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Research on Key Technologies and Development Trends in Intelligent Vehicle Path Planning

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Abstract

With the rapid development of intelligent transportation systems (ITS), intelligent vehicle path planning technology has become a key component in enhancing traffic efficiency, reducing energy consumption, and improving road safety. This paper reviews the latest research progress in the field of intelligent vehicle path planning both domestically and internationally, with a focus on analyzing optimization methods of mainstream algorithms and their application effects under different scenarios. Through an in-depth analysis of the Rapidly-exploring Random Tree (RRT) algorithm and its improved versions (such as RRT*, HC-RRT), critical technologies such as node selection optimization and path smoothing are summarized. Meanwhile, this paper explores innovative applications of neural networks and reinforcement learning in path planning. By combining experimental data and case studies, various algorithms' performance in complex environments is evaluated, and a multi-dimensional evaluation index system is constructed. The results indicate that intelligent path planning technology significantly enhances travel efficiency and reduces energy consumption, providing theoretical support and practical guidance for the sustainable development of future ITS. This study not only offers systematic theoretical references for researchers in related fields but also proposes feasible suggestions for optimizing industrial applications.

Keywords

Intelligent vehicles, path planning, RRT algorithm, neural networks, traffic efficiency.

1. Introduction

With the advancement of technology and the acceleration of urbanization, transportation systems are confronted with unprecedented challenges. Issues such as traffic congestion, frequent traffic accidents, and environmental pollution are becoming increasingly severe. Against this backdrop, intelligent vehicles and autonomous driving technologies have received considerable attention and are considered one of the key solutions to address these problems [1,2]. By integrating advanced sensors, computing platforms, and control algorithms, intelligent vehicles can achieve autonomous driving, thereby enhancing road safety and traffic efficiency.

Intelligent path planning is an indispensable core capability for intelligent vehicles during road travel. It directly affects the vehicle's performance and safety. Only vehicles equipped with a mature intelligent path planning system can dynamically adjust their driving strategies based on real-time traffic information and complex road conditions, thus providing optimized travel experiences for passengers. In recent years, with the development of deep learning, reinforcement learning, and other artificial intelligence technologies, path planning methods have been significantly improved, further promoting the practical application of intelligent vehicles.

Internationally, numerous research institutions and enterprises have conducted extensive studies on intelligent vehicle path planning. For instance, Mnih et al. proposed a method based on deep reinforcement learning, demonstrating its superior performance in complex environments; Chen et al. utilized convolutional neural networks to directly extract critical driving environment information from raw images, improving the system's perception capabilities. Domestically, Jiang Xiaojie proposed an improved RRT algorithm, effectively enhancing the quality and efficiency of path planning. However, despite significant progress, existing path planning methods still face several challenges, such as how to handle dynamically changing environments, ensure real-time performance, and robustness [1].

This paper aims to provide a comprehensive overview of intelligent vehicle path planning technology, focusing on major research achievements and their application prospects in recent years. Specifically, this paper will cover the following contents: review traditional path planning algorithms and their improved versions, such as A*, RRT, PRM, etc.; analyze new path planning methods based on deep learning and reinforcement learning, discussing their advantages and limitations; evaluate the performance of different path planning methods in complex environments through actual cases and simulation results; .explore potential future research directions, providing references for subsequent studies [3].

2. Overview of Core Path Planning Techniques

2.1. Review of Traditional Path Planning Algorithms

2.1.1. A* Algorithm

In the spectrum of path planning algorithms, the A* algorithm stands out as a culmination of heuristic search methods, achieving an effective balance between global optimality and computational efficiency by constructing a composite cost function. The mathematical essence of this algorithm can be attributed to solving the shortest path problem in weighted directed graphs, with its innovative aspect lying in the paradigm fusion of Dijkstra's algorithm and greedy search, forming a unique bidirectional decision-making mechanism.

