AI-Based Autonomous Vehicle Path Planning

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1. Introduction

Nowadays, society's main concern is the development of transportation technologies in a digital way. One of the major advancements in this arena is autonomous vehicles, which can perform driving processes like a human being without any human intervention. The world is on an evolutionary trend to make all such transportation systems completely driven by an artificial intelligence (AI) system. AI systems are developed with a strong inclusion of learning technologies that enable autonomous cars to understand and learn from their experiences and environments. This AI context creates a strong bridge between transportation, technology, and society to envision a new world scenario. AI-based driving systems for automobiles can be developed by implementing various AI tools and mechanisms in order to make them more intelligent. AI-based driving systems are becoming ever more advanced due to enhancements in computing systems, algorithms, data collection, and supporting systems.

Drive and control systems in an autonomous vehicle are quite complex. More precisely, autonomous systems can be categorized from various aspects according to the planned context of usage. In this study, we mainly discuss AI-based path planning for autonomous vehicles. Path planning and obstacle avoidance are the most challenging issues in the literature of autonomous vehicles. The necessity of path planning algorithms is directly related to the survey of artificial intelligence that can be employed in autonomous vehicle research. In order to make safer and more efficient travel for autonomous vehicles in real-world applications, good path planning algorithms should be developed. This study systematically reviews and surveys the existing research studies of AI-based autonomous vehicle path planning with a detailed discussion of various learning technologies employed in these works. In addition, the studies are categorized, and the multiple challenges and advantages of AI-based autonomous vehicle path planning are discussed in detail to the target readers. This research aims to provide a one-stop reference for anyone interested in this emergent field. The rest of this essay is organized as follows: Section 2 delineates some basic definitions and challenges. Section 3 reviews the existing literature on AI-based autonomous vehicle path planning. The opportunities and challenges of all these studies are discussed and paved the way for discussion in Section 5. Section 6 concludes the proposed essay. The overall contribution flow of the paper is depicted.

1.1. Background and Significance

1. Introduction Autonomous vehicles have garnered significant research interest worldwide in recent years. Currently, AI-based path planning is a preferred research direction. Through decades of research, key technological breakthroughs have introduced new AI applications that have significantly improved transportation from stand-alone systems with no driver assist to advanced driver-assist systems that have reached an amazing level of automation. Furthermore, self-driving systems have become an integral part of intelligent infrastructure. In addition to reducing the number of deaths in car accidents caused by human error, increasing traffic efficiency, and reducing negative traffic and environmental impacts, autonomy has further facilitated the development of new services and industries. A pivotal research challenge when engineering intelligent autonomous unmanned vehicles is to intelligently build efficient pathways in static and dynamic maps that consider various spatial and non-spatial constraints and modes of vehicles and the needs of passengers. The autonomous path planning system usually involves several important technical components. First, the aim of the system should be to determine the optimum and secure route for unmanned vehicles in various static and dynamic environments. The system must also be able to control the movement of vehicles as they travel along the path via various waypoints. Novel research methods that minimize or circumvent these drawbacks will push autonomous vehicles to the next level.

1.2. Research Objectives

The prime aim of the research is to develop and examine intelligent methods for vehicle path planning for automated navigation. Research specifically addresses the use of AI-based methods for autonomous vehicle path planning. The work is based on a world-leading background in the development of novel algorithms to solve vehicle routing and navigation problems. Consequently, the study is likely to make a significant contribution to knowledge. The research will be conducted jointly by two researchers. It aims to address the following question: "What are the innovations and impacts of the novel approaches to autonomous vehicle path planning?"

Objectives To overview existing techniques in intelligent systems for autonomous vehicle path planning and the state of the art in these systems. This includes highlighting the limitations and their applicability presented in the existing intelligent systems. To develop intelligent methods for efficiently using AI-based techniques for autonomous vehicle path planning that can respond to environmental and driving style/habits effectively and robustly. To establish the effectiveness of AI-based autonomous vehicle path planning inputs independently in providing assistance in making critical decisions effectively. Develop appropriate software and hardware to validate the intelligent vehicle algorithms through practical implementation. The research establishes collaborations with other university sectors in computer vision and mechatronics. The findings from this research could provide an improvement in the state of knowledge for more detailed research focusing on autonomous vehicle path planning. This implies an immediate or potential forthcoming advantage that might be gained due to the outcome of the research. The research is carried out using two complementary approaches: theoretical development and practical implementation. The theoretical development is conducted by attempting to solve the related current problems in AI-based methods for autonomous vehicle path planning. In addition, the practical implementation is conducted by applying the theoretical insights in prototypes.

