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A review of path planning algorithms in automobile autonomous driving

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Abstract. With the continuous development of science and technology, automobile autonomous driving technology has gradually become a research hotspot. Among them, path planning and optimization technology is the key link to realizing automatic driving. This paper aims to discuss the path planning and optimization technology in automotive autonomous driving, analyze its current situation and development trend, and verify its effect through experiments. The role of path planning in our lives is very much needed and very important. Excellent path planning and optimization techniques can effectively improve the autonomous driving performance of vehicles. Reduce traffic accidents and improve safety and comfort. Through the ongoing route optimization research, autonomous driving technology will also be widely promoted and applied.

Keywords: Automatic driving, Sample-based Algorithms, Grid-based Algorithms.

1. Introduction

According to a recent technical report by the National Highway Traffic Safety Administration (NHTSA), 94% of road accidents are caused by human errors. Against this backdrop, Automated Driving Systems (ADSs) are being developed with the promise of preventing accidents, reducing emissions, transporting the mobility-impaired, and reducing driving-related stress [1]. In recent years, with the rapid development of science and technology, the automobile industry is also developing rapidly. As an important part of the future automobile industry, automobile autonomous driving technology has received extensive attention and research. Among them, path planning and optimization technology is one of the key links to realizing automatic driving. The realization of vehicle autonomous driving technology is inseparable from the cooperation and support of path planning and optimization technology. Path planning in autonomous driving is a very important and challenging task. There are many research institutes that spend a lot of time and effort on this task. Many applications, such as autonomous driving, robotic navigation and aircraft object tracking in complex and changing urban road scenes, need accurate and robust path planning by detecting obstacles in the forward direction [2]. Automated driving has been gaining increasing attention from both academia and industry, as it has great potential to reduce traffic accidents, optimize transportation efficiency, and improve our mobility experience. It is generally believed that the autonomous driving system is divided into four modules, including perception, positioning, planning and control. Autonomous driving planning is to plan a reasonable driving trajectory for the vehicle according to the surrounding vehicle environment and location information received by various sensors and detect the current state of the vehicle. The main

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task of route planning is to find the optimal route based on the given starting and ending points. Optimization technology is to plan the path of automatic driving through the corresponding technology and refine and improve it, thereby improving the safety and comfort of automatic driving. But this is a difficult task. We need to continue to explore and study. A Fundamental skill of any autonomous mobile agent is the planning of appropriate motion [3]. This paper aims to discuss the path planning and optimization technology of automatic driving to provide some theoretical support for the development of automatic driving technology.

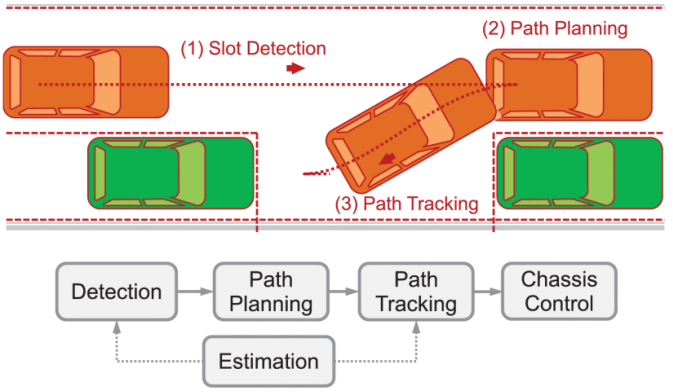

Figure 1. A typical automatic parking system includes the following modules: slot detection, path planning, path tracking, ego-vehicle posture estimation, and chassis control [4].

We organize the remaining paper as follows. In Section 2, two algorithms of autopilot path planning are written; Section 3 is about the use of path planning, Section 4 is about the challenges encountered in path planning, and Section 5 is about the conclusion and future direction.

2. Motion Planning Algorithms

Through the autonomous driving motion planning algorithm, the car can respond to unpredictable situations in the urban scene in a timely manner, and through the appropriate algorithm, the safety and comfort of the driver can be ensured while the path is generated in a wide range of driving scenarios [5]. Since the DARPA Challenge, a large number of autopilot planning algorithms have emerged, but according to their characteristics, they can be divided into two directions. Through the interpretation of the data, I will introduce two algorithms.

