Edge Computing for Intelligent Transportation System: A Review

Qian Li[1], Pan Chen[1], and Rui Wang[1,2,3](✉)

[1] School of Computer and Communication Engineering, University of Science and Technology Beijing (USTB), Beijing 100083, China
wangrui@ustb.edu.cn
[2] Institute of Artificial Intelligence, University of Science and Technology Beijing, Beijing 100083, China
[3] Shunde Graduate School, University of Science and Technology Beijing, Foshan 528300, China

Abstract. To meet the demands of vehicular applications, edge computing as a promising paradigm where cloud computing services are extended to the edge of networks can enable ITS applications. In this paper, we first briefly introduced the edge computing. Then we reviewed recent advancements in edge computing based intelligent transportation systems. Finally, we presented the challenges and the future research direction. Our study provides insights for this novel promising paradigm, as well as research topics about edge computing in intelligent transportation system.

Keywords: Edge computing · Intelligent transportation system · Vehicular networks

1 Introduction

Cloud computing is a resource-rich and large-scale service system. It is an ideal strategy to use cloud computing systems as a platform for processing big data [1]. But, cloud computing systems also bring a lot of problems, such as increasing the delay of requests, serious waste of resources, and unstable connection [2]. Edge computing is a distributed computing structure that divides complex computing tasks into multiple small element units and assigns them to local nearby devices. As an extension of cloud computing, edge computing itself has the characteristics of dynamics, low latency, mobility, and location awareness [3]. Each node in the edge computing is not isolated, and they can perform allocation and cooperation to complete the same task request. At the same time, edge computing is not a substitute for cloud computing and both of them are not isolated. On the contrary, they complement each other and constitute a three-tier architecture, that is, equipment, edge computing, and cloud computing to jointly solve many challenges in the development of the Internet of Things [4]. Its architecture is shown in Fig. 1.

In this paper, we first discuss the research progress of intelligent transportation based on edge computing in the second section. In the third section, we summarize

H. Ning (Ed.): CyberDI 2019/CyberLife 2019, CCIS 1138, pp. 130–137, 2019.
https://doi.org/10.1007/978-981-15-1925-3_10

the challenges faced by intelligent transportation based on edge computing. Then, we summarize the future development direction of intelligent transportation based on edge computing in the fourth section. Finally, we conclude this paper.

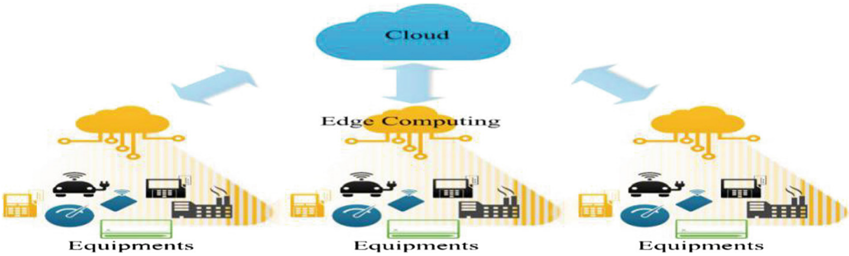

Fig. 1. Edge computing architecture diagram

2 Research on Edge Computing in Intelligent Transportation System

In this section, we will discuss the research progress from the three perspectives of resource management and relay framework, deep reinforcement learning and 5G automotive system, security message authentication.

2.1 Resource Management and Relay Framework

In terms of resource management, [5] conducts research on spectrum resource management. First, the authors used the logarithmic and linear utility functions to develop three aggregated network utility maximization issues. Then, linear programming relaxation and first-order Taylor series approximation are used, and the alternating concave search (ACS) algorithm is designed to solve the three non-convex network maximization problems. [6] proposes an alternating direction method of multipliers (ADMM) scheme. After the scheme adds a set of local variables to each in-vehicle user equipment (UE), the initial variable optimization problem is transformed into a consistency problem with separable targets and constraints. The consistency problem can be further broken down into a set of sub-problems, and the sub-problems are distributed to the UE to be solved in parallel.

In order to efficiently add mobile vehicles to information dissemination and select appropriate relays to meet the diverse transmission tasks, the researchers have done a lot of research work and will introduce the following. In [7], the researchers developes a vehicle content communication framework based on edge computing. In terms of incentives, the framework develops a new theoretical model of auction games that evaluates the resource contributions of idle vehicles by using a Bayesian Nash equalization algorithm based on game theory. [8] studies the problem of optimal deployment and dimensioning (ODD) of in-vehicle networks supported by edge computing, minimizing the cost of developing ODD problems in the form of integer linear programming (ILP), while considering infrastructure deployment, overall network organization, coverage requirements and network latency. The above research work is summarized in Table 1.

