Method for Collision Avoidance by USV Based on Improved Genetic Algorithm

Zhongjian Fu
College of Automation
Harbin Engineering University
Harbin, HLJ, China
1608584670@qq.com

Hongjian Wang
College of Automation
Harbin Engineering University
Harbin, HLJ, China
cctime99@163.com

Yingmin GU
Jiangsu Automation Research Institute
Lianyungang, JS, China
guchen716@sina.com

Chengfeng Li
College of Automation
Harbin Engineering University
Harbin, HLJ, China
lichengfeng@hrbeu.edu.cn

Haiyan Tong
College of Automation
Harbin Engineering University
Harbin, HLJ, China
hyan_tong@163.com

Haibin Wang
College of Automation
Harbin Engineering University
Harbin, HLJ, China
wanghaibinheu@hrbeu.edu.cn

***Abstract*—This paper proposes a method for collision avoidance by unmanned surface vehicle (USV) based on improved genetic algorithm. For the complex marine environment in which static and dynamic obstacles are densely covered, we establish models of the USV system. When the USV encounters dynamic obstacles, we divide scenarios involving encounters and design corresponding collision avoidance strategies; and calculate the motion parameters and risk of collision to determine whether to start collision avoidance. Following this, we improve the genetic algorithm through retention, deletion, and replacement, use the analytic hierarchy process to build the fitness, iteratively optimize the acceleration and yaw rate, and calculate the optimal path for collision avoidance for USV. Finally, we built a simulation platform for USV collision avoidance to verify the proposed method. The results show that the proposed method can be used for the safe operation of USV.**

***Keywords*—Improved genetic algorithm, Unmanned surface vehicle, Obstacle avoidance, COLREGs, Radar detection**

I. INTRODUCTION

The USV is an intelligent unmanned maritime platform that is often used to perform tasks during military activities and maritime supervision that are not suitable for human platforms. It has many virtues in terms of performance, such as flexibility and concealment [1]. In the complex and ever-changing marine environment, it is important to enable USV to safely sail and successfully complete tasks by implementing a collision avoidance function [2].

Local obstacle avoidance planning for USV refers to the use of maneuvering behavior in real time to avoid collisions with static and dynamic obstacles [3]. It consists of two strategies: local path planning based on path search, which can generate a series of reasonable track points, for example, Richard Bucknall applied the cubic spline interpolation to improve the traditional A-star (A*) algorithm, designed three path smoothers to reduce the number of turning points and obtain a relatively smooth path [4]; and reactive collision avoidance planning based on real-time behavior to control velocity and direction, for example, Lifei Song introduced the centrifugal field to improve the artificial potential field, and used the velocity obstacle (VO) algorithm to solve the vector of velocity to avoid obstacles, but this method is not suitable for complex environments featuring multiple obstacles [5].

Although many algorithms for real-time obstacle avoidance have been proposed in dynamic environments in the last few years, local collision avoidance planning persists as a problem that limits the long-term development of USV. For example, in the context of the above two strategies, some proposed methods based on path search do not consider the scenario where dynamic obstacles are encountered in close proximity [6]; reactive obstacle avoidance planning usually only plans the steering angle of the USV without considering the length of the path [7].

Genetic algorithm is a global search algorithm with strong adaptability, parallelism and updating ability. It is applied to multi-model and multi-objective optimization problems such as collision avoidance planning. Liu designed a decision-making system based on the evolutionary genetic algorithm, and adopted a heuristic method for population initialization. Economy of resources, smoothness, and safety were used as factors of fitness, and deletion and repair operations were added to the traditional genetic operation to establish an optimized iterative process [6]. He et al. uses the ability of simulated annealing algorithm to local optimization to prevent the genetic algorithm from falling into local optimum, but this algorithm is difficult to solve and increases the operation hours [8].

While the genetic algorithm has been used for collision avoidance, it generally exists such problems as falling into the local optimum, slow convergence, and the degradation of the solution [9-11]. Given that the literature does not provide an adequate solution to USV collision avoidance, this paper designs a method for collision avoidance by USV based on the improved genetic algorithm with the aim of solving the problem of local obstacle avoidance in the complex marine environment.

