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A Review of Motion Planning Algorithms for Autonomous-driving Vehicles: Advanced Technologies and Future Developments

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Abstract. Autonomous-driving vehicles have consistently attracted significant attention during these years due to their convenience and safety advantages comparing with traditional human driving approach. Currently, autonomous-driving vehicles have achieved high-level of autonomous, and even complete automation, in controlled environments such as highways. However, the development of efficient motion planning algorithms for autonomous driving in many applications still remains a big challenge. To overcome this problem, advanced motion planning algorithms are essential. This paper systematically reviews various motion planning algorithms, including the A* algorithm, RRT algorithm, artificial potential field algorithm, and neural algorithms, and compares their advantages with current limitations. Moreover, this paper deliberates some applications of autonomous-driving vehicles, existing challenges, and future research trends.

Keywords: Autonomous-drivingVehicles, Motion Planning Algorithms, Applications

1. Introduction

As the number of household gasoline-based vehicles increases, the Greenhouse Effect is worsening. To protect the environment, it is crucial to transform from gasoline-based vehicles to electric vehicles and promote development of autonomous vehicles. Autonomous Vehicles (AVs) and Autonomous Electric Vehicles (AEVs) are characterized by operational simplicity, improved safety and comfort. Particularly, autonomous-driving vehicles are proper for physically disabled individuals and elderly populations to improve their quality of life [1]. Moreover, autonomous-driving vehicles demonstrate significant potential in reducing traffic accident probabilities while bringing convenience and safety to people's daily life. For example, the Advanced Driver-Assistance System (ADAS) can effectively avoid sudden encounters with pedestrian or vehicles when the driver is distracted. Research on autonomous-driving vehicles has a long tradition, which dates back as early as the 1920s. However, these vehicles were not massively deployed until the 1980s [2]. Eureka Project PROMETHEUS was carried out in Europe between 1987 and 1995, and it was one of the earliest major autonomous driving studies [3]. Since the first attempt, fully autonomous driving in complex urban traffic conditions has long been the foremost challenge in the field. The 2007 DARPA Urban Challenge stimulated a typical urban scene, and many research teams from the

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globe tried their ADSs to achieve the goal. However, it lacked dynamic elements in real urban driving environments, such as pedestrians and cyclists, so achieving autonomous driving in urban road environments remains an unresolved research challenge [3]. Currently, autonomous-driving vehicles have been used in many domains, for example, logistics [4], agriculture [5] and the military. However, they have not been widely applied in urban private transportation, due to the inability to efficiently avoid dynamic obstacles like pedestrians and the lack of relevant laws and ethical safeguards.

In the architecture of autonomous driving systems, perception, motion planning, and control are core components (Figure 1). This paper provides a comprehensive overview of several typical motion planning algorithms, analyses advanced technologies in conjunction with the application scenarios of autonomous vehicles, and identifies the current challenges and potential future development directions for motion planning algorithms in autonomous vehicles.



Figure 1. Core components of autonomous driving systems

2. State-of-the-art of motion planning algorithms

This section introduces several common motion planning algorithms and analysis of their advantages and limitations.

2.1. Search-based algorithms

The basic idea of search-based algorithms is representing the state space as an occupancy grid or lattice [6]. As shown in Figure 2, the A* algorithm is one of the widely used heuristic search-based algorithms in autonomous driving. It is an extension and improvement of Dijkstra's graph search algorithm [6]. It combines the completeness of Dijkstra's algorithm with the efficiency of the Greedy Best-First Search. A critical design aspect is the determination of the cost function:

$$\mathrm{f}(\mathrm{n}) = \mathrm{g}(\mathrm{n}) + h(\mathrm{n}) \tag{1}$$

where $\mathrm{f}(\mathrm{n})$ represents the total estimated cost of the node, and $\mathrm{g}(\mathrm{n})$, $h(\mathrm{n})$ are the actual path cost from the starting point to the node and the heuristic estimated cost from the node to the target point, respectively.