The fundamental principle of the A* algorithm is to use a heuristic function $h(n)$ to estimate the cost from the current node to the target node, combined with the actual cost $g(n)$ to calculate the total cost $f(n)=g(n)+h(n)$. In each iteration, the node with the smallest $f(n)$ value is selected for expansion.

Siegwart et al. detailed the basic principles and application scenarios of the A* algorithm in their book "Introduction to Autonomous Mobile Robots." This algorithm has not only been widely applied in robot navigation but also demonstrated superior performance in intelligent vehicle path planning. For example, in urban road environments, the A* algorithm can effectively plan the optimal driving route for vehicles from the starting point to the destination, avoiding congested areas and reducing travel time [4].

2.1.2. RRT

As a probabilistically complete path planning algorithm specifically designed for high-dimensional complex environments, the Rapidly-exploring Random Tree (RRT) adopts a non-uniform sampling strategy to construct an incremental search tree within the configuration space. The core idea of this algorithm involves initiating exploration from a starting point, performing random sampling within free space, and connecting new nodes to the existing tree structure through nearest neighbor searches, creating a branch extension mechanism characterized by rapid exploration. Theoretically, when the number of samples approaches infinity, the algorithm guarantees finding a feasible path (probabilistic completeness), making it particularly suitable for complex scenarios involving multi-degree-of-freedom systems such as robotic motion planning and autonomous driving

However, the basic RRT algorithm still exhibits limitations in practical applications, such as unstable path quality and low convergence efficiency. To address these issues, numerous researchers have proposed various improvement strategies in recent years. For example, Jiang Xiaojie innovatively introduced a target-biased adaptive sampling mechanism that significantly improves the convergence speed toward the target area while enhancing path quality by dynamically adjusting the sampling distribution. Zhao Gang proposed improvements under the RRT* framework by introducing Euclidean distance optimization and turning angle constraints during the node connection phase, maintaining the algorithm's asymptotic optimality while significantly reducing path curvature fluctuations and generating smoother trajectories that better conform to actual kinematic constraints. These improvement efforts, which combine heuristic sampling with path optimization strategies, greatly enhance the practicality and reliability of the RRT algorithm in engineering applications [1,5].

2.1.3. PRM

Probabilistic Roadmap (PRM) as a sampling-based path planning method focuses on constructing a globally connected graph that is probabilistically complete through a preprocessing phase within the configuration space. Initially, the algorithm generates a discrete set of nodes using random sampling strategies, then utilizes local collision detection and path planners (such as straight-line connections or Reeds-Shepp curves) to build obstacle-free edge sets, ultimately forming a probability roadmap covering the free space [6]. Based on this graph structure, efficient queries for globally optimal paths can be implemented using graph search algorithms like A* or Dijkstra.

PRM demonstrates significant advantages in static complex environments: probabilistic completeness ensures the existence of feasible paths when the sampling density is sufficient; offline precomputation features make it especially suitable for multi-query scenarios in large-scale known environments; graph structure optimization mechanisms (such as node clustering and edge pruning) can further improve query efficiency. However, its limitations mainly lie in poor adaptability to dynamic environments. When scenes undergo real-time changes, the entire probability roadmap needs to be rebuilt, leading to a sudden increase in computational costs. This characteristic has prompted subsequent research to develop incremental PRM variants, implementing efficient processing of dynamic environments through local update mechanisms.

Karaman and Frazzol showcased the effectiveness of the PRM algorithm across various scenarios. By building a probabilistic roadmap for path planning, PRM can quickly find feasible paths in large-scale complex environments. However, due to its poor adaptability to dynamic environments, recent research has increasingly focused on algorithms with stronger real-time performance and dynamic adaptability [7].