The method establishes the models of the USV system, divides encounter scenarios and designs strategies for collision avoidance, and calculates motion parameters and the risk of collision in real time to determine whether to take collision avoidance measures. Aiming at the limitations of the genetic algorithm, we design retention to solve the problem of degradation and premature convergence, and design deletion and replacement to improve the ability of local search and speed of convergence of the algorithm. We then use the method to iteratively optimize the acceleration and yaw rate,

Hongjian Wang is the corresponding author. (E-mail: cctime99@163.com)

This work was supported in part by the National Natural Science Foundation of China (Nos. 61633008, 51609046), and the Natural Science Foundation of Heilongjiang Province under Grant F2015035.

Global Oceans 2020: Singapore - U.S. Gulf Coast | 978-1-7281-5446-6/20/$31.00 ©2020 IEEE | DOI: 10.1109/IEEECONF38699.2020.9389254

and calculate the optimal path for USV. Compared with the conventional genetic algorithm, the improved algorithm designed in this paper has the advantages of fast convergence, high stability, fast optimization, and low time complexity.

The remainder of this paper is organized as follows: Section 2 describes the basic design of collision avoidance systems, and Section 3 elaborates on the design of collision avoidance based on the improved genetic algorithm. Section 4 details the design of the simulation software and verifies the proposed algorithm. Finally, Section 5 discusses the conclusions of this study and direction for future work.

II. BASIC DESIGN OF OBSTACLE AVOIDANCE

The basic design of collision avoidance includes the establishment of models of the USV system, division of encounter scenarios, design of corresponding measures, and calculation of motion parameters and the risk of collision.

A. USV System Modeling

When studying USV collision avoidance planning, we consider motion only in the horizontal plane and assume the USV as a rigid body. As shown in Fig. 1, we establish the Northeast frame E_0-E-N, the body-fixed frame $o_b-x_b-y_b$, the sensor-fixed frame $o_s-x_s-y_s$ and use symbols and criteria defined by the Society of Naval Architects and Marine Engineers to describe the movement of USV (surge, swaying, and yaw)[12-13].

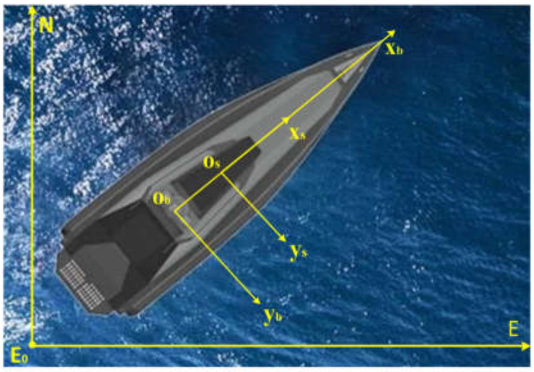


Fig.1. Schematic diagram of USV frames

The USV motion model can be derived:

$$\begin{bmatrix} \dot{n} \\ \dot{e} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ r \end{bmatrix} \tag{1}$$

In the formula, (n,e) is the position of USV in the the Northeast frame, ψ is the yaw, $[u,v,r]^T$ is the velocity vector.

Then, we set the detection range of the radar to 50 m–10 km and the detection range of 0–360 degrees.

B. Encounter Scenario and Collision Avoidance Measures

This paper used the 13th–17th rules of the International Regulations for Preventing Collisions at Sea as reference [13-14], and designed the corresponding collision avoidance measures based on the navigation conditions of USV. As shown in Fig. 2, according to the heading of the USV and other boats, we divide encounter scenarios into seven types and design the corresponding collision avoidance measures:

In area A in Fig. 2, when other boats come from the fan-shaped direction of the right side of the USV, the encounter scenario is one where the right side of the ship crosses at a small angle. The USV need to turn right to avoid collision.

In area B in Fig. 2, when other boats come from the fan-shaped direction of the right side of the USV, the encounter scenario is one where the right side of the ship crosses at a large angle. The USV takes a left turn to avoid collision.

