computing power, which can well compensate for the limited resources of edge computing. The cloud computing layer is usually deployed as the traffic control and management center of a city. This layer employs various AI algorithms and receives data uploaded from a collaborative edge computing networks for storage, comprehensive analysis and design rescue scheme formulation.

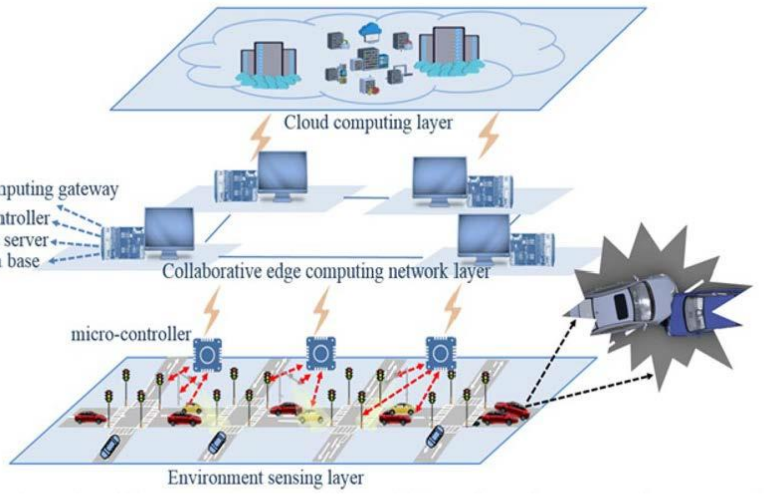


Figure 5. AI-based traffic control system with collaborative edge computing network

3.2 Case Study

In this section, we introduce two typical application scenarios. One is to solve small-scale traffic flow control problems through the cooperation of edge computing devices. On the contrary, the other is to tackle this issue on a larger scale through mutual assistance between edge computing devices and the cloud server center. Specific measures are introduced as follows:

A. Region Traffic Signal Control

With the increase of urbanization, the phenomena of congestion and pollution have become increasingly serious. Congestions, especially on busy routes and during peak traffic periods, have significantly delayed the day-to-day travels of people. Undoubtedly, the reduction of urban traffic congestion is vital to intelligent traffic control. In the proposed architecture, the edge computing device gathers the data transmitted by all the sensors under its jurisdiction to analyze the traffic flow analysis locally. Equipped with various deep learning algorithms, the edge computing device is endowed with powerful signal control functions, which can process data locally. It is noted that the latency is lower than that of transmitting the data to the cloud for obtaining the optimal solutions to control the period of traffic lights in terms of the local region. As a result, the structure can control the traffic lights in real-time, realizing dynamic management towards urban vehicle flow and increasing the throughput at the intersection. In fact, in addition to optimizing traffic performance, adapting this new structure can further reduce fuel consumption and emissions, which is environmentally friendly.

B. Global Traffic Scheduling

When a serious traffic accident occurs, the incident level increases resulting in larger-scale issues, such as continuous rear-end collisions and road damages. Once these issues have not been handled promptly, subsequent traffic congestions will lead to the delay of optimal rescue time. The proposed architecture presented can relieve this phenomenon to some extent, due to the corporation of the edge computing devices and the cloud server center. To be specific, the edge computing devices in each area share and integrate various types of accident information through the edge computing collaboration network, and then transmit it to the cloud service center. This center formulates a global rescue strategy, and then sends out scheduling information for different regions, depending on the current situations.

The typical global rapid rescue system process is as follows: area edge computing equipment provides active vehicle location tracking service and then collects all kinds of information such as tracking video of roads. The collected information will be sent to the cloud server center, which plays an important role in decision-making and coordinating the edge computing devices. Subsequently, edge computing devices provide connected vehicle services and send information to vehicles in every region, warning the vehicles on the route to slow down to avoid the destruction of the accident scenes or the continuous rear-end collisions. The collaborative edge computing network simultaneously informs vehicles in the surrounding regions of accidents driving far away from there and rearranges the routes through connected vehicles service. At the same time, the cloud computing service center informs the rescue department to take appropriate measures to provide assistance. Each area's edge computing device controls the traffic lights globally according to the schedule of the cloud service center. This will benefit rescue workers and ambulances with a quick rescue path, hence ensuring that they reach the scene of the accident promptly.

The proposed architecture presented can relieve this phenomenon to some extent, due to the corporation between the edge computing devices and the cloud server center. This structure with high-efficiency is equivalent to a global traffic scheduling. In fact, it requires that different accidents should use different processing schemes to ensure high-efficient rescue speed, which also accelerates the emergency response and maximizes computing resources.

4 Future Research Challenges

Edge computing has become promising in the field of transportation traffic control. In this paper, we have surveyed the relevant traffic control technologies and also presented a traffic control evaluation based on some key techniques which will be specified in the future as below.

Image recognition: Since edge computing is relatively limited in comparison with cloud computing, the challenge is to find low-complexity image recognition algorithms that can efficiently be used for edge computing devices, and at the same time to ensure the accuracy of identification and provide assistance for traffic flow control. Moreover, the video stream is transmitted to the edge devices through a camera. If traditional two-dimensional image recognition is employed, only some features in a certain direction can be analyzed, resulting in incomplete information acquisition. The challenge is how to use a distributed edge computing device to collect multi-angle video streams to achieve the reconstruction of 3-dimentional (3D) image and generation of 3-D (AR) image.

Path planning: With the rapid development of unmanned vehicle technology and assisted driving systems, driverless technology needs to be coordinated with urban traffic flow control technology. There are two challenges, the one is how to find the method for coordination between individual route planning and urban traffic flow control guidance, while the other one is to find the optimal distance and speed when self-driving vehicles and driver-controlled vehicles sharing a road.

Security issues for edge computing: Due to the large number of personal privacy data to be uploaded by distributed computing to edge computing equipment, such as driving records, vehicle location, and so on, the challenge is to protect these private data in edge computing network with distributed lightweight security schemes. In particular, the real-time attacks will become new fatal problems on edge computing. Therefore, security and privacy-protection in edge computing, including detection, reliability of authentication for various types of sensors, and protection of private data, will be critical research directions in the future.

5 Conclusions

Due to the expansion of metropolis with an increasing number of vehicles, the issues of traffic congestion are gradually severe, which brings new demands to change traditional traffic control. In this article, we have envisioned that AI, as a promising technique emerged recently, can substantially improve traffic control. We have discussed AI-based traffic control systems such as intelligent traffic signal control and guiding traffic flow. There are a number of challenges in AI-based traffic control systems, such as high latency, large bandwidth demand, and so forth. In this direction, a collaborative edge computing network is put forward for AI-based traffic control. The proposed AI-based traffic control system with the synergy edge computing equipment embedded can both support ultra-low responses and share global awareness. Its feasibility and advantages have been demonstrated in the case study through the implementation details of providing real-time responsible servers according to incident levels. Finally, we have also discussed a number of open research issues and indicated future directions including image recognition, path planning, and privacy protection.

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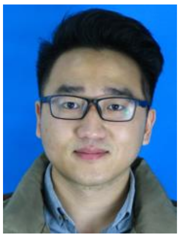
Biographies



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