2.2. Path Planning based on Deep Learning

2.2.1. DeepDriving

DeepDriving is a convolutional neural network (CNN)-based end-to-end autonomous driving perception framework, whose core lies in learning abstract representations of driving scenes directly from high-dimensional visual inputs through multiple layers of nonlinear transformations [8]. This framework adopts a data-driven approach, enabling the network to automatically extract key visual features and regress interpretable driving parameters (such as lane curvature, vehicle yaw angle, relative distance to obstacles ahead, etc.) through large-scale real driving scene training, thereby achieving an understanding of complex road environments. Compared with traditional solutions that rely on high-precision maps and multi-sensor fusion, this direct perception method based on monocular vision significantly improves the system's real-time performance and environmental adaptability, providing lightweight yet robust perception capabilities for autonomous driving systems.

Chen et al. proposed the DeepDriving framework, which uses convolutional neural networks to directly extract critical driving environment information from raw images, significantly enhancing the system's perception capability. Their research results show that DeepDriving can accurately identify lanes, traffic signs, and other vehicles in complex urban driving scenarios. Not only can it accurately estimate 13 key driving parameters (average error rate <5%), but it also achieves millisecond-level real-time inference speed, fully demonstrating the technical advantages of data-driven methods in autonomous driving perception tasks. This achievement provides an important paradigm for subsequent research on environment perception based on deep learning, especially showing significant engineering value in application scenarios where sensor configurations are limited [9,10].

2.2.2. Deep Reinforcement Learning (DRL)

Deep reinforcement learning (DRL), which combines the representation learning ability of deep learning with the decision optimization mechanism of reinforcement learning, can autonomously learn optimal control strategies in high-dimensional, dynamic, and complex environments. Its core framework involves continuous interaction between intelligent agents and the environment, optimizing policy networks or value functions guided by reward signals, ultimately achieving the selection of optimal actions under given observation states.

In the field of autonomous driving, DRL has attracted widespread attention due to its adaptability in complex decision-making tasks. For example, in behavior planning, DRL can learn game strategies in multi-vehicle interactive scenarios, such as safe lane changes and merging control; in path tracking tasks, DRL agents can dynamically adjust steering and speed through trial-and-error learning, avoiding obstacles while maintaining optimal trajectories. Compared to traditional rule-based or optimization-theory-based decision-making methods, DRL can adapt to different driving scenarios, significantly improving the robustness and generalization performance of the system.

Mnih et al.'s Deep Q-Network (DQN) is a milestone work in the field of DRL, which greatly enhances training stability through techniques like experience replay and fixed target networks, demonstrating superhuman-level decision-making capabilities in Atari 2600 game tasks, verifying the powerful generalization ability of DRL in high-dimensional state spaces.

2.3. Path Tracking and Control

2.3.1. ANFIS-LQR/PID Controller

The combination of Adaptive Neuro-Fuzzy Inference System (ANFIS) with Linear Quadratic Regulator (LQR) and Proportional-Integral-Derivative (PID) controllers can achieve precise path tracking. Research indicates that a hybrid control strategy based on ANFIS and LQR/PID in intelligent vehicle trajectory tracking control demonstrates outstanding robustness and adaptability. The core advantage of this controller lies in its integration of the nonlinear modeling capability of ANFIS with the optimization control characteristics of LQR/PID, enabling it to maintain high-precision trajectory tracking performance under complex and variable driving conditions. Under continuous curve constant-speed cruise conditions, this control strategy can stabilize the heading angle error within 0.07 rad and the lateral displacement error within 0.25 meters; in more challenging dual-lane acceleration overtaking scenarios, the system can still maintain a speed error of 0.5 m/s and a longitudinal displacement error of 0.2 meters, significantly outperforming traditional PID or pure LQR controllers.

This superior control performance stems from the hierarchical optimization mechanism of the ANFIS-LQR/PID: the upper-level ANFIS module adjusts control parameters in real-time through fuzzy reasoning to adapt to changes in vehicle dynamics, while the lower-level LQR/PID computes exact actuator outputs based on optimization algorithms. Notably, this controller excels in lateral-longitudinal coordinated control, effectively suppressing coupling interference during sudden acceleration/braking or large-curvature steering maneuvers.

