

Robot path planning based on improved genetic algorithm

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Abstract: In order to solve the problems of the basic genetic algorithm in robot path planning, such as the path is not smooth enough, the number of turns is too many, and it is easy to fall into the local optimal solution, an improved genetic algorithm is proposed. The method introduces the turning angle and turning times as the evaluation objectives, improving the practicability of the fitness function; The elitist retention strategy is added to improve the convergence speed of the algorithm; The adaptive change strategy of crossover probability and mutation probability is optimized, so that the algorithm can adapt to various scenarios and improve the optimization ability and convergence speed of the algorithm. The simulation results show that the improved genetic algorithm is more suitable for robot movement than the basic genetic algorithm.

Keywords: Robot; Path planning; Genetic algorithm.

1. Introduction

Path planning is an important part of mobile robots. Improving the efficiency of mobile robots and reducing the energy consumption of robots are the research hotspots nowadays [1,2]. To solve the problem of robot path planning, researchers have put forward a variety of methods, among which the intelligent optimization algorithm is more widely used, including genetic algorithm [3], ant colony algorithm [4], particle swarm optimization algorithm [5], etc. Genetic algorithm is widely used because of its strong robustness. However, it has the disadvantages of slow iteration speed and easy to fall into local optimal solution, which limits its development. SUN Bo and others added the idea of simulated annealing to the genetic algorithm, effectively improving the global search ability of the algorithm [6]. XU Mengying and others combined immune clonal operator and adaptive operator in genetic algorithm, and changed the coding method to improve the quality of the solution [7]. The above methods improve the optimization ability of the genetic algorithm path planning, but there are still shortcomings such as too many path curves and slow convergence speed.

To solve these problems, this paper modifies the fitness function on the basis of the basic genetic algorithm to adaptively change the crossover probability and mutation probability, and introduces the elitist retention strategy in the selection operation. Experiments show that the improved algorithm effectively improves the path planning performance of the robot.

2. Path planning grid model

Path planning is the robot's automatic avoidance of obstacles from the beginning to the end. Grid map is the most commonly used modeling method in path planning. The actual map is represented by grid. In a grid map, the area where the robot can move freely is called free grid, and the area where the robot cannot move freely is called obstacle grid.

Figure 1 is an example of grid map. The white area in the figure represents the free grid, and the black area represents the obstacle grid. Given a starting point and an end point,

there are many paths between the two points. The purpose of robot path planning is to select the most suitable path without touching obstacles.

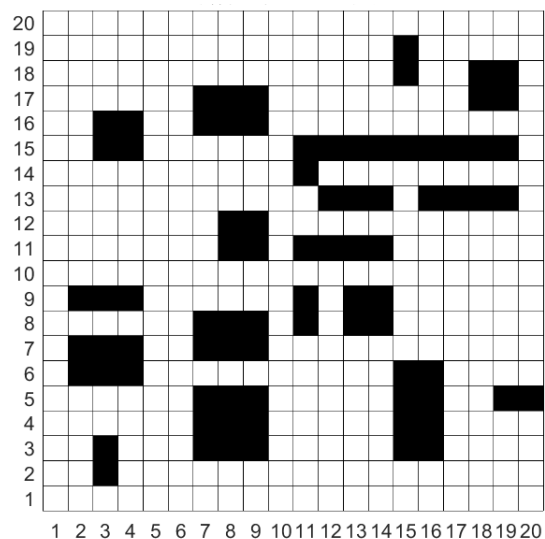


Fig. 1 Path planning grid map

3. Improved genetic algorithm

3.1. Fitness function

Energy consumption is an important consideration for robot movement. The methods to reduce robot energy consumption include shortening the moving distance, reducing the turning angle and reducing the number of turns. The improved fitness function is as follows:

$$fit = a \times fit_1 + b \times fit_2 \quad (1)$$

Where, a and b are the weights of length factor and smoothness factor, fit_1 is the length factor expression as follows:

$$fit_1 = \frac{1}{length} \quad (2)$$

$$l = abs(x_i - x_{i+1}) + abs(y_i - y_{i+1}) \quad (3)$$

$$length = \sum_{i=1}^{end-1} \begin{cases} length + 1 & (l = 1) \\ length + \sqrt{2} & (l > 1) \end{cases} \quad (4)$$

x and y represent the coordinates of the grid, fit_2 is the smoothness factor, and the expression is as follows:

$$fit_2 = \sum_{i=1}^{end-1} \frac{1}{p\theta_i + pt_i} \quad (5)$$

Where, $p\theta_i$ is the penalty imposed by the turning angle between two adjacent grids on the path. The greater the turning angle, the greater the value of $p\theta_i$. pt_i is the penalty for the number of turns of the path. The more turns, the greater the value of pt_i .