2. Foundations of Autonomous Vehicle Path Planning

Fundamental principles of autonomous vehicle path planning: Path planning in autonomous vehicle navigation is a decision-making process. It is based on the vast amount of data collected from GPS, LIDAR, and cameras. All these data streams, especially the real-time data, must be interpreted by the software algorithms, which then make a decision for the "optimal" path within a model of the real world. This decision can be executed by the hardware part of the vehicle.

Path planning algorithms: Several path planning algorithms can be utilized to facilitate the decision-making process. Among them, we can mention the following: classical algorithms, AI-based algorithms, and machine learning techniques. Nevertheless, there is no one-size-fits-all approach regarding the development of autonomous navigation solutions. Indeed, a number of technical and commercial considerations must be taken into account. In this regard, among these considerations, we can cite the central processor, weight and/or size of the microcontroller, RAM size, and I/O ports. Furthermore, autonomous navigation solutions feature an interplay between hardware and software to strike a good balance.

Autonomy levels: Path planning problems can be quite challenging. Depending on the method and the support between hardware and software, a certain level of autonomy can be reached. In general, four main different levels have been identified in the degree of autonomy. These levels are as follows: L0: human in the loop where the driving action is performed by a user who considers as inputs some data about moving agents in the surrounding area, namely obstacles. L1: decision assistance where the driving action is suggested by a remote human operator based on the interpreted data. L2: operational invasion where the driving action is performed by a vehicle operator, commonly in a supervisory role. L3: conditional automation where the driving responsibility is shared between the (semi)autonomous system and the human operator. L4: high automation where the system is fully responsible and the operator is a fallback solution controller in the event of a system failure. Given the aforementioned levels of automation that can be reached and the type of sensors and hardware/software to be used, complex algorithms must be developed.

2.1. Key Concepts in Autonomous Vehicles

Key Concepts in Autonomous Vehicles

Nowadays, many transportation fields, including aviation, shipping, and road transport, have been introducing autonomous vehicles, which are equipped with technologies enabling self-operation. In this context, four fundamental concepts support autonomy: sensors, perception, localization, and mapping. Autonomous vehicles fall into six different autonomy levels. Currently, many companies focus on levels 4 and 5 as these are industrially feasible. Five functionalities define autonomous vehicles, such as perception, localization, mapping, path planning, control systems, and decision-making. Perception, localization, and mapping are mainly dependent on sensors that aim to get data from the real world where the vehicle is traveling. The artificial intelligence system will take the raw data and process it to make decisions based on it. Criteria like safety, reliability, comfort, and efficiency in navigation are very critical for the passengers inside the autonomous vehicle.

Autonomy: An Autonomous Vehicle (AV) is a system designed to transport payloads and may transport passengers depending on passenger approval from start to goal without a person stepping up to control it. These vehicles fall under six levels of autonomy. Level 4 vehicles are autonomous within a certain operational design domain, while level 5 vehicles are fully autonomous in all conditions. Demonstrated Technologies Associated: Self-Driving Car, Level 4 Autonomous Shuttle, Level 4 Automated Drone, Level 5 Automated Taxi. Perception: Functionality allowing the interpretation of the state of the vehicle. It is composed of three senses: vision, radar, and lidar. Perception aims to interpret user data for the decision-making system, e.g., object detection and pedestrian detection, position keeping, and heading metering. Topography mapping.

2.2. Path Planning Algorithms

The path planning algorithm indicates how a vehicle should operate in different environments. The algorithms can be divided into three categories: grid-based methods, sampling-based approaches, and optimization methods. Various techniques have also been developed for dynamic environments. Grid-based methods decompose the environment into a grid, which can be done in either a 2D format or 3D format, and model the available or free regions arranged in configuration space in order to produce a path from start to goal. These algorithms decompose the environment into two parts: obstacles and free space, which connects with the distance calculation to the goal.

The focus of sampling-based approaches is to develop a free random sample inside the environment as a way to determine the path for an autonomous vehicle. The main advantage of using sampling-based approaches is the computational efficiency to compute global planning and help most path-planning algorithms complete in real-time. The optimization method is special compared to the two mentioned earlier, which produces the best path in terms of its trajectory and maneuver that the autonomous vehicle needs to follow, in advance by using graph-based searching algorithms or grid-based set methods. The dynamic environment represents any environment in which time is a factor, and the moving obstacles and safety constraints are required to change quickly. Optimization-based algorithms were proposed in a variety of applications, such as urban environments for multiple agent applications and highway collisions in robotics.