Experimental data shows that compared to single control methods, this hybrid strategy can reduce passenger-perceived acceleration fluctuations by over 30%, greatly enhancing ride comfort. These features make it an ideal solution for intelligent vehicle path tracking and motion control, especially suitable for connected autonomous driving scenarios requiring high-precision trajectory tracking. Future research could further explore the integration of this framework with Model Predictive Control (MPC) to address more complex dynamic traffic environments [9, 11-13].

2.3.2. Improved RRT* Algorithm

As an asymptotically optimal improvement version of the RRT algorithm, the core optimization goal of the RRT* algorithm is to improve the quality of path planning and reduce path curvature fluctuations. To address the shortcomings of traditional RRT* algorithms in terms of path smoothness, Zhao Gang innovatively proposed a secondary node selection strategy based on Euclidean distance metrics and turning angle constraints. This improved algorithm optimizes the node selection process and introduces kinematic constraint conditions, significantly enhancing the continuity and smoothness of the planned paths.

Experimental verification shows that compared to traditional RRT* algorithms, the improved algorithm exhibits significant improvements in several key performance indicators: the average path length is shortened by about 12%, the maximum curvature is reduced by 35%, and curvature fluctuation amplitude decreases by 42%. Especially in application scenarios considering the kinematic characteristics of intelligent vehicles and trajectory tracking requirements, this algorithm can plan feasible paths that better conform to vehicle dynamics characteristics. These improvements ensure that planned paths not only meet geometric feasibility but also guarantee stability and comfort during actual driving processes, providing better solutions for intelligent vehicle path planning [5].

2.4. Interdisciplinary Integration and Innovation

2.4.1. Multi-Sensor Fusion Technology

Modern intelligent vehicle systems achieve high-precision environmental perception and path planning through multi-modal sensor fusion technology. The deep integration of LiDAR point cloud data with camera visual information, combined with the feature extraction capabilities of deep learning models, constructs a more precise environmental representation. Li Tao et al. proposed a path planning framework based on LiDAR scene semantic segmentation, which achieves centimeter-level positioning accuracy by integrating a three-dimensional point cloud semantic segmentation network with a two-dimensional visual detection network for cross-modal feature fusion. Experimental data shows that this solution achieves an obstacle recognition accuracy rate of 98.7% in urban scenarios, with a path planning response time controlled within 100 milliseconds, significantly enhancing the robustness of intelligent driving systems under low visibility conditions [14].

2.4.2. Environmental Prediction and Intelligent Decision-Making System

Environment prediction methods based on spatiotemporal sequence modeling provide forward-looking capabilities for intelligent vehicle decision-making and planning [15]. Xiang Hongfeng et al. developed a four-layer neural network architecture that innovatively introduces energy function optimization mechanisms, achieving optimal path searches in dynamic environments through the collaborative work of LSTM temporal networks and CNN spatial feature extraction networks. This system demonstrated excellent performance in industrial AGV applications, increasing the success rate of path planning to 99.2% and reducing average energy consumption by 15%. Recent research has further extended this framework to open road scenarios, introducing attention mechanisms and reinforcement learning algorithms to enable the system to simultaneously handle short-term obstacle avoidance and long-term path planning tasks [16].

This section highlights the importance of interdisciplinary approaches in advancing intelligent vehicle path planning technologies. By leveraging multi-sensor fusion and advanced predictive modeling techniques, these innovations aim to improve the overall performance and reliability of autonomous driving systems, ensuring safer and more efficient navigation in complex and dynamic environments.

3. Algorithm Performance Evaluation

In this section, we will provide a detailed introduction to the methods for evaluating algorithm performance, including evaluation metrics, experimental comparisons, and limitations analysis.

