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Application of Improved Genetic Algorithm in Cruise Missile Route Planning

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Abstract*—To address the shortcomings of the traditional genetic algorithm in cruise missile route planning, which is prone to "premature maturation" and premature convergence to a local optimal solution, an improved genetic algorithm is proposed that introduces an adaptive operator and a variation ratio strategy. The algorithm processes the individual fitness values in the population by ranking ratio technique, and then adopts a selection strategy combining elite selection and roulette algorithm to add the feasible routes with the best fitness values directly to the children at each evolution, and then roulette selects the remaining feasible routes, which improves the global optimal search performance of the algorithm in the trajectory planning. Meanwhile, an adaptive crossover operator is used to dynamically select the crossover probability based on the individual fitness values of the parents. Finally, the two algorithms are applied to the established map model for route planning separately, and the simulation results show that the path solved by the improved genetic algorithm reduces three planning waypoints and 10.74% of the range compared with the traditional genetic algorithm, and the global search performance of the route planning process applying the improved genetic algorithm is significantly better than that of the traditional genetic algorithm.

Keywords-Improved genetic algorithm; ranking variation ratio; adaptive crossover operator; raster method

I. Introduction

As a long-range combat weapon, cruise missiles are the backbone of modern warfare due to their small size and low flight altitude that are not easily detected, and their high suddenness of attack. Route planning is one of the decisive factors for cruise missiles to successfully strike combat targets. Commonly used path planning algorithms are Dijkstra's algorithm, A* algorithm, and ant colony algorithm, genetic algorithm, simulated annealing algorithm, gray wolf algorithm and other optimization search algorithms on behalf of

Genetic algorithm[11-13], as a classical swarm intelligence optimization algorithm, simulates the evolutionary law of nature "survival of the fittest". It uses three genetic operators: selection, crossover, and mutation to perform global search and iterative evolution. The traditional genetic algorithm has its limitations: 1) If a "super-individual" with a very large fitness level appears in a certain evolution, the genes of the super-individual may rapidly occupy the whole population, resulting in a small search range and a local optimal solution. 2) The same fixed crossover operator and variation operator are used for both individuals with large and small fitness levels. (2) The same fixed crossover operator and variation operator are used for both large and small fitness individuals, which greatly reduces the overall efficiency and search ability of the algorithm. Therefore, this paper improves the GA algorithm and proposes an improved genetic algorithm.

II. Track planning map modeling

In this paper, we use the raster method [6] to model the environment, using a 16*16 raster environment with randomly generated threat points and the following settings for the whole raster environment: 1) the smallest unit of threat and non-threat areas is one raster; 2) if there is an empty part in the middle of the threat area, it is also counted as a whole raster as described in 1); 3) if two adjacent threat rasters are diagonally If two adjacent threat grids are connected diagonally, the part of the grids that are in contact with each other is considered as a passable route. The grid environment is marked with grayscale values for the feasible and obstacle areas. In the simulation program, the feasible area is represented by 0 and the infeasible area is represented by 1. The minimum unit of the raster is 1*1, and the obstacle area and feasible area are divided by the intersection of the midline of the raster with the size of 1*1. A randomly generated 65-unit obstacle raster is shown in Figure 1, illustrated in a 16*16 raster environment as described in the text.

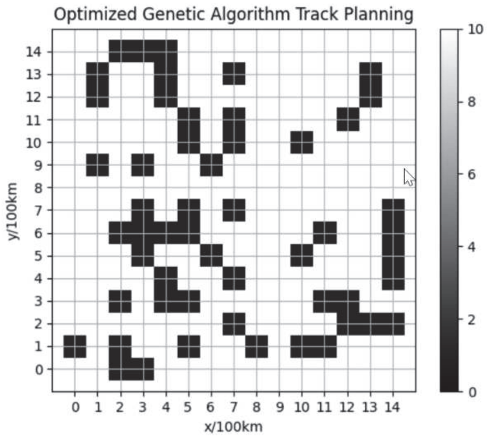

Figure 1. 16*16 Raster diagram

As shown in Figure 1, this paper takes each intersection point in the raster environment as the feasible drop point for each selected path, (0,0) as drop point 1, (1,0) as drop point 2, from left to right, from bottom to top, and so on. Set col as the number of columns of the raster map-1 and k as the feasible drop point, then the conversion relationship between coordinates and feasible drop points is

$$\begin{cases} x = int(k\%col) \\ y = int(k/col) \end{cases} \quad (1)$$

III. IMPROVED GENETIC ALGORITHM

A. Traditional Genetic Algorithm

Genetic algorithm is a swarm intelligence algorithm, which is often used to solve search optimization problems. The algorithm execution process of traditional genetic algorithm is.