In areas C or D in Fig. 2, when other boats come from the fan-shaped direction from the right or left side of the USV and catch up to it, if the oncoming boats can see only the tail of the USV, the encounter scenario is one where other ship right side chasing or other ship left side chasing. Then, before an urgent situation arises, the USV maintains their original course. In case an urgent situation arises, the USV turns left or right according to their relative heading.

In areas E or F in Fig. 2, when other boats come from the fan-shaped direction on the right side of the USV, the encounter scenario is one where the left side of the ship crosses at a small angle or a large angle. At this time, in case an urgent situation arises, if the incoming boats do not take collision avoidance measures, the USV turns right to avoid collision.

In area G in Fig. 2, when other boats come from the fan-shaped direction of the right or left side of the USV, the encounter scenario is encounter, the USV turns right and passes from the left side.

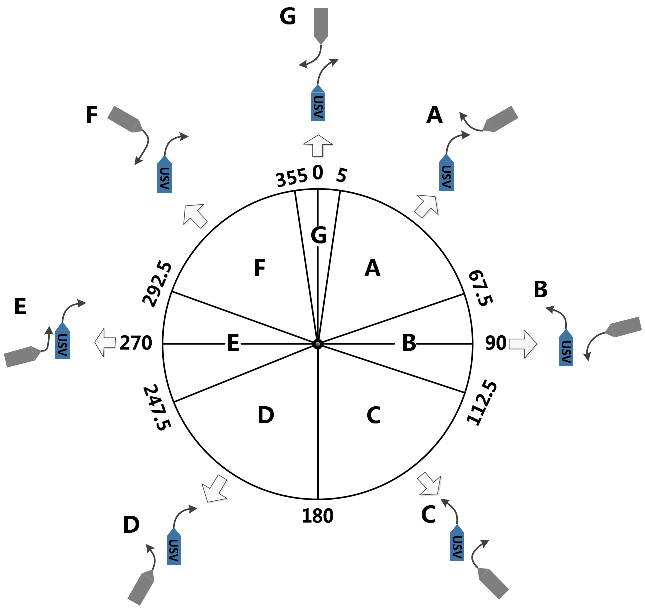


Fig.2. Encounter scenario of USV

C. Calculating Motion Parameters and Collision Risk

As shown in Fig. 3, when USV encounters other boats, we assume that (n,e) is the position of USV in the Northeast frame and (n_t,e_t) is the position of target in the the Northeast frame, the relative distance between USV and the target is:

$$R=\sqrt{(e-e_t)^2+(n-n_t)^2} \tag{2}$$

The orientation of target relative to the heading of the USV is:

$$\alpha=\begin{cases}90^\circ-\arctan\dfrac{e-e_t}{n-n_t} & if: n-n_t\ge 0\\ 270^\circ-\arctan\dfrac{e-e_t}{n-n_t} & if: n-n_t<0\end{cases}\tag{3}$$

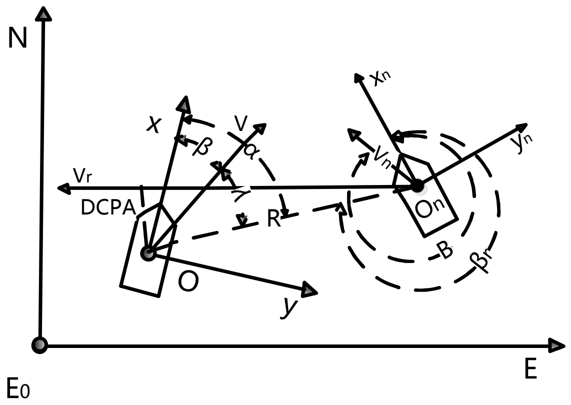


Fig.3. Relative motion parameter of USV

If $\left(n_t',e_t'\right)$ is the position of target in the the Northeast frame at next moment, the distance between the estimated centers of targets at adjacent moments is:

