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V2X Communication Computing Resource Collaboration Technology Based on Deep Reinforcement Learning

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ABSTRACT

In traditional cloud computing, data needs to be transferred from distributed data sources to remote cloud data centers for high-performance computing. However, tasks often experience network transmission delays of hundreds of milliseconds or more from data sources to cloud data centers, which does not meet the need for low latency in V2X (Vehicle to Everything) systems. On the basis of the existing heterogeneous task scenario, this paper proposes a communication computing resource collaboration technology scheme based on heterogeneous task, which can meet the requirements of delay and cost when facing tasks with different delay requirements and different divisibility. This scheme uses the communication computing resources of the roadside unit and the service vehicle, so that the computing task of the task vehicle can be completed within the delay requirement and the cost is minimal. We use the deep reinforcement learning method to study, and finally the performance of the proposed scheme is verified by simulation.

KEYWORDS

V2X; Resource collaboration; Learning algorithm

1. INTRODUCTION

In the face of complex traffic conditions, there are many problems in the development of autonomous vehicles. How to achieve more traffic flow while keeping passengers and other cars on the road is a problem well worth studying. To achieve this goal, autonomous vehicles will need to have the ability to make autonomous judgments and decisions, such as when to speed up to overtake and when to slow down. But these decisions can't be made in isolation from each other; they need to be coordinated with other vehicles around them. Communication is the basis of vehicle-road cooperation, and its reliability directly affects the safety of road traffic and autonomous driving system, especially when the high-channel load and packet collision occur frequently.

V2X refers to the interconnection technology between a vehicle and everything around it, including other vehicles, pedestrians, road facilities, etc. The purpose of this technology is to improve road safety, traffic efficiency and driving experience to support future intelligent transportation systems. With V2X technology, vehicles can drive autonomously and cooperatively between vehicles, increasing traffic safety and efficiency, reducing traffic congestion and improving the driving experience. In addition, V2X technology can also support intelligent traffic management and vehicle management, improving the efficiency and management level of traffic operations in cities.

Cellular network based vehicle wireless communication technology (C-V2X) is one of the important supporting technologies of vehicle-road collaborative perception. C-V2X is a global unified standard communication technology based on the Third Generation Partnership Program (3GPP), and an automotive wireless communication technology based on the evolution of cellular network communication technologies such as the fourth generation mobile communication/the fifth generation mobile communication (4G/5G). It mainly includes two types of technologies: Long-Term Evolution automotive wireless communication technology (LTE-V2X) and 5G system-based automotive wireless communication technology (5G-V2X). V2X technology is a key link between vehicles and surrounding things such as cars, people, traffic side infrastructure and networks. With the help of various wireless communication technologies, V2X technology organically links vehicle, road, people, cloud and other traffic participation elements together, providing important support for the development of vehicle-road collaborative perception technology. Vehicle-road collaborative perception mainly relies on vehicle-road communication technology and vehicle-vehicle (V2V) communication technology in V2X to realize information interaction and fusion between vehicle-road multi-agents.

V2X communication technology also includes Dedicated Short Range Communication (DRSC), which is a V2X communication technology based on the IEEE 802.11 standard, which is mainly used for vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication. The advantages of DSRC technology are fast transmission rate, long communication distance and strong anti-interference ability.

With the continuous development of intelligent connected vehicles, the types of in-car applications have become more and more rich, these applications in increasing the driving experience and safety at the same time, but also bring a large number of computing needs, only the use of the vehicle's own hardware to deal with these applications are often difficult to meet the needs. In order to solve this problem, mobile edge computing technology is beginning to attract attention in the V2X field. Mobile edge computing technology Mobile computing puts computing processing to the edge of the network, which can greatly reduce the response delay and data back load, and has gradually become the mainstream solution used in V2X systems. However, in the face of changing V2X networking topology and increasingly diversified on-board applications, how to use the communication computing resources of V2X system to complete computing tasks with different delay sensitivities and different sizes more efficiently is still a problem worthy of in-depth study. At the same time, how to use the communication resources of various communication modes, so as to apply more efficiently in the field of V2X mobile edge computing, also has important research significance. This paper considers the differences in the size and delay constraints of vehicle applications in the current V2X system, combined with vehicle perception capabilities and perception needs, and considers the V2X communication computing resource collaboration technology under various communication modes, jointly optimizing the delay, overhead and perception accuracy, and improving the performance of V2X communication computing resource collaboration.