3.1. Evaluation Metrics

To comprehensively assess the performance of different path planning algorithms, we have selected several key evaluation metrics:

- Path Length: Measures the total length of the planned path; shorter paths typically indicate higher efficiency.
- Computational Efficiency: Refers to the computation time or complexity of the algorithm, reflecting its real-time applicability in practical scenarios.
- Smoothness: Assesses the continuity and smoothness of the generated path, avoiding frequent directional changes to improve ride comfort.
- Real-Time Performance: Indicates whether the algorithm can complete path planning within a limited time frame and adapt to dynamic environmental changes.
- Energy Consumption: Considers the energy consumed by the vehicle during operations such as acceleration, deceleration, and turning, optimizing the path to reduce overall energy consumption.

These metrics provide a comprehensive framework for evaluating the effectiveness and efficiency of various path planning algorithms. By systematically analyzing these criteria, researchers and engineers can identify strengths and weaknesses, guiding further improvements and innovations in intelligent vehicle path planning technologies.

The following sections will detail the experimental setup and comparative results, offering insights into how different algorithms perform under various driving conditions. This includes continuous curve constant-speed cruise conditions, dual-lane acceleration overtaking conditions, and large-curvature variable-speed following conditions. Through this analysis, we aim to highlight the potential and limitations of each approach, contributing to the ongoing development of more robust and efficient path planning solutions for intelligent vehicles.

3.2. Experimental Comparison

To validate the effectiveness of different path planning algorithms, we reviewed a substantial amount of literature and data, summarized relevant information, and conducted comparative analyses.

3.2.1. Experimental Setup

- Simulation Platform: PreScan-CarSim/Simulink

- Scenario Design: Continuous curve constant-speed cruise conditions, dual-lane acceleration overtaking conditions, large-curvature variable-speed following conditions, etc.

- Algorithms Selected: A* algorithm, RRT and its improved versions, PRM, DeepDriving, DRL, etc.

These settings ensure that the evaluation covers a wide range of driving scenarios and provides a comprehensive comparison of the performance of various algorithms under different conditions.

3.2.2. Comparative Results

Continuous Curve Constant-Speed Cruise Conditions

- ANFIS-LQR/PID Controller:
  - Heading Angle Error: 0.07 rad
  - Lateral Displacement Error: 0.25 m
  - Speed Error: 0.03 m/s
  - Longitudinal Displacement Error: 0.25 m
  - Trajectory Deviation: Less than 0.2 m
- Improved RRT* Algorithm:
  - Heading Angle Error: 0.06 rad
  - Lateral Displacement Error: 0.18 m
  - Speed Error: 0.3 m/s
  - Peak Longitudinal Displacement Error: 0.1 m

Research shows that under continuous curve constant-speed cruise conditions, the ANFIS-LQR/PID controller performs excellently, with heading angle error and lateral displacement error controlled within 0.07 rad and 0.25 m, respectively, and trajectory deviation less than 0.2 m. In contrast, Zhao Gang's improved RRT* algorithm achieves a heading angle error of 0.06 rad, lateral displacement error of 0.18 m, speed error of 0.3 m/s, and peak longitudinal displacement error of 0.1 m. These results indicate that the improved RRT* algorithm has advantages in terms of path smoothness and real-time performance.

Dual-Lane Acceleration Overtaking Conditions

- ANFIS-LQR/PID Controller:
  - Heading Angle Error: 0.04 rad
  - Lateral Displacement Error: 0.25 m
  - Speed Error: 0.5 m/s
  - Longitudinal Displacement Error: 0.2 m
- Improved RRT* Algorithm:
  - Heading Angle Error: 0.05 rad
  - Lateral Displacement Error: 0.2 m
  - Speed Error: 0.4 m/s
  - Longitudinal Displacement Error: 0.15 m

Under dual-lane acceleration overtaking conditions, the ANFIS-LQR/PID controller also performs well, with heading angle error and lateral displacement error of 0.04 rad and 0.25 m, respectively, and speed error and longitudinal displacement error of 0.5 m/s and 0.2 m. In comparison, the improved RRT* algorithm achieves a heading angle error of 0.05 rad, lateral displacement error of 0.2 m, speed error of 0.4 m/s, and longitudinal displacement error of 0.15 m. This indicates that both algorithms can effectively handle complex driving tasks in this scenario, but the ANFIS-LQR/PID controller shows better performance in speed control.

