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THE PATH PLANNING ALGORITHM AND SIMULATION FOR MOBILE ROBOT

[1]ZHANCHUN MA, [2]XIAOMEI NING

[1]Lecturer, College of Science, Qiqihar University, Qiqihar, Heilongjiang Province, China

[2]Lecturer, Modern Education Technology Center, Qiqihar Medical University, Qiqihar, Heilongjiang Province, China

E-mail: [1]mazhanchun9803@163.com, [2]ningxiaomei2002@163.com

ABSTRACT

Research the global path optimization of mobile robot. The traditional evolution algorithm's shortcoming is precocity, in order to overcome the shortcoming and improve the speed and accuracy of the traditional evolution algorithm. The paper combined cloud theory with rough set to use in path planning of mobile robot. In simulation experiment, the environment was described by grid method and random produced initial path group, the first rough set used training initial path group, a series of feasible paths calculated by the minimum decision rule training. The path population optimized by cloud model finally acquired the best path to walk. The simulation results verified special when the initial group was large the convergence speed and search quality had improved by the algorithm combined with the evolutionary algorithm.

Keywords: *Cloud Model, Rough Set, Robots Path Planning*

1. INTRODUCTION

The depth and breadth in the research of mobile robot path planning had a great development. All kinds of algorithms had their own advantages and disadvantages. The traditional evolutionary algorithm search ability is limited and Easy to converge to a local optimal path [1-2]. Improved evolutionary algorithm for robot path planning was proposed. The path will lead to large scale when the path searching space is larger, the ability to remove redundant path is poorer and affect the speed of path planning [3-4].

Rough set theory is a new mathematical tool and has become both at home and abroad in the field of artificial intelligence is a relatively new academic hotspot [5-6].

Cloud model has been applied in mining space, space database query, intelligent control, image processing, network technology [7-8], etc

In order to put the rough sets and the advantages of cloud evolutionary algorithm fusion together in order to achieve better effect, this paper puts forward based on rough set and cloud model evolutionary algorithm.

Section 2 presented the theory of robot path planning by integrated cloud model and rough set algorithm. In section 3, we proposed simulation results. Section 4 gave the conclusion to this paper.

2. THE PRINCIPLE OF ROBOT PATH PLANNING

Mobile robot path planning refers to an indicator for the starting point to the end of the optimal collision-free path.

In order to simplify the problem of path planning the condition was limited:

(1) Movement environment was static.

(2) Obstacles still was static.

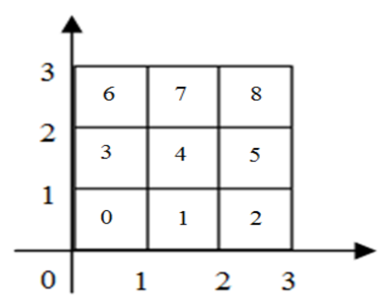

Figure 1. Grid Environment

2.1 Environment description

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Environment was described grid method, Robot activity area was a two dimensional area and coded the grid division. Robot could from a grid along the eight directions to the adjacent grids. Establish plane rectangular coordinate system, the horizontal direction for x axis, vertical direction for the y axis. In figure 1, each grid set a number Index.

Starting point is (0, 0) and target (*x*, *y*). Between (0, 0) and (*x*, *y*) two points the grid method random generated many paths and produced the initial path group. Then the fitness of initial path group was calculated by the formula (1) to (4).

$$D(v_i)=\sum_{j=0}^{n-2}\sqrt{(x_{i,j}-x_{i,j-1})^2+(y_{i,j}-y_{i,j-1})^2} \qquad (1)$$

(x_i, y_i), $(x_{i,j-1}, y_{i,j-1})$ were the robot positions.

$$\varphi_i\begin{cases}=1 & (p_i\in\Delta)\\ =0 & (p_i\notin\Delta)\end{cases} \quad \Delta\in\{obstacle_i \mid i\in 1,2,3\ldots m\} \qquad (2)$$

$$\phi(v_i)=\sum_{i=0}^{n-1}\varphi_i \qquad (3)$$

$$fit(v_i)=\frac{1}{D(v_i)+pow(0.9,\varphi(v_i))} \qquad (4)$$

After calculated fitness function, the higher fitness path group as the basic data of the rough set training.

