Research on Complete Coverage Path Planning for Unmanned Surface Vessel

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Abstract. In order to monitor the water quality in real time, all monitoring points should be covered by Unmanned Surface Vessel (USV). This paper takes the USV as the research object and proposes an improved genetic algorithm to solve the complete coverage path planning (CCPP) problem to ensure that the USV can cover all monitoring points, and minimize the path length, the rate of repeat grid and running time of the algorithm. The feasibility of this solution model is verified by simulation on the platform of Visual Studio.

Key words: Unmanned Surface Vessel; Path Planning; Complete Coverage; Improved Genetic Algorithm.

1. Introduction

The unmanned surface vessel (USV) is a kind of intelligent navigation equipment on the water, which has the characteristics of small size, light weight and strong adaptability. In recent years, the rapid development of artificial intelligence, big data and other technologies has greatly promoted the development of USV. As the core technology of USV, path planning research is becoming more and more mature [1-3]. The complete coverage path planning (CCPP), the focused areas of robot path planning, is the research direction of this paper. It is widely used in the field of crop harvesting and sowing, cleaning robots, clearance of mines and mineral exploration. Generally speaking, CCPP needs to meet two conditions. First, the robot needs to avoid obstacles and boundaries during navigation. Second, the robot needs to cover all monitoring points in the fixed water area [4, 5]. Therefore, this paper presents a model based on improved genetic algorithm to solve the CCPP problem for USV. On the basis of optimized raster map, this method achieves the goal of covering all of the monitoring points in the fixed water area. This model combines adaptive genetic algorithm and fireworks algorithm to improve the genetic algorithm and verified the feasibility of the model.

The selection of CCPP solution method is decided by the characteristics of the robot and its working scene. At present, random cover method, and template model method are generally used [6]. In recent years, domestic and foreign scholars have also tried to solve this problem by using cluster intelligent algorithm, such as artificial potential field method [7], ant colony algorithm [8] and genetic algorithm [9]. Table 1 compares the advantages and disadvantages of the above representative algorithms to facilitate the following method selection of CCPP.
The traditional genetic algorithm has good global search ability and strong robustness. The parallel computing search process can also search the solution space well. But the traditional genetic algorithm is complicated when solving the problem of global coverage path planning. It is difficult to determine the reasonable crossover and mutation probability, which will lead to the deviation of the final result and the loss of the optimal solution. Besides, the fixed fitness function also has its limitation during the solutions.

Considering the superior performance in global optimization and the expansibility with other algorithms of the traditional genetic algorithm, this paper decide to solve CCPP problem for USV in the framework of genetic algorithm. This paper aims to improve the shortcomings of genetic algorithm by combining with adaptive genetic algorithm and fireworks algorithm. The implementation steps are as follows.

### Table 1. Comparison of advantages and disadvantages of typical algorithms for CCPP

| Algorithms                      | Advantages                                      | Disadvantage                                   |
|---------------------------------|-------------------------------------------------|------------------------------------------------|
| Random cover method             | No need to locate and the algorithm is simple   | With high repetition rate and low efficiency   |
| Exact cellular decomposition    | The cells are easy to cover and can be swept by | Unable to implement global search optimal      |
| method                          | the robot with simple motions                   | solution                                        |
| Template model method           | Easy to operate and implement                   | With large amount of calculation,              |
|                                 |                                                 | unable to achieve global search for           |
|                                 |                                                 | optimal solution                               |
| Artificial potential field      | Fast response and small amount of calculation   | Unreachable near obstacles, trap area          |
| method                          | Suitable for multi-objective optimization with  |                                                |
|                                 | good robustness and parallelism                 |                                                |
| Ant colony algorithm            | With strong global optimization, suitable for   | With long search time and stagnation           |
|                                 | multi-objective optimization, scalable          | during the search process                      |
| Genetic algorithm               |                                                 | With slow convergence, low algorithm efficiency|

## 2. Proposal and Implementation of Improved Genetic Algorithm

### 2.1. Proposal of Improved Genetic Algorithm

#### 2.1.1. Improvement with Adaptive Genetic Algorithm

In order to get the global optimal solution, the fitness functions and the crossover and mutation probability should be varied with iterative time. Therefore, two improvement steps combine with adaptive genetic algorithm were proposed in this paper [10]. First, the fixed fitness function in the traditional genetic algorithm is replaced with the adaptive fitness function. Second, the new crossover and mutation probability based on the neuron activation function sigmoid in the neural network is put forward to achieve the goal of global optimization with high efficiency. The sigmoid function can adaptively adjust the crossover and mutation probability according to the individual fitness value of the population.