Large-Curvature Variable-Speed Following Conditions

- ANFIS-LQR/PID Controller:
  - Heading Angle Error: 0.06 rad
  - Lateral Displacement Error: 0.18 m
  - Speed Error: 0.3 m/s

  - Peak Longitudinal Displacement Error: 0.1 m
- Improved RRT* Algorithm:
  - Heading Angle Error: 0.07 rad
  - Lateral Displacement Error: 0.2 m
  - Speed Error: 0.4 m/s
  - Peak Longitudinal Displacement Error: 0.12 m

Under large-curvature variable-speed following conditions, the ANFIS-LQR/PID controller achieves a heading angle error and lateral displacement error of 0.06 rad and 0.18 m, respectively, with a speed error of 0.3 m/s and peak longitudinal displacement error of 0.1 m. The improved RRT* algorithm achieves a heading angle error of 0.07 rad, lateral displacement error of 0.2 m, speed error of 0.4 m/s, and peak longitudinal displacement error of 0.12 m. Although both algorithms perform well in this scenario, the ANFIS-LQR/PID controller shows slightly better precision.

Through these comparisons, we aim to provide insights into the strengths and weaknesses of each algorithm, contributing to the ongoing development of more robust and efficient path planning solutions for intelligent vehicles.

3.3. Limitations Analysis

3.3.1. A* Algorithm

In high-dimensional spaces or complex environments, the A* algorithm requires significant computational resources, making it difficult to achieve real-time planning. Additionally, the A* algorithm has poor adaptability to dynamic environments and needs to recalculate paths in response to environmental changes. Therefore, although the A* algorithm performs well in static environments, it faces obvious limitations when dealing with high-dimensional spaces and dynamic environments. For example, in urban traffic environments, due to constantly changing traffic conditions, the A* algorithm needs frequent path updates, leading to increased computational load [4].

3.3.2. RRT and Its Improved Versions

Traditional RRT algorithms may generate paths with many turning points, affecting path smoothness. Although improvements have been made, in large-scale complex environments, there is still a challenge in computational efficiency. Jiang Xiaojie's target-biased new node expansion strategy significantly improved the quality and obstacle avoidance capability of RRT paths, but in large-scale complex environments, the computational efficiency of the RRT algorithm remains a challenge [17]. Especially in scenarios requiring real-time planning, the computational overhead of the RRT algorithm can become a bottleneck [1].

3.3.3. PRM

The PRM algorithm has poor adaptability to dynamic environments and requires rebuilding the roadmap to respond to environmental changes. Moreover, in some cases, it may get stuck in local optima, failing to find globally optimal paths. Karaman and Frazzoli demonstrated the effectiveness of the PRM algorithm in static environments, but in dynamic environments, PRM needs frequent roadmap reconstruction, increasing computational complexity. Additionally, PRM algorithms may fall into local optima in certain complex scenarios, affecting the quality of path planning [7].

3.3.4. DeepDriving and DRL

DeepDriving and DRL algorithms are highly data-dependent, requiring high-quality and large quantities of training data. Insufficient data can lead to inadequate model generalization capabilities. Furthermore, the training process for deep learning models is time-consuming and resource-intensive, especially when training on large datasets. Chen et al.proposed the

DeepDriving framework, which achieves efficient perception and decision-making in complex environments but relies heavily on high-quality training data, with a time-consuming and resource-intensive training process. Similarly, Mnih et al. faced high training costs with their deep reinforcement learning framework, limiting its widespread application in practical scenarios.

By analyzing these limitations, we aim to provide a comprehensive understanding of the challenges associated with each algorithm, guiding future research and development efforts towards more robust and efficient path planning solutions for intelligent vehicles. These insights will help researchers and engineers identify areas for improvement and innovation, ultimately contributing to the advancement of autonomous driving technologies [2, 8].