3.2. Select Action

Selection operation is the most important step in genetic algorithm. According to the fitness of each individual, individuals with high fitness can be retained through roulette. However, roulette is random, and individuals with high adaptability may also be eliminated. To avoid this, the elite retention strategy is added in the selection process. Before roulette, the individuals with the highest fitness will be selected first, and will not participate in the subsequent roulette. Finally, the individuals with the highest fitness will be selected together with the individuals selected by roulette for the subsequent crossover operation and mutation operation, which can effectively prevent the loss of elite individuals and speed up the iterative efficiency of the algorithm.

3.3. Adaptive change of crossover probability and mutation probability

Crossover probability refers to the probability of crossover operation during each iteration. Crossover operation refers to swapping and recombining two intersecting paths, resulting in two sub-paths. This method can generate new sub-paths, and then retain the paths with good fitness, and discard the paths with poor fitness. The principle of this method is similar to that of gene recombination. After crossover operation, the fitness of the sub-path may be higher than that of the parent path, so as to achieve the purpose of finding the best path.

Mutation probability refers to the probability of mutation operation during each iteration. Mutation operation refers to randomly selecting a new point in the path, and then replacing the original point in the path, so that a new path will be created.

The value of crossover probability and mutation probability will affect the convergence rate and final solution of the algorithm, so it is not suitable to choose a fixed crossover probability and mutation probability. In order to improve the performance of the algorithm, this paper proposes a scheme to adaptively adjust the crossover probability and mutation probability. The convergence speed of the current algorithm is measured by using the sum of the average value of the length factor and the average value of the smoothness factor of the current generation population to compare with the sum of the average value of the length factor and the average value of the smoothness factor of the previous generation population. A larger ratio indicates that the algorithm is close to stable, and the mutation probability and crossover probability need to be increased to generate new individuals and increase the diversity of species. On the contrary, a smaller ratio indicates that the algorithm is converging rapidly. In order not to destroy good individuals, a smaller crossover probability and mutation probability should be used. The evaluation indicators are as follows:

$$\frac{MC}{MP} = \frac{\frac{1}{n} \sum_{i=1}^n fit_1(t, i) + \frac{1}{n} \sum_{i=1}^n fit_2(t, i)}{\frac{1}{n} \sum_{i=1}^n fit_1(t-1, i) + \frac{1}{n} \sum_{i=1}^n fit_2(t-1, i)} \quad (6)$$

MC represents the crossover probability and MP represents the mutation probability. MC/MP is the ratio of length factor and smoothness factor of two generation population. n is the number of individuals for the contemporary population; fit_1 is the length factor; fit_2 is the smoothness factor; t indicates the generation of the current population.

In genetic algorithm, the value of crossover probability and genetic probability can be between 0 and 1. However, considering that too low value will lead to the stagnation of population evolution and fall into local optimal solution, and too high value will destroy excellent individuals in the process of evolution. Therefore, the value range of restricted crossover probability is 0.5 to 0.8, and the value range of restricted mutation probability is 0.01 to 0.3. The specific values of crossover probability and mutation probability are shown in Table 1.

Table 1. Value of crossover probability and mutation probability

$\frac{MC}{MP}$	Pc	Pm
≤ 0.2	0.5	0.01
[0.2,0.4]	0.6	0.1
[0.2,0.6]	0.7	0.2
[0.6,0.8]	0.75	0.25
≥ 0.8	0.8	0.3

3.4. Algorithm flow

The calculation flow of the improved genetic algorithm robot path planning proposed in this paper is shown in Figure 2. The termination condition of the algorithm is to reach the maximum number of iterations.

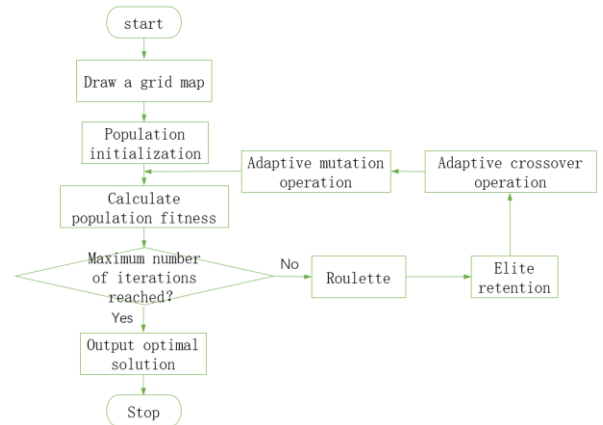


Fig. 2 Flow chart of improved genetic algorithm

4. Experimental analysis

In order to verify the effect of the improved genetic algorithm in robot path planning, this paper uses matlab software to carry out simulation experiments and compares it with the basic genetic algorithm. The starting coordinate is (1,1) and the ending coordinate is (20,20). The number of populations is 200, the maximum number of iterations is 100, the weight coefficient a is 1, and the weight coefficient b is 1.5.