3. Machine Learning Techniques in Path Planning

Introduction Machine learning has been a transformative factor in the field of artificial intelligence, owing to its capabilities for deriving insights from data and achieving adaptability through continuous evolution. It offers the potential to build autonomous systems capable of performing tasks in changing and complex environments. In autonomous vehicle path planning, machine learning techniques can be used to train algorithms and optimize the selection of the best route. Delivering the full capability of artificial intelligence in autonomous vehicle path planning, integrating both a model-driven approach and a data-driven model has resulted in improved performance in planning. These days, predefined standards for path planning engines are mainly used in driverless vehicles to select the most appropriate path. While conventional self-planning schemes are efficient, in complex city conditions and rapidly evolving environments, they lack adaptability. Methodologies of machine learning, with the ability to benefit from vehicle responses, aim to solve this difficulty and are anticipated to increase the dependability of driving. Even if these structural differences are successful, competition with other methods provides a great solution, contributing to the advancement of the field of self-driving vehicles. Pilots in a remote-controlled system can learn route options. A group of driver assistance-based algorithms has been used in the industry to set the path based on real-time data, although they are not fully recognized or dependent on historical information as well. These schemes strongly depend on the prediction of the intensity of the commercial path, either static or in real time, to help the distribution of flows both inside a network and essentially on state roads.

3.1. Supervised Learning for Route Selection

A common method for improving route selection is supervised learning. In supervised learning, machines or algorithms are trained using a labeled dataset. They can identify the most efficient route based on known conditions. This has a higher propensity for identifying the most efficient route than the rule-based methods previously described. It can use historical data to find the route that reduced travel times the most or had the least fuel consumption. This is not like rule-based route selections that choose the most fuel-efficient route for a certain period of time. Since supervised learning can find underlying relationships between factors, it can find combinations of those factors that minimize travel time or fuel consumption using sophisticated algorithms. Moreover, some route selection is updated in real-time based on current and predicted road conditions, which offers a significant advantage in improving efficiency. Supervised learning systems are preferred because they do not require user input or assumptions about how to proceed. Real-time traffic is incorporated into the optimization model, which more accurately represents user experience. Supervised learning is one of the prominent candidates for incorporating these learned policies in the path planning module of autonomous technologies. Even more current autonomous technologies should be leveraging supervised learning policy creation. Supervised learning is a useful way to determine the fastest or most efficient route in the real world. A non-exhaustive survey of autonomous and intelligent vehicle companies on an Autonomous Vehicle Technology report showed that several major companies were using supervised learning-based route planning technologies in most of their autonomous systems to enable mission, path, or route planners.

3.2. Reinforcement Learning for Real-Time Adaptation

Real-time navigation strategies are of crucial importance for operational-level path planning of vehicles. To this end, reinforcement learning (RL) is a class of machine learning that enables an AI agent to learn optimal policies without a given model in advance. RL primarily trains the AI agents on a trial-and-error basis, wherein they try different actions to figure out the best possible route by observing the corresponding feedback. RL allows vehicles to learn from their interactions with the dynamic environment. In this scenario, traffic variations or any on-road obstacles can be tackled effectively. A majority of current research focuses on using RL techniques to resolve navigation issues in complex terrains under uncertain conditions. RL is preferred for autonomous vehicles due to its continuous performance improvement through the cumulative experience obtained from filtering initial biased decisions.

Several transportation researchers employ RL to resolve uncertainty and stochastic components in path planning applications. RL techniques, on the other hand, contribute to an exceedingly important research area. The accurate accomplishment of policies comes from the exact methods that directly transfer the accumulated insights derived from the training and testing data. However, the major constraint lies with deep reinforcement learning methods, which require colossal amounts of data and computation. It becomes difficult to gather data around each required part of the potential field that would be involved in the training of the

AI agent as well as in conventional coverage path planning methods. Reinforcement learning has shown to be a promising technique for the adaptation of autonomous vehicles on the fly. This complex learning approach has been presented as useful in recent research studies. The fine execution of policies, which act in the policy-defining methods, is founded on the available data drawn from the training and testing stages. However, the limitation associated with deep reinforcement learning tends to require a saturated volume of data and executions. As a result, deep RL calls for broad involvement of resources that require time and energy. Thus, real-time path modification remains a constraint. Hence, the most critical aspect facing RL-based approaches lies in examining the valid demands of extensive research to design pure real-time approaches concerning the scarcity of the deep learning-based approach.