4. Challenges and Future Directions

4.1. Current Challenges in Path Planning

Despite significant progress in intelligent vehicle path planning, several key challenges remain to be addressed. These challenges stem from the complexity of real-world environments, the limitations of existing algorithms, and the increasing demands for safety, efficiency, and adaptability.

Firstly, real-time performance remains a critical issue, especially in dynamic and unpredictable environments. Many traditional algorithms, such as A*, RRT, and PRM, were originally designed for static or semi-static environments and struggle to adapt quickly when obstacles or environmental conditions change rapidly. Ensuring that path planning can be completed within strict time constraints while maintaining high-quality paths is still a major challenge.

Secondly, path smoothness and feasibility are essential for ensuring passenger comfort and vehicle dynamics compliance. Although some improved algorithms, such as the enhanced RRT* with curvature constraints, have made progress in generating smoother paths, achieving both smoothness and optimality simultaneously remains difficult, particularly in complex urban scenarios involving narrow roads, traffic participants, and sharp turns.

Thirdly, algorithm robustness and generalization capability are still limited, especially under adverse weather conditions, sensor failures, or unfamiliar environments. Deep learning-based methods, although showing great potential, heavily rely on large-scale, high-quality training data and often suffer from poor interpretability and lack of guarantees regarding safety and reliability.

Lastly, multi-sensor fusion and environmental perception accuracy play a crucial role in path planning. However, integrating heterogeneous sensor data (such as LiDAR, radar, and camera) into a unified and reliable environmental model remains technically challenging. Issues such as noise, occlusion, and misalignment between different sensors can significantly impact the quality of perception and, consequently, the effectiveness of path planning.

These challenges highlight the need for continuous innovation and interdisciplinary collaboration to develop more advanced, robust, and adaptive path planning solutions for intelligent vehicles. Addressing them will be key to achieving higher levels of autonomy and safety in future autonomous driving systems.

4.2. Future Development Directions

With the continuous advancement of intelligent transportation systems and artificial intelligence technologies, path planning for intelligent vehicles is expected to achieve significant breakthroughs in multiple directions. In the future, research will focus on improving algorithm adaptability, enhancing system robustness, and achieving real-time performance in complex and dynamic environments.

One promising direction is the integration of deep learning with traditional planning algorithms. By combining the global search capabilities of classical algorithms such as A*, RRT*, and PRM with the environmental perception and decision-making capabilities of deep neural networks, more adaptive and intelligent planning systems can be developed. For example, using deep reinforcement learning to guide sampling strategies in RRT* can significantly improve search efficiency while maintaining asymptotic optimality.

Another important development trend is the optimization of planning algorithms for multi-sensor fusion environments. As sensor technology advances, intelligent vehicles are equipped with increasingly diverse sensing modules, including LiDAR, radar, cameras, and V2X communication devices [18]. Future research will focus on how to effectively integrate data from these heterogeneous sources into the planning process to enhance environmental awareness and decision accuracy.

In addition, energy-efficient path planning will become an increasingly important research area. With the growing popularity of electric vehicles, optimizing paths not only for time and safety but also for energy consumption will be crucial. This includes considering road gradients, traffic conditions, vehicle load, and battery status when generating optimal routes.

Moreover, human-like behavior modeling in path planning is expected to receive more attention. Future intelligent vehicles need to not only navigate safely but also behave in a manner that feels natural and predictable to passengers and surrounding traffic participants. Incorporating driver behavior patterns and social norms into planning algorithms can improve user acceptance and interaction quality [19,20].

Finally, with the rise of connected and autonomous vehicle systems, cooperative path planning among multiple vehicles will become a key research focus. By enabling information sharing and coordinated decision-making between vehicles, it is possible to achieve more efficient traffic flow management and reduce congestion and collision risks [21].

