A Hybrid Ant Colony Optimization Algorithm for Path Planning of Robot in Dynamic Environment[1]

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Abstract

Ant colony optimization and artificial potential field were used respectively as global path planning and local path planning methods in this paper. Some modifications were made to accommodate ant colony optimization to path planning. Pheromone generated by ant colony optimization was also utilized to prevent artificial potential field from getting local minimum. Simulation results showed that the hybrid algorithm could satisfy the real-time demand. The comparison between ant colony optimization and genetic algorithm was also made in this paper.

Keywords. path planning, mobile robot, ant colony optimization, dynamic environment, artificial potential field

1 Introduction

Path planning is a key step in the control of mobile robot. And the quality of path influences the efficiency of mobile robot. So designing an efficient path planning algorithm is essential. Presently, there are many algorithms for path planning, such as Artificial Potential Field (APF) [1], Fuzzy Logic (FL) [2], Neural Networks (NN) [3], Genetic Algorithm (GA) [4][5], Ant Colony Optimization (ACO) [6] and so on. However, these algorithms can't reach an ideal solution separately in complex dynamic environment. For example, APF usually gets into local minimum easily. Fuzzy logic offers a possibility to mimic expert human knowledge. However, when the input

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increases, the reasoning rules would expand rapidly, and the computation would mount up exponentially. Neural network has the capability to learn from existing knowledge, but the knowledge representation is very difficult. GA is an evolutionary algorithm, and able to resolve composition optimization problems. But it updates the good individuals entirely and doesn't have exploited the characteristics of the path solution space. ACO is fit for the combination optimization problems, such as path planning, but it can't be applied in dynamic environment.

In real system, mobile robot always knows a lot of information about static obstacles in environment, so we can exploit the information to improve the algorithm efficiency. Therefore, mobile robot can plan the global route before moving. This paper combines the characteristics of ACO and APF, and proposes a path planning approach in dynamic environment that integrates the global planner and local planner. The basic idea is that, ACO is used to plan the global route based on static environment information, and then APF is utilized to program the local route. In this paper, the pheromone information obtained from ACO is exploited to prevent it from getting into local minimum.

2 Global Path Planning

For environment part of which is known, global planner would highly improve the quality of the path. In this paper, global planner employs ACO as a path planning method. ACO simulates the behavior of ant colonies in nature when they are foraging for food and finding the most efficient routes from their nests to food sources. ACO has an advantage for resolving the large combination optimization problems, such as Traveling Salesman Problem (TSP), Flow-shop schedule and so on. These problems can't be resolved by traditional algorithm, such as dynamic programming, A* algorithm.

2.1 Ant Colony Optimization Principle

Ants leave some chemical substance, which we call "pheromone", on the route that they have passed. If the route is short, the ant would leave some pheromone to attract other ants, and the quantity of pheromone is in inverse proportion to the length of the path. Ants can also perceive the pheromone when they pass the route, and their actions could be influenced by the concentration of pheromone. They would select a route with a probability in proportion to the concentration of the pheromone. In this way, the shorter of the path, the more frequent visited by ants, the more pheromone accumulated on the path. This process will be lasted until all the ants select the shortest path.

2.2 Algorithm Improvements

Traditional ACO exists some limitations, such as requiring long time, getting into local minimum if the size of the problem is large. In Traditional ACO, the pheromone concentrations of all elements are equally initialized. So the solutions are constructed blindly in the beginning of evolution phase, and it would take a long time to find a better path from a great many smother paths. So we should improve the ACO at some points.

The first step is the initialization of pheromone concentration. Traditional ACO initializes the pheromone concentration equally. This would make the ACO take a lot of time to converge to optimal resolution, and also may make ACO get into local optimal resolution prematurely. So we can build a pheromone field at the beginning of ACO. In this field, the shorter the distance between current position and obstacles, the smaller the pheromone concentration of current position.

$$phe \propto \sqrt{dis} \tag{1}$$

Different from TSP problem, the objective function of path planning not only should include the length of path, but also should include the obstacle-avoidance information and the smoothness of the route. The obstacle-avoidance information mainly relates to the least distance between the path and the obstacles around. In addition, given robot would slow down when it turns around, the route should be smooth. The objective function is

$$F_k = \frac{L_k}{L} + w_1 \sum_{i=1}^{m} \frac{1}{d_i} + w_2 \times T \tag{2}$$

where L is the distance between the starting point and goal point, L_k is the length of the route that the k th ant agent has gone along, T is the number of the turnings. m is the number of obstacles in the environment, d_i is the distance between the i th obstacle and the route that the k th ant agent has passed. w_i is the weight coefficient. The smaller the value of objective function, the better the path.

The ordinary ACO usually updates the pheromone of the best solution or all of the solutions. The former method is only fit for the limit solution space, but not fit for the space when the solution number is very large, because it would lose the diversity of solutions. The later method would occupy a lot of time to update the pheromone when the ant population is very large. So after each iteration, we update the best 1/3 of all solutions. Simultaneously, because of the smoothness of solution, namely, the quality of solution is as well as that of the solutions nearby, so we not only update the pheromone of elements of the selected solution, but also update the pheromone of the elements that near the elements of the solution selected to be updated.

