An Algorithm for Path Planning of Autonomous Ships Considering the Influence of Wind and Wave

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Abstract. Aiming at the problem that external factors such as wind, waves and currents are not considered in the path planning of autonomous sailing ships, which affect the safety of navigation, an improved particle swarm optimization algorithm is proposed. Introduce adaptive inertia weight to improve the convergence of the algorithm, wind and wave influence factors in the algorithm fitness function, increase the wind and wave resistance of the path, and improve the safety of the path. MATLAB simulation experiment results show that the optimized PSO algorithm can obtain the global optimal path and improve the safety of the path.

Keywords: autonomous navigation; path planning; particle swarm optimization (PSO) algorithm.

1. Introduction
Path planning is one of the most fundamental and critical contents of studying the operation of autonomous navigation ships. The purpose is to find a path between the starting point and the target point according to certain evaluation criteria (shortest path, shortest time or least energy consumption, etc.), so that an autonomous ship can safely reach the destination point. Many scholars at home and abroad have done a lot of research on the path planning of autonomous ships. James designed an unmanned autonomous navigation system for unmanned boats based on evolutionary algorithms to realize path planning in a dynamic and unpredictable environment [1]. Yoshiaki applies the speed obstacle method to the collision avoidance system, which can achieve autonomous avoidance behavior in compliance with the international maritime collision avoidance rules under the complex dynamic and static situation [2]. Wasif Naeem proposed a reactive algorithm based on the artificial potential field method for the path planning of unmanned boats [3]. This algorithm can plan the path of multi-ship encounter situations under the premise of observing the rules. Based on the method of spline curve, Lazarowskal has realized the decision model of ship's autonomous collision avoidance in a mixed dynamic and static situation, but planned trajectory is not smooth enough to conform to ship navigation practice [4]. Considering the international maritime collision avoidance rules and the ship kinematics model, Lyu used the artificial potential field method to solve the avoidance problem encountered by multiple ships [5]. To sum up, although the current results of autonomous navigation ship path planning...
have solved certain problems, it is currently considered to add interference from external factors such as wind, waves and currents, which affect the overall safety of the ship's navigation.

2. Analysis of the Influence of Wind and Waves on Ship Navigation

This research only considers the dangers of wind and waves in marine meteorology, and the impact of wind and waves on the ship itself can be calculated.

2.1. The Influence of Sea Breeze on Ships

The impact of sea breeze on ships in navigation is mainly cross wind. Cross wind affects the direction of the ship's navigation, causing it to drift and tilt, which has a great impact on the safety of the ship. According to the Hughes formula, the magnitude of the wind experienced by the ship can be estimated by the following formula

\[ F(\theta) = \frac{9.81}{2} \cdot \rho \cdot C_a \cdot (A_a \cdot \cos^2 \theta + B_a \cdot \sin^2 \theta) \cdot v_w^2 \]  

Where \( F(\theta) \) is the wind force (N) on the hull above the waterline; \( \rho \) is the air density, which is 0.125 kg · sec²/m⁴; \( \theta \) is the windward angle; \( C_a \) is the wind coefficient; \( v_w \) is the relative wind velocity (m/s); \( A_a \) is the orthographic projection area of the hull above the waterline (m²); \( B_a \) is the projected area of the hull above the waterline (m²).

2.2. The Influence of Waves on Ships

When a ship is sailing on the sea, the wave has the most direct and biggest impact on the navigation and safety of the ship. The wave will bring resistance to the ship, lose the speed, and produce a series of motion and swing. When a ship encounters strong wind and waves during navigation, it will tilt, wave on the deck, and the impact of waves will do harm to the hull structure. The calculation of wave force is complex, and only one order regular wave interference force is considered in the study of ship motion.

The calculation expression of the influence of waves on the ship is as follows:

\[
\begin{align*}
X_{wave} &= 2aB \frac{\sin b \cdot \sin c}{c} \\
Y_{wave} &= -2aL \frac{\sin b \cdot \sin c}{b} \\
N_{wave} &= ak \left[ B^2 \sin b \cdot \frac{c \cos c - \sin c}{c^2} - L \sin b \cdot \frac{b \cdot \cos b - \sin b}{b^2} \right]
\end{align*}
\]  

Where

\[ a = \rho g \left(1 - e^{-\omega t}\right) / k^2 \]
\[ b = kL / 2 \cdot \cos \gamma \]
\[ c = kB / 2 \cdot \sin \gamma \]

And in which, \( k \) is the wave number, \( \gamma \) is the angle of encounter, and \( h \) is the wave height here. X, Y and N are the external forces and moments of waves on the ship.