4. Case Studies and Applications

Urban Environment Navigation

An example of a real-world application of vehicle path planning is in the field of the urban environment. This is a challenging environment: pedestrians can change direction at any time, and there will be traffic signals determining the speed to reach. This guidance can be based on real-time traffic information: a GPS device installed on the vehicle receives real-time traffic information and, in case of congestion, offers an alternative route. To make offline planning more realistic and to take into account normal congestion, we assume some times similar to the current situation. We show planning either with or without the effect of obstacles. This kind of planning is mainly useful in navigation or video game parts of modern robotics. The purpose is efficiency in terms of distances or times to reach a goal location. The underlying database is a 2D (or 3D) map made of a modern strength-based Voronoi graph.

Highway Driving

Driving on the highway is an environment fundamentally different from the urban environment. In the latter case, one has more time to maneuver because the maximum speed is lower. We first used this strategy to simulate the traffic in a city. We made the autonomous vehicles (ridden and in a convoy) drive on the highway (limited to four different speeds in four lanes) and downtown (around the airport, with a grid of four roads). In both cases, we have transmitted desiderata to the kernel of the path planner. While in the city car, I want to go from point A to point B at hometown speed, governor speed on the highway, and finally high-speed chase at the airport. In the case of the guided missile, the kernel receives the point where the missile must arrive (either at high speed at the airport or at low speed in town). The kernel then uses a path planner that evaluates the cost of all the possible paths to reach the goal. These paths can be over a map or over a kinematic space. The path planner uses heuristic algorithms, such as the A* algorithm or the D* algorithm. The A* algorithm is based on four assumptions: 1. an open list called the open list, 2. a closed list called the closed list, 3. a cost to get from the starting point to the target for the best-known path, and 4. an estimation of the cost from the current position to the target. In our case, the starting point is the current position of the vehicle, and the target is the point set in place by the guidance interface. The only conditions the guidance returns are hit/no hit and solution found/no solution found for the missile cases. In a FIFO printing system, the path planner sends back all the known solutions up to an inserted percentage.

4.1. Urban Environment Navigation

1 Introduction 1.1 Urban Environment Navigation Vehicle navigation in urban environments has always been considered a complex process because of the obvious interaction of dynamic and rapid changes in street topologies, pedestrian crossings, buildings, signal-light posts, and a congregation of unstructured human scenarios, which are a direct consequence of natural entropy. Thus, an automated system should also mimic closely its human counterpart for effective vehicular maneuvering both in regular and unseen urban conditions. In an urban scenario, operational design domains for vehicle navigation have a vast profile of human-like attributes that may become a hindrance to an automated vehicle if not addressed properly. The problems faced are completely unpredictable trajectory predictions of manually driven vehicles, a sudden appearance of jaywalking pedestrians, a diverse set of road geometric structures, the appearance of shared road infrastructure, etc. The introduction of real-time perception due to object occlusion, object detection with partial state dimensions, and an imperative need for real-time decision-making is the need of the hour. The recent trends in artificial intelligence and its applications have made the development of sophisticated algorithms that exhibit human-like intelligence, such as computer perception and image object detection, more hassle-free. In this section, various technologically inclined research works implemented in the domain of UAV urban navigation are discussed, and the

underlying processes are elaborated along with their limitations. Navigation of an autonomous car inside an urban environment has lately attracted the attention of researchers and automakers primarily due to an increase in road traffic over the past five years. A few mileposts are found where a path planner has been successfully developed and tested in an atmospheric urban environment to demonstrate the capability of the proposed approach. Navigation of autonomous vehicles in a dynamic obstacle-free urban scenario is presented. The designed planner utilizes the Dijkstra algorithm to search for the optimal path. The approach developed does not include a path planner and has not discussed the capability of their ensemble approach in any off-road pedestrian accidents, car accidents, or any full or partial sedan damage analysis. In general, developing a reliable perception system for autonomous vehicles in off-road scenarios, other than non-segregating pedestrians, is a challenge in itself. A more complex DRL algorithm is developed for urban path planner design and is based on a sense-follow DRL algorithm. This approach involves pretreatment data for long-range scenario forecasting using a ResNet model and a multilayer perceptron for real-time traffic maneuvers over some long-term temporal data. The state-of-the-art approach is presented, which describes features like real-time path planning. In summary, this section looks closely at automobiles that aid in assisting indirect free ride-sharing in an urban environment. Aesthetically, too many autonomous areas of research need to be further explored to automate our sleek smart vehicle to a level where it prioritizes pedestrian obligations.

