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# The Path Planning Research with Global Static and Local Dynamic of the AUV

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***Abstract:***

When the autonomous underwater vehicle (AUV) plans a path, there exist various problems, such as the difficulty in environmental modelling and the weak solution ability of algorithms facing global static environment, low autonomy and difficulties of path planning are exist in the process of obstacle avoidance planning in the face of local dynamic obstacles. To solve these problems, form concentric circles of path are used in polar coordinates, and a new path planning algorithm fusing global static and local dynamic which based on improved particle swarm optimization algorithm and velocity obstacle method is proposed under strict mobility constrains. In the environment model represented by polar coordinates, the optimal particle "mutation" process is introduced into the global static planning to enhance the algorithm's solving ability; in the process of local dynamic planning, the velocity obstacle method is used to solve the local collision range and safe path area to acquire the optimal obstacle avoidance path.

***Keywords**: Autonomous underwater vehicles, Particle swarm Optimization (PSO) algorithm, Velocity – obstacles, The dynamic avoidance, Global path planning.*

## I. INTRODUCTION

In-depth exploration of the ocean requires more and more underwater equipment deployment. In the future, large-scale underwater vehicle networking and collaboration will have stricter constraints on the mobility of autonomous underwater vehicles and make path selection more difficult. Therefore, global static and local dynamic path planning algorithms with stronger solving abilities are needed.

Particle swarm optimization (PSO) algorithm has the advantages of simple algorithm and rapid convergence, but the lack of information communication between particles, the "search" ability and "convergence" ability is difficult to balance perfectly, and the "trap" of local optimal solution is difficult to completely avoid. When using PSO algorithm to plan the global path, a large number of literature in particle swarm algorithm, by referring to other algorithms for fusion improvement, and improve the performance of particle swarm algorithm, achieved good results. In the study of global static path

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planning, the reference [1] combines random sampling and uniform variation to update particles and generates high quality optimal paths in the path planning of high mobile rescue robot, but the search capability needs to be improved to obtain more secure activity space. The reference [2] proposes an environmental selection and matching selection strategy to gradually reduce the convergence rate during iteration, but the possibility of falling into the local optimum is also increased. The reference [3] temporarily accepts a little poor quality solution using the annealing algorithm by introducing a simulated annealing algorithm Features, optimize global search ability, improve local search accuracy, but the number of algorithm parameters also increase the computation and complexity. The reference [4] through the differential evolution process of genetic algorithm, generate new particles in the particle group algorithm, increase the information interaction ability of particle groups, but its excessive variation increases the unnecessary computation amount;

Considering the actual Marine environment, the Marine environment model, objective function and optimization constraints were constructed. The multi-objective function was converted into a single objective function through the objective function weighting method, and the emphasis on each objective function was highlighted by adjusting the weighting weight.

By improving the algorithm's solving and convergence ability, the weighted objective function is optimized to obtain the optimal or suboptimal solution, so as to complete the path planning task combining global static and local dynamic.

## II. GLOBAL STATIC PROGRAMMING BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

### 2.1 The Obstacle Treatment and the Polar Coordinate Establishment

In reality, the Marine environment is complex and changeable, and its obstacles are also of different shapes. In order to improve the calculation efficiency, this paper abstracts the obstacles into rectangular or circular objects. For obstacles with a length-width ratio less than 1.5, a circle is used to surround them. Obstacles with an aspect ratio greater than 1.5 are surrounded by rectangles. Considering the time delay required by the speed and direction adjustment of the underwater robot, a safety threshold value $\varepsilon$was added to the outside of the obstacle model, and the area within the obstacle model and the safety threshold value was set as the dangerous area.

The polar coordinate system is established with the line between the starting point and the ending point as the polar axis, with negative clockwise and positive counterclockwise. Path concentric circles were established with the starting point as pole/center and the polar diameter of the circular obstacle as radius. The planned path is represented by path aggregation points $P = P_0, P_1, \cdots, P_i, P_{i+1}$. The starting

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point and ending point respect as $P_i, P_{i+1}$, and the $i$ is the number of path nodes, which is the same as the number of path concentric circles.The path node is located on the path concentric circle, and the path node information is represented by the polar diameter $P_m$ and polar Angle $P_a$.

