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Robot Three Dimensional Space Path-planning Applying the Improved Ant Colony Optimization

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Abstract

To make robot avoid obstacles in 3D space, the Pheromone of Ant Colony Optimization (ACO) in Fuzzy Control Updating is put forward, the Pheromone Updating value varies with The number of iterations and the path-planning length by each ant . the improved Transition Probability Function is also proposed, which makes more sense for each ant choosing next feasible point .This paper firstly, describes the Robot Workspace Modeling and its path-planning basic method, which is followed by introducing the improved designing of the Transition Probability Function and the method of Pheromone Fuzzy Control Updating of ACO in detail. At the same time, the comparison of optimization between the pre-improved ACO and the improved ACO is made. The simulation result verifies that the improved ACO is feasible and available.

Keywords*: 3D space, ant colony optimization (ACO), pheromone, transition probability function, path-planning*

1. Introduction

It has been a hot topic for robot avoiding obstacles in 3D space in the field of the Optimal Search Control in recent years. There are a number of available research methods, such as A* Algorithm [1, 2]、Artificial Potential Field method [3, 4] and Genetic algorithm [5, 6] etc, but these methods have its own limitation to some extent. By the time of the early of the ninth decade of the twentieth century, Italian scholars M.Dorigo et al proposed Ant Colony Algorithm [7, 8], This algorithm is an another heuristic search algorithm which is used to solve the optimization problem. This algorithm has advantages in fast convergence, being not easy to fall into local optimum, which solves the problem of robot 3D path planning better than other algorithms [9]. To the improvement of the conventional Ant Colony Algorithm, Fuzzy Control Pheromone Updating method as well as the improved design of Transition Probability Function is introduced in this paper. What is improved makes the conventional ACO does better in path planning and reducing the number of iterations.

2.Robot Workspace Modeling and its Path-planning Method

2.1 Robot Workspace Modeling

Firstly, A 3D environment with obstacles is constructed and shown by Figure 1. Then this environment is divided equally into M sections, each section is in one unit average grid, as is shown by Figur e2, Figure 3. In this way, the geometry space ABCD-EFGH is constructed. hypothesis: AB=m, BC=n, CG=v, The discrete point in this environment can be looked on as P(i, j, k), where i={0, 1,2, …,m}, j={0, 1,2, …, n}, k={0, 1,2, …,v}, therefore x=i, y=j, z=k .

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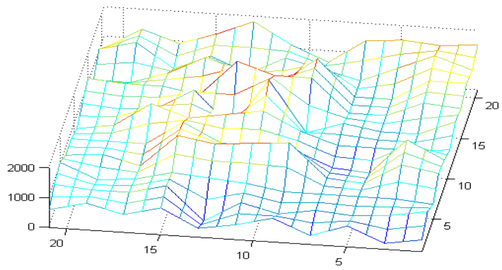