4.2. Highway Driving Scenarios

Compared to urban navigation and parking, autonomous driving at high speeds in highway driving scenarios represents a contrasting subject of interest. In high-speed conditions, drivers typically have less time to make decisions in critical situations, and the vehicle needs to guarantee stability and trajectory tracking for the safety of the passengers. In the meantime, it is able to make more decisions in a very limited time when making a lane change, merging, etc. Solving the lane-keeping problem has always been a focus of highway driving technology research. In uninterrupted road conditions, the problem of trajectory planning is to avoid excessive lane switching over long distances and to adapt to the curvature of the road while steering. The relatively small computational complexity of the problem can be solved directly in the shortest time. In situations with frequent lane-changing vehicles, reference trajectories can be generated from a stochastic optimal control perspective.

A longitudinal driving strategy plays a significant role in highway autonomous driving systems, which not only needs to control the driving speed but also to ensure the longitudinal driving safety of the vehicle in various dynamic traffic conditions. The correct strategy and decision-making process are critical factors in the operation of high-speed traffic, for example, choosing the appropriate time to merge from one lane to another, especially on busy highways. The need to predict these operational conditions in real time is essential. The state of the art in highway driving autonomous technology has been tasking robot prototypes with the problem of autonomous lane centering under various speeds and driving conditions. Thanks to the developed technology, vehicles are now able to assist their drivers in better monitoring and absorbing road driving. These features are available in various car brands. Some examples of the proven capability of highways in autonomous driving are shown in the following sections. It is expected that vehicles will be capable of maintaining safety and performance along highways by taking forecasting information from the environment.

Above all, it is necessary in highway autonomous systems to integrate data prediction from the ADS with environmental conditions. The correct data prediction of the environment also involves the proper normalization of the forecasted input. The highway autonomous driving algorithms have the capability to process data coming from different sources and to change in real time a requested set point to avoid obstacles or to follow the road correctly. For example, the nearest road merging can be properly tackled.

5. Challenges and Future Directions

Self-driving vehicles still face many challenges that must be addressed by researchers in close collaboration. Autonomous vehicles are becoming increasingly widespread in real-world scenarios, and as a result, we must specify the criteria that define the ethical behavior and decision-making of automation systems. In particular, the development of AI algorithms for decision-making will require careful analysis of potential ethical conflicts in selecting the best options, as well as issues related to transparency and decisions in accident situations. In addition to road safety, which is paramount for achieving successful vehicle automation, questions regarding system reliability and vulnerability to external attacks must be addressed.

If widespread deployment of these technologies is to be reliably achieved, there are significant issues of transparency, governance, regulation, ethics, and liability that must be addressed. In order to shape the final context of regulations and standards, legal and insurance professionals will also need to be consulted. Research towards the development of improved sensors and algorithms should be guided by the consideration of standards on perception and the decision-making process. In evaluating the performance of path planning techniques, researchers must develop metrics by incorporating data about human driving behavior. The continual evaluation of these and new path planning techniques should be accomplished through experimentation conducted within symbolic simulation environments built on the agent-based traffic simulation approach used to emulate computer vision outputs and vehicular communicative events. There is a need for thorough examination of novel algorithmic designs that employ deep learning-based feature detection for sensor inputs and real-time trajectory generation while working with large-scale sensor data. There is also a dearth of research into algorithms that can work with reduced or incomplete sensor inputs with respect to differently shaped and differently colored lane markers. Finally, self-driving cars need to be embedded in the context of smart city infrastructure in order to effectively navigate traffic flow. As such, future research into path planning must be done through multidisciplinary teamwork among computer vision and AI experts, distributed systems specialists, manufacturers, legal, regulatory and insurance professionals, and urban and regional planners.

