A Survey of Path Planning Algorithms for Autonomous Vehicles

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Abstract. With the development of artificial intelligence (AI), autonomous vehicle technology has become a hot research spot in this era, which can effectively improve driving safety and greatly secure driver's operations. As one of the key technologies for automated vehicles, planning a safe and highly effective path is the key premise and can guarantee for road safety. Therefore, it has a significant impact on academic research and commercial applications. In this paper, we take autonomous vehicles as our research theme, collect, summarize, compare and evaluate those state-of-the-art algorithms of path planning. Our ultimate goal is to create a novel path planning algorithm based on the unique characteristic of autonomous vehicles, explore and exploit its further value.

Keywords: Autonomous vehicles · Path planning · Vehicle characteristic.

1 Introduction

As global car market continues growing, it has brought great convenience to our daily travel and transportation, and also caused a series of problems such as traffic congestion, frequent accidents and environmental pollution. The autonomous driving is considered to be an effective way to resolve such problems [1]. The key technologies of autonomous vehicles involve environment sensing, behavioral decision, path planning and motion control. Among them, path planning has a dominant impact on the safety and comfort of autonomous vehicles [2].

Generally, according to information acquisition methods, the path planning for autonomous vehicles can be divided into global and local path planning ways. According to the number of target vehicles, path planning methods are grouped into uni-vehicle path planning and multi-vehicle path planning.

The global path planning is based on high-precision maps. Considering known road information such as path length and traffic volume, the collision-free optimal geometric route from initial point to target point is obtained, which is also called static planning or offline planning [2].

The local path planning is to get the optimal driving trajectory of a vehicle in real time, according to surroundings and driving conditions of the vehicle. For example, when the vehicle is being driven following the path of the global path

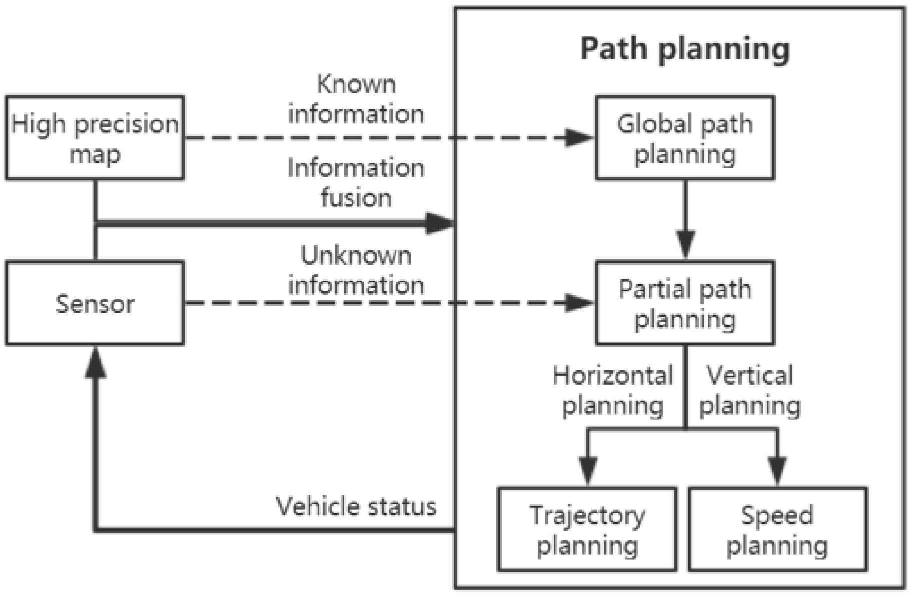

Fig. 1. Path planning structure of auto-driving vehicle

planning, it is sudden necessary to overtake or avoid obstacles, the local path has to be re-planned according to the local environmental information. Because local path planning is based on dynamic real-time environmental information, it is also called dynamic planning or online planning [2]. The structure of this autonomous vehicle path planning is shown in Fig. 1.