2. SYSTEM ARCHITECTURE

In V2X systems, the high-speed mobility of vehicles will cause changes in the network topology, and at the same time, in the current V2X application scenarios, the types of computing tasks are relatively diverse, ranging from relatively complex, data-intensive and delay-sensitive tasks to soft delay-sensitive tasks with relatively moderate data volumes.

To solve the above problems, I adopt a communication computing resource collaboration technology based on heterogeneous tasks. The technology uses deep reinforcement learning to rapidly communicate and coordinate computing resources for vehicles with heterogeneous tasks. Specifically, task vehicles generated by heterogeneous computing tasks can transmit tasks to idle vehicles and RSU through communication resources according to different requirements of computing tasks, so that the two can use idle computing resources to compute tasks, meet the delay constraints of heterogeneous tasks, and minimize overhead to achieve the purpose of coordination of computing communication resources. In this scheme, factors such as task unloading strategy, transmission power and computing resource allocation are comprehensively considered, and a joint optimization problem is proposed to minimize the delay and overhead of heterogeneous computing tasks. Due to the high mobility of vehicles and the high variability of V2X networking topology, it is difficult for traditional methods to solve such problems. So the method of deep reinforcement learning is adopted.

In the running vehicles, there are two types of vehicles, respectively called task vehicles and service vehicles, in which task vehicles refer to different types of computing tasks, and their own computing resources are limited, not enough to complete the calculation under the delay requirements of computing tasks. The service vehicle refers to the vehicle that has its own computing resources idle and can assist the task vehicle in calculating together. In this scenario, due to the limitations of the vehicle's own hardware and the occupation of CPU performance by other tasks, such as on-board navigation and on-board entertainment, the RSU has communication and relatively strong computing power, so the service vehicle and the RSU will cooperate to assist the task vehicle in calculation. Service vehicle and RSU can jointly use their own communication computing resources to provide computing services for mission vehicles.

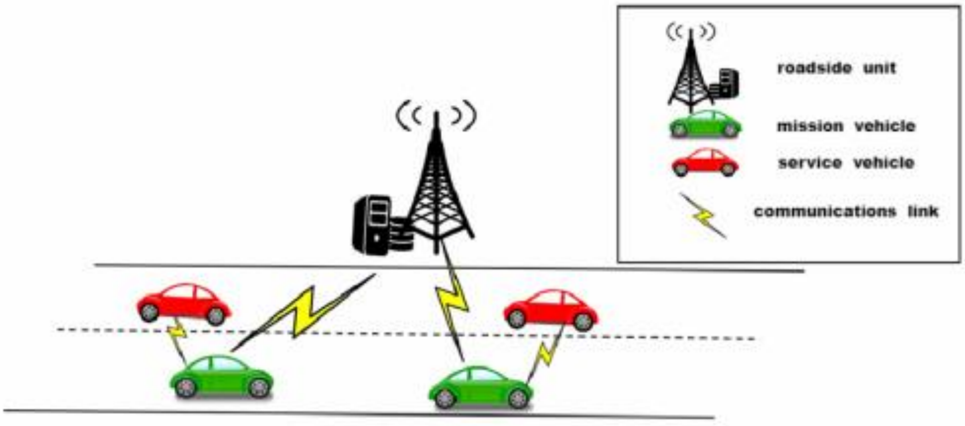

Figure 1. System scenario

3. VEHICLE MANEUVER PREDICTION MODEL

In the V2X system, the communication mode is not only a single mode, the existing standards have DSRC and C-V2X, etc., and the existing intelligent car has the ability to sense, which is also an important research content in the field of automatic driving. However, most of the existing communication computing resource collaboration schemes do not consider the above two.

C-V2X is a cellular network-based vehicle networking technology that enables communication between various objects such as vehicles, pedestrians, and infrastructure. C-V2X mainly enables Communication in two ways: Direct Communication between vehicles and communication between vehicles and infrastructure. With this means of communication, C-V2X can enable applications such as traffic flow control, road safety, and vehicle autonomous driving. DSRC is a wireless communication technology specifically used for vehicle-connected communication. DSRC technology mainly uses the 5.9GHz band for communication, enabling communication between vehicles and between vehicles and infrastructure. DSRC is mainly used in the field of vehicle safety and traffic management, and can be used to implement applications such as traffic signal optimization and traffic safety warnings. The main advantages of C-V2X are a wide range, faster speed, and higher flexibility. The benefits of DSRC include higher reliability, higher security, and lower latency.

