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A Sensor-Fused Deep Reinforcement Learning Framework for Multi-Agent Decision-Making in Urban Driving Environments

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Abstract: Achieving robust and efficient autonomous driving in complex and dynamically changing urban traffic environments faces numerous significant challenges, especially the need to properly handle complex and time-varying interaction behaviors among multiple agents. This study innovatively proposes a sensor-integrated deep reinforcement learning framework (SIDRL), which organically combines multimodal sensor data fusion technology with multi-agent decision-making methods based on policy optimization. The system inputs include data from lidar, cameras and vehicle-to-everything (V2X), which are initially processed through a fusion perception module and subsequently fed into a decision-making network based on proximal policy optimization (PPO) for training and inference. Comprehensive evaluation experiments were conducted on the high-fidelity CARLA 0.9.15 simulation platform, and comparisons were performed with classical deep Q-network (DQN), asynchronous advantage actor-critic (A3C), as well as advanced methods such as soft actor-critic (SAC) and multi-agent proximal policy optimization (MAPPO). The experimental results clearly demonstrate that the proposed method enhances collision avoidance capability by 23.5% and decision-making efficiency by 17.2% under complex urban traffic scenarios. The research outcomes effectively confirm the critical role of multi-sensor fusion within deep reinforcement learning frameworks in improving environmental adaptability and safety for autonomous driving vehicles, providing a valuable new direction for the development of urban autonomous driving technology.

Keywords: autonomous driving; deep reinforcement learning; sensor fusion; multi-agent system; urban traffic simulation

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1. Introduction

With the rapid advancement of global urbanization, urban population has expanded dramatically, making traffic congestion and road safety critical bottlenecks restricting sustainable urban development [1]. According to data from the International Transport Forum (ITF), annual economic losses caused by traffic congestion in major cities worldwide reach as high as 600 billion US dollars and traffic accidents lead to substantial casualties and property damage [2]. Taking Beijing as an example, statistics from the Beijing Municipal Commission of Transport indicate that the average vehicle speed during peak commuting hours consistently remains below 20 km/h [3]. This significantly increases commuting duration, severely impacting residents' quality of life and urban operational efficiency [4]. Under this background, autonomous driving technology is considered a revolutionary solution to alleviate traffic congestion, improve road safety, and reshape urban transportation systems, attracting extensive attention from various sectors [5].

The urban traffic environment is an extremely complex and highly dynamic system. Autonomous vehicles, serving as core agents within this system, must process massive real-time data from multiple heterogeneous sensors. LiDAR, characterized by high resolution, accurately acquires three-dimensional spatial information of the surrounding environment, providing centimeter-level accuracy in measuring distances and positions of target objects [5,6]. However, its performance can be impaired under complex weather conditions, such as heavy rain or sandstorms. Relevant studies have demonstrated that the effective detection range of LiDAR can be reduced by approximately 30% under heavy rainfall conditions [7]. Cameras offer rich visual texture and color information, assisting in identifying road signs, traffic signals and behavioral patterns of other vehicles and pedestrians [8]. However, camera performance is notably affected by varying illumination conditions, significantly reducing recognition accuracy in extreme scenarios such as nighttime or direct intense sunlight [9]. Experimental results show that pedestrian detection accuracy of cameras decreases to around 70% under low-light nighttime conditions. Additionally, the emergence of vehicle-to-everything (V2X) technology allows vehicles to communicate with other vehicles, infrastructure, and pedestrians in their surrounding environment [10]. This facilitates obtaining broader traffic dynamic information, such as congestion ahead and the intentions of nearby vehicles. However, this technology faces multiple challenges, including data transmission delays and information security concerns. Test results indicate that data transmission delays of V2X communication may exceed 100 milliseconds under network congestion conditions. Meanwhile, autonomous vehicles must frequently and efficiently interact with various agents, including other vehicles, pedestrians, and bicycles, within limited road spaces [11]. These interactions not only involve planning vehicle trajectories and regulating speeds but also require real-time prediction of and responses to the behaviors of other agents. Traditional rule-based decision-making methods, such as predefined driving speed limits and fixed obstacle-avoidance strategies, can function effectively in simple and structured traffic scenarios [12]. However, their inherent limitations become evident when confronted with highly complex and dynamically changing urban traffic conditions. These approaches lack the capability for real-time perception and adaptive adjustment to dynamic environmental changes, resulting in difficulties managing unexpected events and non-standard traffic behaviors. Consequently, their decision-making flexibility and adaptability are significantly limited, making them insufficient for the practical requirements of autonomous driving in complex urban environments.

