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Improved MTAPF method for autonomous vehicles

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Abstract. Path planning has evolved into one of the most crucial critical studies with the introduction of numerous autonomous vehicles. The artificial potential field approach is being used by many intelligent vehicles to plan their paths, and a variety of autonomous vehicles may avoid barriers depending on their own conditions and the movement of the obstacles. The design of dynamic real-time paths frequently makes use of artificial potential field (APF) techniques. The issue of local minima and unattainable targets in the APF approach is addressed in this study with a better solution. The global optimum path is first determined using the heuristic A-STAR path algorithm in this work, which is combined with the artificial potential field approach. The global optimal path is then divided into many sub-goals to form a sequence. The artificial potential field approach is then used to produce these targets' final routes sequentially, considerably lowering the likelihood that many unmanned vehicles may simultaneously enter a local minimum. The method could avoid the local minima problem and plan a viable path is supported by simulation results.

Keywords: path planning, artificial potential field, A-STAR.

1. Introduction

With the continuous advancement of technology, unmanned vehicles have been integrated into people's lives and become an integral part of their daily lives. In various unmanned vehicle applications, automatic path planning is one of the very important technologies. One of the commonly used methods for automatic path planning is the artificial potential field method.

The basic idea of the artificial potential field method is to treat the surrounding environment as an abstract artificial gravity field, and to control the movement of the mobile robot by the gravitational or repulsive forces generated by the target point and the obstacles. The closer the robot is to the target point, the greater the gravitational force generated by the target point, and the closer it is to the obstacle, the greater the repulsive force generated by the obstacle. These two forces together control the trajectory of the robot. Compared to other path planning methods, the paths planned by artificial potential field methods are usually smooth and safe, and are therefore widely used in real-life production and applications.

However, the artificial potential field method also has some problems. As the method uses virtual forces, it suffers from problems such as local minima and unreachability of the target. At some points, the robot is likely to fall into local optimum solutions or oscillations because the gravitational and repulsive forces are equal in size and opposite in direction. In addition, where the robot attempts to reach a target point while being close to an obstacle, the increased repulsive force of the obstacle may result

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in the driving vehicle never reaching the target point. The presence of these problems limits the application of artificial potential field methods in certain scenarios.

So far, many scholars have proposed many methods to solve the above limitations. Matoui use the method of nonminimum speed algorithm to handle the local minimum problem [1]. Weerakoonl fixed the local minimum issue by using exponential functions in place of the conventional function, which creates a fresh repulsive force when the robot notices an impediment surrounding itself [2]. Sun addressed the local minima issue by using a dynamic window. The robot analyzes the simulated path using a cost function in order to determine the local minimum region in the preceding phase [3]. Liang put out a sector partition strategy [4]. Around the local minima point, it builds virtual barriers at the proper ranges. Moreover, the combined effect of the original obstacle and the goal point produces a force on the mobile robot. To get around the GNRON issue, Yang developed an innovative repelling potential model that considers how close the robot is to the intended target [5]. Li employs an android -based target and a repelling force disappearance approach [6]. It eliminates the local minimum value caused by conventional APF when the force of attraction and the repelling force are parallel but moving in the opposite direction.

In consideration of the dynamic obstacles, Sun develops an improved minimal hazard index as the foundation for an evolving potential field function [3]. In addition to considering the scale of the BOT and the velocity of obstacles, it may also consider relative distance, speed, and direction information. Ge and Cui suggests a brand-new prospective field technique for use in situations with moving impediments and dynamic items [7]. The new potential function considers both the robot's position and speed in addition to its location. A virtual force is the term used to describe the negative slope of potential about speed and position. Hence, the entire virtual force of the BOT manipulator determines its mobility. Montiel presents an artificial potential field for parallel development in dynamic situations. If there is a set of configurations that can be reached, it offers controllability in challenging real-world situations with dynamic impediments [8]. Zhu considers both the impacts of moving obstructions and ocean currents underwater [9]. It suggested a combined robot route planning system using augmented APF and velocity synthesis. Cheng recommended merging the velocity formulation and APF technologies to create a revolutionary integrated robot path planning method [10]. The velocity synthesis technique may be used to create the optimal path, and the improved artificial potential field method can effectively navigate around dynamic obstacles. This method may be used by robots to resolve GNRON problems and carry out intelligent path planning.

In this study, the multi-subobjective artificial potential field is created by combining an updated A-STAR intuitive path planning approach with an upgraded APF high degree of certainty (MTAPF). Using the upgraded A-STAR algorithm, MTAPF generates the global best route in advance, which is then split into several sub-goal points to produce a series of sub-goal points. The APF technique is used by MTAPF to create a logical path that leads to these sub-target sequences in the proper order.

