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REVIEW OF DEEP LEARNING AND MOBILE EDGE COMPUTING IN AUTONOMOUS DRIVING

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In recent years, mobile edge computing and deep learning have attracted strong industry attention in the application scenario of autonomous driving. Mobile edge computing reduces the transmission delay of autonomous driving information by offloading computational tasks to edge servers to reduce the network load; deep learning can effectively improve the accuracy of obstacle detection, thereby enhancing the stability and safety of autonomous driving. This paper first introduces the basic concept and reference architecture of MEC and the commonly used model algorithms in deep learning, and then summarizes the applications of MEC and deep learning in autonomous driving from three aspects: target detection, path planning, and collision avoidance, and finally discusses and outlooks the problems and challenges in current research.

Key words: mobile edge computing; deep learning; autonomous driving; internet of vehicles.

Introduction

With the development of machine learning, autonomous driving has gradually come into the limelight and has been applied in specific environments in recent years. Self-driving cars must also evolve into intelligent terminals equipped with multiple types of on-board sensors such as on-board radar, high-definition on-board cameras, positioning sensors, etc., supplemented by the latest communication technologies and powerful independent on-board computing units to connect directly or indirectly with all devices in other vehicles and the surrounding environment for data interaction. However, traditional self-driving vehicles are affected by the number of connected vehicles, road environment, traffic conditions, etc. Self-driving vehicles with limited computing resources may be constrained by computationally intensive applications, making it difficult for the vehicles to ensure the required quality of service. At the same time, self-driving vehicles with limited communication resources are vulnerable to mobility and cannot receive information about the external environment in real time due to their communication level.

The emergence of MEC (Mobile Edge Computing) [1] and deep learning [2] can help solve the problem of autonomous driving in terms of insufficient computing and communication resources and improve the intelligence of self-driving vehicles. Taking target sensing and detection technology, the core technology of autonomous driving, as an example, traditional autonomous driving relies on the redundant stacking of multiple sensors and a chip platform that meets the requirements of vehicle regulations, and a violent scanning scheme of sensors such as LIDAR, supplemented by appropriate image processing algorithms, so as to outline the range of surrounding obstacles [3]. This method places high demands on the number of on-board sensors, as well as the computational resources of the self-driving car, and the high latency caused by insufficient computational resources makes safety a serious challenge. Deep learning-based approaches allow for more accurate target sensing and detection, and the process can be offloaded to edge servers for processing, alleviating the demand on the vehicle's computational resources and significantly reducing the latency of processing tasks. The convergence of deep learning and MEC in the connected vehicle environment will open up new possibilities for the development of autonomous driving.

The applications of deep learning and mobile edge computing in autonomous driving are summarized and outlined in detail, including target detection, path planning, and collision avoidance problems in autonomous driving, discussing the advantages and shortcomings of existing approaches, and providing an outlook on the problems and challenges that need to be addressed in existing work.

1. Mobile edge computing and deep learning

1.1 Mobile edge computing

Almost all of the existing autonomous driving processes require real-time, latency, and energy consumption. With the expansion of data volume in the Telematics, each business also puts forward more stringent conditions on computation volume and real-time, and the traditional method of offloading computation tasks to the cloud for processing can no longer meet the requirements of latency-sensitive applications in the Telematics system, and the MEC architecture with terminal layer, edge layer, and cloud layer can help solve a series of problems in the Telematics [3].

Terminal layer: the terminal layer includes sensors that can be worn by mobile users as well as smartphones and smartwatches with execution capabilities. Initial data processing is usually executed on the smartphones and watches of mobile users, and with the computing power provided by the terminal devices, real-time services can be provided to the end mobile users and bandwidth consumption can be reduced. However, due to the limited computing power and storage capacity of end-user devices, some computationally intensive applications cannot guarantee their quality of service on mobile user's smart devices. Therefore, end devices in this layer can choose to upload difficult tasks to edge servers.