Most of the current autonomous vehicle path planning is based on uni-vehicle path planning. Multi-vehicle path planning is generally suitable for a swarm of autonomous vehicles which is generally designed for a multi-agent system [4]. For example, the leading vehicle will take the leadership position; other vehicles will follow it through aggregation, separation, and adjustment for local behavior planning, so as to ensure the stability of the swarm formation avoiding collision.

2 Path planning algorithms

Path planning algorithms of autonomous vehicles are mainly implemented based on various search algorithms [2]. These algorithms usually are categorized into traditional algorithms, graph search algorithms and group optimization algorithms.

2.1 Traditional Algorithms

The traditional algorithms for path planning mainly include artificial potential field algorithm (APF) [5], rapidly-exploring random tree (RRT) algorithm [6], simulated annealing (SA) algorithm [7] and Tabu search algorithm (TS) [8], etc. The APF algorithm has been widely applied to automated driving.

The basic idea of APF algorithm is to construct a virtual force field, visualize the autonomous vehicles as mass points, and present the environmental information in the target gravitational field and the obstacle repulsive field. According to the movement of the mass points in the direction of the force, a smooth and collision-free path is obtained. The basic principle of the APF method is shown in Fig.2.

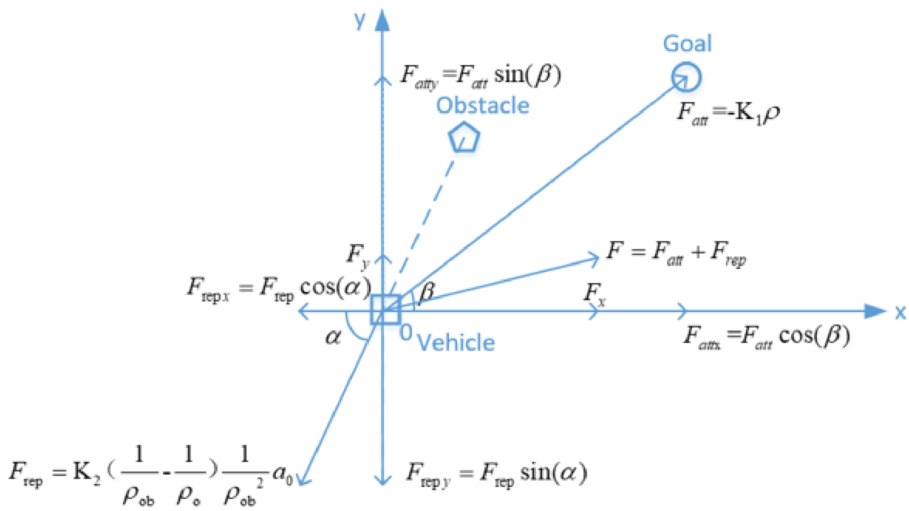

Fig. 2. Basic principle of the APF algorithm

In Fig.2, we assume that the location of a vehicle is at the origin of a two dimensional coordinate system, the goal is the target point, where $F_{att}(\cdot)$ is the gravitation function of the vehicle moving toward the target point, F_{attx} and F_{atty} are the coordinates of the gravitation. α is the angle between the line connecting the origin of the obstacle and the x-axis, β is the angle between the line, which connects the origin and the target point, and the x-axis, ρ_{ob} is the distance between the vehicle and the obstacle, ρ_o is the radius of the range of obstacle. Within the rangethe obstacle continuously generates a repulsive force F_{rep} to avoid collisions, F_{repx} and F_{repy} are the coordinates of the repulsion. F is the combined force of gravity and repulsion, which determines the direction of the vehicle. By improving the gravitational field function and repulsion function, a variety of improved APF algorithms have been proposed [9, 10] so as to effectively avoid falling into local optimum and improving the rationality and accuracy of the planning path.