2. Traditional artificial potential field

The Artificial Potential Field method (APF) is a physics-based path planning algorithm designed to develop navigation routes for robots, autonomous vehicles, and other unmanned systems. The method uses potential fields in a virtual scene to describe the location of targets and areas to avoid obstacles, and uses these potential fields to guide the robot or unmanned system through its movements.

In the artificial potential field method, the target is considered as an attraction point and the obstacles are considered as repulsion points. Thus, during motion planning, the robot is subjected to mutual forces from the target and the obstacle. These forces are used to calculate the recommended direction of motion for the robot's current position and to move it towards the target and avoid collisions with the obstacles.

In practice, the artificial potential field method is usually divided into two phases: building the scene and planning the path. First, the map needs to be converted into electronic form and the positions of the targets and obstacles need to be determined. Next, a potential field is created for each target and obstacle, and then the total force on the robot in the potential field is calculated. Finally, the robot is made to follow the potential field and move to the target location by continuously updating its position and velocity.

Although the artificial potential field method has many advantages, such as better adaptability in dynamic environments and fast computational speed, it also has some disadvantages. Some studies have shown that in some cases, the robot may fall into local extremes and fail to reach the target. Furthermore, in complex environments, the interaction forces between obstacles may lead to unstable behaviour of the robot.

In conclusion, the artificial potential field method is a simple and effective path planning algorithm that can be applied to many practical scenarios. Although the method still has some challenges and limitations, various improved and developed versions will make it more complete and widely applicable.

3. Traditional A-STAR algorithm

The A-STAR algorithm is a well-known informed incremental heuristic search technique that is utilized in several path planning forms and applications. A-STAR algorithm that utilizes Euclidean distance may be used to find the target site, and edge costs can be used to calculate the shortest path. The A-STAR method is more dependable and efficient than other path planning algorithms, and it can ensure the development of shortest pathways.

Even though the A-STAR algorithm can ensure the creation of shortest paths, the cleanliness and coherence of the pathways must be enhanced for it to correctly follow the fastest route. As a result, the method must be further optimized for actual applications in order to enhance the routes' continuity and smoothness. However, the A-STAR method still cannot properly resolve the dynamic constraint problem since it doesn't take the changing vehicle heading angle into account. This restricts its use in some circumstances. To overcome these drawbacks, the formation's local path planning procedure must make use of the global path planning algorithm's path in order to increase the path's smoothness and continuity.

A-STAR chooses which node to extend during each iteration of the main loop based on the expected cost of reaching the target point as well as the route cost. A-STAR specifically chooses the path that minimizes:

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

Regarding the equation (1), for the following route node, $g(n)$ represents the price of the route from the original point to n point, while a heuristic FUNC $h(n)$ calculates the price of the least expensive route from n points to the target points. A-STAR may yield a minimum-cost route from the start point to the destination point if the heuristic function is valid, and it will never overstate the true cost of getting there. A common A-STAR method is to continually choose the best point to pass in order to increase the number of minimal estimated cost points. These points may be divided into two categories using the algorithm：

- OPEN: The OPEN list, which is the collection of currently discovered nodes that have not yet undergone evaluation, is the name of this priority queue.
- CLOSED: These points have been assessed.

The node with the least $f(x)$ value is eliminated from the queue at each algorithmic step, and the nearby nodes that are not included in the CLOSED set are inserted into the queue. When the target point enters the queue or the queue is empty, the algorithm will terminate. At the goal node, $h(n)$ is zero. Thus, the $F(N)$ value equals the shortest path's cost. The final node will refer to its previous once this procedure has been repeated until a node's predecessor is made the start node.

4. Improved artificial potential field method

This study improves the traditional APF method by A-STAR. Firstly, the A-STAR algorithm is improved so that the planned path is not close to the obstacle and reduces its calculation load, and an intermediate path is generated based on the algorithm; secondly, the APF algorithm is adjusted, and its original single target point is changed to a series of the sub-target sequence of the target point, so that the robot can generate a more reasonable path and avoid the problem of GNRON and local minimum by continuously converting the target point.

4.1. Improved A-STAR algorithm

The classic A-STAR method requires a lot of work and cannot ensure the vehicle's safety. It disregards the expense of turns and the drawbacks of duplicate waypoints. As a result, the following upgrades are implemented.

(a) First, fewer search locations should be used while the BOT is approaching an obstacle to shorten the distance between it and the robot. Second, the robot must take the proper steps while nearing an obstruction in order to keep a safe distance and prevent crashes. The grid map produced by the typical A-STAR algorithm does not, however, simplify the grid adjacent to the obstruction, expanding the search region and resulting in a path that is closer to the obstruction, endangering the safety of the BOT.