Edge layer: The edge layer is located near the mobile user, between devices such as sensing and smart terminals and the cloud layer. The edge layer includes devices capable of running more complex applications, and the endpoint layer is processing, filtering, and aggregating sensor data. In addition, most of the image recognition and video analysis tasks using deep learning are managed on the edge devices.

Cloud layer: The servers in the cloud layer need to have powerful computing and storage capabilities. Cloud servers can meet the resource and storage requirements of different applications, and this layer also supports the interaction between multiple MEC servers, including mutual collaboration and data exchange. Cloud servers have massive resources and are deployed far away from end devices. End devices will face the challenge of high transmission latency when offloading the sensed and aggregated data to cloud servers.

1.2 Deep learning

Compared with traditional machine learning methods, deep learning has powerful information extraction and processing capabilities. The combination of deep learning and reinforcement learning helps to further enhance the decision-making capability of the system, but it also requires a large amount of computational resources. The continuous improvement and breakthrough of related technologies in the field of deep learning further expands the application of MEC in various scenarios to improve its performance, efficiency and management. This section focuses on some typical deep learning models that are widely used in autonomous driving.

Deep Boltzmann machine: A Boltzmann machine is a generative architecture model that uses many hidden layers with no physical connections between variables in the same layer. Boltzmann machines have the ability to learn internally complex representations and can provide a good solution for signal processing type of applications in vehicular networking processes. In addition, multiple restricted Boltzmann machine layers can be stacked to form a deep confidence network consisting of visible layers and multiple hidden layers, which is widely used for fault and anomaly detection in vehicular networking.

Deep reinforcement learning: deep reinforcement learning focuses more on reinforcement learning. Unlike traditional reinforcement learning, deep reinforcement learning has a strong ability to approximate the representation of value functions or direct policies, and it uses deep neural networks to represent policies. Deep reinforcement learning algorithms can be divided into two categories: value-based models and policy gradient-based models. Using deep learning for target perception and detection, the value function or policy is fitted to solve a series of state-behavior space problems with the powerful representation capability of deep neural networks, and then a series of decisions for path selection and vehicle control in the field of autonomous driving are completed [4].

Deep forests: although the above-mentioned deep learning models have achieved great success in the field of Telematics, they also have shortcomings. Deep neural networks require appropriate hyperparameters, such as learning rate, optimizer type, etc., to achieve good results, and the large number of hyperparameters places higher demands on the storage capacity of edge servers. Therefore, the training of neural networks usually requires researchers to spend a lot of effort on fine-tuning the hyperparameters. Zhou et al. proposed deep forest gcForest [5], an integration of traditional tree-based methods in terms of breadth and depth, which is more explanatory compared to neural networks. Deep forests can effectively handle data of different sizes and have more stable and good learning performance. With almost identical hyperparameter settings as deep neural networks, deep forests can achieve excellent performance in processing different data from different domains.

2. Deep learning in MEC environment for telematics

Autonomous driving is one of the typical applications of combining edge computing and deep learning. As technology advances day by day, smart transportation systems in cities are not out of reach from ideal to reality. As we all know, autonomous driving technology is an effective combination of sensors, video processing, target recognition, radar localization, and road decision making. In reality, urban road conditions change in real time, and the sensors in a moving vehicle receive a large amount of data from the surrounding environment every moment. The combination of deep learning and edge computing can greatly reduce the delay in data transmission and thus improve the safety of connected vehicle systems. Several researchers in China and abroad have carefully studied the field of autonomous driving in which edge computing and deep learning are closely combined [6, 7]. The flow and architecture diagram of deep learning for autonomous driving in MEC scenario is shown in Fig. 1. In this section, the current state of research in this area in recent years is detailed in terms of target perception, path planning and collision detection and avoidance.