Table 1. Summary of research work on resource management and relay framework

Application scenario	Research work		Application Technology	Experimental program
Resource management	[5]	Dynamic spectrum resource management framework	ACS algorithm, etc.	Linear programming relaxation; first-order Taylor series approximation; ACS algorithm
	[6]	ADMM solution	ADMM algorithm, etc.	Decompose the consistency problem into a set of sub-problems and processing them in parallel
Relay framework	[7]	Vehicle content communication framework	Bayesian Nash Equilibrium Algorithm Based on Game Theory etc.	Game theory as an incentive mechanism; content cache to ECD; ECD selection relay
	[8]	ODD problem optimization	ILP, coupling, decoupling	ILP minimizes the cost of ODD problems; develops coupling and decoupling models to compare

2.2 Deep Reinforcement Learning and 5G Automotive System

The Internet of vehicle has a certain deployment structure and specific connections. It is easier to capture multi-dimensional data from the environment, including vehicle behavior, mission information and network status. [9] proposes a DRL-based offloading decision-making model based on the effective use of deep reinforcement learning to assist the vehicle interconnection network to make better computing and offloading decisions, combined with knowledge-driven (KD) method. In [10], the author uses D2D communication and heterogeneous network HetNets to cooperate with the base station (BS) and the roadside unit (RSU) to increase the on-board caching capability. On the other hand, a deep Q-learning multi-time scale framework was developed, and the parameters required for compute, communication, and caching were optimally configured to determine the best choice for idle vehicle and edge nodes.

Researchers have also proposed introducing 5G technology into in-vehicle systems to improve the quality of in-vehicle application services. In [11], the author introduces the concept of Follow Me Edge Cloud (FMeC) to maintain the requirements of 5G automotive systems by using the Mobile Edge Computing (MEC) architecture. Based on the LTE-based V2I communication type, the author introduces its SDN/OpenFlow-based architecture and a set of algorithm-based mobile sensing frameworks, which enable autopilot QoS requirements in 5G networks, meeting autopilot delay requirements.

[12] proposes a new in-vehicle network architecture that integrates 5G mobile communication technology and software-defined networks. On the basis of the traditional 5G vehicle network, the author combines software-defined network (SDN) with cloud computing and edge computing technology, and divides the network into application layer, control layer and data layer that can divide control and data functions to improve the vehicle network. The above research work is summarized in Table 2.

Table 2. Summary of research work on vehicle network based on deep reinforcement learning and 5G automotive system

Application scenario	Research work		Application Technology	Experimental program
Deep reinforcement learning	[9]	DRL-based offloading decision model	Knowledge driven algorithm, A3C algorithm	Mobility to judge task delay; online learning KD service; exploring A3C algorithm optimization offloading decision
	[10]	Deep Q-learning multi-time scale framework	D2D communication, heterogeneous network HetNets, deep Q-learning	D2D communication, heterogeneous network HetNets improve cache computing power; optimal configuration of Q-learning parameters
5G automotive system	[11]	Follow Me Edge Cloud Architecture	FMeC Architecture, 5G, Mobile Perception	Follow Me Edge Cloud Architecture for Automated Driving
	[12]	SDN-based 5G automotive system	5G, SDN etc.	Hierarchical structure processing control and data request, SDN, cloud computing, edge computing, 5G combination

2.3 Secure Message Authentication

The communication protocol in VANET should satisfy the anonymity, that is, the vehicle should communicate with all entities through pseudo-identities rather than real identity. In [13], the authors incorporated a novel edge computing concept into VANET's message authentication process. In this scenario, the RSU acts as a cloud for the vehicle, and the system selects a number of edge computing vehicles (ECVs) to assist the RSU in verifying the message signature sent by nearby vehicles and then transmitting the results to the RSU based on the vehicle's limited computing power. Finally, the RSU verifies the results sent from the ECV, obtains the legitimacy of these messages, and broadcasts information about legality to the vehicle through the filter at the end.

[14] advocates the introduction of edge computing in the IoV, referred to as F-IoV. The author proposes a privacy-preserved pseudonym (P3) scheme in F-IoV and introduces an edge computing node that is deployed in different regions to directly manage the pseudonyms of passing vehicles. [15] proposes a novel edge computing based anomaly detection, coined edge computing based vehicle anomaly detection (EVAD). Edge-based sensors obtain data through Fourier transform formula, and the time domain characteristics, that is, the correlation between different onboard sensors and the frequency domain characteristics of the sensor data, are used to determine whether an abnormality has occurred in the vehicle.