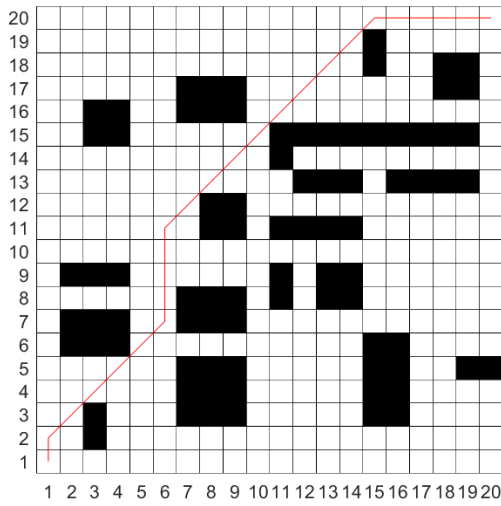


Fig.3 Results of improved genetic algorithm

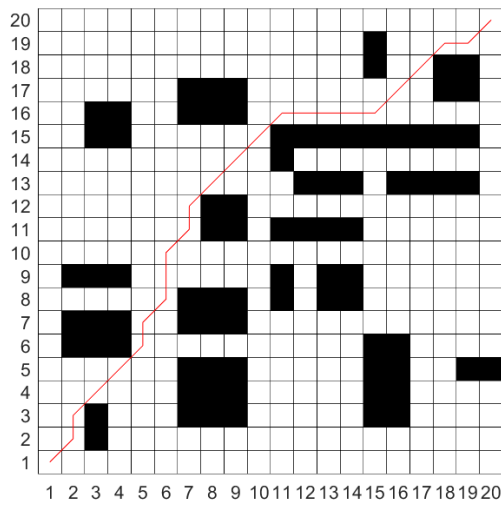


Fig.4 Basic genetic algorithm results

Figure 3 shows the improved genetic algorithm path planning results, and Figure 4 shows the basic genetic algorithm path planning results. It can be seen that both algorithms can find a shortest path for the robot. However, the improved genetic algorithm results in fewer turns, which is more suitable for robot motion.

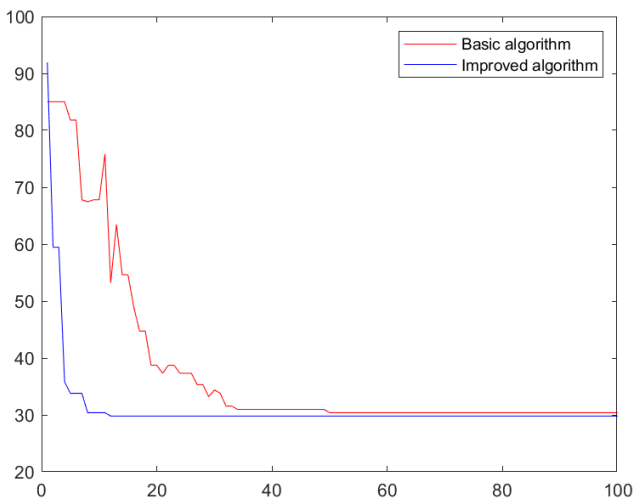


Fig.5 Comparison of convergence curves of two algorithms

Figure 5 shows the comparison of the convergence curves of the two algorithms. It can be seen that the improved genetic algorithm converges faster. These advantages come from

adaptive adjustment of crossover probability and mutation probability and elite retention strategy.

Since genetic algorithm is a random algorithm, in order to avoid chance, 20 simulation tests were carried out on the basic genetic algorithm and the improved genetic algorithm respectively, and the results are shown in Table 2.

Table 2. Comparison of multiple simulation results

Item	Basic genetic algorithm	Improved genetic algorithm
Optimal length	29.8	29.8
Average number of turns	12.5	5
Average length	30.703	30.9
Average number of iterations	18.5	11.25

The analysis shows that the theoretical shortest path of the map is 29.8, and both the basic genetic algorithm and the improved genetic algorithm are capable of finding the shortest path. However, because sometimes the number of turns of the shortest path is too many, it is not suitable for the robot to move, so the path calculated by the improved genetic algorithm may not be the shortest path. The number of turns calculated by the improved algorithm is greatly reduced, and the convergence speed of the algorithm is fast, which can preliminarily prove the superiority of the improved genetic algorithm.

5. Summary

This paper proposes an improved genetic algorithm path planning for robots. The algorithm modifies the basic genetic algorithm: changing the fitness function; Making crossover probabilities and mutation probabilities adaptively altered; An elite retention strategy was introduced. The improved genetic algorithm reduces the number of turns in the path, reduces the turning angle, accelerates the convergence speed of the algorithm, and significantly reduces the energy consumption of the robot. There are still many aspects to be improved in the research content of this paper, such as how to apply the algorithm to the dynamic obstacle environment, and improve the adaptability of the algorithm to the complex environment.

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