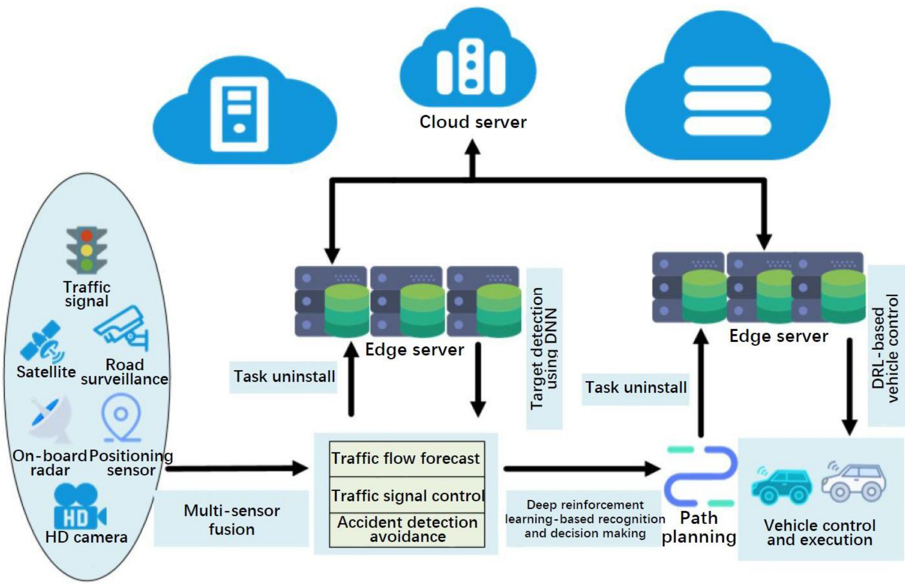

Fig. 1. Deep learning process and architecture diagram of autonomous driving in the MEC scenario

2.1. Target perception and detection

Target detection is one of the most important research problems in the field of autonomous driving. As described in the literature [8], the basis of autonomous driving technology that enables autonomous driving lies in the ability of intelligent vehicles to understand the environment, i.e., to sense the surrounding targets. Different on-board sensing will use different sensors to perform the corresponding sensing tasks, such as road detection, vehicle detection and pedestrian detection. The results of different detection tasks will be used for the subsequent implementation of path planning, vehicle control and other tasks.

In recent years, a lot of research has been done on vehicle detection and counting in roads, pedestrian detection, etc., mainly based on shallow learning. Shallow learning generally relies on manual feature extraction. The basic steps for vehicle detection are described in the literature [9], starting from selecting areas where cars are likely to be present and extracting two sets of histogram gradient features for both vertical and horizontal filtering directions. The distinction between cars and objects is done mainly through techniques such as mutual information measurement, normalized correlation, and combining correlation measurements with support vector machines. Then by associating the direction values with the points classified as cars, the points belonging to the same car are merged to complete the detection of the vehicle. In the development of autonomous vehicles, a variety of emerging sensors are installed, which also place high demands on the accuracy and real-time detection. Due to the huge amount of sensed data, intelligent vehicles face a huge computational burden, and the computational power will become a bottleneck that prevents vehicles from benefiting from the high system accuracy brought by high-resolution cameras. At this point, applying deep learning to target detection can help improve the accuracy of detection. However, the deep learning training process requires large computational and storage resources, and performing the above tasks in cloud-based servers leads to high bandwidth consumption, latency, and reliability issues. With the development of edge computing, deep learning-based target detection can be migrated to the vicinity of the data source, i.e., to end devices or edge nodes. In the terminal layer, devices such as in-vehicle radar and high-definition in-vehicle cameras are responsible for image video resource acquisition and use the terminal's smart devices to perform operations such as compression, pre-processing and image segmentation, and then offload the data to be computed to the edge nodes. By reducing unnecessary filters in the convolutional neural network layer, the resource consumption of the edge layer can be effectively reduced while ensuring the analysis performance and improving the overall performance. The next section will further elaborate on the deep learning-based target detection.