$$R'=\sqrt{(e_t'-e_t)^2+(n_t'-n_t)^2}\tag{4}$$

When the interval $\vartriangle t$ is set to one second and the velocity of USV is V , if $R'\le 3V$, the obstacle is static and if $R'>3V$, the obstacle is dynamic. In turn, we can estimate the velocity and heading of the dynamic target:

$$V_t=\frac{R'}{\vartriangle t}\tag{5}$$

$$\beta_t=\begin{cases}90^\circ-\arctan\dfrac{e_t'-e_t}{n_t'-n_t} & if: n_t'-n_t\ge 0\\ 270^\circ-\arctan\dfrac{e_t'-e_t}{n_t'-n_t} & if: n_t'-n_t<0\end{cases}\tag{6}$$

The component of the velocity of the dynamic target in the x_b, y_b axis is:

$$\begin{cases}V_{tx}=V_t\bullet\cos\beta_t\\ V_{ty}=V_t\bullet\sin\beta_t\end{cases}\tag{7}$$

The component of the velocity of the USV relative to that of the dynamic target is:

$$\begin{cases}V_{rx}=V_x-V_{tx}\\ V_{ry}=V_y-V_{ty}\end{cases}\tag{8}$$

The velocity of the USV relative to the dynamic target is:

$$V_r=\sqrt{{V_{rx}}^2+{V_{ry}}^2}\tag{9}$$

Distance at closest point of approach ($DCPA$):

$$DCPA=R\bullet\sin\left(90^\circ-\arctan\frac{V_{rx}}{V_{ry}}-\alpha\right)\tag{10}$$

Time at closest point of approach ($TCPA$):

$$TCPA=\frac{R}{V_r}\bullet\cos\left(90^\circ-\arctan\frac{V_{rx}}{V_{ry}}-\alpha\right)\tag{11}$$

The risk of spatial collision of USV is:

$$u_D=\begin{cases}1 & |DCPA|<l_1\\ \dfrac{1}{2}-\dfrac{1}{2}\sin\left[\dfrac{\pi}{l_2-l_1}\bullet\dfrac{DCPA(l_1+l_2)}{2}\right] & l_1\le|DCPA|\le l_2\\ 0 & l_2<|DCPA|\end{cases}\tag{12}$$

Where l_1 is the distance between USV and the dynamic target when the former takes measures to avoid collision, l_1=1.5ρ; l_2 is the critical distance between USV and the dynamic target that constitutes a challenging situation.

$$\rho=\begin{cases}1.1-0.2\bullet\dfrac{\gamma}{180^\circ} & 0^\circ<\gamma\le 112.5^\circ\\ 1.0-0.4\bullet\dfrac{\gamma}{180^\circ} & 112.5^\circ<\gamma\le 180^\circ\\ 1.0-0.4\bullet\dfrac{360^\circ-\gamma}{180^\circ} & 180^\circ<\gamma\le 247.5^\circ\\ 1.1-0.4\bullet\dfrac{360^\circ-\gamma}{180^\circ} & 247.5^\circ<\gamma\le 360^\circ\end{cases}\tag{13}$$

In the formula， $\gamma=\alpha-\psi$.

The temporal risk of collision of USV is:

$$\begin{aligned}TCPA>0\quad u_T&=\begin{cases}1 & TCPA\le t_1\\ \left(\dfrac{t_2-TCPA}{t_2-t_1}\right)^2 & t_1<TCPA\le t_2\\ 0 & TCPA>t_2\end{cases}\\ TCPA\le 0\quad u_T&=\begin{cases}1 & |TCPA|\le t_1\\ \left(\dfrac{t_2+TCPA}{t_2-t_1}\right)^2 & t_1<|TCPA|\le t_2\\ 0 & |TCPA|>t_2\end{cases}\end{aligned}\tag{14}$$

Where $t_1=\dfrac{\sqrt{l_1^2-DCPA^2}}{V_r}$ and $t_2=\dfrac{\sqrt{l_2^2-DCPA^2}}{V_r}$

Combining the spatial and temporal risks of collision, we derive the risk of USV: $u=u_D\oplus u_T$

Where $\oplus$ means the following:

If u_D=0 or u_T=0 , u=0;

If $u_D\ne 0$ and $u_T\ne 0$, u=max(u_D,u_T) .