The position of the rectangular obstacle is determined by 4 vertices. In order to better reflect the obstacle information and improve the computational efficiency, 2 vertices are selected to establish path concentric circles. There are 2 selection methods according to the length of the polar diameters of the rectangular vertex: the 2 vertices with the longest and shortest polar diameters; 2 points of the sub-length and sub-length of the polar diameter.

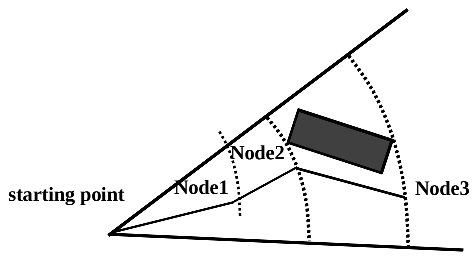


Fig 1: Path concentric circle established by the longest and shortest vertices of polar radius

As Figure 1, when the vertices with the longest and shortest diameters are selected, obstacles will "protrude" between path nodes. It is a great challenge to the robot's turning performance to adjust the heading Angle close to the obstacle, and there is a high risk. Therefore, path concentric circles are established in Figure 2.

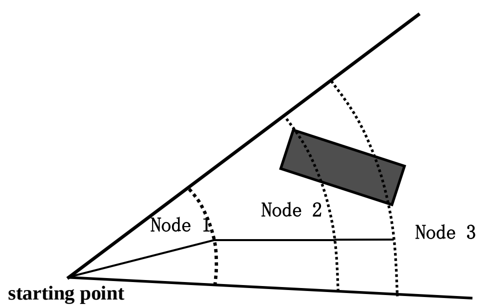


Fig 2: path concentric circle established by the second longest and the second shortest vertices of polar radius

Polar coordinates were established based on the starting point and obstacle information. Arc-shaped dotted lines were used to represent path concentric circles, and the center of concentric circles was the starting point. Circular and rectangular solid lines represent obstacles; The circular and rectangular dotted lines represent the boundary after the safe expansion threshold $\varepsilon$of the obstacle.The global static environment information in the polar coordinate system is shown in Figure 3, where Path1 and path2

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represent the path nodes existing on the path concentric circles, and will be represented by P1 and P2 in the set of path nodes.

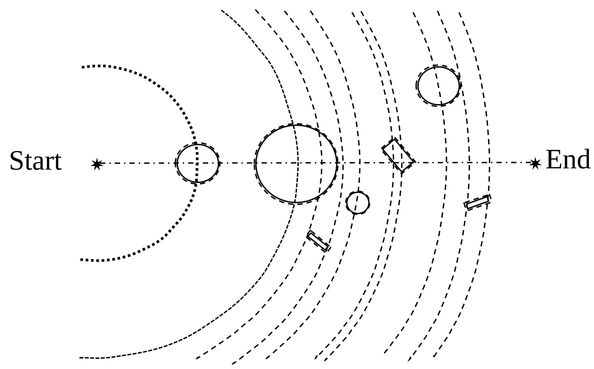


Fig 3: obstacle model in the polar coordinate

2.2 Build Fitness Function

In the global path planning of underwater robot navigation, it is necessary to construct an optimal path from the start point to the end point. The optimal path not only meets the constraints of the robot's own velocity, acceleration and angular velocity, but also ensures the shortest path under the safety conditions.

The path length function is established to represent the path length of the robot from the Start point to the End point, where L (.,.) Is the Euclidean distance of two path points, as follows:

$$J_1 = \sum_{i=0}^{n} L(P_i, P_{i+1}) \tag{1}$$

The path feasibility function is established to represent the navigational path feasibility, as follows:

$$J_2 = \sum_{i=0}^{n} D_{(i)} \tag{2}$$

In order to prevent path-points from being located within obstacles or threshold areas, the risk function is set up as follows:

$$D_{(i)} = \begin{cases} +\infty, & P_{i-1}P_i \cap OB = \emptyset \\ 0, & P_{i-1}P_i \cap OB \neq \emptyset \end{cases} \tag{3}$$

Where, $D_{(i)}$ represents the risk between the i point and the i-1 point; OB stands for danger area. If the path intersects the danger area, the danger degree is infinite. If they do not intersect, the risk is 0.