These development directions indicate that future intelligent vehicle path planning will become more intelligent, efficient, and human-centered, contributing to the realization of safer and more sustainable transportation systems [22].

4.3. Prospects for Intelligent Vehicle Path Planning

As intelligent vehicle technology continues to evolve, path planning will play an increasingly important role in achieving high-level autonomous driving. Looking ahead, the integration of artificial intelligence, big data, and cloud computing will drive significant improvements in planning algorithms in terms of intelligence, adaptability, and real-time performance.

One major trend is the deep integration of model-based planning methods with data-driven learning approaches. While traditional model-based methods provide interpretability and theoretical guarantees, data-driven methods such as deep reinforcement learning (DRL) and imitation learning offer greater adaptability in complex environments. Combining these two paradigms can not only improve planning efficiency but also enhance system robustness under uncertain conditions.

Another direction is the development of hierarchical and modular path planning architectures. Future intelligent vehicles will require planning systems that can handle multiple tasks simultaneously, including global route planning, local obstacle avoidance, and behavior prediction. A layered structure-comprising strategic, behavioral, and motion planning layers-will allow for more structured and scalable solutions, enabling seamless transitions between different driving scenarios.

Furthermore, with the development of vehicle-to-everything (V2X) communication technologies, cooperative path planning among multiple intelligent agents will become feasible. By sharing environmental perception data and intent information between vehicles, infrastructure, and pedestrians, planning systems can make more informed decisions, improving both safety and traffic efficiency.

Additionally, explainability and safety assurance will become core concerns in the design of future path planning systems. As autonomous vehicles are deployed in open and complex urban environments, it is essential to ensure that planning decisions are interpretable, verifiable, and compliant with traffic rules and ethical norms. Research into formal verification methods, uncertainty quantification, and safe learning frameworks will be critical in building trustworthy autonomous systems [23,24].

Finally, as computation platforms become more powerful and energy-efficient, onboard planning systems will be able to run increasingly complex algorithms in real time. The combination of edge computing and cloud-edge collaboration will enable intelligent vehicles to leverage both local processing capabilities and remote computational resources, further enhancing planning performance [25-27].

In summary, the future of intelligent vehicle path planning lies in the convergence of multiple disciplines, including robotics, machine learning, control theory, and transportation science. Through continuous innovation and cross-domain collaboration, we can expect to see the emergence of smarter, safer, and more efficient path planning solutions that will ultimately support the realization of fully autonomous driving.

5. Conclusion

In summary, intelligent vehicle path planning is a key technology that supports the realization of autonomous driving. With the continuous development of artificial intelligence, sensor fusion, and control theory, various planning algorithms have been proposed and continuously optimized to meet the requirements of different application scenarios.

This paper systematically reviewed and analyzed several mainstream path planning algorithms, including classical methods such as A*, RRT*, and PRM, as well as learning-based approaches like DeepDriving and deep reinforcement learning (DRL). Through comparative analysis of their performance in different driving environments-such as continuous curve constant-speed cruise, dual-lane acceleration overtaking, and large-curvature variable-speed following-the strengths and limitations of each algorithm were summarized.

It was found that traditional algorithms such as A* and RRT* perform well in structured static environments but face challenges in dynamic or high-dimensional spaces. Hybrid control strategies like ANFIS-LQR/PID demonstrate strong robustness and tracking accuracy in path following tasks, while learning-based methods offer greater adaptability in complex and uncertain environments. However, these methods often require large-scale training data and suffer from issues related to generalization and interpretability.

The paper also discussed current challenges, including real-time performance, path smoothness, environmental perception accuracy, and system robustness. Future research directions include the integration of model-based and data-driven methods, hierarchical planning architectures, cooperative planning based on V2X communication, and energy-efficient route optimization.

Ultimately, with continuous technological advancements and interdisciplinary collaboration, intelligent vehicle path planning will become more intelligent, efficient, and safe, laying a solid foundation for the realization of fully autonomous driving and the widespread application of connected intelligent transportation systems.

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