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Coverage Path Planning for Mobile Robot Based on Genetic Algorithm

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***Abstract*—Environment modeling for mobile robot is built up by using Boustrophedon cell decomposition method, and each sub-region is set numbers and basis point based on the characteristics of modeling, and connectivity relations among all sub-regions are established. All sub-regions are encoded by genetic algorithm (GA), and information of basis points between the sub-regions and sub-regions inside are set up and also achieved by GA, the optimal coverage sequences are obtained with GA, and in each sub-region a partial coverage is realized in the form of reciprocating movement, then problem of complete coverage for mobile robot is changed into a traveling salesman problem (TSP). Finally, the relationships between parameters of GA and search abilities are deeply studied, then the best parameters of GA are obtained. Simulation results show the effectiveness of GA for mobile robot's coverage path planning.**

Keywords-mobile robots; environment modeling; coverage path planning; genetic algorithm

I. INTRODUCTION

Path planning is a core issue in the field of robotics; robotics is also an important aspect in the study of artificial intelligence. Path planning of mobile robot working environment given that information, according to some optimization index, from the starting point and destination point plan a collision with an obstacle in the path environment [1][2]. Complete coverage path planning is a special one, its goal is to find a collision-free path which coverage the space of all areas that can be achieved. Complete coverage path planning studies are more and more concern and attention with the industrialization process of promoting commercial and domestic robots, such as cleaning robots, automatic harvesters, mowers, vacuum cleaners and other independent. Obviously, complete coverage path planning is more complex than traditional point to point (PTP) path planning. The paper proposes a method of complete coverage path planning with the combination of local sub-regions coverage.

The methods for path planning can be divided into traditional methods and intelligent methods. The former includes the free space approach, artificial potential field (APF) method, grids, and so on. The free space approach is more flexible. The intelligent methods include fuzzy logic, GA, ant colony algorithm, and so on [3]. As we all known, GA is stochastic search techniques analogous to natural evolution, GA has the features of fast random searching and global convergence and it is easy to obtained the better solution during the evolutionary iterative search process[4][5]. GA has already been applied in path planning for mobile robots [6]. The paper changes the problem of complete coverage path planning into a TSP problem at first, secondly makes full use of the advantages of GA to solve the coverage path planning for mobile robot.

II. ENVIRONMENT MODELING FOR PATH PLANNING

Environment modeling is used to describe the workspace of mobile robot, the requirement of establishing environment modeling is efficient and reasonable, and it is the basis of mobile robot path planning. Good environment model of the robot to understand the environment plays a promoting role; it can greatly reduce the amount of calculation and improve the efficiency of the robot. In this paper, Boustrophedon cell decomposition method is used to divide environment. The basic idea of this method is: assume a line which is perpendicular to x-axis scans from the left to the right of the map according to the connectivity to produce changes scanning lines coverage the region, seen from Fig.1. Scanning lines from the left of Fig.1, then the sub-region 1 is produced, when the scanning line passes through the obstacle, the connectivity occurs, it produces sub-region 2, 3 and 4, the final environmental map for mobile robot is shown in Figure1, the environment map model is composed by 11 obstacles and 27 sub-regions. End-use Boustrophedon cell decomposition method decomposed by 11 obstacles and 27 traverse the zone.

Information of obstacle or traversing region is expressed as: sub-region coordinate information and vertex attributes sub-area contained in each divided area. Since the traversing region must have two sides are parallel and adjacent to the two sides, so if mobile robot traverses to the public side, then the mobile robot has traversed to the public regions.

III. COVERAGE SEQUENCE OBTAINED BY GA

For environment map shown in Fig.1, the basic idea of coverage path planning for mobile robot is: it uses GA to carry out permutations and combinations of all sub-regions, and then calculates the length of each path, and then compares, then the shortest path is achieved. Because every time the mobile robot traverses all sub-regions, it only compares the distance between each sub-region.