2.1.1. Road detection

A moving vehicle needs to detect lane lines in real time to determine the forward direction. The lane marker detection algorithm proposed in the literature [10], which first removes the road surface that forms the background of the lane markers and then uses a set of waveforms from local images to generate regions, shows that its detection error rate is only 0.63 % in daytime and 1.14 % even at night. However, the algorithm failed to demonstrate its low error rate even in complex scenes. To test the accuracy in complex scenarios, the literature [11] used data from various sensors such as LIDAR and high-speed cameras and used deep neural networks for lane detection in 3D space, and the proposed method showed good performance in complex scenarios such as blocking, bifurcation, merging and intersection. The literature [12] proposes a method to train the lane detector in an end-to-end manner by first predicting a segment-like weight map for each lane line using a deep network, and then returning the parameters of the best-fit curve for each lane line by weighted least squares. The results are significantly improved over the traditional two-step method at 70 frames. To address the problem of ambiguous lane lines and boundaries of roads, the literature [13] uses a recursive neuron layer for structured visual detection, which can automatically detect lane boundaries. However, the model is relatively large and the training time may be too long. To further reduce the training time, the full convolutional network algorithm proposed in the literature [14], by learning more road boundary recognition features and considering the location prior as a feature map directly added to the final feature map to improve the detection performance, has a 30 % faster convergence rate compared with the traditional model and can effectively save the training time.

2.1.2. Vehicle and environmental detection

To avoid accidents, self-driving cars need to detect and track other vehicles on the road as well as suspicious obstacles that obstruct the vehicle’s movement. In this task, factors such as the shape of the surrounding vehicles or obstacles, their relative speed to the vehicle, and their relative 3D position need to be estimated. The vehicle counting system introduced in the literature [15] mainly uses convolutional neural networks to regress vehicle spatial density maps on aerial images, and the evaluation results on the study dataset using Munich and overhead images show that it has high accuracy and completeness. The method proposed in the literature [16] is mainly based on convolutional neural networks and uses fast feature points to extract vehicle trajectories and obtain data on the number, direction of travel, vehicle type, and vehicle number of different vehicles. Compared with traditional hardware methods for monitoring vehicle traffic, it is less expensive and more stable, and does not require large-scale construction or installation of existing monitoring equipment in the mobile edge computing environment. The literature [17] proposes a fusion strategy of camera and LIDAR for target recognition by projecting the LIDAR 3D onto a 2D image plane and then using an up-sampling strategy to generate a high-resolution 2D distance view, using a convolutional neural network for three-channel color image classification and depth image classification to incorporate the actual distance to the recognized vehicle and the environment into the sensing system. The high complexity algorithm shortens the system response latency while putting new requirements on the computing power and energy consumption of the edge server. The literature [18] uses spiking neural networks for target recognition using temporal coding pairs, which has the advantage of effectively reducing the energy consumption and latency of the system when performing target recognition on real-world environments, but there is still room for further increase in recognition accuracy. How to balance recognition accuracy, system latency, and energy consumption metrics using deep learning approaches in edge computing environments will be the vane of future research in this field.

2.1.3. Pedestrian detection

Pedestrians are of higher importance than other objects, so it is necessary to distinguish common targets to be detected from pedestrians. Vision cameras are used on self-driving cars to detect, track and identify pedestrians to avoid collisions with them. The recognition framework proposed in the literature [19], although it can obtain higher accuracy in pedestrian detection, has the shortcoming of significantly higher processing time than other models. The literature [20] proposes a hybrid local multi-system based on convolutional neural networks and support vector machines, dividing the complete image into multiple local sub-regions, using principal-formation analysis to filter discriminative features, and applying empirical minimization and structural risk minimization methods into multiple support vector machines, with an average accuracy of over 90 % for pedestrian detection. The literature [21], on the other hand, uses the proposed partial context network to detect pedestrians through body part semantic information and contextual information to design a stronger complementary pedestrian detector with low bit error rate and high localization accuracy especially for obscured pedestrians, thus improving the detection of pedestrians in driverless cars and thus improving the safety factor.