The RRT algorithm is also used in the path planning for decision making. The idea is to use the starting point as the root node and grow the tree randomly in the feasible space until it touches the end point (leaves). Finally, we get a collision-free path from the starting point to the ending point. Based on the bidirectional RRT algorithm, Domokos Kiss et al. proposed the RTR (Rotate-Translate-Rotate) algorithm [11]. The tree is rotated at the current point to find the corresponding location of the guiding point, and finally reach the guiding point by using back and forth translation. This method is suitable for path planning in a narrow space.

2.2 Graph Search Algorithm

Graph search algorithms generally represent a map based on the grid method, which is to decompose the map into interconnected and non-coincident grids. Search for an optimal path from the starting grid to the target grid therefore can avoid collisions, The A^* and D^* algorithms are much popularly used in path planning for autonomous vehicles [12][13].

The A^* algorithm [13] combines the Dijkstra algorithm [14] with the Best First Search algorithm so as to obtain the optimal path through establishing an open list and a closed list, where the grid points for selecting are placed in the open list and the selected path grid is placed in the closed list. First, the starting grid number of the autonomous vehicles is placed in the open list; then we put the adjacent grids which it may pass through into the open list. The evaluation function $f(n)$ of the adjacent grid of the starting point in the open list is calculated; then, the starting point is moved into the closed list so as to set the grid point with the smallest value as the new starting point. The loop works in this way until the target point raster is placed in the open list. Finally, the points in the closed list are connected in order to get the optimal path. The valuation function is generally expressed as

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

where $g(n)$ is the actual cost of the starting point to the current point, the heuristic function $h(n)$ is the estimated cost of the current point to the target point. The cost function in path planning is usually expressed by using Euclidean distance. The change of cost function can effectively improve the performance of A^* algorithm [15].

The D^* (Dynamic A^*) algorithm [12] is the most significantly improved one of the D^* algorithm. It will continue using the original path after crossing the obstacle, which improves the efficiency of the secondary path planning. By improving the D^* algorithm, the exploration space can be further reduced and the computational efficiency can be greatly improved [16].

2.3 Group Intelligent Optimization Algorithm

The group intelligent optimization algorithm mainly simulates the cluster behavior of biological groups. Each member of the group continuously optimizes the search direction through its own experience and learning from the experience of other members [17]. The ant colony algorithm (ACO) [18] and particle swarm optimization (PSO) algorithm [19] are mainly used in path planning of autonomous vehicles.

The principle of ACO algorithm [18] is the foraging behavior of the ant colony. Based on the random search of individual ants, the agent refers to the pheromone left by other ants to decide the next step, and the pheromone will volatilize over time.

The method of implementing path planning of autonomous vehicles by using ACO algorithm is as follows. First, all the ants are placed at the starting point of the vehicle, and each ant selects the next position according to the state transition until the ant arrives at the destination or its walking path is invalidated. Then, all the ants have found their way, the optimal path is chosen for the ant colony. Finally, the optimal path is found by iterating the ant colony path. The state transition formula is the core part of the ACO algorithm. The state transition formula of the ant k moving from the node i to node j at time t is as follows.

$$p_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\tau_{ik}(t)]^{\beta}}{\sum_{j\in\{C-T_k\}}[\tau_{ij}(t)]^{\alpha}[\tau_{ik}(t)]^{\beta}} & j \in \{C - T_k\} \\ 0 & \text{others} \end{cases} \tag{2}$$

The pheromone adjustment formula as follows:

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{3}$$

where $\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta_{ij}^{k}(t)$, $\{C - T_k\}$ is an optional set of nodes for the next move of ant k, τ is a pheromone matrix, $\eta = 1/D$ is a heuristic function, α is an information heuristic factor, β is the desired heuristic factor. By combining with other algorithms, it shows that the ACO algorithm is easy to prematurely or fall into the local optimal solution [20].

