Research on Improving Genetic Algorithm in Mobile Robot Path Planning

Xiaoxiang Xia
School of Information Engineering, Ezhou Polytechnic, Ezhou, China
360464526@qq.com

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***Abstract*—Sound path planning is essential for mobile robots to carry out exploration tasks. To date, the use of various intelligent algorithms in robot path planning has yielded significant advancements, particularly in areas such as path planning, obstacle avoidance, and collaborative control. These advancements enhance the robots' capabilities, collaboration, and efficiency in complex environments. However, traditional algorithms like particle swarm optimization, ant colony algorithms, and dynamic window algorithms face challenges in robot path planning, including slow convergence and a tendency to get stuck in local optima. Addressing the complexities of mobile robot path planning, genetic algorithms have been integrated. Yet, standard genetic algorithms suffer from slow convergence and low efficiency. An enhanced mobile robot path planning scheme using an improved genetic algorithm has been proposed. Simulation tests in a grid environment demonstrate that this approach narrows the local search range for paths, enhancing the algorithm's adaptability, convergence speed, and global search capabilities. Overall, it outperforms the standard genetic algorithm, offering valuable insights for researchers studying and applying algorithms in mobile robot path planning.**

Keywords—Genetic algorithm; Mobile robots; Path planning

I. INTRODUCTION

Path planning technology is one of the key technologies for achieving autonomous navigation of mobile robots and can also be widely applied in fields such as automation systems, unmanned vehicles, logistics management, and robotic arm movements. In the autonomous navigation process of mobile robots, the main purpose of path planning algorithms is to enable the robot to plan a collision free path from the starting state to the target state according to certain evaluation criteria[1].

The so-called path planning is the process in which a mobile robot can move from its initial position to the target position in a complex environment, avoiding all obstacles during the movement and finding a shorter path as much as possible.

Robot path planning involves specifying a starting and ending point within an environment filled with obstacles. It entails devising an optimal route from the starting point to the end point while avoiding obstacles under set evaluation criteria, requiring the robot to minimize time spent, travel the shortest distance, and consume the least energy along the route. Currently, numerous studies have been conducted on robot path planning, encompassing methods such as simulated annealing algorithms, neural networks, artificial potential fields [2], particle swarm optimization, and ant colony algorithms [3,4]. However, these algorithms face challenges such as extensive search spaces, complexity, low efficiency, and local optima [5,6]. Genetic algorithms, with their robust global search capabilities and high efficiency, stand out as optimal search algorithms for global optimization in complex environments. They are known for their robustness and flexibility, making them ideal for path planning in complex environments for mobile robots. Standard genetic algorithms, however, are also complex, require a long time to select optimal paths, and often get stuck in local optima. This paper integrates an improved genetic algorithm into the path planning strategy for mobile robots and confirms its effectiveness and feasibility through simulation experiments [7,8].

II. PATH PLANNING SCHEME BASED ON IMPROVED GENETIC ALGORITHM

A. Individual coding

The workspace of mobile robots is modeled using a grid method, assuming the robot operates within a static two-dimensional space filled with obstacles. This two-dimensional space is divided into grids of equal size. If a grid contains an obstacle, it is referred to as an obstacle grid; otherwise, it is a free grid. As illustrated in Figure 1, the black grids represent obstacle grids, while the others are free grids [1] .

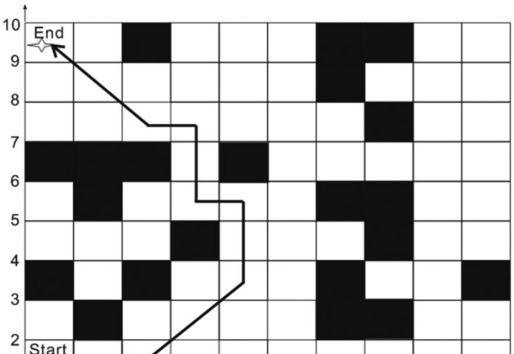

Figure 1. Barrier grid distribution map

The path of an individual from the starting point to the ending point can be represented by the Cartesian coordinates of the grid it traverses, as illustrated in Figure 1. The path is denoted by the coordinates {(0,1), (1,1), (2,1) ..., (0,9)}. Each coordinate is represented by a 4-bit binary, allowing the individual to be expressed as {0000,0001,0001, 0001,..., 0000,1001}. Thus, the coordinate method enables tracking of the grid path traversed by the robot. The binary-encoded representation of individuals is succinct, facilitating computer processing and enhancing the benefits of genetic algorithms.