2.2. Path planning

For path planning problems, traditional path planning algorithms mainly include fast exploration random tree algorithm, particle swarm optimization algorithm and A* algorithm. The traditional algorithms are designed with a single arrival point, which ignores the possible obstacles at any time and limits the scalability of the method, such as unexpected car and pedestrian flows. In addition, traditional shortest path algorithms cannot adapt to the dynamic nature of road networks, and their applicability to dynamic maps has not been tested in practice. Applying deep learning and MEC to vehicular networks for path planning of autonomous driving is expected to bring a new solution to the problem. The flowchart of path planning based on traffic flow prediction is shown in Fig. 2. The literature [22] applies a deep learning model to route planning, taking into account the requirements of route length, edge centrality, and the car's own speed, and increases the successful arrival rate of vehicles to 90 %, which can adapt to dynamic maps with less energy consumption. However, the shortcoming is that only local optimal selection can be achieved. The literature [23] proposes a method for predicting road routes from camera sensors using deep learning techniques to identify road pixels by training a multiscale convolutional neural network on a large number of full-scene labeled nighttime road images containing severe weather conditions, and based on this proposes a framework for applying the method to longer distance road route estimation, which in turn lays the foundation for the application of augmented reality navigation. The method can improve the reliability of detecting roads with or without lane markings, thus improving the robustness and usability of road route estimation and augmented reality navigation. The evaluation of a large amount of high-precision ground truth data acquired by differential GPS and inertial measurement units shows that it achieves significant performance while eliminating the need for existing lane markings.

Telematics in the MEC environment needs to consider not only the self-driving car's own movement but also the influence of other vehicles and human movement patterns on path selection. With the distributed nature of edge servers, MEC can be an ideal approach for vehicle traffic analysis and prediction. The combination of deep learning and reinforcement learning provides a powerful learning tool, as traditional path planning path decisions do not take into account traffic flow prediction and traffic signal control. With the full integration of edge-side, the traffic flow conditions and traffic signals in each corner of the city are taken into account to develop a more reasonable path planning strategy. The literature [24] proposes a multi-layer perceptron model based on the traffic history conditions, where the traffic conditions at the expected travel time are predicted before the route planning, and the Dijkstra algorithm used by the system takes the vehicle speed condition as one of the constraints, which leads to the optimal path. The literature [25] investigates the application of multi-task learning back propagation networks in traffic flow modeling and prediction, and the results outperform other traffic flow prediction accuracies such as Bayesian models and multivariate nonparametric regression models. The literature [26] proposes a deep architecture for traffic flow prediction using multi-task learning and demonstrates good results on real traffic flow datasets. Its underlying stack structure uses a dynamic Bayesian network for unsupervised feature learning, an upper regression layer for supervised training, and the Bayesian network is constructed as a stack of Boltzmann machines, and the activation of the training unit in each Boltzmann machine is passed to the next Boltzmann machine in the stack.