2.2 Rough set training path group

If a robot for the current position of the grid number was P_i (P_i did not belong to the boundary point), robot has eight direction is feasible as following figure 2.

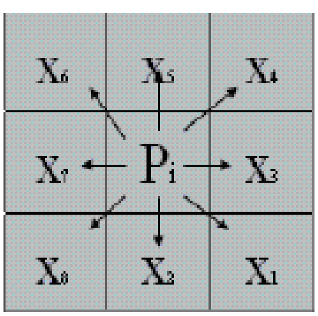

Figure 2. Path Figure

Feasible path as condition attributes ($C=\{X_1,X_2,X_3,X_4,X_5,X_6,X_7,X_8\}$)was quantized, 1 representative obstacles grid, 2 representative free grid P_{i-1}, 3 representative free grid. Initial decision grid described as table 1.

Table 1. Initial Decision Grid

U	*X₁*	*X₂*	*X₃*	*X₄*	*X₅*	*X₆*	*X₇*	*X₈*	*Y*
1	2	2	2	1	1	1	1	1	1
2	2	2	2	1	1	1	1	2	1
3	2	2	2	1	1	1	1	3	1
4	2	2	2	2	1	1	1	1	1
5	2	2	2	2	1	1	1	2	1
6	2	2	2	2	1	1	1	3	1
7	2	2	2	3	1	1	1	1	1
8	2	2	2	3	1	1	1	2	1
9	2	2	2	3	1	1	1	3	1
10	2	2	2	1	1	2	1	1	1
...									
4374	1	3	3	3	3	3	3	3	8

To compatible decision the data in the table, with rough set to calculate the minimum number of attributes the optimal attribute set.

$C=\{X_1,X_2,..X_n\}$ was attribute set, if $\bigcap(C-X_i)=\bigcap H_c$, X_i could omit in C, else X_i could not omit. According to these characteristics, it can simplify the initial decision diagram; get a simplified decision diagram, as shown in table 2 shows.

Table 2. Removing The Redundant Attributes

U	*X₁*	*X₂*	*X₃*	*X₅*	*X₇*	*Y*
1	2	2	2	1	1	1
2	2	2	2	1	2	1
3	2	2	2	1	3	1
4	2	2	2	2	1	1
5	2	2	2	2	2	1
6	2	2	2	2	3	1
7	2	2	2	3	1	1
8	2	2	2	3	2	1
9	1	2	2	1	1	2
10	2	2	2	1	1	2
…						
162	1	3	3	3	3	8

Does not affect the decision of the custom process decision rules can be the elimination, finally to obtain the minimum decision rules as shown in table 3.

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Table 3. Minimum Decision Rules

U	*X1*	*X2*	*X3*	*X5*	*X7*	*Y*
1	2	2	2	1	-	1
2	2	2	2	2	-	1
3	2	2	2	3	-	1
4	2	2	2	-	1	1
5	2	2	2	-	2	1
6	2	2	2	-	3	1
7	1	2	2	1	-	2
8	1	2	2	2	-	2
9	1	2	2	3	-	2
10	1	2	2	-	1	2
…						
80	-	1	3	3	3	8

Through the table 1 to table 3 treatment process can be seen that the rough set training after the population scale quickly narrow, the guarantee is not lost on the basis of feasible solution to improve the efficiency of the algorithm.

Rough set training get path group as a cloud model evolution of the initial path of evolution and variation.

2.3 Cloud model evolution path group

In life, there are many problems attributes can use "cloud" concept to describe. One-dimensional normal cloud $C\ (Ex,\ En,\ He)$ described the "young" the qualitative linguistic value as figure 3 and 4.