2.1. Sample-based Algorithms

The first faction is the sampling faction. This sampler pays attention to the effectiveness and dispersion of sampling and whether it can increase the relative completeness of the algorithm. There are two types of sampling: random sampling and deterministic sampling. In fact, the purpose of sampling is to improve the search efficiency, but at the same time, the completeness of the algorithm is lost. No matter what sampling method, in short, it is to generate an effective trajectory, and then the trajectory generation algorithm, there are many schools, such as direct dispatch and reconciliation couplers, optimizations and optimal control schools and so on. It is divided into two categories. Random sampling is the position coordinate generated by a random function, and the collision detection algorithm is used to remove the sampling points with collision risk. PRM and RRT family, random sampling in autopilot, the use of vehicle platform is not a lot, the early MIT used, and can play with not many patterns, now in a specific space for deterministic sampling and cost function evaluation of the planning algorithm has overshadowed the popularity of random sampling algorithm [6].

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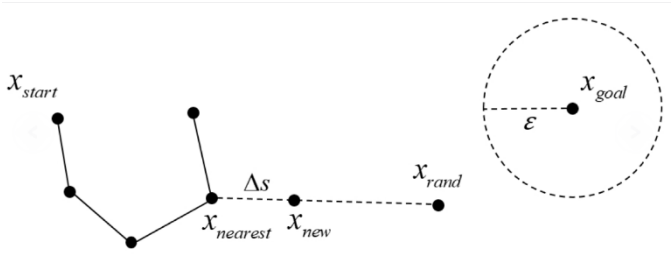

Figure 2. Example and extension mechanism of the RRT algorithm [7].

Deterministic sampling sets some sampling rules artificially, such as the normal vector sampling along the center line of the road in the carriageway, and the heading angle and curvature of the sampling point are related to the tangent vector of the center line of the road. Divided into control space sampling and state space sampling, one of them is the inverse solution, and the other is a positive solution. In addition, there is a state lattice sampling.

2.2. Grid-based Algorithms

This paper proposes a grid-based evolutionary algorithm (GrEA) to solve many-objective optimization problems [8].

The second faction is the optimizer. If the optimizer does path optimization, it discretizes x, optimize y, and if it is trajectory optimization, y. The convex objective function is established, and the convex feasible domain is established by discrete t to optimize y. A star algorithm determines an optimal routing path from the source to the destination by favoring the highest remaining battery power, minimum number of hops, and minimum traffic loads [9].

Most algorithms have some defects when they are applied to solving vehicle path planning problems, so the current research focuses on constructing hybrid algorithms by using the fusion of multiple algorithms.

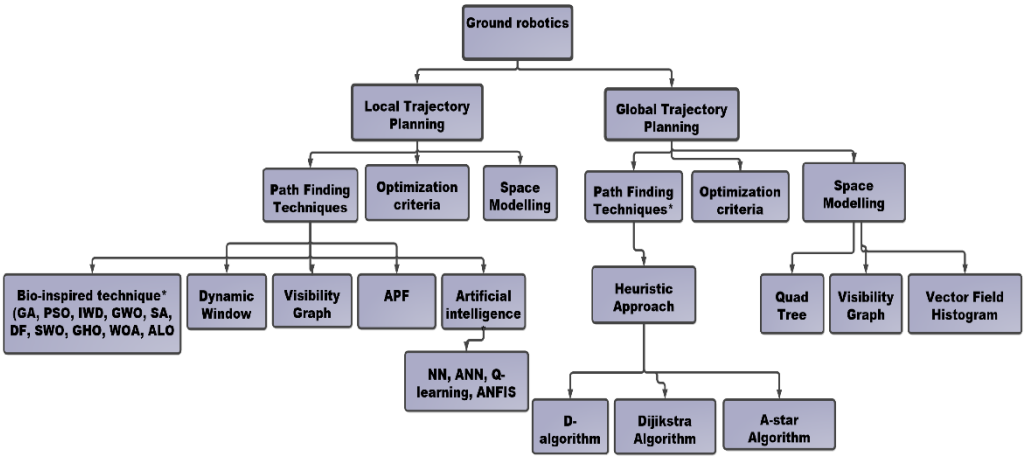

Figure 3. Several methods are applicable to ground robot technology [10].

3. Applications

Vehicle trajectory planning and intelligent decision-making are two of the key technologies to realize vehicle intelligence. Its main task is to plan the vehicle trajectory according to the environmental signal and prior map information processed by the environmental perception system, and with the purpose of optimizing a certain performance index under the premise of meeting many constraints of vehicle driving. This section is divided into two parts, one is to affect the safety and comfort of driving, and the other is to improve our driving safety.