3. An Improved PSO Algorithm

In PSO, each alternative solution is called a particle, which is an effective path from the starting point to the end point. The particle Xi is calculated according to the shortest path objective function; According to the fitness value, we can measure the quality of the products. The position and velocity of particles are updated at any time during the operation of the algorithm. The update formula of position and speed of PSO algorithm is

\[
V_i(k+1) = wV_i(k) + c_1 r_1 \left(P_i(k) - X_i(k)\right) + c_2 r_2 \left(P_g(k) - X_i(k)\right)
\]  

where

\[
V_i(k+1) \text{ is the velocity of particle } i \text{ at time } k+1,
\]

\[
V_i(k) \text{ is the velocity of particle } i \text{ at time } k,
\]

\[
P_i(k) \text{ is the personal best position of particle } i \text{ at time } k,
\]

\[
P_g(k) \text{ is the global best position of all particles at time } k,
\]

\[
X_i(k) \text{ is the current position of particle } i \text{ at time } k.
\]
\[ X_i(k+1) = X_i(k) + V_i(k+1) \] (5)

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Where \( i = 1, 2, \ldots, m; \) \( c_1 \) and \( c_2 \) are learning factors, generally non-negative constants; \( r_1 \) and \( r_2 \) are random numbers between \([0,1]\); \( w \) is a constant used to balance global search and local search, and the value range is \([0,1]\); \( k \) is the number of times.

3.1. Adaptive Variable Weight

According to [3], it can be seen that the value of inertia weight \( w \) has an impact on the performance of the algorithm. If the value of \( w \) is large, the global search ability of the particle is strong. On the contrary, if the value of \( w \) is small, the local mining ability of the particle is enhanced. However, according to the general linear reduction strategy, the value of \( w \) will decrease rapidly and cannot keep a large value at the beginning of the algorithm. In view of this, this paper uses the adaptive change of \( w \) value to control the algorithm process to ensure the global and local search ability of particles. The formula of \( w \) is as follows:

\[
w(k) = \frac{1}{1 + \exp(\alpha \Delta w(k - 1))}
\] (6)

Where \( \alpha = \ln \frac{1 - w_{\text{max}}}{w_{\text{max}}} \), \( \Delta w = \delta \times \beta \), \( \delta = \frac{w_{\text{max}} - w_{\text{min}}}{G_{\text{max}}} \) and \( \beta = \frac{2 \parallel V_{k-1} \parallel}{\parallel V_k \parallel} \), \( w_{\text{max}} = 0.9 \), \( w_{\text{min}} = 0.2 \), \( G_{\text{max}} \) is the maximum number of iterations.

It can be seen from (3) that after introducing the scale factor, the particle can adaptively choose how to update the velocity at the next moment. When \( \parallel V_{k-1} \parallel < \parallel V_k \parallel \), \( \beta > 1 \), \( \Delta w > \delta \), the \( w \) decreasing largerly; When \( \parallel V_{k-1} \parallel > \parallel V_k \parallel \), \( \beta < 1 \), \( \Delta w < \delta \), the \( w \) decreasing range is reduced; When \( \Delta w = \delta \), the value of \( w(k) \) decreases nonlinearly. At the beginning of the iteration, \( w \) keeps a large value and can search in a wide range. At the later stage, \( w \) becomes smaller and the change speed decreases, which can enhance the local search ability of particles.

3.2. Selection, Crossover Process

The improved PSO algorithm in this paper uses the idea of combination crossover and mutation in genetic algorithm to generate the population representing the new solution set by using crossover and mutation factors.

Firstly, \( M \) individuals are selected according to the value of fitness function from large to small, and \( M \) is even. Then, pairing the selected individuals, according to the crossover strategy of intercepting the local same path information from the two particles for mutual exchange, the crossover operation is performed. If there is no same path segment, the crossover operation is not performed. For the offspring particles generated by crossover operation, the position and velocity of the offspring are updated according to (7)-(10)

\[
\text{child}^i_k (x) = p_c \cdot \text{parent}^i_k (x) + (1 - p_c) \cdot \text{parent}^i_k (x)
\] (7)

\[
\text{child}^i_k (x) = (1 - p_c) \cdot \text{parent}^i_k (x) + p_c \cdot \text{parent}^i_k (x)
\] (8)

\[
\text{child}^i_k (v) = p_c \cdot \text{parent}^i_k (v) + (1 - p_c) \cdot \text{parent}^i_k (v)
\] (9)

\[
\text{child}^i_k (v) = (1 - p_c) \cdot \text{parent}^i_k (v) + p_c \cdot \text{parent}^i_k (v)
\] (10)

Where \( p_c \) is a random number in \([0,1]\), \( k \) is the number of iterations, \( \text{parent}^i_k (x), \text{parent}^i_k (v), \text{parent}^i_k (v) \) are the position vector and velocity vector of the selected two parent individuals, and \( \text{child}^i_k (x), \text{child}^i_k (x), \text{child}^i_k (v) \) are the position vector and velocity vector of the offspring individuals generated after the crossover operation.
3.3. Mutation Operation
For each individual child who has finished the crossover operation, $child^i(x)$ perform the mutation operation according to (11)

$$child^{i+1}_k(x) = \begin{cases} 
child^i_k(x) + C_k & \text{if } \text{fitness}(child^i_k(x) + C_k) > \text{fitness}(child^i_k(x)) \\
child^i_k(x) & \text{otherwise}
\end{cases}$$

(11)

If the fitness value of $child^i_k(x) + C_k$ is greater than that of $child^i_k(x)$, then it goes into (a), otherwise it goes into (b). $C_k$ is the random number uniformly distributed on the interval $[x^L - child^i_k(x), x^U - child^i_k(x)]$, $x^L$ and $x^U$ are the upper and lower limits of the search interval respectively.

