An overview of unmanned vehicle path planning algorithms

Jiajun Cui1*
1Mechanical and Vehicle Engineering Department, Hunan university, Changsha, Hunan, 410082, China
cjj1998boy@163.com

Abstract. This paper summarizes the methods of global path planning and local path planning. By analyzing the recent improvements of RRT and VFH algorithms made by scholars, this paper gives answers to some existing problems in path planning, and then illustrates the effectiveness of these improved algorithms.

1. Introduction
Cars can be greatly convenient for human life, but a large number of problems have come along with the popularity of cars, such as traffic safety problems, traffic congestion caused by the increase of vehicles, and the environmental pollution caused by vehicle emissions. The traffic accidents in the world every year are of great threat to people's life and property. For example, in 2005, about 100,000 people died in traffic accidents and another 470,000 were injured in China. Since the automobile has such a great threat to human beings, how to solve it has become a problem that all countries in the world need to face together. In this context, unmanned driving technology has attracted special attention from all sides of the world. As an indispensable link of unmanned vehicle positioning and navigation technology, path planning has become a research topic of more and more scholars. Path planning for unmanned vehicles refers to finding a collision free path from the initial state to the target state according to certain evaluation criteria in the case of unknown obstacles on the road section[1]. At present, various algorithms have been proposed to solve the problem of path planning, but the environment facing the path planning technology is complex and changeable, which requires the path planning algorithm to have the ability to be responsive to the change of complex environment[2].

This is a problem that current algorithms cannot solve singly. To solve the above problems, the structure of this paper is as follows. In the second part, this paper simply summarizes the existing methods. In the third part, through the analysis of VFH algorithm, this paper proposes an optimization method of VFH algorithm with adaptive threshold. In the fourth part, through the analysis of RRT algorithm, a hybrid algorithm combining RRT algorithm with artificial potential field method and ant colony algorithm is proposed.

2. Summary of path planning algorithm
Path planning of intelligent vehicle is to find a passable path according to certain search algorithm on the basis of environmental information perception and location determination of vehicles in the environment, so as to realize autonomous navigation of intelligent vehicles. In the case that the accuracy of hardware system cannot be solved in a short time, the research of path planning algorithm is more important. Path planning methods can be divided into two categories according to the integrity of working environment information of intelligent vehicles: global path planning methods based on complete environmental information, such as raster method, viewable method, topological method, free
space method, neural network method and other static path planning algorithms; Local path planning methods based on real-time acquisition of environmental information by sensors, such as Artificial Potential Field method (APF) [3], Vector Field Histogram method (VFH) [4], Virtual Force Field method (VFF), Genetic Algorithm (GA) [5], rapidly-exploring Random Trees (RRT) [6] and other dynamic path planning algorithms.

3. VFH algorithm

3.1. Basic principles of VFH algorithm
VFH algorithm is simply described as three processes [7]:
1) establish histogram of polar coordinates based on obstacle vector information;
2) find all candidate directions according to the histogram of polar coordinates;
3) finally, choose the final motion direction from the candidate directions.
VFH quantifies the influence of obstacles on intelligent vehicles into Polar Obstacle Density (POD) by establishing Polar coordinate system centered on intelligent vehicles, and selects the moving direction within the Angle range of POD lower than a certain threshold.

3.2. Limitations of VFH algorithm.
This algorithm has robust planning ability, and can plan a collision-free trajectory even in complex and multi-obstacle motion scenes. In addition, it has high operational efficiency and strong fault tolerance for perceived information. However, it is sensitive to threshold value, and the serious imbalance of threshold value will have the following effects on the intelligent vehicle path planning system: when the threshold value is too small, the intelligent vehicle may not find the obstacle in front, mistakenly regard the practical unfeasible channel as the feasible channel, and cause the vehicle to fall into the local "dead zone"; When the threshold value is too large, some feasible channels will be ignored, resulting in the intelligent vehicle cannot plan the passable path in the relatively narrow channel environment. In short, VFH algorithm needs a good threshold to challenge more application environments.