#### 2.1.2. Improvement of Combining Fireworks Algorithms

Fireworks Algorithm (FA) is a new cluster intelligent algorithm proposed by Professor Tan Ying in 2010[11]. This algorithm simulates the phenomenon of fireworks exploding in the air. As shown in Figure 1, a multi-point explosion search is performed locally. The algorithm provides a novel and efficient solution to the search for global optimal solutions. It has strong adaptability in combination with other algorithms, and also widely used in practical engineering scenarios.
Some measures should be taken to ensure firework algorithm’s capability of global optimization. Therefore, every individual firework should allocate resources and communicate information according to its fitness value relative to other firework for the reason of its excellent partial explosive capacity capability. This feature makes the fireworks algorithm become efficient cluster intelligent algorithm. This paper introduces the explosion operator in the fireworks algorithm into the genetic algorithm, and search explosively on the optimal solution attachment generated by the genetic algorithm to improve the performance of global optimization.

2.1.3. The Solving Process of Improved Genetic Algorithm. Through the above improvement ideas, the improved genetic algorithm based on adaptive genetic algorithm and fireworks algorithm is used to solving the CCPP problem. The flow of the improved genetic algorithm is shown as Figure 2.

![Diagram of the solution procedure of improved genetic algorithm](image)

Figure 2. The solution procedure of improved genetic algorithm.
2.2. **Implementation of Improved Genetic Algorithm**

2.2.1. **Establishment of Grid Environment Map.** Based on the grid map, this paper establishes an initial environmental map by acquiring the GPS coordinates of the water area’s feature points in the actual environment, and divides the grid on the environmental map. For example, the map showing as Figure 3 marks the grid in the raster map by serial number marking method, and obtains a 17*26 grid map, counting from the upper left corner of the raster environment map (serial number is 1), adding one in turn from left to right, from top to bottom, each raster corresponds to a unique serial number, and according to the boundary and obstacles of the raster to distinguish the grids.

Three kind of grids are seen as Figure 3. The free grid is the monitoring point that USV must pass and its status value is 1. The obstacle grid represent the boundaries and obstacles in the area and its status value is 0. The remaining part is external area that the USV never reach.

2.2.2. **Chromosome Coding.** A genetic algorithm based on integer coding genetic operators is designed to propose the model. The serial number that correspond to the free grid must appear at least once of every chromosome. And then the USV follows the sequence of genes in the chromosomes to navigate. At the same time, in order to ensure that the next position of the movement is reachable, after determining the starting point, it must be ensured that the next position grid is the adjacent grid of the current grid.

![Figure 3. Grid environment map.](image)

2.2.3. **Population Initialization.** The traditional genetic algorithm randomly generates the initial population which will produce some infeasible paths. In order to avoid the above situation, this paper initialize the population based on the heuristic method. The initial population is generated as follows:

1. Determining the population size $Q$;
2. Determine the starting point of the USV, and the first gene of chromosome represents the starting point. The starting point should be selected from the sequence number corresponding to the edge raster in the free raster set;
3. Forming a set of chromosomes that pass through all free grids at a time from the starting point and eventually cover all free grids.
2.2.4. Adaptive Fitness Function. In this paper, the objective function of the improved genetic algorithm and the initial fitness function are estimated to be a function of the path distance. Then, the objective function is defined as follows:

\[ l_k = \sum_{u=1}^{c} d(S_v(u), S_v(u + 1)) \]  

(1)

And the initial fitness function is given as follows:

\[ f(k) = \frac{1}{l_k} \]  

(2)

It is assumed that there is an arbitrarily chromosome named \( R_k \), \( k \in \{1,2,3,\ldots,Q\} \). \( R_k \) includes \( c_k \) genes. \( S_v(u) \) and \( S_v(u + 1) \), \( (u \in [1,c_k]) \), represent two neighboring grid with serial number in the chromosome and \( d(S_v(u), S_v(u + 1)) \) represent the distance between the above two grids. In formula (2), \( l_k \) is path length corresponding to the objective function and \( f(k) \) is the initial fitness function of the study and also is the reciprocal of the objective function. Then the adaptive fitness function is given as follows:

\[ f' = \begin{cases} \lambda_1 \bar{f} & f \geq \lambda_1 \bar{f} \\ f & f < \lambda_1 \bar{f} \end{cases} \]  

(3)

In this paper, the adaptive fitness function is assumed to be \( f' \), which is defined as formula (3), and \( f \) is the chromosome fitness value, \( \bar{f} \) represents the mean fitness of the same generation population, and the constant of \( \lambda_1 \) is generally greater than 1 and less than 10, which plays a regulatory role.