3.4. Fitness Function
In particle swarm optimization, the quality of particles is judged by the fitness value of particles. In the path planning, the primary index of the objective function is the distance of the path, in addition to energy consumption, running time and other factors. In this paper, the goal of path planning is the shortest and safest path under the influence of wind and waves. Therefore, the penalty coefficient $\alpha$ for turning is introduced. Here, the fitness function of PSO is positively correlated with the objective function. The smaller the impact of wind and wave on a path is, the smaller the objective function value is, the smaller the fitness function value is, and the better the particles are and the closer to the optimal solution is. The objective function formula is

$$f_a = \sum_{i=1}^{n} d(p_i, p_{i+1}) + \alpha f$$

(12)

Where $f_a$ is the objective function; $f$ is the fitness function; $n$ is the number of all elements in a particle; $d$ is the distance between the elements $p_i$ and $p_{i+1}$ in a particle; $\alpha$ is the penalty coefficient.

According to the previous section, the constraint function is constructed as follows:

$$f = F(\theta) + F_2(\omega)$$

(13)

$$F_2(\omega) = \sqrt{X_{\text{wave}}^2 + Y_{\text{wave}}^2 + N_{\text{wave}}^2}$$

(14)

3.5. The Running Steps of PSO Algorithm
To sum up, the specific implementation steps of path planning based on PSO are as follows:

1) According to the grid method, the running environment model of the ship is constructed, and the coordinate information of each grid is obtained:

2) The population size $N$, acceleration coefficient $c_1$, and $c_2$, the maximum number of generations $G_{\text{max}}$ are selected. Initialize the velocity, position and iteration number of particles;

3) Calculate the fitness value of each particle according to (9);

4) compare the fitness value of each particle, put the result into the current particle fitness value, and compare it with the historical optimal fitness value, if the result is less than the historical optimal, put the current particle position and fitness value into the historical optimal;

5) The minimum fitness value is found from the historical optimal fitness value, and compared with the previous global optimal fitness value. If it is less than the previous global optimal value, the corresponding particle position and fitness value are put into the global optimal value;

6) According to the velocity and position of the particle swarm, (4) and (5) are updated to change the velocity and position of the particle, and $w$ in (4) is replaced by $w(k)$;

7) According to the fitness value calculated in step 3), the particles satisfying the crossover operation are selected according to the linear arrangement;

8) According to the crossover strategy, the selection and crossover operations are performed to generate a new generation of population, and the generated population is mutated according to (11);
9) Check whether the termination conditions of the algorithm are met. If not, go to step 4) to continue running; On the contrary, the optimal solution is obtained.

4. Simulation and Verification of PSO Algorithm
In this paper, the grid method is used to construct the space environment of autonomous navigation ship, and various shapes of obstacles are "inflated", that is, less than one grid is treated as one grid. There are obstacles in the motion space. Path planning is to find the optimal path from the starting point to the target point, in which green is the starting point and red is the end point, as shown in Fig.1.

![Figure 1. Grid chart of ship navigation](image)

In order to verify the performance of the optimized PSO algorithm in path planning, the simulation is carried out on the MATLAB platform, and the variable parameters in the experiment are shown in TABLE 1

| Parameter | Parameter definition |
|-----------|----------------------|
| Starting point position | S=[1,1] |
| Target point location | G=[20,15] |
| Running speed | 0.1 |
| Number of particles | N=200 |
| Iterations | Nc=1000 |
| Learning factors | c1=c2=1.5 |
| Inertia weight | ω(k) |
| Penalty coefficient | α=1 |
| Crossover probability | Pc=0.8 |

![Figure 2. Iteration times of PSO algorithm](image)
Fig. 3 is the path planning from the starting point to the target point (red) by the standard particle swarm optimization algorithm, and the line segment in Fig. 3 is the optimal path planned by the particle swarm optimization algorithm. On the basis of Figure 1, the wind wave effect is introduced in the direction perpendicular to the route. In Fig. 4, the optimized particle swarm optimization algorithm is used to plan the route between the same two points. It can be seen from the figure that a safer route is adopted to ensure the safety of the route. It shows that the algorithm has good stability and robustness.

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**Figure 3.** Standard PSO algorithm search path

**Figure 4.** Improved PSO algorithm for searching path

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5. Conclusion
The simulation results show that the optimized particle swarm optimization algorithm can reduce the impact of wind and waves on the ship, and effectively solve the safety problem of particle swarm optimization algorithm applied in the path planning of autonomous navigation ship. At the same time, it also shows that the PSO algorithm proposed in this paper is feasible and effective for autonomous navigation ship path planning.

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