(b) Figure 1 displays the limitation on maximum route lengths and search distance. Reduce the search area, the search time, and the maximum search distance. The longest possible path through this node is L_{mp} , and L_{md} is the maximum distance throughout the search from the origin to the destination point. The additional search restrictions include:

$$\begin{cases} h(n) \leq k \cdot L_{md} \\ f(n) \leq \lambda \cdot L_{mp} \end{cases} \tag{2}$$

In the above equation (2) and are scaling factors

(c) In order to reduce the robot's need to often turn and to make the path slicker, include the turning cost $h(\delta)$ in the heuristic function, refer to equatin (3). In order to reduce the number of turning locations along the course and avoid frequent detours and turns of the robot, the shifting price is applied to the heuristic FUNC.

$$f(n) = g(n) + h(n) + h(\delta) \tag{3}$$

(d) The produced path is optimized, duplicate points are removed, and the path length is reduced using a suggested trajectory optimization technique. The optimization method divides the path that results. Each waypoint is evaluated to see if there are any obstructions nearby before being classified as a duplicate waypoint.

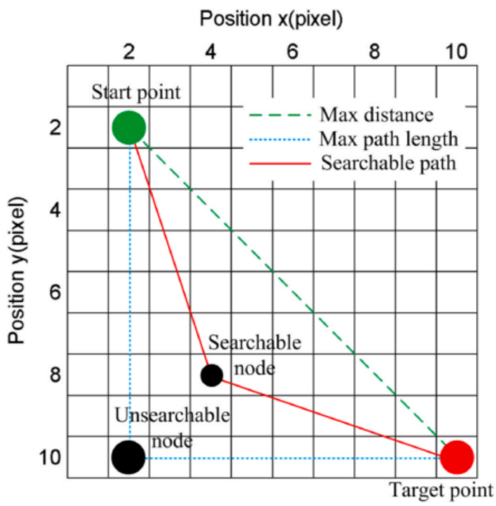

Figure 1. The limitation on maximum route lengths and search distance.

4.2. Local trajectory planning algorithm based upon improved APF

The procedure of the enhanced APF planning path is depicted in figure 2.

The following enhancements are made to the standard APF algorithm to address its flaws:

(a) Potential fields are created from the gravitational field of the robot's goal and the repellent field of the barrier.

(b) A novel MTAPF algorithm that combines with the enhanced A-STAR algorithm is suggested. The robot's route planning method divides several target locations into a succession of sub-target points, considerably lowering the likelihood that the robot will hit the local minimum. Even when the robot enters a local minimum and moves at almost zero velocity. Using the next goal in the sub-target point list as the present target position, the robot may now delete the local minimum.

(c) The augmented A-STAR algorithm divides multi-objective points in accordance with the global optimal path discovered by it, which establishes the robot's prioritizing strategy under dynamic constraints. The trajectory must be created in a way that satisfies the robot's dynamic constraints.

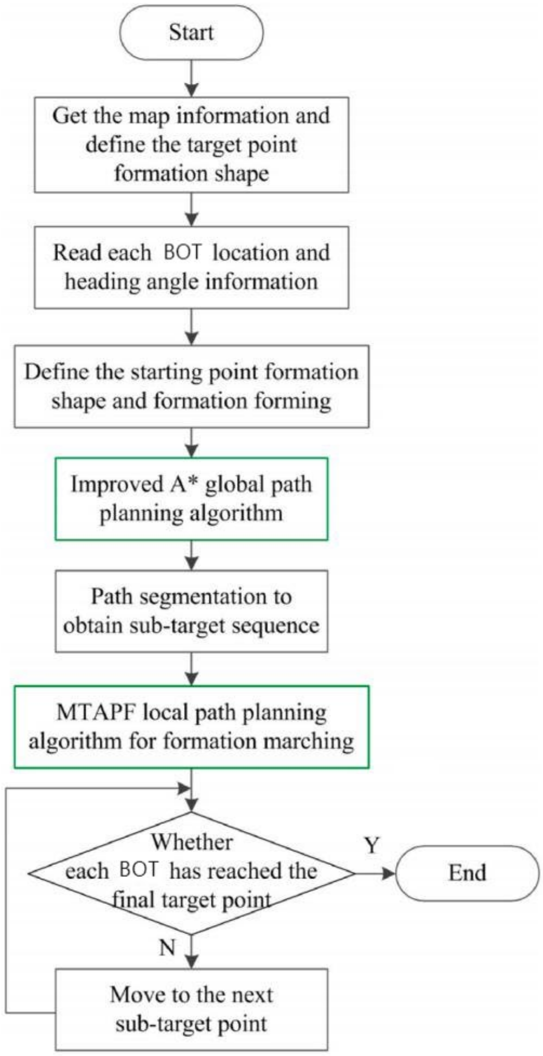

Figure 2. The procedure of the enhanced APF planning path.