Figure 1. 3D Environment with obstacles

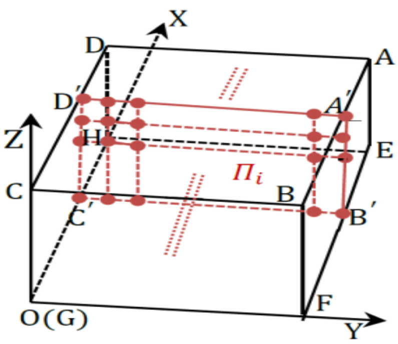

Figure 2. Environment Sections

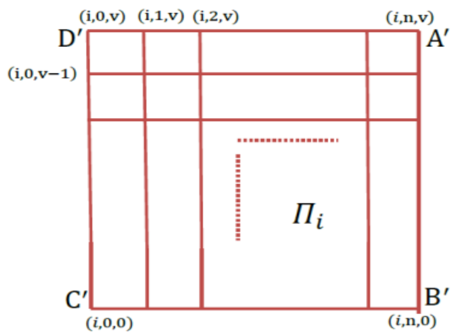

Figure 3. The gridded section

2.2. Three Dimensional Path-planning of Robot with ACO

In the gridded three-dimensional space, a certain point P_{i-1} (i-1,j,k) on the plane Π_{i-1} (i taking values 1,2, …, m) making a line to a certain point P_i (i,j,k) on the plane Π_i (i taking values 1,2, …, m) does not keep in touch with any obstacles, then the path from the point P_{i-1} (i-1,j,k) to the point P_i (i,j,k) is called the feasible route, at the same time, this feasible route is stored in the list $Allowed(\mathrm{i},\mathrm{j},\mathrm{k})$. ACO 3D path planning is simply that finding out the feasible optimal path（the shortest path）from the starting point to the target point In the gridded three-dimensional space. According to the ACO Transition Probability Function [10] and Pheromone Updating Rule [10], under the pre-condition of all passing points belonging to $Allowed(\mathrm{i},\mathrm{j},\mathrm{k})$, in the O-XYZ coordinate system with obstacles, the robot can set out from the starting point Son Π_0, to reach a certain point P_1 (1, j, k) (where j∈{ 0, 1, …, n} ,k∈{ 0, 1, …, v}), and then to reach a certain point P_2 (2, j, k) (where j∈{ 0, 1, …, n} ,k∈{ 0, 1, …, v}) from the point P_1 (1, j, k）, taking turns reaching a certain point P_{m-1}（m-1, j, k）(where j∈{ 0, 1, …, n} ,k∈{ 0, 1, …, v}) on the plane Π_{m-1} ,in the end, to reach the destination point D from the point P_{m-1}（m-1, j, k）, Above all, a optimal path between the starting point to the destination point is constructed : S→ P_1 (1, j, k) → P_2 (2, j, k)→…→ P_{m-1}（m-1, j, k）→D.

3. The Improved Designing ofACO

3.1. The Improved Designing of the Transition Probability Function

According to geometric principles, connection (straight line)L from the starting point to the target point is the shortest path, under the pre-condition that there is no obstacles forpassing directly. That is to say, selectinga certain point relatively close to the line L on the next plane can approximately approach to this line, therefore the distance from the point P on the next plane to the line L has an effect not only on the Transition Probability Function, but also it plays a decisive role in the convergence of the algorithm,thus the Distance Factor concept is introduced in this paper.

Definition: The Distance Factor $D = 1 - \frac{PL_{i+1}}{\sum PL_{i+1}}$, where PL_{i+1} is the distance from the point P_{i+1} (i+1,j, k) belonging to $Allowed(\mathrm{i,j,k})$ to the straight-line L. The Distance Factor D plays a role in selecting the next feasible point which approximately approaches to the optimal path L (the shortest path).

The conventional Transition Probability Function takes α = 1, β = 1, then which is multiplied by the Distance Factor. A brand new Transition Probability Function for a certain point P_i (i,j,k) on Π_i (i=0, 1, 2, …, m-1) getting to a certain point P_{i+1} (i+1,j,k) on Π_{i+1} is formed:

$$P_{i,i+1} = \begin{cases} \dfrac{\dfrac{\tau_{i+1}}{d(\mathrm{P}_i,\mathrm{P}_{i+1})}}{\sum \dfrac{\tau_{i+1}}{d(\mathrm{P}_i,\mathrm{P}_{i+1})}} \bullet D,\ P_i\ to\ P_{i+1} \in Allowed(\mathrm{i,j,k}) \\ 0 \qquad , \quad else \end{cases} \tag{1}$$

Where, τ_{i+1} is the Pheromone value of the point P_{i+1} (i+1,j, k) on the plane Π_{i+1} $d(\mathrm{P}_i,\mathrm{P}_{i+1})$ is the distance from the point P_i (i, j ,k) to the point P_{i+1} (i+1, j, k).

3.2. The Pheromone Fuzzy Control Updating Method

Ant Colony Algorithm applied to three-dimensional path planninggenerally puts pheromones on the connection between the gridding points, this sort of designing for ACO will lead to a particularly large amount of computation. If the Pheromone is simply placed on the gridding points instead of the connection between the gridding points, then this designing will not only greatly reduce the computational complexity of the algorithm [11], but also it will be very convenient for updating the Pheromone value. Fuzzy Control Pheromone global updating is applied in this paper, the updating formula from the period t to the period(t + n):

$$\tau_{ijk}(\mathrm{t+n}) = (1-\rho) \bullet \tau_{ijk}(\mathrm{t}) + \Delta\tau_{ijk}{}^{t} \tag{2}$$