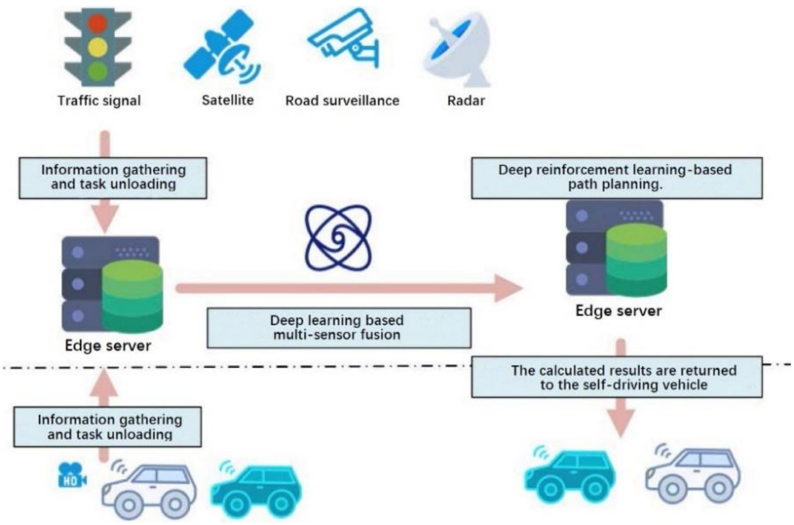

Fig. 2. Flow chart of route planning based on traffic flow prediction

2.1 Collision detection and avoidance

According to the Global Status Report on Road Safety 2018 released by the World Health Organization in December 2018, the number of road traffic fatalities reached 1.35 million that year, and more than 60 % of the injured died due to lack of timely and effective medical treatment, making road traffic injuries now the number one killer of people aged 5 to 29. How to adopt timely and effective accident detection and accident-avoidance mechanisms will significantly improve this urgent problem. In a vehicle network where deep learning and MEC are intertwined, the system will utilize various edge resources and on-board communications to help self-driving vehicles acquire, aggregate, and process data in real time, aiming to improve the safety and efficiency of autonomous driving. The previous section showed that important objects associated with self-driving vehicles can be identified and tracked by deep learning-based methods, but this is not enough to assist the autonomous driving system in making decisions. During autonomous driving, important decisions and actions are made by the self-driving vehicle collision avoidance system. In a connected vehicle system where mobile edge computing and deep learning are intertwined, the combination of their strengths will further leverage the contribution of collision avoidance systems to safety. The traffic accident risk map prediction applied to crash avoidance is shown in Fig. 3.

The model proposed in the literature [27] learns collision avoidance strategies based on deep neural networks using deep neural networks derived from noise perception measurements, and the learned strategies can also be extended to various situations not detected by visual sensors. However, its shortcoming is that the accuracy of the model still has a great potential for improvement by training multilayer perceptron as collision avoidance strategies. In addition, its effectiveness in encountering static obstacle scenarios is not demonstrated and it may not perform well in some special scenarios. The literature [28] proposed a method to detect high-speed head-on collisions and single-vehicle collisions with collision sensors and a deep learning platform, and the accuracy of its traffic collision detection could reach 96 %, but the persuasive power of its experiments needs to be further strengthened due to the small number of samples in the training model. The literature [29], on the other hand, takes the camera must be fixed as an entry point to design vehicle-based camera-based traffic accident detection, and uses an unsupervised learning framework to detect anomalies by predicting the location of future traffic participants. The innovation of the traffic accident risk prediction model established in the literature [30] is that it combines the characteristics of spatio-temporal distribution based on the frequency of traffic accidents and proposes the spatio-temporal correlation of traffic accident occurrence, mainly using recurrent neural networks, which can explore the deep connection between traffic accidents and their spatio-temporal distribution patterns and has certain reference value for traffic accident prediction systems. However, its shortcoming is that the prediction model only relies on traffic accident data, but ignores some other factors that may affect the occurrence of accidents, such as the traffic flow, road characteristics, and weather conditions of the accident area. To this end, the literature [31] used more than six months of traffic accident data and millions of users' GPS records in Japan as a training set to build a deep model of stack denoising autoencoder and proposed to use human mobility to predict the risk of traffic accidents. The practical significance is that the effective integration of edge computing and deep learning can be used to assess the risk of upcoming traffic situations in real time, so that the risk of traffic accidents can be warned and a safer route for driverless cars can be planned in conjunction with the route optimization problem.