Different communication modes of Multiple Access will also be different, common Carrier Sense Multiple Access (CSMA), Time Division multiple access (Time Division Multiple Access), carrier Sense multiple access (CSMA), time division multiple access (Time Division multiple access), carrier sense multiple access (CSMA). TDMA), Frequency Division Multiple Access (FDMA) and Wavelength Division Multiplexing (WDM).

TDMA is a time-based multi-access technology, its principle is to divide the time into non-overlapping time slots, each terminal device in a time slot exclusive channel and send its own data. Different end devices send data in different time slots according to a predetermined schedule, thus avoiding conflicts. TDMA can achieve strict slot allocation, so it has high communication efficiency and reliability.

CSMA is a kind of multi-access technology based on monitoring. The principle is that before sending data, the terminal device first listens to the wireless channel. If no other device is sending data on the channel, the terminal device can send data. If it detects that another device on the channel is sending data, the terminal device waits for a random amount of time before listening to the channel again, and does not send data until the channel is free. In this way, data conflicts caused by multiple devices sending data at the same time can be avoided. There are three common variants of CSMA: 1-persistent CSMA, non-persistent CSMA, and p-persistent CSMA.

In general, C-V2X and DSRC each have their own advantages and application scenarios. C-V2X mode needs to pass the base station, usually the roadside unit will adopt a certain fee policy, so the cost will be larger than DSRC communication mode, but the transmission rate of C-V2X communication mode will be larger. After comprehensive consideration of these two communication modes, the C-V2X communication mode adopts TMDA, and the DSRC communication mode adopts CSMA. In persistent CSMA, the node continuously listens for the channel before sending data, and if the channel is free, the data is sent immediately. If the channel is busy, the node will continue to listen until the channel is free, and then immediately send data.

4. SIMULATION ENVIRONMENT

I completed the simulation experiment using Network Simulator 3 (NS3), a free and open source discrete event-driven network simulator used to simulate and evaluate the performance of communication networks. It provides a rich network model and protocol stack, and can write new modules according to their own needs, simulate network nodes, protocol stacks, etc., and add new modules to the structure of NS3. The communication module is built based on NS3, which is used to simulate the communication protocol and communication process in V2X communication, so as to obtain the communication delay of task transmission, calculate the corresponding target value, and finally obtain the corresponding reward value.

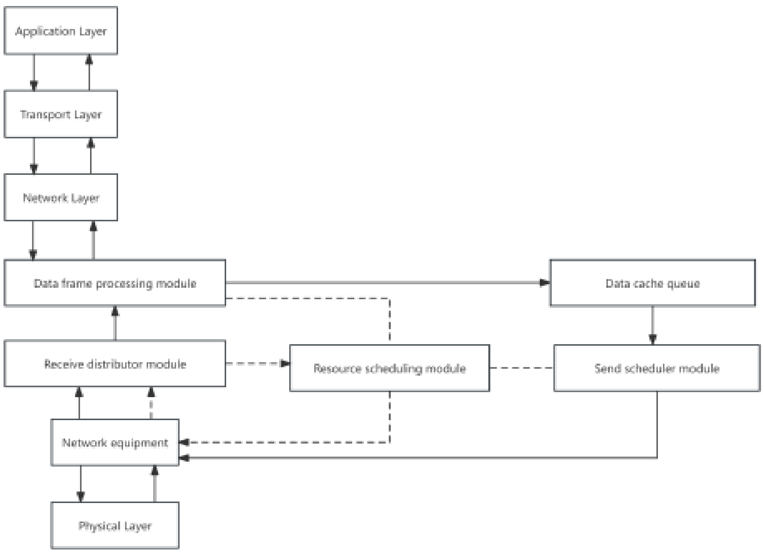

Figure 2. Communication simulation platform module overview

The figure above is an overview of the components of the communication simulation platform module. The sending scheduling module is the center that controls sending and is responsible for generating and processing messages. The function of the receiver and distributor module is to judge the information frame transmitted by the network device, divide it into data frame and management frame, and deliver it to the data frame processing module and the sending scheduler module respectively according to the different frame types. The data frame processing module sends the data frames received from the distributor to the network layer, and the data frames received from the network layer to the data cache queue. The sending scheduler module sends the datagram from the data cache queue to the network device. The resource scheduling module allocates channel resources for upstream and downstream channels, and can control the data frame processing module and the sending scheduler module through management messages.

The system scenario is a V2X system consisting of one two-way lane, one roadside unit, two service vehicles and multiple mission vehicles. The interval length of each time slot is 0.1s. In each initial training test, the vehicle is randomly initialized on the two-way lane, the initial speed of the vehicle is randomly between 4m/s and 7m/s, and the vehicle keeps a uniform speed on the two-way lane, and the task vehicle will have a calculation task in each time slot.