B. population initialization

The robot's initial path generation process begins at the starting point, leveraging environmental data and local search strategies to randomly choose a free grid adjacent to the starting point as the next path point. This process repeats until the endpoint is reached. To prevent the creation of loops, the robot must not traverse the same grid twice [9]. As illustrated in Figure 1, the robot's path from the starting point to the endpoint is denoted by the sequence of grids traversed, and the initial population is defined by Equation (1).

$$P=\{p1,p2,\cdots,pn-1,pn\} \quad (1)$$

In equation (1), p_i (i=1, 2,…n) is the path individual.

C. Fitness function

Genetic algorithms evolve the next generation by selecting through a fitness function to find the optimal solution to a problem. Therefore, the choice of fitness function is critical, directly impacting the algorithm's convergence speed and the search for the optimal solution. When choosing paths, robots assess the quality of each path based on the fitness function.

When choosing the optimal path to proceed, the standard genetic algorithm selects the best path solely based on its length. The enhanced fitness function evaluates based on both the path length and the extent of obstacle intersections, guiding the solution towards reducing these metrics. This approach more accurately reflects the path's true quality. This function is described in equation (2).

$$f(T_i) = \gamma_1 \sum_{i=1}^{N-1} p_i + \gamma_2 \sum_{i=1}^{N-1} \gamma_i \quad (2)$$

In equation (2), γ_1 represents the weight factor of the path length, γ_2 represents the weight factor of obstacles, which signify the importance of different optimization indicators. $\sum_{i=1}^{N-1} p_i$ represents the total length of path T_i, and p_i represents the length of the i-th straight line in path T_i. The algorithm seeks to minimize the cost function, with the solution that achieves the minimum value being designated as the optimal solution.

D. Selection Operator

The selection operation is modeled after the natural principle of "survival of the fittest," where individuals within a population are selected based on their merits. The goal is to ensure that the superior genes of the individuals within the population are passed on to the next generation. An individual's likelihood of being selected for genetic transmission to the next generation is related to their fitness. The higher an individual's fitness value, the greater their chance of being selected for genetic transmission to the next generation, and vice versa.

In the improved genetic algorithm, the roulette wheel method is employed for individual selection. First, the fitness function determines the fitness value of each individual and the total fitness of the population. Subsequently, the proportion of an individual's fitness value to the total is calculated, determining its selection probability $p_s(a_i)$ Then, the cumulative selection probability $p_s(a_i) = \sum_{i=1}^{k} p_s(a_i)$ for the k-th individual is computed. Next, a random number α between 0 and 1 is generated. If $p_s(a_{k-1}) < \alpha < p_s(a_k)$, the k-th individual is chosen. This selection algorithm is highly stochastic and ensures that individuals with superior fitness values are more likely to be passed on to the next generation. Where $p_s(a_i) = \frac{f(T_i)}{\sum_{i=1}^{N} f(T_i)}$, N represents the population size, and the greater an individual's fitness $f(T_i)$, the higher its selection probability.

E. Crossover operator

Crossover involves replacing and recombining parts of the structures of two individuals to create the next generation. It plays a crucial role in global search during genetic evolution. Choosing the optimal gene for crossover at each iteration can easily trap the algorithm in local optima, leading to premature convergence. This paper employs a hybrid method of single-point and coincident-point crossovers. Coincident-point crossover involves randomly selecting two individuals and choosing points with identical grid coordinates for the crossover operation. If there are multiple coincident points, one is randomly chosen for crossover. If no coincident points are found, random crossover points are selected for single-point crossover, exchanging partial chromosomes at the coincident points along the path with a crossover probability, thereby preventing the formation of discontinuous paths and enhancing the algorithm's search capabilities while preserving the validity of the path individuals [10,11].