III. DESIGN OF PLANNING ALGORITHM

We use retention, deletion, and replacement to improve the genetic algorithm, and the analytic hierarchy process to build fitness. Following the population initialization of the genetic algorithm, establishment of fitness, selection, crossover, and mutation, the system iterates real-time the optimal acceleration and yaw rate of USV to calculate the optimal path.

A. Individual Coding and Population Initialization Design

The motion control of the USV usually functions according to the strategy of "heading control" and "velocity control." [15-16]. We thus used acceleration and yaw rate as control variables in this paper. The population initialization of the improved genetic algorithm used float coding, and we employed a certain range of float to code and express the acceleration and yaw rate.

We set the initial population to 50 individuals with a coding length of two. Each individual included acceleration and yaw rate. When we know the position, velocity, heading of USV and the optimal solution of the genetic algorithm at the given time, we can calculate the velocity, heading and position of the next moment. Once the USV had completed the optimization at the given time, its motion parameters changed, and it was necessary to re-initialize the population and iterate to the optimal solution in the next moment. In these iterations, the optimal acceleration and yaw rate at each moment constituted the optimal path of USV.

Then, to ensure the stability and avoid large-angle steering, we set the range of acceleration to (-2, +2) kn/s and the range of yaw rate to (-5, +5) $^{\circ}/s$.

B. Fitness Model

When constructing fitness in this paper, we considered such factors as the distance between the given position of the USV and the end point, the distance between the given position of the USV and obstacles, the distance between the given position of the USV and other boats, the given velocity and heading, and the positions of obstacles and other boats[17].

As shown in Fig. 4, the USV simultaneously detects the positions of an obstacle and a boat. The circle represents the range of the radar's detection, d_0 is the shortest distance between the origin in the sensor-fixed frame of the USV and obstacle A, d_1 is the shortest distance between the origin in the sensor-fixed frame of the USV and the boat, d is the distance between the origin in the sensor-fixed frame of the USV and the end point, μ is the start angle of the obstacle (the angle of the lower boundary of the obstacle detected by radar), ν is the end angle of the obstacle (the angle of the upper boundary of the obstacle detected by radar), δ is the start angle of the boat (the angle of the lower boundary of the boat detected by radar), and γ is the end angle of the boat (the angle of the upper boundary of the boat detected by radar).

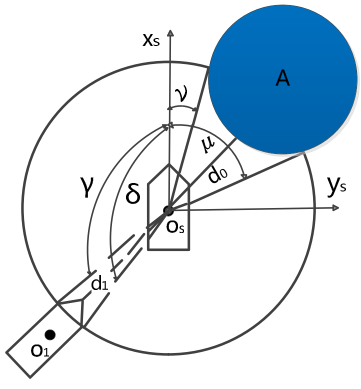


Fig.4. Radar search parameters

The fitness of the improved genetic algorithm in this paper:

$$f=\begin{cases}\dfrac{1}{\lambda}\bullet\left(k_1\bullet c+k_2d_0+k_3d_1\right) & \mu\le\psi_{i+1}\le\nu \ \text{ or } \ \delta\le\psi_{i+1}\le\gamma \\ \lambda\bullet\left(k_1\bullet c+k_2d_0+k_3d_1\right) & else\end{cases} \tag{15}$$

In the formula, $c=1\times10^5/d$, k_1,k_2,k_3 are constants, ψ_{i+1} is the heading if selects an individual at next moment, f is value of fitness. This paper set the maximum value convergence: That is to say, the greater the value of f is, the more likely is the relevant individual to be selected.

We introduce the reward and punishment factors in fitness to increase the degree of discrimination. If the angle of the next moment is within the range of angles of the obstacles or other boats, and the USV continues to sail close to obstacles or other boats, the value of fitness is reduced λ times to reduce the probability of being selected; If the angle of the next moment is not within the range of angles of obstacles or other boats, the value of fitness is expanded by a factor of λ to increase the probability of being selected. In addition, we apply the analytic hierarchy process to calculate the coefficients of each factor according to the influence of various factors on fitness. As shown in Table I, the left half is the designation standard level matrix, and the right half is the results of operation that pass the consistency test.