The PSO algorithm [19] uses multiple particles to search the path in the given space. Each particle combines its own experience with the best experience of particle swarms to adjust the search direction, thereby obtaining an optimal solution. The path planning process of the PSO algorithm is similar to the ACO algorithm in which all particles are placed at the start of the autonomous vehicle, and each particle updates its speed v_i and position x_i according to eq.(4) and eq.(5).

$$v_i(t+1) = v_i(t) + c_1 r_1(t)[p_{best}(t) - x_i(t)] + c_2 r_2(t)[g_{best}(t) - x_i(t)] \tag{4}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

where c_1 and c_2 are learning factors, r_1 and r_2 are random numbers, p_{best} is the individual optimal value, g_{best} is the global optimal value. After each iteration, the individual optimal value and the global optimal value are updated until the particle reaches the target point so that the optimal path is obtained.

By improving the PSO algorithm [21], the optimal position information of each individual can be fully utilized to make the planned trajectory smoother.

Intelligent Water Drops (IWD)algorithm [22] has been applied to local path planning for obstacle avoidance in autonomous vehicles.

2.4 Other Algorithms

Genetic Algorithm (GA) [23] is the most widely used meta-heuristic algorithm to simulate the characteristics of biological evolution in nature. In the path planning of autonomous vehicles, this algorithm calculates the fitness value of each path, selects two paths according to the probability and the fitness value, and crosses and mutates the two paths to generate a new path. To get the optimal path until the end condition is reached [24].

Artificial neural networks (ANNs) [25] mimic the structure of biological nerve tissue, which is composed of input layer, hidden layers and output layer. In the path planning for autonomous vehicles, the input can be the position of autonomous vehicles or the grid number after rasterization of the environment. The hidden layers usually contain constraints, such as obstacle position and other constraint information, cycling training by selecting the appropriate activation function. Thus, it achieves the goal of path planning and path optimization during the working time [26].

Q-learning in reinforcement learning [27] has been applied to dynamic path planning [28]. Corresponding to state s and action a, reward and punishment matrix R and Q-table are established for recording the learning process based on the feasible area and the obstacle. The autonomous vehicles in a random position, i.e., under state $s$according to the matrix R and Q value function, select and calculate the next state s' and action a'. Consequently, the optimal estimated value of the future selected position to the Q-table and the Q-table are continuously updated until the Q-table converges to its limit. Each action of the corresponding state is written into the Q-table, and the table can be used as the basis for selecting the next action of the autonomous vehicles; therefore, after several rounds of iterations, an optimal path will be obtained. The Q value function is defined as

$$Q(s,a) = R(s,a) + \gamma \max_{a'}(Q(s',a')) \tag{6}$$

From Table 1, we see that each algorithm has its own advantages and disadvantages. In practice, it is difficult to meet the requirements of the path planning of autonomous vehicle in complex environments. Therefore, it is necessary to conduct targeted research on the path planning algorithm applied to autonomous vehicles.

3 Applications of Path Planning of Autonomous Vehicles

Currently, path planning has been widely applied to various scenarios of autonomous driving, especially closed or semi-closed specified areas [30]. Throughout the path planning, the self-driving vehicles can realize not only the position-

Table 1. Comparisons of advantages and disadvantages of the algorithms

Category	Name	Advantages	Problems	Efficiency	Stability
Traditional algorithm	APF [10]	Simple structure	Easy to fall into local optimum	High	Low
	RRT [11]	Simple structure	Narrow space search failure	Middle	Middle
	SA [7]	Simple structure	Sensitive to parameter selection	Low	High
	TS [8]	Simple structure	Easy to fall into local optimum	Low	Middle
Graph search algorithm	A* [29]	Complicated structure	Only suitable for static path planning	High	High
	D* [16]	Complicated structure	Only for short distance dynamic path planning	High	High
Group intelligent optimization algorithm	ACO [20]	Complicated structure	Easy to fall into local optimum	Low	High
	PSO [21]	Simple structure	Easy to fall into local optimum	Low	High
	IWD [22]	Simple structure	Easy to fall into local optimum	Low	Middle
	GA [24]	Simple structure	Easy to fall into local optimum	Low	Middle
	ANN [26]	Complicated structure	Data processing is opaque	Low	High
	Q-learning [28]	Simple structure	Long learning time	Low	High

ing and navigation, but also the coordinated path of multiple vehicles relying on the automatic driving function.