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Route planning has a wide range of applications. For example, route planning of robot mobilization, route planning of aircraft, route planning of cruise missiles, route planning of travel attendant problem (TSP) and its derived vehicles. (VRP), virtual assembly path planning, path planning, road network, electronic map GPS navigation path search and planning, according to the routing problem, combined with the classification of road planning problems corresponding to the path planning algorithm, summed up the application of the path planning algorithm as follows.

3.1. Highway Navigation

From the point of view of path planning, when the environmental information is known and the environmental information is static information, how to find the shortest path to the destination in the safe range to avoid obstacles. Solving this kind of problem usually depends on the combination of intelligent algorithm and environment modeling. A path-planning algorithm is directly applied to this kind of problem. The algorithms used directly are visibility method, free space method, Voronoi graph method, grid method, penalty function method, simulated annealing algorithm and so on. The intelligent algorithms used indirectly are A* search algorithm, ant colony algorithm, genetic algorithm, particle swarm optimization algorithm, artificial potential field method and so on.

AI logic-based methods are mostly suitable in constrained and predictable environments, such as nominal high-way driving. Their intuitive and fast architectures are widely promoted for use in critical safety environments where cause-and-effect reasoning is necessary [11].

3.2. Urban Road Navigation

In short, path planning is the core part of an autonomous driving system, and its task is to calculate the driving route and driving behavior of the vehicle. The pipeline method is a common path planning method, which divides the path planning into global path planning and local behavior/trajectory planning and realizes the path planning through perception, positioning, planning, and other steps. Path planning is a highly complex task, which needs to consider a variety of factors, such as traffic rules, vehicle dynamics, road conditions and so on. With the development of autonomous driving technology, path-planning algorithms will become more intelligent and efficient, bringing people a safer, more comfortable, and more efficient driving experience.

The autonomous driving behavior of intelligent cars is to "transport" the car from the starting position to the target position because the movement of the vehicle is limited, it cannot adjust the heading Angle at will like a drone in the air. Therefore, in addition to considering the shortest distance and no collision, the planning of the path also needs to consider the enforceability of the vehicle's motion trajectory. Because the existing static route planning does not allow us to change the travel route in time, especially in the case of accidents or traffic jams. Therefore, we should choose dynamic route planning to help us drive safely. Therefore, the hot issue that the new generation of intelligent vehicle navigation system needs to pay attention to is the dynamic path planning of vehicle navigation. Vehicle dynamic path planning is based on the timely detection of traffic information data by the vehicle system through the prediction of future traffic to achieve timely adjustment of vehicle driving status and update the best route to effectively reduce and avoid road congestion and traffic accidents.

With the rapid development of computer science technology, wireless communication technology, and the transportation industry, the research trend of dynamic path planning of vehicle navigation systems will also develop in the direction of coordinated planning of multiple navigators. At present, vehicle navigation is guided by a single vehicle for the object without considering the overall coordination, which easily causes new traffic congestion and other problems, so multi-navigator coordination planning will be more in line with the actual needs of the planning method.

3.3. Parking Lot Navigation

In this regard, the researchers proposed a parking optimization algorithm. This algorithm can optimize the parking place and time of the vehicle according to the vehicle endurance, very little fuel consumption, convenient transportation, the shortest limit (for example, to avoid spending too much time and fuel

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costs, not allowing too far away) and other conditions, so that the vehicle's driving trajectory is more reasonable.

4. Challenges

This section is divided into three challenges: the promotion of different environments, the estimation of uncertainties, and the achievement of safe and efficient automatic driving in different scenarios.

4.1. Model Generalization

Autonomous vehicles must have the ability to operate in a variety of environments and diverse conditions. However, these environments and conditions may differ from the training data used to develop the decision model, resulting in inadequate generalization of the model, i.e. poor performance in new and unencountered situations. Autonomous driving models should have the ability to adapt to changing environmental conditions, such as different lights, bad weather, sudden obstacles, unusual traffic patterns, multiple traffic participants, and different road surfaces, to achieve the ability to generalize multi-agent interaction models in these variable environments [12].

To ensure the safety and reliability of autonomous vehicles, models must demonstrate robustness to environmental changes. On the other hand, models that are too sensitive to these changes may not generalize enough, resulting in unsatisfactory performance in actual driving scenarios.