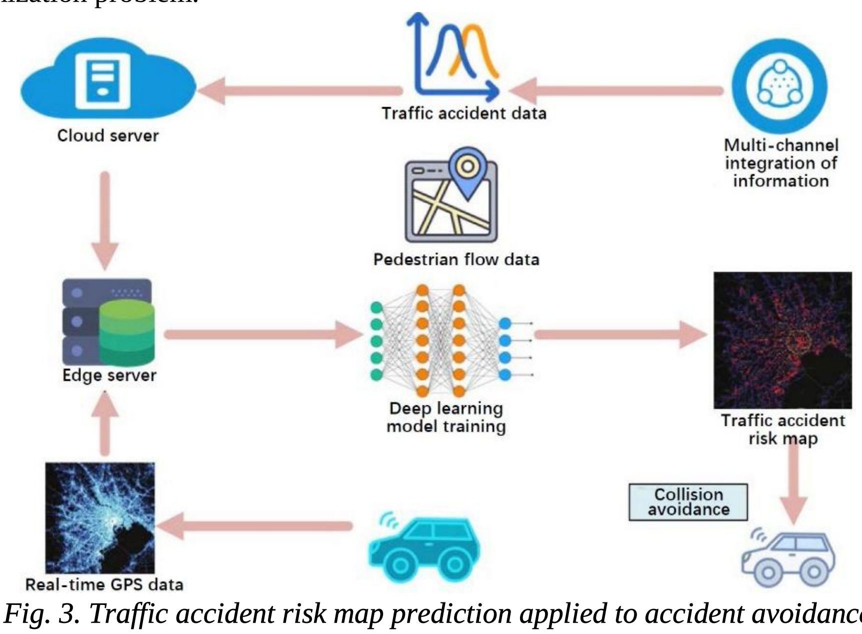

Fig. 3. Traffic accident risk map prediction applied to accident avoidance

3. Issues and challenges

Although the convergence of deep learning and edge computing has made significant progress in autonomous driving, there are still some key aspects that need further research.

Real-time nature of tasks: self-driving cars emphasize real-time nature of computational tasks, requiring ultra-low latency interactions and powerful computations.5G communication technologies bring new possibilities for reducing transmission latency, but aspects such as timely analysis of image and video data collected by on-board sensors and real-time transmission of processing results to the autonomous driving system, although a preliminary feasibility basis is available, need to be Further in-depth research is needed before practical application.

Privacy protection: Although the characteristics of mobile edge computing can ensure that data can be processed at the edge side, thus reducing the chance of being attacked during transmission. Its security is generally studied in the context of distributed deep learning, but there are still aspects that deserve further improvement, e.g., the membership attack problem. Successfully attacking the deep learning model training process of an edge server means that data items can be more easily identified as belonging to a small subset of users accessing that edge server, resulting in a compromise of user privacy. Nowadays, with the development of smart technologies, people are more concerned about personal privacy and future research will have higher requirements for privacy protection.

Vehicle mobility: High mobility of self-driving vehicles is a major feature of the connected vehicle environment with the fusion of MEC and deep learning. The high mobility of vehicles will bring new difficulties to the wireless link stability, computation and communication resources allocation in the connected vehicles. It is crucial to collect real-world vehicle mobility information more effectively and explore its patterns further.

Conclusion

By analyzing and summarizing the literature in mobile edge computing and deep learning, this paper details the reference architecture of MEC, introduces typical deep learning models such as deep Boltzmann machines, deep reinforcement learning, and deep forests, and then discusses the literature on the application of deep learning to self-driving target detection from three aspects: road detection, vehicle and environment detection, and pedestrian detection. Further, the research on MEC and deep learning in helping self-driving cars for path planning, collision detection and avoidance is summarized and concluded, and the remaining problems and challenges in current research are discussed.

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ОГЛЯД ГЛИБОКОГО НАВЧАННЯ ТА МОБІЛЬНИХ ПЕРИФЕРІЙНИХ ОБЧИСЛЕНЬ В АВТОНОМНОМУ ВОДІННІ

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Останніми роками мобільні периферійні обчислення і глибоке навчання привернули пильну увагу галузі в сценарії застосування автономного водіння. Мобільні периферійні обчислення зменшують затримку передавання інформації про автономне водіння, вивантажуючи обчислювальні завдання на периферійні сервери для зменшення навантаження на мережу; глибоке навчання може ефективно збільшити точність виявлення перешкод, тим самим підвищуючи стабільність і безпеку автономного водіння. У цій статті спочатку введено базову концепцію та еталонну архітектуру МПО та загальновживані модельні алгоритми глибокого навчання, а потім узагальнено застосування МПО та глибокого навчання в автономному водінні з трьох аспектів: виявлення цілей, планування шляху та уникнення зіткнень, і, нарешті, проаналізовано та розглянуто проблеми і виклики в сучасних дослідженнях.

Ключові слова: мобільні периферійні обчислення; глибоке навчання; автономне водіння; інтернет транспортних засобів.