The rotation feasibility function $J_3$ is established to represent the rotation Angle feasibility of the robot during navigation, as follows:

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$$J_3 = \sum_{i=0}^{n} W_i \tag{4}$$

The rotation evaluation function is established as follows:

$$W_i = \begin{cases} 0, & |w_{(i)}| \leq \ w_{l(i)} \\ +\infty, & |w_{(i)}| > \ w_{l(i)} \end{cases} \tag{5}$$

Where, the $W_i$ represents the rotation Angle of the robot at the point i; $w_{l(i)}$ is the maximum rotation Angle of the robot. Since the autonomous underwater robot cannot adjust the head quickly, the rotation Angle of the robot is restrained. The $J_3$ avoid turning angle is too large.

Particle swarm optimization (PSO) is a decisive factor for approximating the optimal solution, and the choice of fitness function will directly affect the performance of the algorithm. In static obstacle environment, a feasible path with the shortest path length and maximum Angle of rotation is sought.

The linear weighting method is adopted to transform $J_1$,$J_2$,$J_3$ into a single objective function, and the fitness function is established as follows:

$$F_{it(i)} = a_1 J_1 + a_2 J_2 + a_3 J_3 \tag{5}$$

If the path meets the navigation conditions, the fitness is the sum of the paths. If the path does not meet the navigation conditions, the fitness is infinite. In order to compare the advantages of particles, the following particle preference conditions are formulated:

1) If $F_{it(i)} < F_{it(j)}$, then particle i is superior to particle j;
2) If $F_{it(i)} = F_{it(j)}$, $w_{(i)} < w_{(j)}$ ,then particle i is superior to particle j;

2.3 Improved Particle Swarm Optimization (PSO)

PSO algorithm is a random search algorithm, which designs a particle swarm to simulate a flock of birds. The particle in the flock has only two attributes: velocity V and position X, and the formula is:

$$\begin{cases} V_i^{t+1} = w_i V_i^t + c_1 r_1 (P_i^t - X_i^t) + c_2 r_2 (G_i^t - X_i^t) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases} \tag{7}$$

$$1 \leq i \leq N$$

The selection and control of learning factor $c_1$,$c_2$ and inertia weight w and other parameters determine the performance of PSO algorithm to a certain extent.The learning factor is the reflection of the self-experience summary and learning ability of the particle, $c_1$ remains large and the particle search range is large but the convergence is slow.$c_2$ remains large and the particle can learn from group experience to achieve rapid convergence but small search scope .The algorithm needs to search in a wide range in the early stage and fast convergence in the late stage, so it needs $c_1$ to be larger in the early stage and $c_2$ larger in the late stage of the search, as follow:

$$c_{1,2} = c_{1,2min} + \frac{run_{max} - run}{run_{max}} \times (c_{1,2max} - c_{1,2min}) \tag{8}$$

Where, run is the current iteration number; $run_{max}$ represents the maximum number of

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iterations; $r_1, r_2$ is a random number evenly distributed between 0 and 1.

The inertia weight $w$ affects the global and local search ability, and an appropriate value of $w$ can balance the global and local search ability, so as to achieve strong search ability in the initial stage of the algorithm, fast convergence in the later stage, and obtain the optimal solution with fewer iterations.Therefore, the linear decreasing inertia weight is as follows:

$$w = w_{max} - \frac{(w_{max} - w_{min}) \times run}{run_{max}} \tag{9}$$

Where, $w_{max}$ is the maximum inertia weight;$w_{min}$ is the minimum inertia weight;$run$ is the current iteration number;$run_{max}$ is the maximum number of iterations.

The final convergence position of the particle is determined by the optimal position of the swarm and the optimal position of the individual history .The algorithm is in a state of slight convergence if the particle swarm is not found to be better than the historical optimum after several generations of updating. The "variation" process of genetic algorithm is introduced to make the optimal position "variation". Since the particle swarm falls into the local "trap" gradually, the optimal position of the swarm needs to be changed in combination with the solution stage, that is, different mutation ways should be adopted to guide the swarm to continue searching in a favorable direction.

Define the dimensional distance between particle K and its contemporary best position:

$$d_k = \frac{1}{d}\sqrt{\sum_{j=1}^{d}(x_{kj} - gb_j)^2} \tag{10}$$

Where, d is the algorithm dimension, in the global static planning the path node is i; The dimensional distance can reflect the particle aggregation to the one-dimensional interval comparison. If the fitness value of the algorithm is ideal and the particle aggregation degree is high, it indicates that a better position has not been found in the convergence process. At this time, the mutation should be carried out in a small range to avoid repeated search process. If the fitness is not high or the particle aggregation degree is low, it indicates that the search process is still in progress and the spatial search is not sufficient. Therefore, the variation is carried out in a large range to improve the global search ability and avoid falling into local extremum. When the algorithm is in the state of slight convergence, the optimal position after mutation is determined by the original optimal position and the variation range, and the variation range is constantly adjusted according to the convergence reason.