3.1 Autopilot Positioning Navigation

The navigation for self-driving vehicles is mainly based on high-precision maps and external environmental information transmitted by various sensors. After set the starting and ending locations, the path planning algorithm determines the pathfinding method so as to plan the best road that is suitable for autonomous vehicles, including the shortest distance, the shortest time, fewer turns, fewer obstacles, etc. [31].

Among the path planning algorithms based on positioning navigation, the D* algorithm and its improved algorithm are widely used, due to the introduction and maturity of heuristic algorithm, the planned path is not necessarily the shortest, but it can be guaranteed to be optimal. At present, information fusion of sensors is still on its way, real-time information cannot be provided correctly, and serious errors in path planning are the main reason of traffic accidents of autonomous vehicles. With the development of sensor information fusion technology and the Internet of Vehicles (IoV) technology, path planning will play a more important role in the application of autonomous vehicles.

3.2 Intelligent Formation of Autonomous Vehicles

With the development of the IoV technology, intelligent formation of a fleet of vehicles has become a research arena. With the assistance of IoV technology, the distance and speed of vehicles in formations are coordinated and controlled.

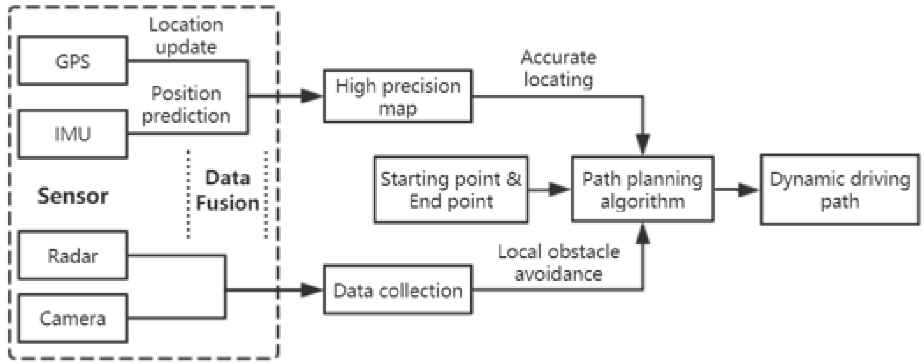

Fig. 3. Autonomous vehicle positioning navigation structure

Under the premise of safely avoiding obstacles, the autonomous vehicles can be kept at a small distance, which can effectively reduce resistance of other vehicles, low fuel consumption and carbon dioxide emissions [32].

The current intelligent formation of autonomous vehicles generally adopts a multi-agent model, which maintains team formation through coordinated planning in multiple workshops, matches or disbands formations, and tackles obstacles or emergencies. Intelligent formations of a swarm of automated vehicle generally uses a leader-follower model [33]. The leader mainly plans the global path; the follower follows the leader's path and performs local path planning. The main goal of the intelligent formation is to apply to industrial transport vehicles, high-speed road logistics trucks and passenger vehicles etc. It can greatly reduce operating costs, improve transportation efficiency and safety, and achieve efficient integration of limited resources, which has great industrialization prospects.

4 Conclusion

At present, autonomous vehicles and relevant technologies are in a rapid development stage; the relevant research of path planning has made great progress. In particular, static global path planning algorithms have been developed more quickly, but dynamic local path planning still needs further work. By analyzing the prevalent algorithms of path planning, this paper helps us construct a more reasonable path planning algorithm and further combines the co-evolutionary algorithm with multi-vehicle path planning to realize multiple vehicle integrated with path planning for better applications of autonomous vehicles technology.

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