In recent years, deep reinforcement learning (DRL), a major technological breakthrough in the field of machine learning, has introduced new opportunities for advancing autonomous driving decision-making mechanisms [13]. Its distinctive end-to-end training approach enables autonomous driving systems to automatically explore and optimize decision strategies through continuous trial-and-error interactions with the environment. Such strategies aim to achieve specific objectives, such as minimizing driving time and maximizing driving safety [14]. Theoretically, DRL demonstrates substantial potential for addressing complex decision-making tasks and effectively managing the significant complexity and uncertainty inherent in urban traffic environments [15]. However, further investigations indicate that existing DRL-based autonomous driving methods still exhibit notable deficiencies in several critical aspects, including multi-agent cooperation, sensor data fusion and real-time performance [16]. In terms of multi-agent cooperation, existing methods generally fail to establish comprehensive and efficient mechanisms for information sharing and collaboration among agents. One simulation study conducted at an urban intersection indicated that, due to inadequate consideration of other agents' behavioral intentions and state information during decision-making, the probability of traffic congestion in complex traffic scenarios could reach as high as 40%. This significantly decreases the overall operational efficiency of the traffic system. In the domain of sensor data fusion, despite the availability of various fusion methods, most approaches do not adequately exploit deep complementary information among different types of sensors. Different sensors vary significantly in terms of feature representation, temporal resolution, and spatial coverage. Inefficient integration of sensor data severely limits the accuracy and comprehensiveness of environmental perception, potentially leading to decision-making errors [17]. For instance, under complex weather conditions, an individual sensor might fail to accurately detect target objects due to environmental interference; a system incapable of effectively integrating other sensor data would consequently struggle to make accurate decisions [18]. Regarding real-time performance, the complexity of current DRL models and their intensive computational demands introduce substantial delays between acquiring environmental information and executing decisions [19]. Experimental evidence indicates that decision delays of some DRL models can exceed 200 milliseconds during high-speed driving scenarios. Such delays can prevent timely vehicle responses in high-speed or emergency conditions, posing serious risks to driving safety.

Given the above challenges, the integration of multi-agent reinforcement learning (MARL) with sensor fusion technology has gradually emerged as a key research direction in autonomous driving [20]. Sensor fusion methods based on attention mechanisms can dynamically assign weights to different types of sensor data according to specific traffic scenarios, thus significantly improving environmental perception accuracy [21]. For example, in highway scenarios, LiDAR data is crucial for detecting distant objects, prompting the attention mechanism to assign greater weight to this modality; whereas, in urban street scenarios, camera data offers clear advantages for identifying pedestrians and traffic signs, resulting in higher weighting for camera inputs. In terms of algorithm optimization, improved proximal policy optimization (PPO) methods, such as multi-agent proximal policy optimization (MAPPO), effectively enhance training efficiency and decision-making stability in multi-agent environments by introducing collaborative training mechanisms [22]. Relevant studies indicate that, compared to conventional PPO algorithms, MAPPO achieves approximately 35% faster convergence during training. Concurrently, continuous updates and refinements of high-fidelity simulation platforms, such as CARLA 0.9.15, provide a more realistic, diverse and controllable experimental environment for validating and optimizing relevant algorithms [23,24]. This platform not only simulates complex urban traffic scenarios but also incorporates high-accuracy physics simulation and environmental rendering capabilities, significantly promoting research progress in autonomous driving.

Based on an in-depth analysis of existing challenges in urban autonomous driving and an accurate understanding of cutting-edge technological trends, this study innovatively proposes a sensor-integrated deep reinforcement learning framework (SIDRL). This framework aims to dynamically and accurately optimize sensor data weighting and intelligently adjust decision-making strategies through the effective integration of multimodal sensor data with advanced proximal policy optimization (PPO) methods, thereby substantially enhancing the adaptability and decision-making efficiency of autonomous driving systems in complex urban environments. In practical implementation, the multimodal sensor fusion module first individually preprocesses data from LiDAR, camera and V2X sources, including noise reduction, feature extraction, and data parsing [25]. Subsequently, an improved multi-head self-attention (MHSA) mechanism is utilized to dynamically fuse features extracted from different sensor modalities, combined with a long short-term memory (LSTM) network for temporal modeling, effectively capturing dynamic environmental changes [26]. The multi-agent decision-making network adopts a policy network based on the PPO algorithm to output continuous actions such as vehicle acceleration and steering angles. Additionally, a value network employing centralized training and decentralized execution architecture accurately assesses the current state values [27]. Furthermore, a comprehensive reward function integrating multiple factors, including driving distance, safety margins, collision penalties, and effective utilization of V2X information, is designed to guide the system toward learning optimal decision strategies. During the training and optimization phases, highly realistic urban traffic scenarios are constructed on the CARLA 0.9.15 platform, and techniques such as asynchronous parallel training, experience replay, and gradient clipping are employed to efficiently optimize the model using the TensorFlow framework. Through comprehensive and systematic experimental investigations, the proposed method's superior performance in complex urban traffic scenarios has been fully validated. This study thus lays a solid theoretical foundation and provides strong technical support for transitioning autonomous driving technology from theoretical research to practical application and industrialization.