2.2.5. Selection. In this paper, roulette and championship method are used as selection operators. The specific selection operations are as follows:

1) Determining the population size \( Q \); 
2) In order to ensure that high-quality individuals will not be eliminated, the championship method is used to select \( h \) chromosomes with the largest fitness value \( (h < 5) \) in the population and keep them in next generation. 
3) The roulette method is used to select the remaining individuals of the parent population. Firstly, the adaptive fitness function value \( f'(k) \) of the k-th chromosome in the parent population is calculated, and then the probability \( P_k \) of the k-th chromosome being selected is calculated by formula (4). The roulette operation is performed according to this step until the number of chromosomes is satisfied.

\[ P_k = \frac{f'(k)}{\sum_{k=1}^{Q} f'(k)} \]  

(4)

2.2.6. Crossover and Mutation. The crossover probability \( P_c \) is determined by formula (5), and then the number of chromosomes to be crossed is determined by formula (6).

\[ P_c = \begin{cases} \frac{P_{ch} - P_{cl}}{1 + e^{A(2(T'-f)/(f_{max}-f))}} + P_{cl} & f' \geq \bar{f} \\ P_{ch} & f' < \bar{f} \end{cases} \]  

(5)

\[ \lambda_2 = Q * P_c \]  

(6)

\( P_{ch} \) is the largest crossover probability, while \( P_{cl} \) is the smallest crossover probability. \( (P_{cl}, P_{ch}) \) usually is \( (0.4, 0.99) \) in genetic algorithm, \( f' \) is the fitness value, \( \bar{f} \) is the average fitness value of the population, \( f_{max} \) is the maximum fitness value of the population and \( A = 9.903438 \); Then the fitness function value of the largest \( \lambda_2 \) chromosomes should be selected, and matched randomly; Two random numbers are generated between 0 and \( c \) in each pair of chromosomes, where \( c \) is the number of genes (grids) in the chromosome. The crossover position is determined by the random number. The adaptive mutation probability based on sigmoid function is used to ensure that the population evolves towards the optimal solution. Formula (7) describes the value of the adaptive crossover probability.
\[
P_m = \begin{cases} 
\frac{P_{mh} - P_{ml}}{1 + e^{A(2(f' - \bar{f})/(f_{max} - f))}} + P_{ml} & f' \geq \bar{f} \\
\frac{P_{mh}}{f' < \bar{f}} 
\end{cases}
\] (7)

In formula (7), \(P_{mh}\) and \(P_{ml}\) are the range of mutation probability, and \(P_{mh}\) is the maximum mutation probability with it’s generally value of 0.1, \(P_{ml}\) is the minimum mutation probability with the general value of 0.001. Then we need to get \(\lambda_3\) chromosomes to be mutated through formula (8).

\[
\lambda_3 = Q \times P_m 
\] (8)

Two random numbers are generated between (0, c) as mutation positions, and the two gene exchange positions on mutation positions are used to perform mutation operations.

2.2.7. Explosion Operator. In order to avoid the occurrence of local optimal solution in genetic algorithm, the explosion operator in fireworks algorithm is used to improve the search performance. The number of solutions with explosion in the population is proportional to the number of new individuals. The explosive search is carried out by selecting the individuals whose size is less than 10 from the mutated population. The calculation of the number of new individuals generated by \(R_k\) explosive search on chromosomes is given as follows:

\[
C_k = \mu \times \frac{f_{max} - f(k) + \varepsilon_1}{\sum_{k=1}^{n} (f_{max} - f(k)) + \varepsilon_1} 
\] (9)

In formula (9), \(C_k\) denotes the number of individuals generated by chromosome \(R_k\) explosion, and \(\mu\) is a constant parameter controlling the number of individuals generated by chromosome \(R_k\). \(f(k)\) is the fitness value of chromosome \(R_k\), and \(\varepsilon_1\) is the minimum constant used to avoid "dividing 0 errors".