Where $\tau_{ijk}(\mathrm{t})$ represents the not updated pheromone valueon the point $\mathrm{P}_i(\mathrm{i,j,k})$. ρ is the Pheromone Evaporation Rate, 1-ρ represents the Pheromone ResidueFactor, taking ρ = 0.7. $\Delta\tau_{ijk}{}^{t}$ =Q/Nt, where Nt is the number of points passed by the ant, Q represents the total amount of each ant's pheromone, Q parameter is very important, This paper uses fuzzy reasoning methods to control the amount of each Ant's Q in order to get a more reasonable amount of Q. there are twovalues determines the amount of Q, the first is NC the number of iterations of ACO [12-14], and the second is dthe length of each ant's path from the starting point S to the destination point D. Q the amount of pheromone carried by each ant is a fixed value in the conventional Ant Colony Algorithm, it is unscientific. In the early period of the Pheromone Updating, if Q is so large, then the Ant Colony Algorithmwill quickly fall into local optimum, on the other hand, if the Q is solittle, then the convergence speed of the Ant Colony Algorithm will be slow. above all, the best way is that Q is set little when NC is little, Q is set large when NC is large. Furthermore, the path (the straight line) between the target point and the starting point is the best shortest route, if there is d the length of path made by an certain ant very close to the ideal straight-line L, then the Q ofthis ant shouldbe set larger in order to improve Probability forother ants choosing this path, making optimization again on this path could improve the convergence speed. According to the input and output reasoning rulesin Fuzzy Control Algorithm, Membership Function applied triangular [15]. NC the amount of Iterations is the input taking values from 0 to 100 times (experience value) in Figure 4, d the length of the path is another input taking values from 20 (Figure 1 the axial length is the shortest) to 200 (experience value) in Figure 5, Q the carrying amount of pheromone is the output shown in Figure 6.

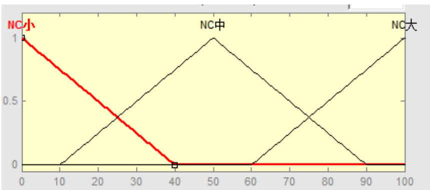

Figure 4. NC the iterations input

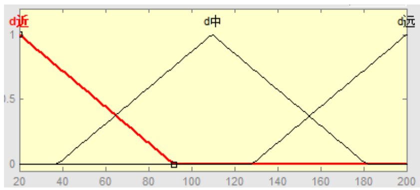

Figure 5. d the length of path input

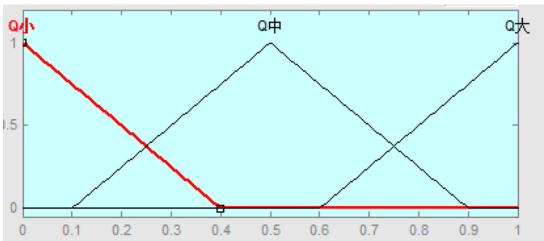

Figure 6. Q the carrying amount of pheromone

In this paper, mamdani reasoning is applied, Fuzzy Reasoning flow diagram shown in Figure 7:

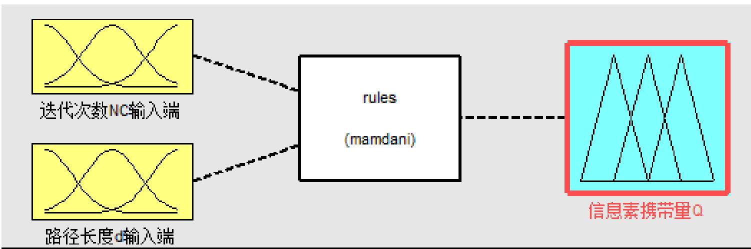

Figure 7. Fuzzy Reasoning

Fuzzy Reasoning rules are shown in Table 1, Figure 8 is a Fuzzy Reasoning rule table in graphic form.

Table 1. Q value of Fuzzy Reasoning

Q Carrying pheromone / NC Iterations	dS	dM	dB
NCS	QM	QS	QS
NCM	QM	QS	QS
NCB	QB	QM	QS

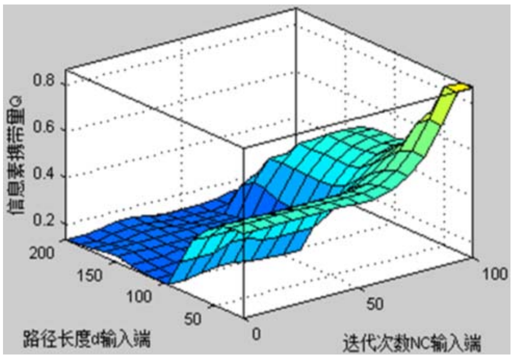

Figure 8. Fuzzy Reasoning rule table in graphic form

4. The Designing for the Fuzzy ACO

Steps of the algorithm is as follows:

Step 1: The 3D space environment with obstacles is initialized , establish the linear equation from the starting point to the destination point, calculate PL the length of each point belonging to $Allowed(\mathrm{i}, \mathrm{j}, \mathrm{k})$ to the straight line L.