We find that the strategy in multi-communication mode is significantly better than the strategy in single DSRC communication mode, single C-V2X communication mode and random communication mode in terms of delay. In C-V2X communication mode, RSU will charge a certain amount of cost, so the policy cost in multi-communication mode is lower than that in single C-V2X mode and random communication mode, and slightly higher than that in single DSRC mode. The cost of random communication mode strategy is between single DSRC communication mode strategy and single C-V2X communication mode strategy, which conforms to the theoretical expectation.

Since this is a joint optimization problem for task completion delay, total vehicle cost and average vehicle perception accuracy, the performance cannot be explained by a single index, so the advantages and disadvantages of the four schemes can be seen from the corresponding reward value. Since the reward value is negative, in order to facilitate viewing, we take an absolute value. The closer the absolute value of the reward value is to 0, the better the performance. It can be concluded that under all vehicle numbers, the random communication mode strategy has the largest absolute reward value and the worst performance. When the number of vehicles is small, the reward value of the single DSRC mode communication mode strategy is similar to that of the multi-communication mode strategy, indicating that when the number of vehicles is small and the computing resources are not tight, the cost of the single DSRC strategy is smaller, so this scheme is better. When the number of task vehicles is large, the performance of the single C-V2X strategy is better than that of the single DSRC strategy. The multi-communication mode strategy has the smallest absolute reward value and better performance.

By assigning different weight values to different optimization objectives, tradeoffs between multiple optimizations can be realized. We propose optimization strategies under four different weight values. Scheme 1 is an equilibrium optimization strategy, in which the algorithm strategy equally considers the average task completion time delay, average perception accuracy and total vehicle cost. The algorithm strategy only focuses on maximizing the average perception accuracy of the vehicle when it meets the constraints of the three indexes. Scheme three delay optimization strategy. The algorithm strategy only focuses on minimizing the average task completion delay when the three indicators are met. Scheme 4 is the cost optimization strategy. The algorithm strategy only focuses on minimizing the total vehicle cost when the three indexes are met.

We then tested 500 episodes with a well-trained model, and calculated the average task completion delay, average vehicle perception accuracy, and total vehicle overhead for each strategy.

Under the precision optimization strategy, the average perception accuracy of the task vehicle is the highest, the average task completion delay is larger, and the total cost of the vehicle is the largest.

When the maximum tolerable delay of the task is satisfied and the cost of the task vehicle is less than the maximum cost constraint, more perceptual tasks will be offloaded to the RSU for calculation and fusion with a better algorithm. Therefore, the average completion delay and cost of the task will increase relatively, but the perceptual accuracy of the task vehicle will also be improved.

Under the delay optimization strategy, the average task completion delay of the task vehicle is the lowest, the average perception accuracy is low, but the cost is also relatively low. If the delay optimization strategy meets the constraints of the three performance indicators, it will make a decision to reduce the average completion delay of the perceptual task. When the computing resources and communication resources of RSU or soft service vehicle are not tight, the task delay can be effectively reduced by choosing to unload to the two for calculation. Vehicles will put a larger proportion of sensing tasks in local processing of sensing tasks, so when the number of vehicles is large, the delay lead difference of the delay optimization strategy decreases compared with other schemes.

Under the cost optimization strategy, the total vehicle cost of the task vehicle is the smallest, and the average completion delay of the task is relatively low. Under the condition that the cost optimization strategy meets the constraints of the three performance indicators, in order to reduce the cost of transferring perceptual tasks to RSU and task vehicle, the task is more inclined to be calculated locally in the task vehicle. Therefore, the average task completion delay under this scheme will be larger, and the perception accuracy will be smaller than that of other schemes. However, with the increase of the number of mission vehicles, the gap between the average completion delay and other schemes is also narrowing.

Finally, under the balanced optimization strategy, it can be seen that the average task completion delay, total vehicle cost and perception accuracy are not optimal, but they are not the worst, and each item is in the middle level. Because the tradeoff strategy gives the same weight to each of the three optimization objectives, it optimizes all three optimization objectives at the same time.

Through the above simulation results and analysis, it can be concluded that the strategy we studied can change the optimization target of the strategy by changing the weight value of the corresponding optimization target, so that the average task completion delay, the average perception accuracy of the task vehicle and the vehicle cost can be optimized.