F. Mutation operator

Mutation operators allow individuals to undergo transformations with a low probability, bringing them closer to optimal solutions. Mutation can extend new search spaces, preserve population diversity, and prevent premature convergence during localized convergence of the population. Additionally, to maintain local search capability, the mutation probability should not be excessively high. If the mutation rate exceeds 0.5%, the genetic algorithm deteriorates into random search. This paper sets the modified mutation probability function as Equation (3).

$$P_m = \begin{cases} k_1 \frac{(f_{max}-f)}{(f_{max}-f_{av})} f \geq f_{av}) \\ k_2 f \leq f_{av} \end{cases} \quad (3)$$

In Equation (3), f_{max} represents the maximum fitness within the population, f_{av} denotes the average fitness value across generations, and f signifies the fitness value of the individual subject to mutation. By incorporating an adaptive mutation probability function, the probability of mutation can be dynamically adjusted based on the population's fitness. This not only enhances the convergence speed towards the optimal solution but also prevents the algorithm from becoming trapped in premature convergence[12].

III. IMPROVING THE GENETIC ALGORITHM PROCESS

The path planning process for mobile robots based on improved genetic algorithm is shown in Figure 2.

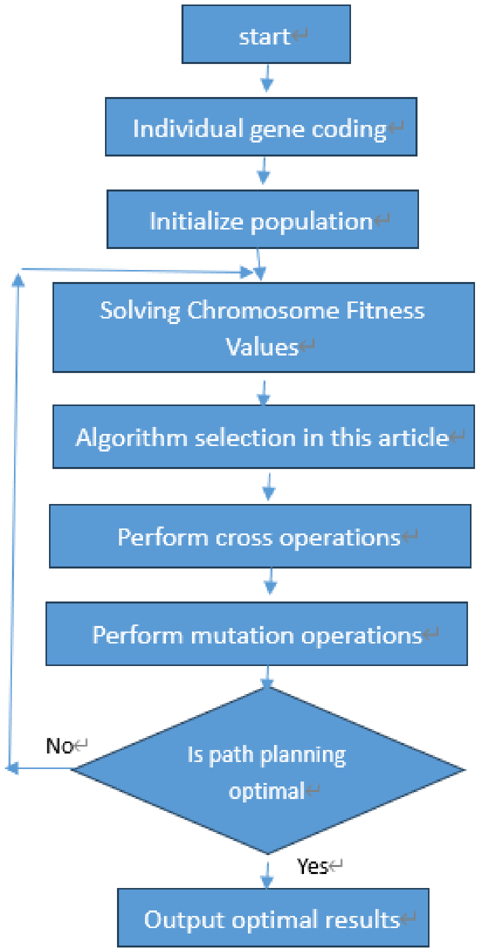

Fig.2 Path planning process based on improved genetic algorithm

IV. SIMULATION EXPERIMENTS AND ANALYSIS

A. Simulation environment

To validate the mobile robot path planning with the improved genetic algorithm, Matlab simulation experiments were carried out in a predefined environment. The simulation environment is depicted in Figure 3, where obstacles are arranged within a predefined global static 10×10 grid matrix. The robot begins at the Start point in Figure 3 and aims to reach the End point in Figure 3. The marker at the Start position in Figure 3 indicates the mobile robot, while the obstacles are cells filled in black. The values of parameters utilized in the experiment are detailed in Table 1.

Table 1 Experimental Parameters

γ_1	γ_2	k_1	k_2	Number of cycles
0.8	0.1	0.004	0.005	100

B. Experimental analysis

The initial population consists of 80 individuals, and the genetic algorithm is executed 100 times, with each run generating 300 generations. Figure 3 shows the dashed line representing the path from the (0,0) initial point to the (9,9) target point found by the standard genetic algorithm GA, and the solid line indicating the path found by the improved genetic algorithm IGA. The experimental results indicate that, within the same environment, the improved genetic algorithm IGA considers both path length and obstacle intersection degree as weight factors in fitness calculations. It employs the roulette wheel method for individual selection and a hybrid approach of single and coincident points for crossover. By incorporating an adaptive mutation probability function, the algorithm adjusts mutation probability based on population fitness, thereby preventing the algorithm from getting stuck in local optima. This enhances the efficiency of finding the optimal path, and the resulting optimal path significantly surpasses that of the standard genetic algorithm GA. This verifies the robustness and effectiveness of the improved genetic algorithm IGA proposed in this article [13].