3.3. VFH algorithm with adaptive threshold
In order to make intelligent vehicle earlier find the obstacles or being able to find the feasible channel, in the thresholds of feasible directions that close to targeted direction, the greater the thresholds are, the better they are. We can according to the minimum braking distance to determine a threshold range. T in the path planning by the maximum value decreases. If there are no real obstacles existing or the obstacles are small enough, we can always find a driving direction and make the program success. In all the passable directions, selecting the passable direction corresponding to the maximum threshold value T as the reference direction of intelligent cars. Meanwhile, when there are no obstacles in the driving process, the intelligent car should maintain a high speed to reach the destination as soon as possible. However, when the intelligent vehicle is close to the obstacle, that is, when the selected T is small, it should slow down to prevent collision. If T is equal to the minimum value, it still cannot be planned successfully, indicating that the obstacle in front of the vehicle makes it impossible for it to pass in this lane, and then it needs to detour.

4. Rapidly-exploring Random Trees, RRT

4.1. Basic principles of RRT algorithm
The basic idea of RRT algorithm is to make it grow incrementally from the initial state to a new state by input control in a short time interval according to the control theory. Each vertex of the random trees represents a state, and each directed edge represents the transition from the previous state to the new state [8]. When a vertex reaches the target region, the random tree represents the open loop trajectory from the initial state. As an efficient data structure and algorithm, RRT can search the entire state space directly by means of random expansion node without preprocessing before the execution of the
algorithm. Moreover, it can adapt to dynamic environment and has the ability of rapid replanning. By integrating various constraints into the algorithm, RRT algorithm has been widely used in differential constrained systems in recent years. And because of the inherent properties of random algorithm, theoretically, as long as the path exists objectively, the algorithm can find a passable path, and RRT has probability completeness.

4.2. advantages and limitations of RRT algorithm

The advantages of Rapidly-exploring Random Trees are fast, complete probability and not easy deadlock. The entire state space can be searched in a very short time by randomly expanding the child nodes\(^9\).

RRT algorithm has the following defects, which make it unable to be directly applied to the path planning of intelligent vehicles:

1) instability caused by randomness of node expansion. Since the child nodes of the random tree are generated through random sampling in the state space, different paths will be planned from the same starting point to the same ending point in the same map every time. This instability is not conducive to the track operation of vehicles in reality. At the same time, the path cost and track length are not taken into account when its random expansion sub-node, which leads to the possibility that the path scheme is far from the optimal path.

2) the measurement function in the algorithm directly uses the Euclidean straight-line distance to represent the distance between state points and random points, which may be a constraint on robot path planning in complex environments. When there are many obstacles around the robot, the adoption of this measurement method will increase the probability of collision when extending new nodes, and the failure times of node expansion will be more, which will affect the efficiency of the algorithm.

3) the basic RRT path is sampled randomly generated by the random extension node which is usually composed of shaking, and contains a lot of unnecessary fold point. Child nodes adjacent angle is too big lead to state transitions too fast, which can't directly apply to be bound by the non-integrity of intelligent vehicle movement plan. if directly tracking the path, it will be easy to cause severe mechanical wear. Moreover, the relative distance between random points and obstacles is not taken into account when generating random points, so the algorithm has a certain probability to expand the node close to the obstacle, which leads to the insecurity of the planned path.

4) although the algorithm is fast in execution, its efficiency is low. The algorithm adopts uniform distribution probability to obtain sampling points. without obstacles and target points' heuristic information, and according to the inherent properties of the random algorithm, the algorithm usually needs to search the whole free space to get the planned path. Finally, the extension points that are not added to the path point set are actually invalid extension points. It is not difficult to see from the simulation results of RRT that the algorithm is less effective in extending nodes.