Step 1: Based on the initial coding method, the chromosomes are coded to generate multiple chromosomes, and then the fitness of each chromosome is calculated and generated into a population based on the fitness function selected in advance.

Step 2: The initial population is selected to obtain the parents of the new population. The common selection algorithms are elite selection strategy, fitness proportional selection strategy and tournament selection strategy.

Step 3: Crossover and mutation are performed on the selected chromosomes, i.e., the new parents, to generate a new population. The crossover probability and mutation probability in traditional genetic algorithms are usually fixed values, and the probability values are usually selected empirically, which are not discussed in this paper.

Step 4: Evaluate whether the new population satisfies the termination rule, if it does, the algorithm ends; if not, repeat steps 1, 2, 3, and 4.

The specific steps are shown in Figure 2.

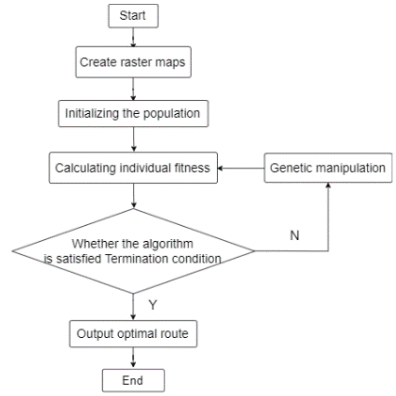

Figure 2. Genetic algorithm flow chart

B. Ranking Variable Ratio

The ranking variation strategy [3] is to vary the original fitness values in some way before selecting the parents. The advantage of this is to eliminate as much as possible the influence of "super individuals" in the roulette algorithm on the selection results and to improve the global search ability of the algorithm. As shown in TABLE .

TABLE I. PRE- AND POST-RANKING FITNESS VALUES

Individuals	Initial fitness value	New adaptation value
3	19.6	1
2	7.8	2
4	4.3	3
1	0.5	4

C. Improved genetic algorithm

In traditional genetic algorithms[9], selection, crossover, and variation are the three cores of the algorithm. For the selection operation, usually the algorithm will simply select each individual based on its high fitness value combined with a roulette strategy, such a selection strategy has two drawbacks: 1) Although it is the parent individual that is selected based on the fitness value of the parent, but because it is a combined probabilistic selection strategy, there are high fitness individuals that are not selected or low fitness individuals that are selected, both of which will 2) If there is a parent with great fitness in a certain evolutionary generation, the individual will always be selected in the selection process, which will lead to the rapid occupation of the entire population by the genes of that individual, making the algorithm end early or fall into a local optimum solution.

In this paper, we adopt the ranking variation ratio strategy to first adjust the initial fitness value and thus change the scoring criteria, then use the elite retention strategy to directly retain the individuals with the highest fitness values into the next generation, and finally select the remaining individuals using the roulette wheel strategy. For the crossover operation, the traditional genetic algorithm generally uses a fixed crossover probability, and the size of the probability is usually chosen empirically. If the crossover probability is too large, the search range of feasible solutions will be larger, but the overall efficiency of the algorithm will be affected by the larger search range; if the crossover probability is too small, the diversity of feasible solutions will be reduced, and the performance of the algorithm will be correspondingly lower.

In order to solve this problem, this paper adopts an improved crossover operator, which does not use a fixed crossover probability for different fitness values in the population, but calculates the crossover probability dynamically according to the different chromosome fitness in the population, which can better accomplish the crossover operation For the purpose of maintaining chromosome diversity in the population and improving the global search capability, the crossover operator is as follows.

$$P_r \begin{cases} k_1 \frac{S_{max}-S_c}{S_{max}-S_{min}}, S_c \neq S_{max}, S_{min} \\ k_2, S_c = S_{min} \\ k_3, S_c = S_{max} \end{cases} \quad (2)$$

where P_r is the crossover probability, Sc is the side with the larger fitness value among the two parents before the crossover operation, and S_{max}, S_{min} are the maximum and minimum values of fitness in the whole population k_1, k_2, k_3 are constants between 0 and 1, where $k_2 > k_3$.