4.3. Improved MTAPF model

An enhanced APF model is created based on the findings of the better measurement. The goal point of the mobile robot's gravitational potential field model is

$$U_{attr} = \lambda_{attr} \cdot [\cos\theta(X,G), \sin\theta(X,G)] \cdot [\rho(X,G)]^k \tag{4}$$

In the above equation (4), the distance $[\rho(X,G)]$ between the starting position $X(x,y)$ and the desired goal $G(x,y)$. λ_{attr} is the gravitational potential field's scaling factor, its minimum magnitude $\lambda_{attrmin}$ is bigger than 0. $k = 2.5$ is a calculated field's index. $\theta(X,G)$ is the angle of present point $X(x,y)$ and the goal $G(x,y)$. The target point's repelling potential field equation for the mobile robot is

$$U_{repu} = \lambda_{repu} \cdot \left[\frac{1}{\rho(X,O)}\right]^k \cdot [\sin\theta(X,O), \cos\theta(X,O)] \tag{5}$$

In the above equation（5）, the distance $\rho(X,O)$ between the starting position $X(x,y)$ and the barrier $O(x,y)$. λ_{repu} is the scaling factor of the repulsive potential field, whose minimum magnitude $\lambda repu_{min}$ is bigger than zero. The index used to determine the potential field is k=2. $\theta(X,O)$ is the angle of the present point $X(x,y)$ to the barrier $O(x,y)$. The angles between the BOT and the obstacles need also be adjusted. Obstacles are situated in the, front left, left, front right, right and front of the robot.

$$U_{total} + U_{attr} - U_{repu} \tag{6}$$

In the above equation (6) U_{attr} is the gravitational potential field，U_{repu} is the repulsive potential field，U_{total} is the total potential field.

Based on the enhanced APF algorithm, MTAPF is a multi-subobjective APF method. As the BOT constructs the path, the method of MTAPF separates the improved A-STAR algorithm's path into several target points to produce a series of sub-target points. Next, using the provided objective points as a guide, MTAPF is applied to each robot to produce the proper trajectories. In order to ensure that each robot has a random initial position, establish its starting point and destination point first. Then, read each robot's information. The updated A-STAR algorithm then launches the global route planning algorithm after initialization is finished and each robot has arrived at its beginning location in order to determine the best path and sub-goal point sequence. At the third step, the MTAPF algorithm uses the dynamic constraints of the robot to start the local forming path planning process. Prior to reaching the final target point, use the sub-target position as the currently created target point and then apply the MTAPF technique to get there.

5. Algorithm verification

In a 15 by 15 area, several static obstacles were placed and specified that the robot starting and ending points are respectively (0.75, 0.75) and (12.75, 12.75). The robot can accomplish these sub-goals and eventually arrive at the end point in figure 3 thanks to the MTAPF approach. Figure 4 depicts the traditional artificial potential field approach. As can be seen, the robot finally becomes stuck in the middle of the map and is unable to get there. Due to the obstacles between it and its objective position, the robot's gravity is equal to the repelling force, causing it to sink into a local minimum.

The MTAPF is less prone to local minimum and target unreachable difficulties than the regular APF since its route is the one determined by the A-STAR algorithm, which means that there are essentially no barriers between the series of sub-targets that it generates.

The simulation findings indicate that the strategy put forth in this study has the potential to address the issues with conventional APF.

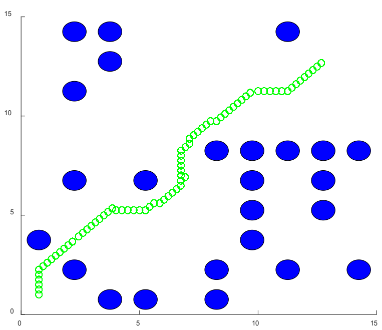

Figure 3. Result on the improved method.

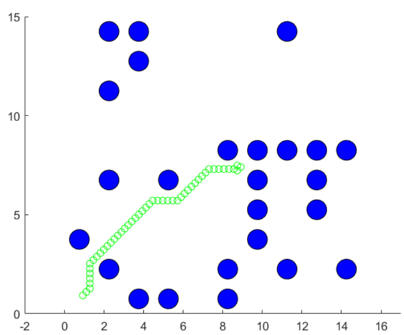

Figure 4. Result on the traditional method.

6. Conclusion

This study examines the robot's reliability and path selection while also proposing an improved MTAPF algorithm. The method of MTAPF approach is used to plan local routes, and the upgraded A-STAR

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algorithm is employed to determine the optimal course. On the premise that the robot's dynamic characteristics are met, the continuity and smoothness of the path are guaranteed. To avoid accidents, a priority technique is used when building the local planning path. Results from simulations confirm the algorithm's efficacy. This approach still has certain drawbacks, though. Even with two obstacles uniformly spaced along either side of the path, the issue of local minimum will persist. Future research will focus on developing collision avoidance and path planning algorithms for robots operating in dynamic and three-dimensional settings.

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