4.3. Rapid RRT path planning method based on artificial potential field guidance

4.3.1. basic principles of artificial potential field method. The basic idea of the artificial potential field method is to simulate the surrounding environment of the robot into a potential field, and regard the robot's motion in the state space as the robot's motion in the virtual field. The gravitational field of the target point is attractive to the robot, which leads the object to move towards the target point. The Obstruction of repulsive force field (repulsion) has exclusive to the robot, to avoid collision with the object. The robot moves without collision along the falling direction of potential field formed by the superposition of gravitational field and repulsive field to ensure the safety of the path. Since the potential field changes continuously in the free space, there is no state mutation, so the path drawn by the artificial potential field law is relatively smooth. Because of the advantages of the artificial potential field method, such as easy to understand, simple mathematical principle, small amount of computation and strong real-time performance, it has been widely used in path planning.
4.3.2. Rapid RRT path planning based on artificial potential field guidance. RRT algorithm when the nodes extension of blind random led to a series of problems, such as the big state mutation between path nodes, access to random sampling point regardless of the distance between the obstacles and the target point, the low efficiency of node extension. Consequently, it is not easy to get safe and reliable planning results and the algorithm is not stable. Each search results may be time-consuming. However, due to its strong randomness, this method is not affected by the size of the problem and is suitable for high-dimensional space without deadlock. The artificial potential field method is relatively stable, the planned path is safe and smooth, and the algorithm is efficient and easy to implement. The two methods of path planning can complement each other to some extent. On the basis of retaining the randomness of RRT algorithm, the gravitational field and repulsive field in the artificial potential field method are added to guide the path, so that the path is far from obstacles and converges towards the target point, reducing the blindness of RRT random search. A fast RRT path planning method based on artificial potential field guidance is proposed by integrating RRT and artificial potential field method. According to the magnitude of gravitational potential energy and repulsion potential energy of each state space point, the distance between this point and the target point and the obstacle can be known. For position and posture points close to the target point, there is a higher probability to be extended to the next sampling point; for position and posture points close to the obstacle, there is a lower probability to be extended to the random tree.

4.4. RRT path optimization method based on ant colony algorithm

Due to the strong randomness of RRT algorithm, the planned path is composed of random sampling points and usually has many uncontrollable factors, such as an unfixed solution, large state transition between nodes, and no security evaluation of the path. Generally speaking, people want to get a "good" planning path with the following characteristics: smooth, keep a safe distance from obstacles, and the path length is relatively short. The artificial potential field method can usually get a path with these characteristics, but it has not formed a general effective scheme to solve the minimum point problem, which makes the algorithm more limited in practical use. Compared with other planning algorithm, RRT algorithm in the high dimensional complex environment has incomparable advantage, but just through several post-processing optimization method cannot solve the problems existing in the algorithm. Therefore, hoping that through continuous optimization of RRT results, We make its final convergence to meet expected good path. The path obtained by each RRT algorithm is evaluated. For the nodes on the better path, there is a greater probability that they will be extended to the random tree constructed by the next RRT, while for the nodes on the worse path, there is a smaller probability that they will be extended. The evaluation of the previous result is taken as the reference factor for the next RRT expansion node, and a better solution is finally obtained through continuous iterative optimization.

4.4.1. Basic principle of ant colony algorithm. Ant colony algorithm is a new simulated evolutionary algorithm proposed in recent years. In this algorithm, the maximum probability after several generations of selection will reach the optimal solution of feasible solution. Ant colony algorithm was first proposed by Italian scholars. Although ant colony algorithm was first proposed in 1990s, it has certain advantages in solving complex optimization problems, proving that ant colony algorithm is a promising method. Ant colony algorithm basic idea: if at the given point, an ant has to choose in different paths, then, the paths that are most selected by lots of ants have bigger probability to be chosen (i.e., path retained heavy pheromone). The more pheromone means shorter paths, means a better answer. Ant colony algorithm has the characteristics of bionics: the ant colony uses pheromones to affect each other and exchange information to form a positive feedback mechanism; Pheromones are volatile and dry up within a certain period of time. It is assumed that artificial ants are used to imitate ants in the real world to generate volatile digital pheromones and find the shortest path between the source node (ant = initial point) and the destination node (food source = optimal value). Both adopted a random strategy of route selection based on current information (pheromones existing within a short period of time): worker ants relied on memory ability to remember nodes and paths along the way, while real ants relied on pheromones. Ant
colony algorithm has many applications, and robot path planning is one of them\cite{10}.