4.2. Uncertainty Estimation

The operation of autonomous driving systems relies on sophisticated and complex decision-making methods, which require accurate estimates of uncertainty and a thorough evaluation of the quality and quantity of data [13]. These highly advanced systems utilize a variety of sensors, such as cameras, lidar and radar, to obtain detailed information about the surrounding environment and make driving decisions based on this data. However, this data is often noisy, incomplete, and subject to various sources of error, which can lead to inaccurate decisions and potentially unsafe driving behaviors. Therefore, when developing and optimizing autonomous driving systems, it is critical to design algorithms that can effectively identify and deal with these issues, ensuring stable and safe driving in all situations [14].

4.3. Multi-agent and Agent-environment Interaction

In complex traffic scenarios, autonomous vehicles need to interact efficiently and safely with a variety of agents on the road, including other autonomous vehicles, human-driven cars, pedestrians, and cyclists [15]. The behavior of these agents can be of a nature that is difficult to predict and, therefore, poses a great challenge to the decision-making systems of autonomous vehicles.

The behavior of one agent may set off a chain reaction that affects the behavior and dynamics of other agents in the environment. To cope with this complexity, autonomous driving systems need to be highly adaptable and responsive in order to make effective decisions in a real-time changing traffic environment [16]. In addition, autonomous vehicles need to be able to predict the intentions and behaviors of other agents based on actual conditions, thereby improving road efficiency while ensuring driving safety.

5. Conclusion

Through the research and analysis of references, we can easily find the following conclusions. Driving for long periods of time can be tiring, and many drivers need breaks or other activities during the drive.

Traffic speed optimization for cities with dense traffic flow: traffic speed optimization can reduce congestion and improve road capacity.

According to the above, we know that there are many methods of route planning; each has its own advantages and disadvantages, and the appropriate algorithm should be selected according to the prediction of the vehicle function. This paper mainly introduces the traditional algorithm, graphics method and A star algorithm. Route planning is used in highway Navigation, Urban Road Navigation

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and Parking Lot Navigation. According to different algorithms, the role of path planning is also differentiated.

To this end, the researchers proposed speed optimization based on a state quadratic programming (SOSQP) algorithm. The algorithm will optimize the acceleration and braking force of the vehicle so that the vehicle can meet the distance, time, and speed limits during the driving process. Future autonomous vehicle technology will be based on advanced machine learning algorithms capable of automatically adjusting path planning and speed optimization based on large amounts of data to improve driving efficiency. Do example, researchers may use deep learning algorithms to identify traffic signs and markings on the road in real time and make more optimized routes based on the information found. Its effectiveness has been proven in difficult and challenging emergency situations such as sharp turns and sudden accidents.

Through the reading of the literature, we know that the relevant principles are analyzed from automatic driving trajectory planning and driving motion planning. The input of trajectory planning includes extended map, obstacle or obstacle forecast track, traffic sign status, positioning, navigation, vehicle status and other information. Trajectory planning is essentially an optimization problem, which often requires knowledge of optimization constraints and optimization objectives. Optimization constraints include compliance with traffic rules and simultaneously the realizability of the program in the self-driving car. The goal of optimization is to ensure that self-driving cars are infinitely similar to human drivers. A more advanced approach is to sample the driving behavior of veteran drivers to generate recommendations for autonomous driving control.

In this paper, the path planning and optimization technology of automotive automatic driving is deeply studied, and its effect in practical application is verified. The results show that excellent path planning and optimization technology can effectively improve the automatic driving performance of vehicles and reduce the incidence of traffic accidents, which is of great significance in promoting the wide application of automatic driving technology. At the same time, we also realize that the existing technology still has some limitations and shortcomings, which need to be further improved and perfected. In the future, with the continuous development of technology, we expect to be able to achieve more intelligent, safe, and efficient autonomous car driving.

In conclusion, our research aims to provide a systematic review for better applications of automotive autonomous driving technology. The algorithms and techniques used in the research institute can effectively improve the efficiency and accuracy of automotive autonomous driving systems. In the future, we will continue to conduct in-depth research and explore more beneficial knowledge and novel methods to bring better development to the automotive autonomous driving industry.

There is a chance that we will be able to optimize the path, drive autonomous cars more safely and efficiently, and create a better life for the future.

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