$\gamma$ (t) was defined as the range of optimal position variation.

$$\gamma(t) = \mathrm{rand}() \times \mathrm{gb}(t) \times F_{itbest} \tag{11}$$

Where,$\mathrm{rand}()$ represents the random number distributed on the interval of (0,1) evenly;$\mathrm{gb}(t)$ represents the original best position.The area of variation range was controlled by $F_{itbest}$;The closer the optimal position is to the ideal value, the smaller the fitness value is, the smaller the degree of location

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variation is.

## 2.4 Improved PSO Program

The global path planning is divided into the following steps, as fig 4:

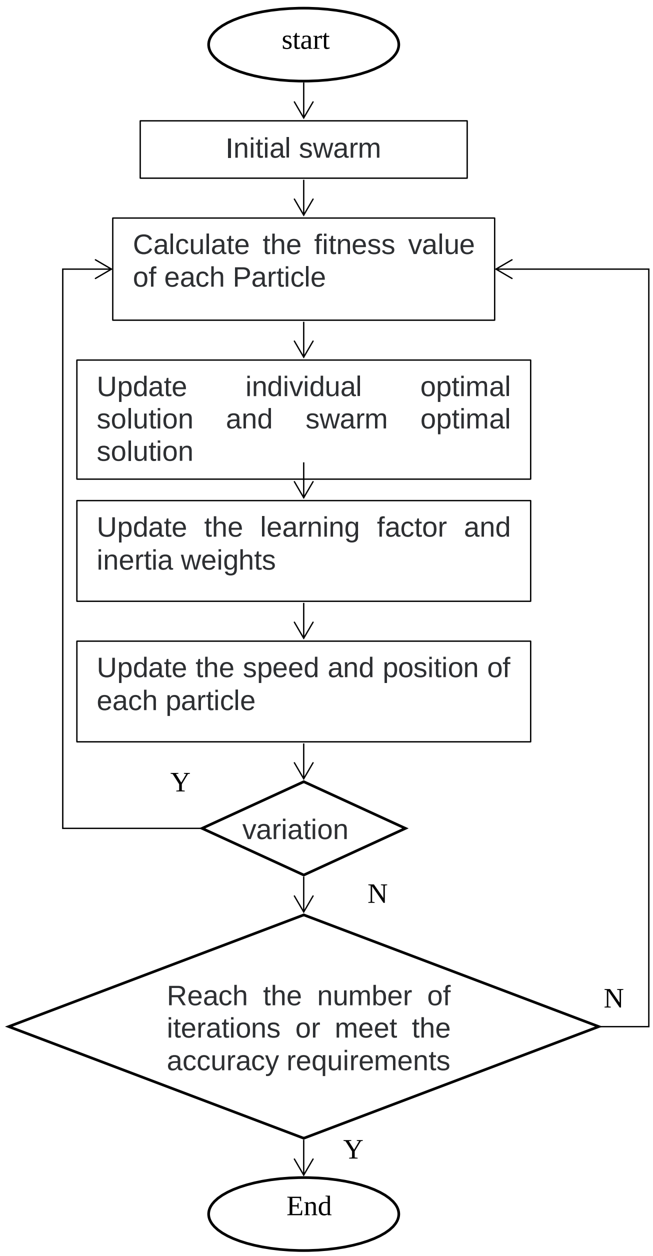


Fig 4: flowchart of improved PSO algorithm in static obstacle environment

1) Initialize the swarm, including setting the number and dimension of particles, the position and speed

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of each particle, the maximum number of iterations $run_{max}$, initializing the inertia weight W and learning factor $c_1$ ,$c_2$.

2) Calculate particle fitness.

3) Find the individual optimal solution and the swarm optimal solution according to the particle preference rule.

3) Update learning factor and inertia weight, and update particle speed and position.

5) After the specified update, if the particle still does not generate a new optimal swarm solution, it can judge whether it is in a state of slight convergence. If it is in a state of slight convergence, the optimal solution is varied and the 2nd step is carried out. Otherwise, proceed to Step 6th.