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \sum_{k=1}^{NUM} \Delta\tau_{ij}^{k} \tag{3}$$

$\tau_{ij}(t)$ is the pheromone concentration of grid (i,j). *NUM* is the number of ant agents. ρ is the evaporate coefficient. $\Delta\tau_{ij}^{k}$ is the pheromone increment left by ant agent *k* on grid (i,j).

2.3 Algorithm Description

The description of the ACO employed in this paper is as follows.

Step1: Initialize the pheromone according to the method stated above.

Step2: Construct a route solution from the starting point to the goal point based on the pheromone information. First generate a random number p , if $p > q_0$ (q_0 is a number defined in advance). Then select the element whose pheromone concentration is largest, namely

$$j = \max(\tau_i) \tag{4}$$

where j is the element to be selected, i is the element which is next to current element. If $p \le q_0$, then select a node as the next element with a probability computed by following formula

$$P_i = \frac{w_i\tau_i}{\sum_i w_i\tau_i} \tag{5}$$

where w_i is the weight of direction, its computation notation is

$$w_i = \frac{3\pi/2 - \theta_i}{\pi} \tag{6}$$

where θ_i is the angle between the direction of goal position relative to current element position and the direction of the next element position relative to current element position. $\theta_i \in [0,\ \pi]$, so $w_i \in [0.5,\ 1.5]$. Because the bigger the θ_i, the probability of the corresponding grid to be selected is smaller.

Step3: Update pheromone. Update the pheromone of elements of the routes according to the method stated above.

Step4: Exit and output the optimal solution if the solutions have converged or reach the up limit of iteration, otherwise jump to Step2.

3 Local Path Planning

Local planner determines the navigation ability of mobile robot and obstacle-avoidance in unknown environment or in dynamic environment. In this paper, the local planner is triggered only when the mobile robot finds that the position which is planned by global planner and it's about to pass by has been occupied or to be occupied by other dynamic obstacles. The local planner adopts Artificial Potential Field (APF) as its path planning algorithm, because it is a good method for real-time obstacle-avoidance, and can also utilize the pheromone generated by ACO to avoid local minimum.

3.1 Artificial Potential Field

Artificial potential field was introduced by Khatib [7][8]. He defined obstacles as repelling force sources, and goals as attracting force sources. Mobile robot is driven by the composition of the two forces. The influencing scope of attracting force is larger than repelling force. The repelling is effective only in a small scope, so this method is also called local algorithm.

In this paper, the mobile robot receives three sorts of forces: the repelling force $\vec{F}_r$, the attracting force from the goal $\vec{F}_a$ and the attracting force from the pheromone generated by ACO $\vec{F}_p$. Then the driving force of robot

$$\vec{F} = \vec{F}_r + \vec{F}_a + \vec{F}_p \tag{7}$$

The value of repelling force $\vec{F}_r$ is in reverse proportion to the distance between current position and the position of obstacles around it, and in proportion to the density of obstacles near mobile robot. The value of attracting force $\vec{F}_a$ is in proportion to the distance between the mobile robot and the goal. And the value of another attracting force $\vec{F}_p$ is in proportion to the concentration of pheromone and the distance to the nearest obstacle.

$$\| \vec{F}_p \| \propto phe \times dis \tag{8}$$

3.2 Local Path Planning

APF is propitious to path planning of mobile robot in dynamic environment. It can easily be implemented, and has characteristics for real-time obstacle-avoidance and route smoothness. So applying APF as a local path planning method is very suitable.

In this paper, mobile robot first goes forward according to the path planned by global planner. When finding there are some dynamic obstacles on its way or near the position where it's about to pass, the robot employs the information of dynamic obstacle and the pheromone generated by ACO to build an APF.

Traditional APF algorithm usually gets into local minimum because of not enough information about global environment. The pheromone generated by ACO can provide useful global information. So employing the pheromone information would help APF avoid getting into local minimum.

The algorithm stated above has a bug. Suppose there are two positions A and B, and A is next to B. If mobile robot finds that B has the smallest value among all positions next to A and A also has the smallest value among all positions next to B, then the mobile robot would wander between A and B. To remedy this fault, we set a taboo table, which records all positions the robot has passed. If the robot discovers that the position, which has the smallest force value among all positions next to current position, has already been in the taboo table, it would select an position whose value is the second smallest of all positions next to current position.

4 Simulation Results and Analysis

We implement the hybrid algorithm in simulation system developed by ourselves.