For the fitness function in the improved genetic algorithm, first, the distance between two points is formulated according to [11] as follows.

$$L_i = \sqrt{(x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2} \quad (3)$$

Combining the distance formula of Eq. (3), the fitness function of the improved genetic algorithm should be Eq. (4)

$$Fit = d + \alpha \sum_{i=0}^{n} L_i \quad (4)$$

Where Fit is the fitness of the chromosome, the value of d is related to the complexity of the environment, α is the penalty coefficient, when the path crosses the obstacle, α that is taken as a very large number, from the formula (4) can be seen that the path length is the shortest and will not cross the obstacle when the fitness value is the smallest.

IV. SIMULATION VERIFICATION

The simulation experiment is run in python 3.6.7 environment, and the environment model introduced in this paper is chosen for the route planning, the size of the raster environment is 16*16, and the ratio between the simulation environment and the real environment is a raster side length equal to 100km. The starting point of the cruise missile is set as (0,0), the mission end point is (14,14), and the size of the whole planning map is 1400km*1400km. In this simulation environment, the traditional genetic algorithm is used to plan the route first, and the crossover method is single point crossover.

The parameters of the traditional genetic algorithm are shown in TABLE.

TABLE II. PARAMETER SETTINGS

Number of evolutions	Population size	Crossover probability	Mutation probability
100	50	0.8	0.09

After 100 iterations, the traditional genetic algorithm outputs the path shown in Figure 3.

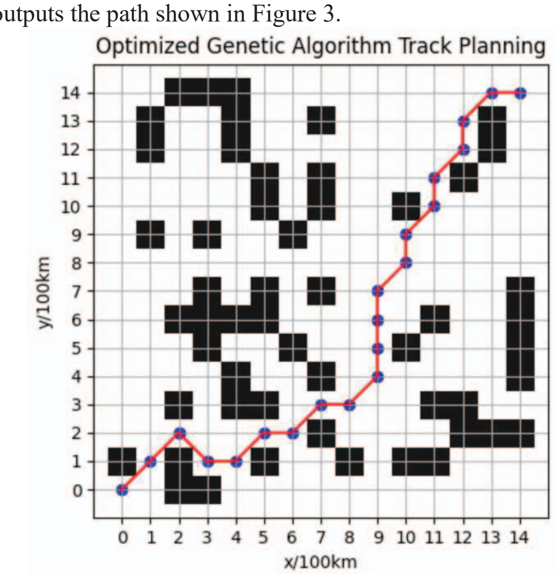

Figure 3. Planning path map

Using the improved genetic algorithm for the same raster environment, the results are as follows:

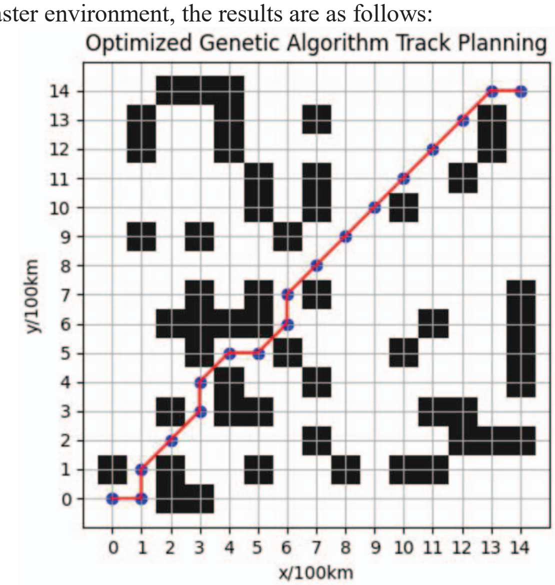

Figure 4. Planning path map

The improved algorithm searched for the optimal path in a shorter time by preserving the optimal individuals and changing the fitness scoring criteria. Moreover, compared with the traditional genetic algorithm, the planning path length is reduced by 259KM, and if the fuel consumption of the missile is proportional to the navigation distance, the improved algorithm will save 10.74% of missile fuel. Meanwhile, in this raster environment, the number of waypoints before the improvement is 21, and the number of waypoints after the improvement is reduced to 18.

V. CONCLUSION

In this paper, based on the need for accurate and efficient target striking of cruise missiles, the problems related to the environment and route planning of missiles in flight are analyzed, and the obstacles and threats in the navigation process are modeled, and genetic algorithms are used to solve their route planning problems. In the simulation experiments, it is found that the traditional genetic algorithm is easy to fall into the problem of local optimal solution, and the efficiency is low, and more iterations of evolution are needed to achieve the same result. . The validation shows that the improved genetic algorithm achieves better results on the trajectory planning problem.

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