6) If the number of iterations is reached $run_{max}$ and end the algorithm; Otherwise, go to step 2.

## III. LOCAL DYNAMIC PROGRAMMING BASED ON VELOCITY BARRIER METHOD

### 3.1 Speed Barrier Method

When the robot meets dynamic obstacles such as fish, floating objects and ships during navigation, it can change its head direction to bypass the obstacles or adjust its speed to avoid them. When the robot meets dynamic obstacles, if the speed needs to be adjusted as $V^{new}$, it should be as close to the optimal speed as possible. Firstly, the velocity coordinate system of the obstacle relative to the robot is constructed, and the map system of the obstacle relative to the robot is constructed by collecting data from the sonar system carried by the robot, including the position $S_{ob\varphi}$ and distance $S_{ob}$ of the obstacle relative to the robot. With the robot sonar position as the origin (0, 0), cartesian coordinate system $O_s$and robot body coordinate system ($X_a$,$Y_a$) are established. The robot's heading is defined as axis Y, and the horizontal disposal is defined as axis X. Assume that in time Δt, the heading Angle $\varphi_r$ of the robot, the speed $v_r$ is fixed. During robot navigation, cartesian coordinate system $O_s$ is updated with robot pose. When the robot sails at a fixed heading Angle $\varphi_r$ and speed $v_r$, the movement of the origin of the coordinate system on X-axis and Y-axis is expressed as($\Delta$x, $\Delta$y)

$$\Delta x = v_r * \Delta t * \cos(v_r) * \cos(\varphi_r) \tag{12}$$

$$\Delta y = v_r * \Delta t * \cos(v_r) * \sin(\varphi_r) \tag{13}$$

It is assumed that in time $\Delta t$, the movement direction $\varphi_0$ and speed $v_0$ of the obstacle are fixed. Sonar detects the position of the obstacle relative to the current coordinate system position$(x_1, y_1)$, the newly measured position of the obstacle$(x_2, y_2)$. Then the position of the obstacle relative to the current coordinate system at the last moment is:

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$$(x_{21}, y_{21}) = (x_1 - \Delta x, y_1 - \Delta y) \tag{14}$$

The movement speed of the obstacle is:

$$v_0 = \sqrt{(x_1 - \Delta x - x_2)^2 + (y_1 - \Delta y - y_2)^2} / \Delta t \tag{15}$$

The movement direction of the obstacle is:

$$\varphi_0 = arctan((y_{21} - y_2)/(x_{21} - x_2)) \tag{16}$$

According to the obstacle contour of sonar image, the length to width ratio of the obstacle is discriminated and then the obstacle is surrounded. As shown in Fig5, both robot A and obstacle B move in a fixed course and speed.

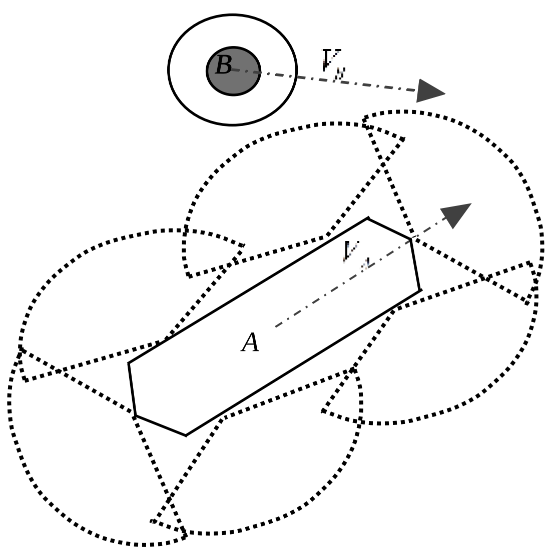


Fig 5: The motion of vehicle and obstacle

The robot A is regarded as A particle, and the obstacle B is expanded according to the robot size and safety threshold. Calculate the relative velocity of A and B, $V_{BA} = V_A - V_B$, and define the ray starting from point P along the direction of V as:

$$\lambda(P, V) = \{P + tV | t \geq 0\} \tag{17}$$

When the rays $\lambda_{BA}$ emitted from point A along the direction $V_{BA}$ intersect with obstacle B, that is, when the rays $\lambda_{BA}$ fall within the included Angle of two tangents of obstacle B relative to robot A, the two will collide, as shown in Fig 6.