Step 2: According to formula (1) use roulette method to determine the next point of each ant, ants reaching the target point apply Fuzzy Control Pheromone Updating formula (2) to update the pheromone.

Step 3: Determine whether each set of all the ants have completed path planning, if not, go to step 2.

Step 4: Determines whether the stopping condition of this algorithm is met, if it is, output the optimal path and end, otherwise, go to step 2.

5. Simulation Results

As shown in Figure 1, A robot in a three dimensional terrain with obstacles applies fuzzy Ant Colony Algorithm to find out an optimal path from the starting point (0,10,0) to thedestination point (20,8,0). Hypothesis: There are 20 ants in each set, make an experimental comparison of conventional Ant Colony Algorithm and the improved Ant Colony Algorithm, Matlab 2008 obtains the simulation results shown in Figure 9 and Figure 10.

These results clearly show that the improved algorithm not only gets a better path in the path planning, but also reduces approximately Ant Colony Algorithm iterations to the half amount of work, the convergence rate also improves a lot. Specific experimental data results are shown in Table 2:

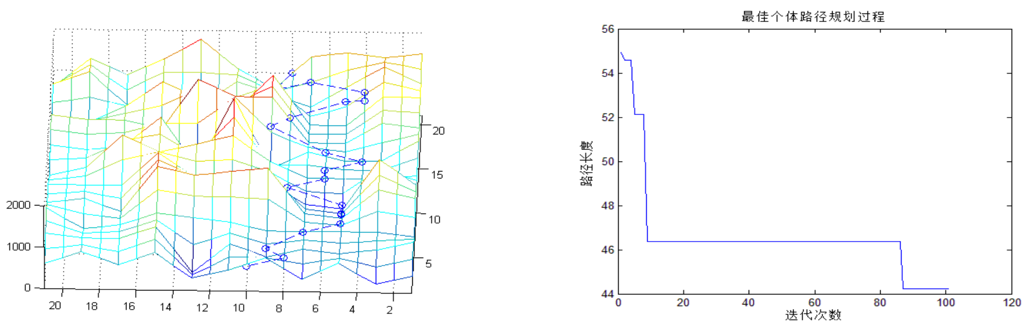

Figure 9. The conventional ACO for path-planning

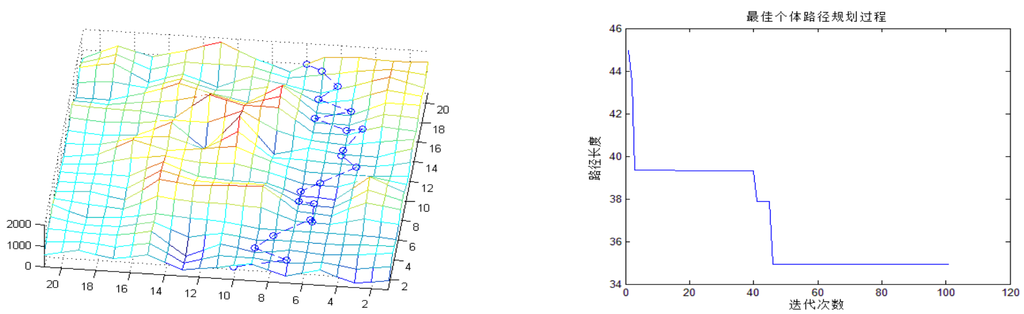

Figure 10. The improved ACO for path-planning

Table 1. Comparison of two algorithms

algorithm	comparison	Experiment 1	Experiment 2	Experiment 3	Average
improved ACO	Best path length	35.032	34.871	34.904	34.936
	iterations	43	46	50	47
conventional ACO	Best path length	44.381	45.082	45.128	44.864
	iterations	90	88	85	88

6. Conclusion

The improvement of the Transition Probability Function and Pheromone Updating methods in conventional Ant Colony Algorithm greatly increases the convergence rate of the Ant Colony Algorithm, reduces the number of iterations, effectively avoids fallinginto local optimal problem, enables antsto find the first pathwith good results. In addition, the location of the pheromone is on the pointsinstead of the connection between the points, which greatly improves the computational speed. Clearly, the improvement of Ant Colony Algorithm can better improve the rate of three-dimensional path planning and optimization. Therefore, this designing can provide broad prospects for further optimization of three-dimensional robot path planning.

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