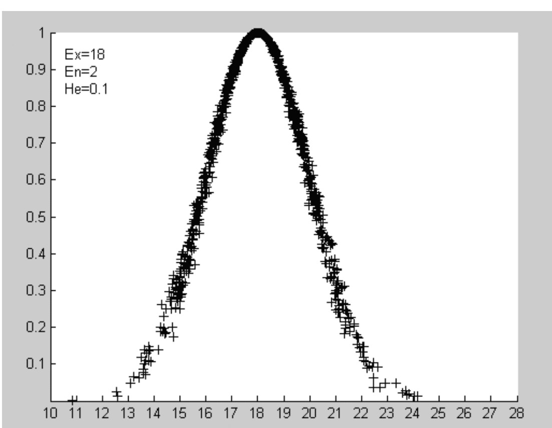

Figure 3. Cloud Figure

The initial path group through the rough set training, The algorithm got the highest fitness before article N path, called the best path. One-dimensional normal cloud operator produced next-generation path.

$$\begin{cases} \Theta = \{t_i \mid Norm(En, He) \quad i = 1 \ldots N\}, \\ X = \{x_i \mid Norm(Ex, t_i) \quad t_i \in \Theta, i = 1 \ldots N\}, \\ \Pi = \{(x_i, y_i) \mid x_i \in X, y_i = \exp(-(x_i - Ex)^2 / (2t_i^{\ 2}))\}, \end{cases} \quad (5)$$

$Norm(\mu, \delta)$ is normal random variable, μ is expectation, δ is variance and N is individual number.

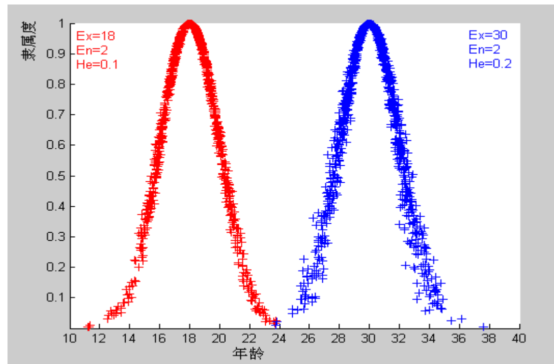

Figure 4. Cloud Figure with Different Parameters

Define 1 Feasible path refers to the initial path in the path of rough set training, get the highest fitness before article N path.

Define 2 Optimal feasible path is population evolution the process of getting the fitness of the highest path, divided into contemporary optimal feasible path and cross generation optimal feasible path.

Define 3 Contemporary optimal feasible path is in an evolutionary path all of the highest degree of viable path.

Define 4 Cross generation optimal feasible path refers to multiple evolution and fitness of the highest. The result of the algorithm for all evolution and the cross-cultural generation optimal feasible path.

Define 5 evolutionary generation of the optimal path across the generations called nontrivial evolutionary generation.

Define 6 The evolution no cross generation optimal path called the ordinary evolution generation.

Define 7 Two optimal path across generations between the evolution of algebra are called continuous ordinary algebra.

Feasible path as a father calculated the next generation of path by formula (5) cloud operator. The evolutionary process, if appear cross generation optimal feasible path, the algorithm may

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be in neighborhood found a new optimal feasible path, the need to reduce En and He values, thus increasing the search accuracy and stability, this is the local refinement operation.

Some evolutionary generation found no new cross generation optimal feasible path, continuous ordinary algebra to achieve a certain threshold value λ_{local} , the algorithm into a local optimum feasible path neighborhood to find than the current optimal feasible path fitness higher feasible path, the need to jump out of the small local variation operation, the operation method is to improve En and He value.

After several generations to achieve the global threshold λ_{global} , evolution has not been fitness higher feasible path, then variation operation failure, the algorithm needs mutation operation, here take history cross generation optimal feasible path mean mutation as the best possible route to produce the next generation.

3. THE SIMULATION RESULTS

In matlab7.0 environment the algorithm simulation results, the algorithm of parameter for 40×40 grid said working environment. (0,0) is initial position, (40,40) is end. The population size for 100 in the photo, black for obstacles, white for free grid.