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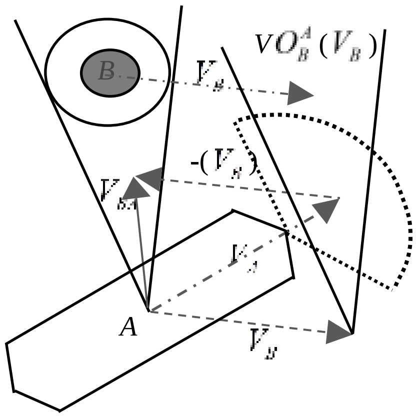


Fig 6: Determination of collision condition

According to the velocity obstacle method, the collision range is defined as:

$$VO_B^A(V_B) = \{V_A | \lambda(P_A, V_A - V_B) \cap (B \oplus -A) \neq \emptyset\} \quad (18)$$

$$\mathrm{A} \oplus \mathrm{B} = \{\mathrm{a}+\mathrm{b} | \mathrm{a} \in \mathrm{A}, \mathrm{b} \in \mathrm{B}\} - \mathrm{A} = \{-\mathrm{a} | \mathrm{a} \in \mathrm{A}\} \quad (19)$$

If the navigation state of robot A is not changed, the robot will collide with an obstacle at some point. In order to escape from the collision range, it needs to adjust its position to A safe area.$t_1$ According to the collision range, the complement of: $VO_B^A\ (V_B)$ is the safe navigation area.

3.2 Fitness Function

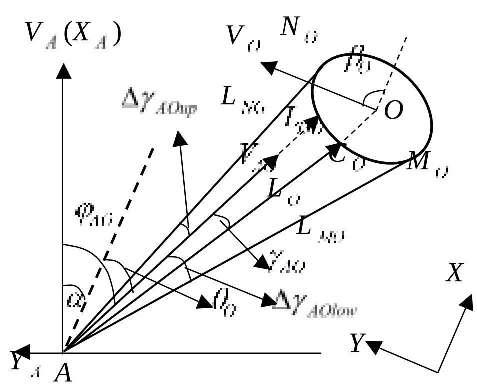


Fig 7: relative velocity coordinate system of vehicle-obstacle

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The robot and obstacle relative velocity coordinate system is established as shown in Figure 7.

In the global coordinate system (X, Y), the robot moves with speed VAand heading Angle α.Robot body coordinate system $(X_a, Y_a)$.O is the obstacle, and the velocity in the coordinate system (X, Y) is $V_O$, and the direction Angle $\beta_O$.$L_{MO}$,$L_{NO}$ is the tangent line on both sides of the robot obstacle;$L_O$ is a directed line segment from the robot to any point $C_O$ on the edge of the obstacle.$\theta_O$ is the positive Angle $L_O$ with the X-axis, and $\gamma_{AO}$ is the Angle $V_{AO}$ with $L_O$.The collision avoidance Angle $V_{AO}$ is defined as the adjustment Angle for the robot to avoid obstacles.$\Delta\gamma_{AOlow}$, $\Delta\gamma_{AOup}$ respectively are $V_{AO}$the rotation angles to $L_{MO}$,$L_{NO}$, and let counterclockwise be positive.

If the robot avoids an obstacle in the time interval $[t_k, t_{k+\Delta t}]$, it should deviate from the collision range $O_i$ in the time interval $V_{AOi}$, namely $VO_B^A(V_B)$, one of the following inequalities holds:

$$-\pi \leq \Delta\gamma_{AOi} \leq \Delta\gamma_{AOlow} \tag{20}$$

$$\Delta\gamma_{AOup} \leq \Delta\gamma_{AOi} \leq \pi \tag{21}$$

Assuming that the velocity of the obstacle in the interval $[t_k, t_{k+\Delta t}]$ is constant, then

$$\Delta\gamma_{AOi} = \Delta\gamma_{AOi} * \Delta t = -\frac{\sin\varphi_{AOi}}{V_{AOi}}\Delta V_A + \frac{\cos\varphi_{AOi}}{V_{AOi}}\Delta V_A * \Delta\alpha - \Delta\theta_{Oi} \tag{22}$$

Where,$\Delta\theta_{Oi} = V_{AO} = \sin\gamma_{AOi}/L_{Oi}$, collision avoidance Angle is determined by $(\Delta V_A, V_A\Delta\alpha)$.It can be seen that adjusting the speed and heading of the robot are two effective behaviors for obstacle avoidance, and only one of them can basically fulfill the obstacle avoidance requirements. For the moving obstacles in the sub-target segment, the dimension number of particle swarm is fixed in two dimensions: the speed and heading of the robot, and its optimization adjustment variables are these two values.