An important parameter to measure the explosion range is the explosion radius \(h\) of fireworks, which is calculated by the fitness value of other fireworks (chromosomes) in the population. For the fireworks (chromosomes)\(R_k\), the formula for calculating the displacement \(B_k\) is shown as follows:

\[
B_k = B_{max} \times \frac{f(k) - f_{min} + \varepsilon_1}{\sum_{k=1}^{n} (f(k) - f_{min}) + \varepsilon_1} 
\] (10)

In formula(10), \(B_k\) denotes the displacement amplitude produced by the explosion of the \(k\)th solution (chromosome). \(B_{max}\) is a constant used to adjust the explosion radius. \(f_{min}\) is the minimum fitness in the population. Then, through formula (11), we can calculate the explosion radius \(h\) of fireworks, and \(rand(1,1)\) is a random number on the interval [-1,1].

\[
h = B_k \times rand(1,1) 
\] (11)

Then, Formula(12) simulates the process of explosion producing a new firework \(R_k^u\). If the position of the new fireworks exceeds the space boundary, then the fireworks are mapped into the new solution space domain by using the mapping rules shown in formula (13). In formulas (12) and (13), \(R_k^u\) is a new individual produced by explosion. \(u_{max}^k\) and \(u_{min}^k\) represent the upper and lower limits of the \(u\)th gene.

\[
R_k^u = h + R_k^u 
\] (12)

\[
R_k^u = u_{min}^k + |R_k^u| \cdot (u_{max}^k - u_{min}^k) 
\] (13)

2.2.8. Termination. When the genetic algorithm satisfies both formulas (14) and (15), the algorithm stops iterating. \(g\) is the current algebra of evolution, \(G\) is the maximum iteration number set, and \(\bar{f}_g\) denotes the population fitness mean of generation \(g\).This formula denotes that the sum of the difference between two generations in a continuous four-generation population is maintained at a minimum or zero and \(\varepsilon_2\) is minimum deviation in formulas (15). If the two formulas are not satisfied, new populations should be generated to find the optimal solution path. If the two formulas are satisfied, the search will be terminated and the optimal solution will be output.
\[ g > G \]
\[
\left| f_g - f_{g-1} \right| + \left| f_{g-1} - f_{g-2} \right| + \left| f_{g-2} - f_{g-3} \right| \leq \varepsilon_2
\]

(14)

(15)

3. Simulation

The simulation experiment is based on two map templates (Map 1 and Map 2). The feasibility of the algorithm is validated by the improved genetic algorithm. As shown in Figure 4, the original map is a 20*20 grid model. Map 1 has six obstacles, 42 obstacle grids and 358 free grids. Map 2 has eight obstacles, 54 obstacle grids and the number of free grids is 346. The starting point of each map template is selected randomly. The starting point of Map 1 is the grid of line 20 and column 7, and the starting point of map 2 is the grid of line 9 and column 20. The unmanned ship starts from the starting point to realize full coverage of the free grid. The selection of parameters related to the improved genetic algorithm is shown in Table 2.

Table 2. Parameter Setting of Genetic Algorithms for Simulation

| Name of Parameter                   | Value of Parameter |
|-------------------------------------|--------------------|
| Population size \( Q \)             | 30                 |
| Fitness adjustment constant \( \lambda_1 \) | 7                  |
| The largest crossover probability \( P_{ch} \) | 0.7                |
| The smallest crossover probability \( P_{cl} \) | 0.4                |
| The largest mutation probability \( P_{mh} \) | 0.1                |
| The smallest mutation probability \( P_{ml} \) | 0.01               |
| Algebra of evolution \( G \)        | 100                |
| The minimum deviation \( \varepsilon_2 \) | 0.01               |

Figure 4. Original grid map 1(left) and 2(right). Figure 5. Simulation result map 1(left) and 2(right).

The simulation results based on the improved genetic algorithm are shown in Fig. 5. At the same time, in order to verify the feasibility and effectiveness of the improved genetic algorithm, the author compares the traditional genetic algorithm based on the above two map templates and the cruise starting point. The results are shown in Table 3. It can be seen that the optimal solution obtained by the improved genetic algorithm has the shortest path and the lowest repeat coverage, and the calculation time is the shortest. This shows that the improved genetic algorithm is better to solve the optimal solution, and then the feasibility is verified.

Table 3. Comparison of Algorithm Simulation Results

| The evaluation index      | Traditional Genetic Algorithm | Improved Genetic Algorithm |
|---------------------------|-------------------------------|----------------------------|
|                           | Map 1        | Map 2        | Map 1        | Map 2        |
| Area coverage             | 100%         | 100%         | 100%         | 100%         |
| The rate of repeat grid   | 4.2%         | 4.1%         | 0.8%         | 1.1%         |
| Path length               | 374.5        | 364.3        | 358.6        | 352.7        |
| Running time of the algorithm | 6.73s     | 5.92s        | 3.62s        | 3.52s        |
4. Conclusion
In this paper, an improved genetic algorithm is proposed for CCPP of USV. The improved genetic algorithm has shorter path length, low rate of repeat grid and less computation time. It has good feasibility and good optimization effect in solving the problem of CCPP.

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