However, it has some drawbacks, such as, high memory consumption and difficulty in adapting to dynamic environments.. Additionally, the A* algorithm cannot find a perfect balance between computational time and the optimal path.

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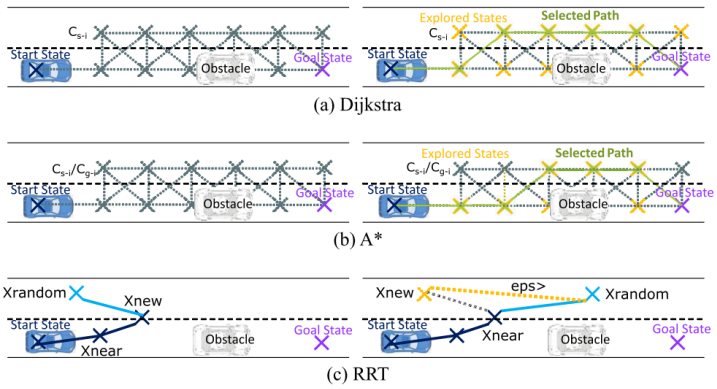

Figure 2. The workflow of A* algorithm [2]

2.2. Sample-based algorithms

The approach explores connectivity in high dimensional spaces by randomly sampling the state space (or configuration space) (Figure 3). The RRT (Rapidly-exploring Random Trees) algorithm is a typical example of probabilistic sampling-based motion planning approach. It is particularly effective in high-dimensional applications, such as drones and robotic manipulators [7-8]. In contrast with the A* algorithm, its outstanding advantage is the great adaptability to dynamic environments. It also has less memory consumption and faster computational speed. However, the paths produced by RRT exhibit inconsistent quality.

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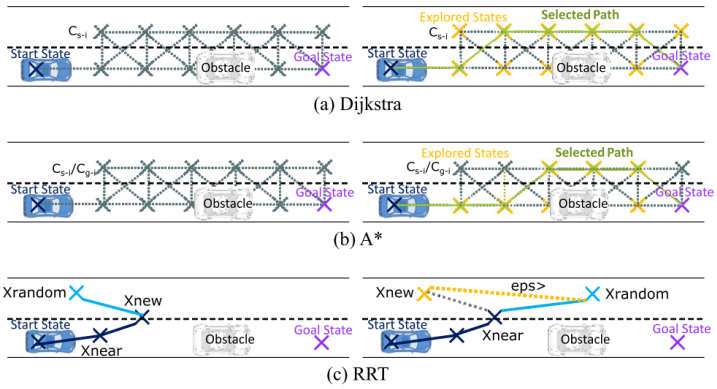

Figure 3. The workflow of RRT algorithm [2]

2.3. Potential-based algorithms

The potential field algorithm is a virtual force field-based motion planning method. It can be seen in Figure 4, the core concept is modeling the environment as a potential field, then the target produces an attractive force to guide vehicles toward the target position, and the obstacles induce a repulsive force to steer the vehicles away from the danger areas. This algorithm can effectively find out an optimal path in dynamic environments. It is applicable for emergency obstacle avoidance in autonomous driving systems. But it has some limitations, like local minima, oscillations, and

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parameter sensitivity [1]. Therefore, it can be combined with other algorithms to get new methods to overcome these problems, such as Artificial Potential Field (APF), which solves the local minimum problem [1].

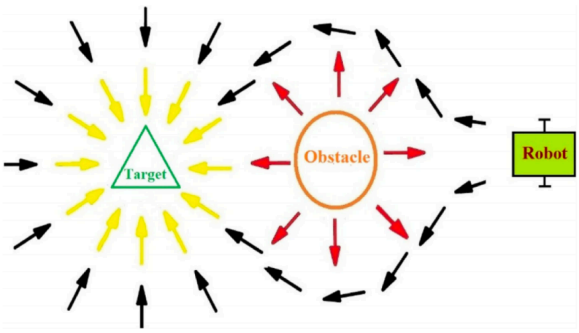

Figure 4. Artificial potential field algorithm [1]