5. CONCLUSION

In this paper, we first explains the importance of communication computing resource collaboration in the V2X system. In the current V2X system, the types of tasks of vehicles are becoming more and more abundant, with different task sizes and delay sensitivity, etc. However, most of the existing researches only consider the communication computing resource collaboration under a single task, which cannot fully meet the needs of existing intelligent vehicles. This paper introduces a scheme of using the idle computing and communication resources of RSU and service vehicles to better meet the computing task requirements of mission vehicles. According to the different delay requirements of heterogeneous computing tasks and the difference of whether tasks can be split, a joint optimization problem is proposed to minimize the delay and cost of heterogeneous computing tasks. At the same time, we use the deep reinforcement learning algorithm and the simulation results show that the method has better performance and effectiveness than the benchmark algorithm.

REFERENCES

[1] M. Saifuddin, M. Zaman, B. Toghi, Y. P. Fallah, and J. Rao, “Performance analysis of cellular-v2x with adaptive and selective power control,” 2020.

[2] S. Kim and M. Bennis, “Spatiotemporal analysis on broadcast performance of dsrc with external interference in 5.9 ghz band,” 2019.

[3] M. Nadeem Hangar, Q. Ahmed, F. Khan, and M. Hafeez, “A survey of autonomous vehicles: Enabling communication technologies and challenges,” Sensors, vol. 21, p. 706, 01 2021.

[4] A. Elbery, Sameh Sorour, and H. Hassanein, “To DSRC or 5G? a safety analysis for connected and autonomous vehicles,” Accepted and to appear in the Globecom 2021 proceedings, 2021.

[5] 3GPP, “Study on enhancement of 3GPP Support for 5G V2X Services,” 3rd Generation Partnership Project (3GPP), Technical Specification (TS), 12 2018, v16.2.0.

[6] A. Masmoudi, K. Mnif, and F. Zarai, “A survey on radio resource allocation for v2x communication,” Wirel. Commun. Mob. Comput., vol.2019, pp. 2 430 656:1–2 430 656:12, 2019.

[7] F. Abbas and P. Fan, “A hybrid low-latency d2d resource allocation scheme based on cellular v2x networks,” in 2018 IEEE International Conference on Communications Workshops (ICC Workshops), 2018, pp.

[8] H. Chour, Y. Nasser, H. Artail, A. Kachouh, and A. Al-Dubai, “Vanet aided d2d discovery: Delay analysis and performance,” IEEE Transactions on Vehicular Technology, vol. 66, no. 9, pp. 8059–8071, 2017.

[9] U. R. Mughal, M. Ahmed Khan, A. Beg, and G. Q. Mughal, “Ai enabled resource allocation in future mobile networks,” in NOMS 2020 - 2020 IEEE/IFIP Network Operations and Management Symposium, 2020, pp.

[10] J. Schlechtriemen, F. Wirthmueller, A. Wedel, G. Breuel, and K.-D.Kuhnert, “When will it change the lane? a probabilistic regression approach for rarely occurring events,” in 2015 IEEE Intelligent Vehicles Symposium (IV), 2015, pp. 1373–1379.

[11] M. Schreier, V. Willert, and J. Adamy, “Bayesian, maneuver-based, long-term trajectory prediction and criticality assessment for driver assistance systems,” 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 334–341, 2014.

[12] A. Khosroshahi, E. Ohn-Bar, and M. M. Trivedi, “Surround vehicles trajectory analysis with recurrent neural networks,” in 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016, pp. 2267–2272.

[13] D. J. Phillips, T. A. Wheeler, and M. J. Kochenderfer, “Generalizable intention prediction of human drivers at intersections,” in 2017 IEEE Intelligent Vehicles Symposium (IV), 2017, pp. 1665–1670.

[14] E. Kafer, C. Hermes, C. W ¨ ohler, H. Ritter, and F. Kummert, “Recog- ¨ nition of situation classes at road intersections,” in 2010 IEEE International Conference on Robotics and Automation, 2010, pp. 3960–3965.

[15] A. Houenou, P. Bonnifait, V. Berge-Cherfaoui, and W. Yao, “Vehicle ´ trajectory prediction based on motion model and maneuver recognition,” 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 4363–4369, 2013.

[16] Khaled Kord, Ahmed Elbery, Sameh Sorour, Hossam Hassanein, Akram Bin Sediq, Ali Afana, Hatem Abou-Zeid. "Enhanced C-V2X Uplink Resource Allocation using Vehicle Maneuver Prediction", ICC 2022 - IEEE International Conference on Communications, 2022.