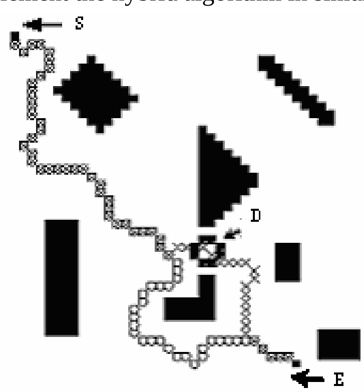

Fig.1 The result of hybrid algorithm in simple environment

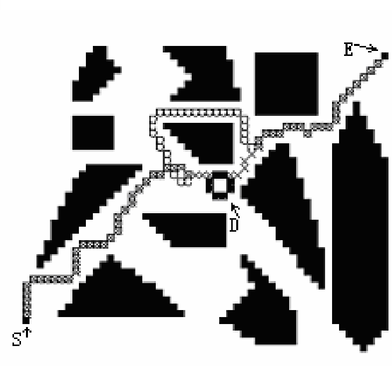

Fig.2 The result of hybrid algorithm in complex environment

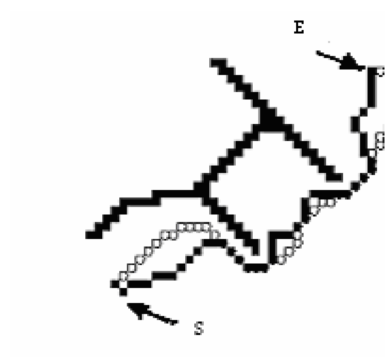

Fig.3 GA and ACO simulation results in simple environment

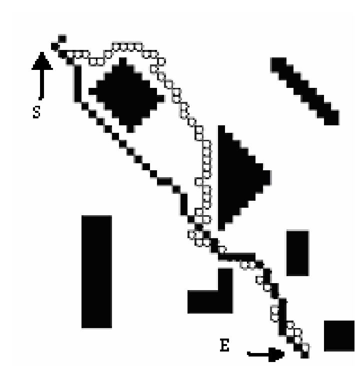

Fig.4 GA and ACO simulation results in simple environment

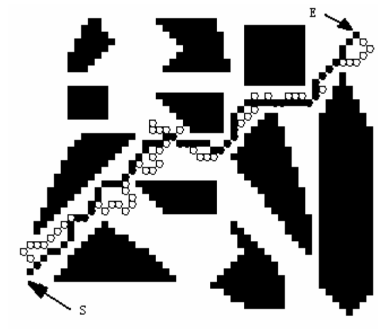

Fig.5 GA and ACO simulation results in complex nonstructural environment

The simulation results shown in Fig.1 and Fig.2. In the figures, 'S' and 'E' stand for the start point and the end point respectively, and letter 'D' stands for the dynamic obstacle. The "×"s compose the path planned by global planner, and the small circles compose the real route passed along by mobile robot when it comes across dynamic obstacle.

From the simulation results above, we can conclude that the path planning method based on ACO and APF together can find a near optimal path and avoid obstacles timely both in simple and complex environment.

We also compare the performance of ACO and that of GA. Fig 3~5 show the simulation results of these two algorithms. In these figures, the solid rectangles represent the path planned by ACO, and the hollow circles represent the path planned by GA.

We define

$$Performance = \rho_1 \times time + \rho_2 \times length + \rho_3 \times turnings \quad (7)$$

as an evaluation function to estimate the performance of the two algorithms, where parameter $time$ is the running time of the algorithm, $length$ is the length of the path, and $turnings$ is the number of turnings in the path planned by the algorithm. ρ_1, ρ_2 and ρ_3 are the coefficient weights of $time$, $length$ and $turnings$ respectively, and they are depending on the importance of the parameters. In this paper, we set $\rho_1 = 3$, $\rho_2 = 1$ and $\rho_3 = 5$. The comparison results are shown in Table 1.

From Table 1, we can see that the performance of ACO overmatches that of GA obviously. No mature $time$, $length$ and $turnings$, the ACO excellent over GA in the gross. The reason for this is that ACO exploit the characteristic of solution space in path planning. In the path planning, the solutions near best solution are also good ones, which we call the smoothness of solution. ACO can reach good performance because it updates the pheromone concentration around the elements of current best solution. Whereas GA intensifies the current best solution as an individual, and the solutions near it can't get intensified.

Table 1 Comparison between ACO and GA

		Fig 3	Fig 4	Fig 5
GA	Length	46	59	72
	Time (ms)	301	340	1001
	Turnings	18	34	44
	Performance	529	687	1437
ACO	Length	48	46	60
	Time (ms)	83	246	560
	Turnings	23	17	30
	Performance	342	469	890

5 Conclusions

In this paper, a new hybrid method for path planning of mobile robot is developed and tested very well. It employs ACO as global path planning algorithm and APF as local planner method. We also exploit pheromone generated by ACO as global information to guide the APF to jump to local minimum. From the simulation results, we can see that by synthesizing APF and ACO algorithm, global optimal and real-time obstacle avoidance can be both satisfied. We also compare the performance between ACO and GA, and induce that ACO outmatches GA in path planning. In the future, we will consider the velocity of dynamic obstacles, and forecast the probability of collision between dynamic obstacle and mobile robot.

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