2.4. Learning-based neural algorithms

Learning-based neural algorithms rely on neural networks to learn laws or strategies from data, which can replace traditional algorithms based on mathematical models. Its core idea is training data to optimize network parameters. For instance, Neural RRT and Motion planning networks (MPNet) are computationally efficient and learning-based neural algorithms that can solve complex robotic motion planning problems. Additionally, MPNet includes two modules, a planning network (Pnet) and an encoder network (Enet). Enet is used to receive the robot's surrounding information, and the Pnet generates path or tree samples using encoded environment information along with the robot's current and goal states. The paths planned by MPNet are forward-backward bidirectional and recursive divide-and-conquer. Then it can generate a critical, collision-free, and feasible trajectory. The most valuable feature of MPNet is its optimality, which means that under similar path cost conditions, MPNet paths demonstrate at least 100 times faster than RRT* in terms of the computational time, and eventually are almost globally optimal [9].

3. Applications

This section deliberates several applications across diverse domains to demonstrate the value of autonomous-driving vehicles. For instance, urban public transportation, logistics, and agriculture are all influenced by autonomous driving systems.

3.1. Urban public transportation

The earliest application of autonomous vehicles in urban public transportation can be traced back to 2001, the Rivium ParkShuttle in the Netherlands (Figure 5), which is the world's first commercial autonomous bus system and is still operational now [10]. Another example is a fully automated underground vehicle in Denmark. Based on the commissioning of the self-driving cars in question, it is expected that local residents and governments will further apply them to different transport systems [11]. Additionally, autonomous vehicles are now being increasingly adopted in urban public transportation. For instance, the Panda Bus in Shenzhen, China, was officially opened in 2017. It is the first self-driving bus operating on open roads in China, and it provides relevant experience and opportunities for subsequent applications of self-driving cars.

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Figure 5. The Rivium ParkShuttle in Netherlands [10]

3.2. Logistics

Autonomous vehicles are reforming the logistics industry, achieving cost reduction and efficiency enhancement across operations from warehousing to long-haul transportation. Amazon has secured patents for large-scale drone fulfillment centers designed for high-density urban areas (Figure 6) [4]. A beehive-shaped base for drones was proposed by Amazon in 2017 [4]. Using autonomous-driving vehicles for delivery reduces labor costs and produces less greenhouse gas compared to traditional truck delivery. Particularly, during the pandemics, using autonomous vehicles for logistics is also a good way to effectively reduce infection risks.

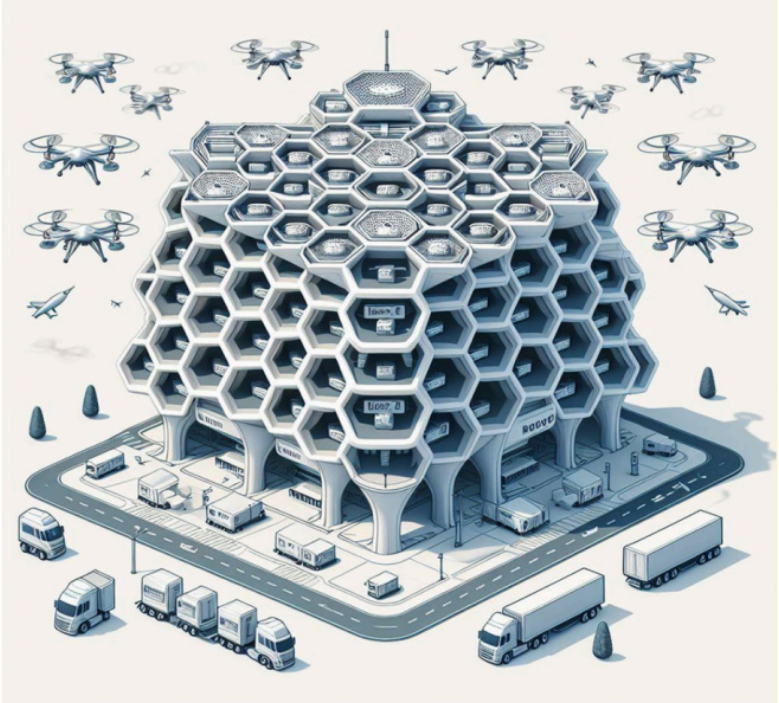

Figure 6. A beehive-shaped base suggested in Amazon patent [4]