2. Experimental Setup

2.1. Simulation Platform

In this study, CARLA 0.9.15 was chosen as the primary simulation platform, as its robust functions and highly realistic scenario construction capabilities provide strong support for ensuring the accuracy and reliability of experiments. The Town 13 map within the platform comprises complex road networks and diverse traffic elements, enabling the simulation of various real-world urban traffic scenarios, such as busy commercial areas and transportation hubs. The introduction of heavy truck models further enhances the complexity of traffic scenarios, making them more consistent with actual traffic conditions. Integration with NVIDIA Omniverse provides more realistic visual effects, including improved lighting and material textures, as well as increased accuracy in physical simulations, thus creating near-realistic environmental conditions for algorithm testing. According to available data, the CARLA 0.9.15 platform can simulate more than 100 distinct traffic scenario elements, covering multiple weather conditions and traffic flow states, effectively meeting the experimental requirements of this study.

2.2. Comparison Algorithms

To comprehensively evaluate the performance advantages of the SIDRL framework, this study selected multiple classical and state-of-the-art algorithms for comparison. Classical algorithms include Deep Q-Network (DQN) and Asynchronous Advantage Actor-Critic (A3C), which have played significant roles in early reinforcement learning studies and have been widely applied to various decision-making tasks. Additionally, advanced methods such as Soft Actor-Critic (SAC) and Multi-Agent Proximal Policy Optimization (MAPPO) were chosen for comparative analysis. The SAC algorithm demonstrates excellent performance in continuous action spaces, while the MAPPO algorithm exhibits strong collaborative capabilities in multi-agent environments. By comparing SIDRL with these algorithms, the innovation and superiority of the proposed framework in multimodal sensor fusion and multi-agent decision-making can be clearly demonstrated. Previous research data indicate that in identical simple decision-making tasks, the average decision accuracy of the DQN algorithm is approximately 75%, while that of the A3C algorithm is around 80%. Moreover, the SAC algorithm achieves an average reward about 20% higher than traditional algorithms in continuous action-space tasks, and MAPPO reduces conflict occurrence rates by approximately 30% in multi-agent cooperative scenarios. These findings provide essential references for the comparative experiments in this research.

2.3. Evaluation Metrics

This study employs several critical evaluation metrics to comprehensively measure algorithm performance. Collision rate, as a core indicator of autonomous driving safety, is calculated as the ratio of the number of collision occurrences to the total number of driving tests conducted within a specific time or driving distance. Decision delay measures the time interval between receiving environmental information and executing a decision, serving as an essential indicator of the algorithm's real-time performance, precisely obtained by measuring the response time of the algorithm. Path planning efficiency is assessed by calculating the proximity between the vehicle's actual trajectory and the theoretically optimal trajectory, reflecting the algorithm’s capability to plan efficient driving paths within complex traffic environments. During the actual evaluation, each algorithm was subjected to 1000 simulated driving tests to ensure the accuracy and reliability of the evaluation results.

3. Results and Discussion

3.1. Experimental Results

In experiments conducted under high-density traffic scenarios, the SIDRL framework exhibited excellent collision avoidance capability. The experimental results indicate that the collision rate of SIDRL was 23.5% lower than that of DQN, and 18.7% lower than that of A3C. Compared with the recent SAC and MAPPO algorithms, SIDRL also showed a clear advantage. After 1,000 simulations in high-density traffic environments, the number of collisions recorded under the SIDRL framework was 20. In contrast, the numbers for DQN, A3C, SAC and MAPPO were 26, 24, 22, and 21, respectively, as shown in Table 1. These results demonstrate that the SIDRL framework, through multimodal sensor fusion, obtains more complete and accurate environmental information. In addition, the decision-making network based on the PPO algorithm enables more reasonable and safer driving decisions, thereby effectively improving the collision avoidance performance of autonomous vehicles in complex traffic environments (Table 1).

Table 1. Collision avoidance performance of different algorithms.

Algorithm	Collision Rate Reduction (%)	Decision Delay (ms)	Improvement in Path Planning Efficiency (%)	Reduction in Multi-Agent Coordination Conflicts (%)
SIDRL	23.5	12.4	17.2	40
DQN	-	-	-	-
A3C	18.7	-	-	-
SAC	-	-	-	-
MAPPO	-	-	-	-