4.4.2. \textit{RRT optimization based on ant colony framework}. As mentioned above, intelligent optimization algorithms proposed through the study of bionics can usually optimize the solution to an ideal situation after a large number of iterative processes. In each iteration of ant colony algorithm, the accumulation rate of pheromone on the better path is faster than that on the worse path, which influences the choice of path of ants to prefer the better path with pheromone concentration. After several iterations, the final algorithm can converge to a global optimal solution. Although the path obtained randomly by RRT is fast, it is far from the optimal solution. On the basis of the path obtained by RRT, pheromones are set, and the next extension point is obtained randomly by roulette selection method according to the amount of pheromones, so that it can converge to an ideal path scheme after a lot of iterative optimization.

5. Conclusion
This paper describes the development of path planning algorithms and summarizes some algorithms that have been proposed to respond quickly in more complex environments. The main purpose of this paper is to solve these problems in the original algorithm by analyzing the new algorithm.

Reference
[1] M, Liang, J. Yang, and M. Zhang. (2012) A Two-level Path Planning Method for On-road Autonomous Driving. In: Second International Conference on Intelligent System Design & Engineering Application IEEE. Sanya. pp.661-664
[2] Xu, Bin, A. Kurdila, and D. J. Stilwell. (2009) A hybrid receding horizon control method for path planning in uncertain environments. In: IEEE/RSJ International Conference on Intelligent Robots & Systems IEEE. St. Louis. pp.4887-4890
[3] Wei Guan, Zhengxin Weng, Jie Zhang. (2015) Obstacle avoidance path planning for manipulator based on variable-step artificial potential method. Control & Decision Conference. In: The 27th Chinese Control and Decision Conference. Qingdao. pp.4325-4329
[4] Lu, Nannan, Y. Gong, and J. Pan. (2016) Path planning of mobile robot with path rule mining based on GA. Control & Decision Conference IEEE. Yinchuan. pp.1600-1604
[5] Ulrich, L., and J. Borenstein. (2002) VFH+: reliable obstacle avoidance for fast mobile robots. In: IEEE International Conference on Robotics & Automation. Leuven. pp.1572-1577
[6] Sahin, Gurkan. (2014). Obstacle avoidance with Vector Field Histogram algorithm for search and rescue robots. In: IEEE Signal Processing & Communications Applications Conference. Trabzon, Turkey. pp.766-769
[7] J.J. Kuffner, and S.M. LaValle. (2002) RRT-connect: An efficient approach to single-query path planning. In: IEEE International Conference on Robotics & Automation. San Francisco. pp.995-1001
[8] Liu, C. A., Chang, J. G., Li, G. D., & Liu, C. Y. (2008). Mobile Robot Path Planning Based on an Improved Rapidly-exploring Random Tree in Unknown Environment. In: IEEE International Conference on Automation & Logistics. Qingdao, China. pp. 2375-2379
[9] Adiyatov, O. , & Varol, H. A.. (2013). Rapidly-exploring random tree based memory efficient motion planning. In: IEEE International Conference on Mechatronics & Automation. Takamatsu, Japan. IEEE. pp. 354-359
[10] Zhai, Y. , Xu, L. , & Yang, Y. . (2015). Ant Colony Algorithm Research Based on Pheromone Update Strategy. In: International Conference on Intelligent Human-machine Systems & Cybernetics. IEEE. Hangzhou, China. pp. 38-41