3 Challenges

3.1 The Vehicular Environment Is Dynamic and Uncertain

The dynamic and uncertainty of vehicle environment is mainly reflected in the varying network topologies, wireless channel states, and computing workload. These uncertainties bring additional challenges to task offloading. Sun et al. [16] consider the task offloading among vehicles and then they designed an adaptive learning-based task offloading (ALTO) algorithm in order to minimize the average delay. The algorithm is based on the multi-armed bandit theory. Vehicles can learn the delay performance of their neighboring vehicles while offloading tasks. The proposed algorithm is proved under both synthetic scenario and realistic highway scenario.

3.2 Lack of Effective Incentives

The deployment of Vehicular fog computing (VFC) still confronts several critical challenges, such as the lack of efficient incentive. Zhou et al. [17] investigated the task assignment and computation resource allocation problem in VFC from a contract-matching integration perspective. An incentive mechanism based on contract is proposed to promote resource sharing among vehicles. At the same time, a stable matching algorithm based on pricing is proposed to solve the task assignment problem.

3.3 Security and Privacy

In the research of vehicle edge computing, due to the distributed and heterogeneous characteristics of edge nodes, some original security mechanisms related to cloud computing are not fully applicable to edge computing, and they bring new challenges to authentication and access control etc. Cui et al. [13] put forward a valid message authentication scheme for the redundancy in the communications security mechanism in the VANET authentication problem, this scheme introduce the edge of computing concept into the VANET message authentication, the roadside unit can efficiently authenticate messages from nearby vehicles and broadcast the authentication results to the vehicles within its communication range, in order to reduce the redundant certification, improve the efficiency of the whole system.

4 Future Research Direction

4.1 Task Offloading and Resource Allocation

In the existing research on vehicle edge computing, most of the research on task offloading is to design an offloading architecture, jointly consider the network, communication and computing resources, and design the resource allocation algorithm, so as to achieve the minimum energy consumption, delay or the system cost. For the problem of computing offloading decision, the decision algorithm is designed, aiming at the minimum delay or energy consumption. But these algorithms lack of performance optimization and analysis, how to design a low complexity approximate optimal algorithm is a worthy research topic. In addition, there are dependencies between subtasks in some complex applications, which makes task scheduling more complicated and brings additional challenges to the framework. Designing a task scheduling algorithm with reasonable computational complexity and good performance is a field worthy of research. Many current studies are conducted in some simple hypothetical scenarios. In the future, we need to consider more realistic situations, such as unpredictable vehicle mobility and dynamic resource utilization, to find more feasible solutions.

4.2 Incentive Mechanism

In vehicle network, content dissemination usually relies on roadside infrastructure and mobile vehicles to deliver and disseminate content. Due to vehicle mobility, selfishness and limited communication capabilities of infrastructure, how to effectively motivate vehicles to participate in content dissemination is a challenging task. To solve this problem, Hui et al. [7] put forward a novel edge computing-based content dissemination framework in which the contents are uploaded to an edge computing device(ECD). A two-stage relay selection algorithm is designed based on the selfishness and transmission capability of the vehicle, to help edge computing devices selectively transport content by vehicles to infrastructure (V2I) communication. Experiments show that the framework can transmit content to vehicles more effectively than traditional methods and bring more benefits to content providers. Therefore, the vehicle edge computing system needs the assistance of nearby vehicles or roadside units. How to motivate vehicles to participate in the vehicle edge computing is another direction of future research.

4.3 Collaborative Computing

In the internet of vehicles environment, each edge node has certain computing resources, such as vehicles and roadside units. They can cooperate with each other to complete computing tasks, which can not only improve the utilization rate of resources, but also improve the completion efficiency of tasks. Vehicle-to-everything (V2X) technology enables collaboration between roadside units and vehicles. They share their information and task offloading through V2X communication to achieve the purpose of collaborative computing. However, there are still some challenges with the technology [18], for example, how different vehicles work together to make perception and planning decisions; how to dynamically balance the cost of infrastructure sensors and on-board sensors; and how to share traffic information in real time. Therefore, how to design a collaborative strategy so that edge nodes can coordinate task scheduling is a future research direction.

4.4 Security and Privacy

Privacy and security are very important in vehicle network. Data generated by vehicles are very sensitive to privacy, such as vehicle location information, user entertainment preference information, etc., all of them need to have a good protection mechanism [19]. Offloading vehicle tasks to nearby vehicles or roadside units can also lead to information leakage, raising security and privacy issues. In addition, the deployment, operation and maintenance of cloud computing are operated by specific service providers, while the deployment and maintenance of nodes in edge computing are operated by third-party developers or even directly by users. Therefore, ensuring the security and privacy protection of vehicle edge computing is a future research direction.