Establish the robot-target area relative velocity coordinate system, as shown in Figure 8, which is defined in the same way as the robot-obstacle relative velocity coordinate system.

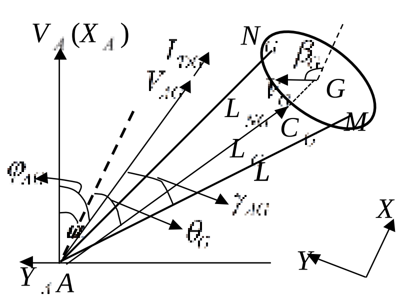


Fig 8: relative velocity coordinate system of vehice-target

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It is assumed that the end point of the robot sub-path is located in the feasible region G, and is the termination point $C_G$. It is expected to always point $V_{AG}$, and the collision avoidance Angle $C_G$ is as close as possible to the included Angle between $V_{AG}$ and $L_G$, so as to ensure that the following formula is minimal:

$$J_{G1} = |\gamma_{AG} + \frac{\sin \varphi_{AG}}{V_{AG}} \Delta V_A - \frac{\cos \varphi_{AG}}{V_{AG}} V_A \Delta \alpha + \Delta \theta_G| \tag{23}$$

In order to reduce yaw time and make the robot return to normal course as soon as possible, the minimum time function is established. Specifically, in the route direction before obstacle avoidance, when the speed of the robot's heading component is the maximum in this direction, yaw time can be the shortest, then

$$J_{G2} = \frac{\Delta V_{AGmax}}{V_{AG}} - \frac{\cos \varphi_{AG}}{V_{AG}} V_A - \frac{V_A \sin \varphi_{AG}}{V_{AG}} \Delta \alpha \tag{24}$$

Using linear weighting method, the objective function $J_{G1}$, $J_{G2}$ is respectively normalized into a single objective function, and the single objective function is obtained as follows:

$$F_{(i)} = \omega_1 J_{G1} + \omega_2 J_{G2} \tag{25}$$

Where, $\omega_1$ and $\omega_2$ are the weights of $J_{G1}$ and $J_{G2}$, respectively. Considering that in the process of dynamic obstacle avoidance, the rotation Angle is required to be higher and the change of speed is required to be smaller, when the parameter value is selected, and $\omega_1 > \omega_2$,and $\omega_1 + \omega_2 = 1$.

Path planning in a dynamic obstacle environment is planned among path nodes, and obstacle avoidance is carried out during the navigation of the current waypoint to the next waypoint. The specific algorithm flow is shown in Fig 9.

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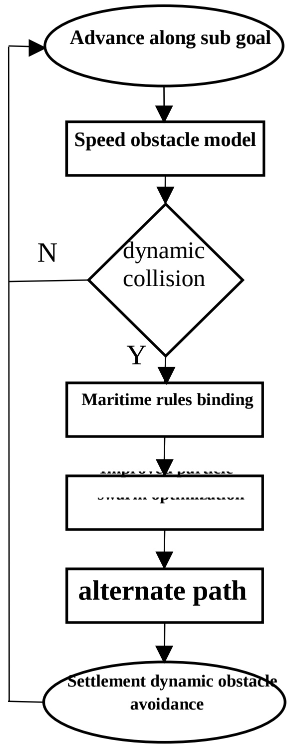


Fig 9: Flowchart of improved PSO algorithm in dynamic obstacle environment

## IV. CONCLUSION

In this paper, based on the passive sonar equation, the narrow-band underwater acoustic detection modeling of underwater vehicle is completed and the safety situation analysis of underwater vehicle is carried out by focusing on the main parameters of acoustic performance, such as sound source level, underwater acoustic propagation loss and array gain, combined with numerical calculation. The main conclusions are as follows:

The peak line spectrum of underwater vehicle radiated noise has a significant influence on the detection efficiency of receiver. The vibration and noise reduction design of low and medium frequency line spectrum noise should focus on the control of line spectrum.

The detection range varies greatly along each direction Angle θ, and the main factors affecting the detection range include the sound absorption effect of seawater and the intensity of target sound radiation.

With the increase of analysis frequency, the spectral density level of sound source of underwater vehicle structure shows a general trend of decline

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