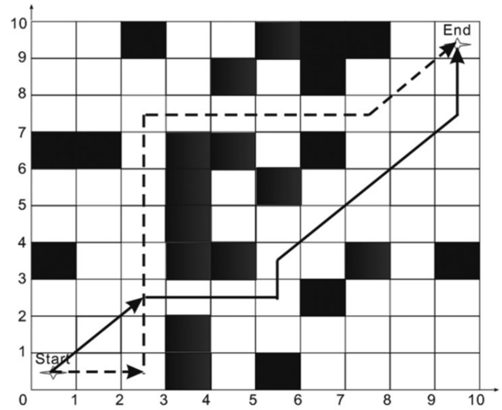

Figure 3 GA and IGA algorithm path planning diagram

Because the formation of the initial population in genetic algorithms is largely random, a single experiment's outcome cannot accurately determine the relative merits of two algorithms. In the scenario depicted in Figure 3, the maximum number of generations is set to 300, with the termination criterion being a maximum fitness of 472 or higher. Algorithms GA and IGA are each applied in 50 experiments, with the results detailed in Table 2. Fmax denotes the maximum fitness within the population, while fav represents the average fitness per population. Gen signifies the generation number; a generation number less than 300 signifies convergence, while a generation number of 300 or higher indicates the population has not converged by that point [14].

Table 2 GA and IGA algorithm comparison of evolution

	GA	IGA
f_{max}	464.52	483.25
f_{av}	390.49	390.36
Gen mean	148.35	98.7
Gen≥300 times	14	5
Gen≥300ratio	30%	11%
Number of cycles/ Total number of times	35/51	46/51
Mean number of convergences	88.92	81.25

As indicated in Table 2, the maximum and average fitness levels for both algorithms are comparable. The IGA algorithm chooses the next generation for evolution based on path length and the degree of obstacle intersection, significantly enhancing the efficiency of identifying optimal solutions. Additionally, the enhanced operator selection function guarantees that individuals with high fitness values have a greater chance of being passed on to the next generation, leading to a reduction of approximately 70% in the proportion of evolutions exceeding 300 times for the IGA algorithm compared to the GA algorithm. The adaptive mutation probability function employed by the IGA algorithm allows for adjustments in mutation probability based on population fitness, resulting in superior convergence compared to the GA algorithm. Consequently, the improved genetic algorithm exhibits significantly higher efficiency than its standard counterpart [15].

V. CONCLUSION

Path planning is a critical challenge for mobile robots. Securing a swift and efficient route is vital not only for the robot's safety but also ensures its effectiveness and reliability. Addressing the complexities of path planning for mobile robots, a path planning scheme is proposed using enhanced genetic algorithms. This approach mitigates the issues of slow convergence and premature convergence often associated with genetic algorithms. Simulation tests demonstrate that this strategy narrows the search scope for the optimal path and cuts down on the number of evolutionary generations required. Consequently, it significantly reduces the time taken to locate the optimal path, enhancing the efficiency of the search process [16].

In practical applications, the improved genetic algorithms proposed above have advantages, but also have their own shortcomings. In specific scenarios, improvements can be made to them, not only optimizing their own parameters, but also flexibly selecting other algorithms to improve computational performance according to specific application scenarios and needs [17].

By improving the robot path planning method, we can find that future research directions will focus on improving the stability and adaptability of algorithms, researching new intelligent optimization algorithms, and combining them with other optimization methods. With the continuous deepening of these studies and the expansion of application fields, using algorithms to solve robot path planning problems plays a more important role [18,19].

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