5 Conclusion

Edge computing is viewed as a promising technology to provide massive connectivity and support delay-sensitive applications for the vehicle network. In this paper, we first briefly introduced the edge computing and then we reviewed recent advancements in edge computing based intelligent transportation systems (ITS). Last, we presented the challenges and the future research direction for ITS based on edge computing. These open issues are expected to be a prime focus for researchers in the next decade.

Acknowledgment. This work was supported in part by the National Key Research and Development Program of China under Grant No. 2016YFC0901303.

References

1. Sahni, Y., Cao, J., Zhang, S., Yang, L.: Edge mesh: a new paradigm to enable distributed intelligence in internet of things. IEEE Access **5**, 16441–16458 (2017)
2. Ning, Z., Wang, X., Huang, J.: Mobile edge computing-enabled 5G vehicular networks: toward the integration of communication and computing. IEEE Veh. Technol. Mag. **14**(1), 54–61 (2019)
3. Swarnamugi, M., Chinnaiyan, R.: IoT hybrid computing model for intelligent transportation system (ITS). In: 2nd International Conference on Computing Methodologies and Communication (ICCMC), Erode, pp. 802–806 (2018)
4. Liu, K., Xu, X., Chen, M., Liu, B., Wu, L., Lee, V.C.S.: A hierarchical architecture for the future internet of vehicles. IEEE Commun. Mag. **57**(7), 41–47 (2019)
5. Peng, H., Ye, Q., Shen, X.: Spectrum management for multi-access edge computing in autonomous vehicular networks. IEEE Trans. Intell. Transp. Syst. Early Access, 1–12 (2019)
6. Zhou, Z., Feng, J., Chang, Z., Shen, X.: Energy-efficient edge computing service provisioning for vehicular networks: a consensus ADMM approach. IEEE Trans. Veh. Technol. **68**(5), 5087–5099 (2019)

7. Hui, Y., Su, Z., Luan, T.H., Cai, J.: Content in motion: an edge computing based relay scheme for content dissemination in urban vehicular networks. IEEE Trans. Intell. Transp. Syst. **20**(8), 3115–3128 (2019)
8. Yu, C., Lin, B., Guo, P., Zhang, W., Li, S., He, R.: Deployment and dimensioning of fog computing-based internet of vehicle infrastructure for autonomous driving. IEEE Internet of Things J. **6**(1), 149–160 (2019)
9. Qi, Q., et al.: Knowledge-driven service offloading decision for vehicular edge computing: a deep reinforcement learning approach. IEEE Trans. Veh. Technol. **68**(5), 4192–4203 (2019)
10. Tan, L.T., Hu, R.Q.: Mobility-aware edge caching and computing in vehicle networks: a deep reinforcement learning. IEEE Trans. Veh. Technol. **67**(11), 10190–10203 (2018)
11. Aissioui, A., Ksentini, A., Gueroui, A.M., Taleb, T.: On enabling 5G automotive systems using follow me edge-cloud concept. IEEE Trans. Veh. Technol. **67**(6), 5302–5316 (2018)
12. Ge, X., Li, Z., Li, S.: 5G software defined vehicular networks. IEEE Commun. Mag. **55**(7), 87–93 (2017)
13. Cui, J., Wei, L., Zhang, J., Xu, Y., Zhong, H.: An efficient message-authentication scheme based on edge computing for vehicular ad hoc networks. IEEE Trans. Intell. Transp. Syst. **20**(5), 1621–1632 (2019)
14. Kang, J., Yu, R., Huang, X., Zhang, Y.: Privacy-preserved pseudonym scheme for fog computing supported internet of vehicles. IEEE Trans. Intell. Transp. Syst. **19**(8), 2627–2637 (2018)
15. Guo, F., et al.: Detecting vehicle anomaly in the edge via sensor consistency and frequency characteristic. IEEE Trans. Veh. Technol. **68**(6), 5618–5628 (2019)
16. Sun, Y., et al.: Adaptive learning-based task offloading for vehicular edge computing systems. IEEE Trans. Veh. Technol. **68**(4), 3061–3074 (2019)
17. Zhou, Z., Liu, P., Feng, J., Zhang, Y., Mumtaz, S., Rodriguez, J.: Computation resource allocation and task assignment optimization in vehicular fog computing: a contract-matching approach. IEEE Trans. Veh. Technol. **68**(4), 3113–3125 (2019)
18. Liu, S., Liu, L., Tang, J., Yu, B., Wang, Y., Shi, W.: Edge computing for autonomous driving: opportunities and challenges. Proc. IEEE **107**, 1697–1716 (2019)
19. Khattak, H.A., Islam, S.U., Din, I.U., Guizani, M.: Integrating fog computing with VANETs: a consumer perspective. IEEE Commun. Stand. Mag. **3**(1), 19–25 (2019)