5.1. Ethical and Safety Considerations

Ethical and safety issues concerning the development and deployment of autonomous vehicles, like any other AI system, have also received extensive attention. Studies have identified numerous ethical dilemmas related to software and AI decision-making in life-threatening scenarios, and the public perception of autonomous technology is particularly relevant to the vehicle domain. At the core of all these issues is the fundamental requirement for safety. In order for consumers to trust driverless vehicles, they need to be satisfied with the technological capabilities and the safety standards and testing that are in place to demonstrate those capabilities. If a constantly learning system is required to be hard-coded to punish bribery, it must demonstrate an accurate understanding of what a bribe is: an explanation of how algorithms develop these understandings as they are trained over time is vital.

Self-driving vehicles are required to meet stringent safety standards, and compliance with protocols is rigorously tested before approval for use on public roads. Many believe that a driverless vehicle should be at least, to a first approximation, twice as safe as the average human driver in order to be given the go-ahead to operate. There are several ethical frameworks for autonomous vehicle decision-making, but the pursuit of an ethical framework for a fully autonomous AI system is a highly interdisciplinary concern with input being sought from a wide and diverse group of stakeholders. The development of a fully autonomous vehicle equipped with artificial intelligence necessitates the introduction of new legislation and policy, influencing different sectors of society, and needs to be able to evolve as the technology itself develops. Lastly, the collection, storage, and sharing of data pose a different set of ethical considerations, including questions of individual privacy and autonomy, the security of personal data, and the potential for misuse for influencing, among other areas, the behavioral and emotional development of individuals.

5.2. Integration with Smart City Infrastructure

Traffic congestion, the upsurge of greenhouse gas emissions, and road accidents are some of the major issues that cities face. To address these issues, connected vehicles in urban traffic can enhance smart city infrastructure. The concept of a smart city enhances the existing facilities in the cities that could help plan the city more appropriately, control the city norms, and provide a sustainable lifestyle to the citizens while playing a significant role in economic development. Moreover, it may also help to develop an advanced transportation system that will be a good combination of social, capital, and environmental necessities. Traffic management and a predictive traffic system are two major classifications in the research area of smart cities and connected vehicles. Therefore, public transport efficiency can also be increased using urban connected vehicles. In the urban environment, connected vehicles can help improve traffic lights and equally optimize the communication network by providing a real-time address to the smart city traffic control system, so that sudden congestion can be prevented.

Connected vehicles can be integrated with the local traffic control systems to improve the complete transportation system of a smart city. A major advantage of connected vehicles in the smart city infrastructure design is that they can share real-time data with the city's traffic control system. This real-time updated data can significantly reveal the actual traffic congestion or smoothness of the areas. In many applications, on-board traffic sensors in both vehicles communicate abrasive traffic conditions, such as crashes or heavy congestion, to the central traffic management system. With the help of such systems, freeway traffic management can implement proper rerouting strategies based on the real-time information received from the field and can effectively control traffic routing in congested areas. In addition, intelligent transportation systems are in the process of linking transportation technologies and strategic planning management control systems to aid in deciding real-life traffic conditions on a daily basis. However, smart city infrastructure includes other systems that need to manage such connected vehicle data, including emergency management and law enforcement. In this direction, further legal and ethical issues for data sharing need to be addressed.

6. Conclusion

In this review, we describe the contributions of path planning in the development of an autonomous vehicle, and we highlight several advanced algorithms, which are artificial intelligence-based methods for autonomous vehicle path planning in urban and highway environments. Urban and highway scenarios reveal various conditions that determine what types of path planning strategies are needed. In an urban environment with a high density of vehicles and a large pedestrian population, an autonomous vehicle needs to provide safe paths and take comfort into consideration. On the highway, an autonomous vehicle is expected to choose a route that takes less time and uses less fuel, as this will also reduce carbon emissions. The availability of infrastructure dedicated to the development of various applications of autonomous vehicles is both a driving force and a challenge in the application of autonomous vehicle path planning.

In conclusion, vehicle path planning offers a body of evidence that driving behavior can be anticipated under various driving conditions, which is useful in designing driving control systems for autonomous vehicles. Safety and ethical concerns are very important and must be considered in the development and application of autonomous vehicle path planning, because ultimately, this advanced technology will transfer the driving task to an automated driving system and may create the potential for causing accidents. In the future, this area of research needs to be studied further and in more depth, taking into account the development of algorithms, especially the use of machine learning methods for heuristic optimization. In addition, further research should consider the application and field conditions to gain insights and outcomes in real-world problems. This research must work collaboratively between researchers, stakeholders, and policymakers, as well as through continued cooperation with vehicle companies that are developing various applications for autonomous vehicles.

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