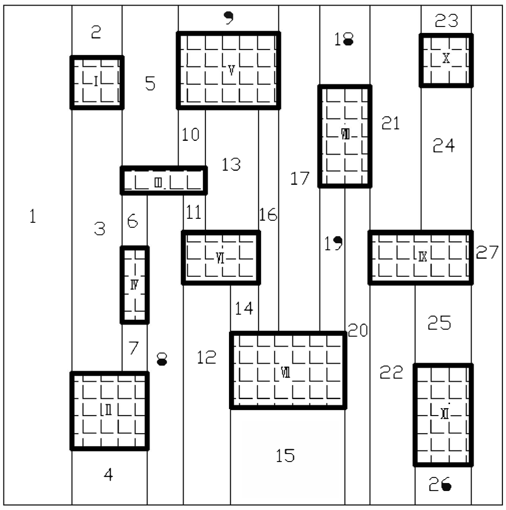

Figure 1. Environment map obtained by Boustrophedon cell decomposition method

The processes of GA solving the problem of coverage path planning for mobile robot are as follows:

(1) Determine the coding scheme, initial population. The paper uses decimal coding scheme. For example, it adopts (1, 4, 6, 8,9,10,2,11, 5, 12, 13, 7, 3, 15, 17, 18, 16, 20, 19, 21, 14, 24, 23,22,26,27, 25) to represents a path that departs from sub-region 1, and then by regions 1→4→6→8→9→10→2 →11→5→12→13→7→3→15→17→18→16→20→19→ 21→14→24→23→22→26→27→25, eventually returns to sub-region 25.

(2) Set the fitness function and calculate the fitness value of each individual. Calculate the length of each sub-region and take it as evaluation criteria, that is, as its fitness function, the fitness function is

$$f(x)=\sum_{i=1}^{k} d(i,j) \tag{1}$$

Where $d(i,j)$ represents the closest distance between the sub-region ***i*** and sub-region ***j***. The smaller the individual fitness value, the shorter its path, indicating that the more the individual meets the requirements.

(3) Judge whether GA satisfies iteration termination conditions If the termination condition satisfies, GA is complete, and the results solution output; if it does not reach the termination condition, then continue the calculation to solve. Since the beginning, the shortest path length is unknown, so this paper uses iterations as the termination condition.

(4) Determine the fitness function value, and then copy other operations related to the implementation of the fitness function based on the size of the value. Depending on the value of fitness function, it calculates the fitness value, namely the path length values are sorted from small to large.

(5) Design crossover operator. The paper selected from a fragment of a parent, relative preservation in order to construct the sub-region for future generations. For example,

$P_1 =$(1 2 13 4 5 | 6 7 11 9 | 10 8 12 3 |14 16 17 18 15 19 |20 21 23 22 24| 26 25 27)

$P_2 =$ (4 5 11 3 10 | 1 8 7 6 | 9 13 12 2 | 15 18 16 14 17 | 20 21 22 19 23| 24 25 26 27)

G1 x x x x x 6 7 11 9 x x x x

G2 x x x x x 1 8 7 6 x x x x

For obtaining *G1*, then in the region *G2*, 6, 7, 11, 9, which were in *G1*,were removed, it obtained 4→5→3→10 →1→8→13→12→23→14→16→18→15→17→19→20→ 24→26→23→21→20→27, then this sequence is placed in G1, then

G1 4 5 3 10 1 6 7 11 9 8 13 12 2 23 14 16 18 15 17 19 20 24 26 23 21 20 27

Similarly, another offspring was obtained

G2 2 13 4 5 11 1 8 7 6 9 10 12 3 23 14 16 18 15 17 19 20 24 26 23 21 20 27

(6) Design mutation operator. It used an inverted variation, i.e., randomly selected points on the chromosome, the between two sub-string was inverted.

(7) Return to step (3).

IV. Optimization of GA Parameters and Simulation Results

In order to verify the effectiveness of GA algorithm, simulation experiments were carried out based on MATLAB platform. In the simulation, the effects of system parameters for the search ability of GA curve were studied, and finally the optimal parameters were selected; quickly and the optimal solution were efficiently obtained.

Firstly, effects of population size on search capabilities of GA. When crossover ratio is 0.8, mutation probability is 0.01, the number of iterations is 200, only changing the number of the initial population; the results are shown in Fig.2. Seen from Fig.2, the size of the population has a direct impact on the search capabilities: when population size increases, the search capability is increasing, the relationship between the two is nonlinear; when the number of initial population is greater than 40, the search capability trend is smooth, with no significant increase or decrease. Therefore, the size of the population in the paper is 40.

Secondly, effects of crossover probability on search capabilities of GA. When the initial population size is set to 40, variation rate is set to 0.008; the number of iterations is fixed to 200, the calculation results shown in Fig.3. Seen from Fig.3, the search capability increases with the crossover probability increasing, but when the crossover probability exceeds 0.7, search capabilities remain stable and not increase, so when other parameters are fixed, the crossover probability of GA is selected 0.8, at the same time system searching ability is the strongest, while smaller computation are needed.