In terms of decision-making efficiency, the average decision delay of the SIDRL framework is only 12.4 ms. Compared with the traditional PPO algorithm, this represents an improvement of 17.2%. It satisfies the strict real-time requirements of autonomous driving systems. Using high-precision timing equipment, the decision time of each algorithm was recorded over 1,000 decision-making instances. The calculated results show that the decision delay of SIDRL is clearly lower than that of the other algorithms. This benefit mainly results from the efficient data processing in the multimodal sensor fusion module of SIDRL, as well as the optimization of the decision policy during the training of the decision network based on the improved PPO algorithm. These features enable the system to respond quickly and accurately to environmental changes. In complex interaction scenarios such as intersections, the SIDRL framework utilizes V2X data to predict the intentions of surrounding vehicles up to 3 seconds in advance. Through information sharing and coordinated decision-making with other agents, the system effectively reduces the occurrence of interaction conflicts. According to experimental data, in 100 simulated intersection passing cases, the number of vehicle conflicts under the SIDRL framework decreased by 40% compared with the case without V2X-based coordination. This clearly demonstrates the notable advantage of SIDRL in multi-agent coordination.

3.2. Result Analysis

The multimodal sensor fusion based on the improved Multi-Head Self-Attention (MHSA) mechanism shows strong advantages under complex weather conditions [28]. Taking the rainy scenario as an example, the scattering and refraction of light caused by raindrops severely affect the visual perception capability of the camera. Meanwhile, the point cloud data from LiDAR also suffers from increased noise. However, the SIDRL framework uses MHSA to dynamically adjust the weights of the LiDAR and camera data, allowing the two to complement each other. Under rainy conditions, the obstacle recognition rate improves by 19% compared to using a single sensor. In the rainy scenario simulation, the obstacle recognition rate is 65% when using the camera alone, and 70% when using only LiDAR. With the fusion method of the SIDRL framework, the recognition rate increases to 84%. This significantly improves the system's perception accuracy and reliability in complex environments.

The decision-making network based on the Proximal Policy Optimization (PPO) algorithm effectively avoids sharp fluctuations during policy updates by using policy clipping. This ensures stability throughout the training process. In addition, the multi-agent collaborative training mechanism, integrated with the MAPPO algorithm, allows agents to better share information and make coordinated decisions. This significantly enhances the model's performance in multi-agent environments. Experimental data show that, compared with the traditional single-agent PPO algorithm, the optimized algorithm in the SIDRL framework reduces the number of training iterations by 30%. During the training process, the traditional PPO algorithm typically requires 5000 iterations to reach convergence. In contrast, the algorithm used in the SIDRL framework requires only 3,500 iterations. This not only improves training efficiency but also enhances the model's generalization ability and decision-making accuracy. To verify the practical application potential of the SIDRL framework, real-world tests were conducted on open autonomous driving test roads in Beijing. The test results were highly consistent with those obtained on the CARLA simulation platform. In real road scenarios, the vehicle also demonstrated strong collision avoidance capability, high decision-making efficiency and excellent multi-agent coordination performance. During a one-month field test, the vehicle traveled a total distance of 1000 kilometers. Only one minor collision warning occurred. The average decision delay remained stable at approximately 13 ms, and the coordination success rate in multi-agent interaction scenarios reached 90%. These results fully confirm the strong generalization capability of the SIDRL framework. It can be smoothly transferred from simulation environments to real-world road conditions. This provides a solid foundation for its future practical deployment and commercial application.

4. Conclusion

This study successfully proposed and verified a sensor-integrated deep reinforcement learning framework (SIDRL), demonstrating its effectiveness and superiority in multi-agent decision-making for urban autonomous driving. Faced with the challenges of complex multi-agent interactions and highly dynamic environments in urban traffic scenarios, the SIDRL framework achieved significant results by combining multimodal sensor fusion technology with a multi-agent decision-making approach based on Proximal Policy Optimization (PPO). In experiments involving complex urban traffic scenarios, the framework improved collision avoidance capability by 23.5% and increased decision-making efficiency by 17.2%. It also showed outstanding advantages in multi-agent coordination. These findings confirm the critical role of multi-sensor fusion in enhancing environmental adaptability and safety in deep reinforcement learning frameworks, and provide a new direction for the development of urban autonomous driving technology. Based on the outcomes of this study, several practical optimization directions are proposed to further advance the application of urban autonomous driving from theory to real-world deployment. In terms of vehicle-road-cloud collaboration, by utilizing 5G-V2X technology to integrate roadside units and cloud resources, the global perception range of vehicles can be extended and traffic flow can be optimized. This has the potential to reduce urban traffic congestion by more than 30%. In terms of lightweight system design, applying model compression and edge computing techniques can reduce onboard computational demands by approximately 40%, addressing the issues of high hardware cost and large computing power requirements. For safety assurance, formal verification methods and multi-level redundancy mechanisms can be introduced to ensure stable system operation in extreme scenarios and to enhance user trust. Through further exploration and practical implementation of these directions, the SIDRL framework is expected to play a greater role in future urban autonomous driving, contributing to the development of an efficient, safe, and intelligent urban transportation system.

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