In the cloud model planning path experiment En and He values is nonlinear empirical value, for different *En* and *He* values, the test result as shown in table 4 shows. Improper parameters can lead to local optimum even make algorithm failure in the calculation of the optimal path.

Table 4. The Results with Different En and He

Parameters	fitness	result
En=2,He=0.1	0.012486	local optimal
En=2,He=0.2	0.013324	Global suboptimal
En=2,He=0.3	0.011470	local optimal
En=3,He=0.1	0.015541	local optimal
En=3,He=0.2	0.011634	local optimal
En=3,He=0.3	0.005240	No global solution
En=1,He=0.1	0.015541	No global solution
En=1,He=0.2	0.011409	local optimal
En=1,He=0.3	0.011894	local optimal

Combined with rough set and cloud model path planning, random generation initial population, with rough set training initial population, it is genetic group of simplified, again by cloud operator on heredity and variation in this algorithm, the evolution and variation is unified, evolution type variation is the evolution and variation fusion, the algorithm can tell the current evolution condition, and can be adaptively adjusted. Experimental set up many obstacles to observe the algorithm can efficiently complete path planning.

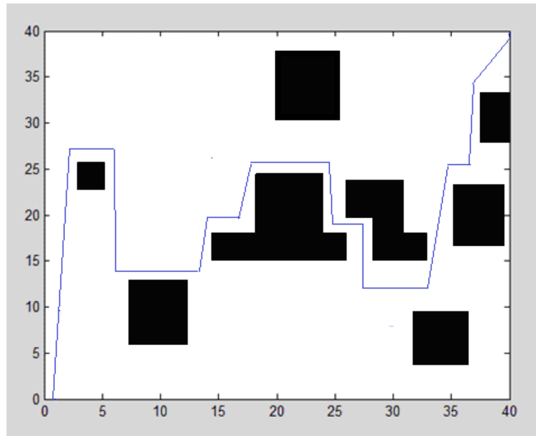

Figure 5. Rough Set Training The Optimal Path

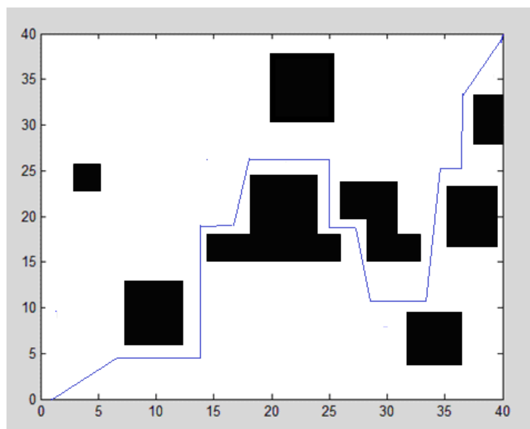

Figure 6. The Algorithm of The Optimal Path

From figure 5 and figure 6 planning results can see, in rough set after training the optimal path based on cloud operator evolution algorithm variation, and finally the best path generation and reliable.

In order to validate the efficiency of the algorithm, this paper for fifty times of trial and error, the structure is as shown in table 5 shows, cloud evolutionary algorithm and time are obtained, and the optimal feasible path algorithm has 46 times get a feasible optimal feasible path. From that the algorithm in the optimization efficiency is improved.

Table 5. Contrast Test Results

Algorithm	traditional algorithm	this algorithm
Optimal path	38	46
Optimal rate	76%	92%
Average path length	81.45	61.33

4. CONCLUSIONS

This paper puts forward the rough set and cloud model introduced in evolutionary algorithm for path planning. When the initial path group of search space is very large, through the rough set training effectively remove redundant path, improve the search efficiency, so as to avoid the evolutionary algorithm convergence speed is low, easy to fall into the local extreme faults. The simulation results verify the path in a large group, the algorithm of average cost smaller, more short path. Using this algorithm can achieve satisfactory planning effect and convergence speed.

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