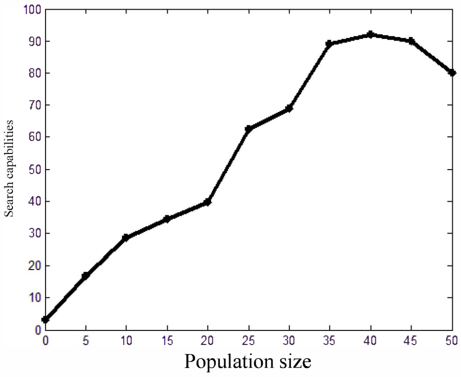

Figure 2. Relationship between population size and search capabilities

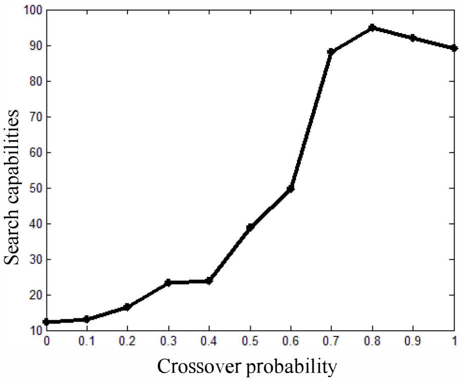

Figure 3. Relationship between crossover probability and search capabilities

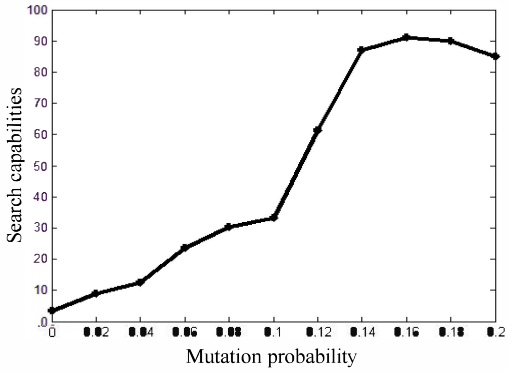

Figure 4. Relationship between mutation probability and search capabilities

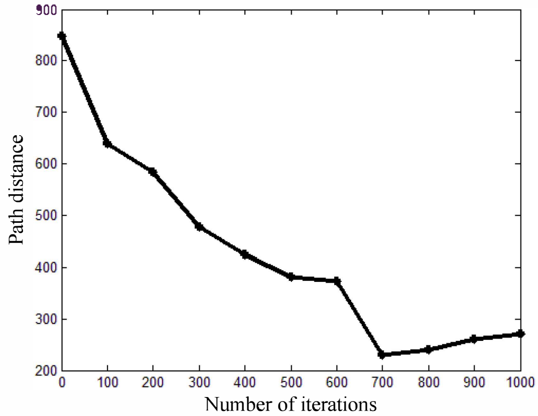

Figure 5. Relationship between number of iterations and path distance

Thirdly, effects of mutation probability on search capabilities of GA. mutation probability factor is also a critical parameter to GA, its impact on search capabilities are shown in Fig.4. When crossover probability is 0.8, initial population is 30, number of iterations is 200, by changing mutation probability, and the search capability also undergoes a corresponding degree of changing. When the mutation probability is 0.16, the search capabilities are the best. Thus, mutation probability in GA is set to 0.16.

Fourthly, number of iterations is also a key parameter to GA, and its impact on the search capabilities are shown in Fig.5. It can be seen from Fig.5, when the crossover probability, mutation probability, size of the initial population are confirmed, between the number of iterations and the path distance is not a linear relationship. When number of iterations is less than 600, the path distance gradually increase; when the number of iterations reaches 700, the path distance tends to decline. Therefore, number of iterations in GA is set to 700.

Finally, GA parameters were obtained as follows: population size is 40, crossover probability is 0.8, mutation probability is 0.16, number of iterations is 700. Using GA, the final results of the optimal coverage path planning are:1 →2→5→10→13→16→17→18→21→24→23→27→26→25→22→19→20→15→12→8→4→3→6→7→14→11→9.

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V. CONCLUSIONS

The method combining Boustrophedon cell decomposition and GA are introduced in this paper, and it obtained the best choice, and also obtained the optimal solution of the system. Meanwhile, effects of population size, crossover and mutation probability, and algebra for evolutionary search ability on GA were studied, the study of GA parameters to determine the best choice, and obtain the optimal solution of the system. The simulation results indicate that GA has an excellent performance in convergence rate and optimization efficiency. It makes great sense in the task of coverage path planning for mobile robot.

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