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3.3. Agriculture

Autonomous driving technologies in agriculture manifest in several operational applications, including automated harvesting, intelligent weeding, and precision spraying. With autonomous vehicles, the efficiency of agricultural work has significantly increased. Moreover, autonomous/unmanned ground vehicles (AGVs/UGVs) are playing a vital role in industry vehicles due to their capacity for real-time autonomous operation in field environments and minimized reliance on humans. The DEDALO UGV prototype, which was specially designed for precise management in orchard and vineyard was recently created by the Alma Mater Studiorum University Bologna [5], as seen in Figure 7.



Figure 7. The DEDALO UGV designed at the UNIBO [5]

4. Challenges

Although autonomous driving systems have been applied in many applications, achieving fully autonomous driving and widespread commercial deployment still faces many challenges.

4.1. Computational time

Real-time calculation in dynamic environments remains an unsolved challenge. Urban environments involve many dynamic obstacles such as cyclists, pedestrians, and other vehicles that must be taken into account carefully. Existing algorithms cannot compute a local obstacle-avoidance path quickly. Due to these constantly changing factors, continuous evaluation and recalculation of the local trajectory are required. What mainly causes this problem is the time-consuming perception algorithms and limited time for avoiding the dynamic obstacles [6]. Therefore, this demands a significant improvement in the computational speed of motion planning.

4.2. Optimality

With the invention and improvement of different algorithms, finding the optimal or near-optimal path before the navigation task is difficult and time-consuming. However, many researchers have combined deep learning with traditional algorithms to create new algorithms that can find the optimal or near-optimal paths. For example, MPNet can find near-optimal paths in less than 1 second in all scenarios [9]. However, the precomputed paths may become invalid because of

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suddenly appearing vehicles. Thus, continuous and fast calculation is necessary for finding a perfect path that can avoid all possible obstacles at a safe distance. Moreover, because decision-making of autonomous driving systems heavily relies on real-time perception data, when perception errors accumulate excessively, they will also influence the generation of the optimal paths.

4.3. Ethical issues and legal gaps

Besides some technical limitations, there are also some ethical problems that need to be tackled. One typical example is that prioritizing younger lives could be seen as discrimination against the elderly. Moreover, accountability is another major problem. It is difficult to identify the bearer of responsibility for accidents caused by algorithmic errors as the vehicle owner or developer.. Additionally, current legal systems lack clear regulations for AI decision-making based on motion planning algorithms. Thus, it will cause some complex legal disputes between the involved drivers. Thus, ethical issues and legal gaps must be considered before achieving widespread commercial deployment.

5. Conclusion

Recent years have witnessed remarkable breakthroughs in autonomous driving systems. However, the full commercialization and widespread adoption remain unachieved, still needing substantial efforts to develop efficient motion planning algorithms. In this paper, several typical motion planning algorithms are reviewed and some applications are shown to demonstrate the great potential of autonomous driving systems. Moreover, this research discuss some challenges that autonomous-driving industries are confronting. To achieve full commercial deployment, the future development trend lies in addressing algorithm limitations to find global optimal paths with the fastest time in dynamic environments. For example, reinforcement learning and deep learning are effective methods to overcome these limitations, which can be utilized to adapt to dynamic environments through simulation training [12]. There is still a long way for us to go, but with directed efforts toward the future developments, optimal and safe paths are just within our reach.

However, there are some shortcomings in the analysis process of this paper, including the absence of empirical analyses and a narrow reference to the literature. Subsequently, with the accumulation of expertise, this research topic will be further optimised.

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