TABLE I
PARAMETER TABLE OF ANALYTIC HIERARCHY PROCESS

Judging matrix of criteria level				**Results**
Parameter	c	d_0	d_1	CI=0, RI=0.58,
c	1	0.25	0.25	CR=0<0.10
d_0	4	1	1	Satisfying consistency test
d_1	1	1	1	[0.112,0.444,0.444]

C. Design of Evolutionary Operations

In this paper, we adopt roulette selection. The system calculates the probability that each individual is selected according to fitness, and randomly select individuals to form progeny populations according to the probability. The larger the value of fitness is, the greater is the probability of being selected [18-19].

Then, we use discrete cross [20]. Individuals exchange variable values, and sub-individuals randomly select the parent individual with a certain probability. Before the crossover, individuals of the population were randomly paired and the crossover probability was set to 0.8. When crossing, the acceleration and yaw rate were separated.

Then, we adopt Gaussian mutation. The system generates a random number obeying the Gaussian probability distribution instead of a gene part of the individual selected with a certain probability. If the initialization sets the population capacity to 50, the reciprocal 0.02 of the population capacity is set as the mutation probability.

To effectively improve the speed of optimization and solve the problems of the local optimum, premature convergence, and sub-optimal superiority to the parent, this paper adds retention, deletion, and replacement. As shown in Fig. 5, the retention operation refers to preserving the optimal individual of this generation in the next generation, which ensures that good genes are inherited by the offspring population and prevents sub-optimal solutions. The deletion and replacement operations refer to determining whether the heading is within the range of the start and end angles of the target when considering the yaw rate of the individual. If it is within the range, the USV approaches the obstacle while continuing to sail. At this point, we replace the yaw rate of the individual with that of the best individual in this generation. This is equivalent to adding a way to generate new individuals, complementing the reward and punishment mechanism to enhance protection for good genes and avoid local optima to some extent.

Finally, after several generations of populations have been iterated, the system determines whether the end condition is satisfied. If it is, the optimal acceleration and yaw rate of the optimal individual are output; if not, fitness is reconstructed and iterated.

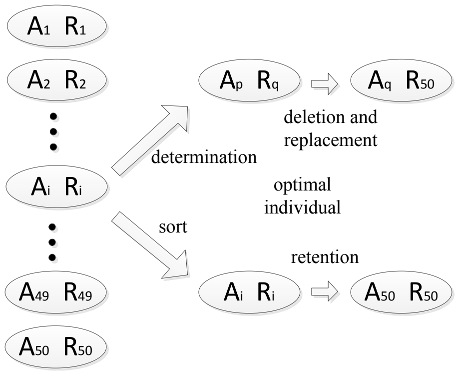


Fig.5. Retention, deletion, and replacement

IV. EXPERIMENTAL ANALYSES

To verify the effectiveness of USV collision avoidance planning based on the improved genetic algorithm, this paper selected the QT software to establish the simulation platform, designed typical simulation cases for experiment, and analyzed the experimental results and data.

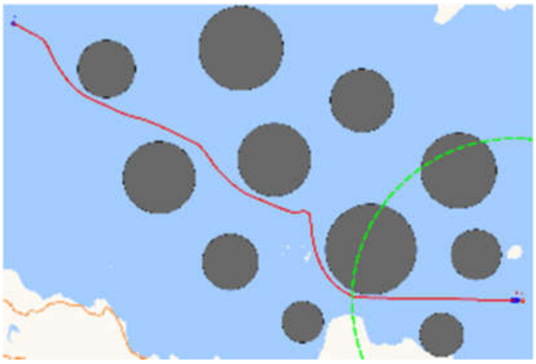
As shown in Fig. 6, the software's initial window of the USV simulation environment was maximized by default. The lower-left corner of the screen was the origin of the Northeast frame, the right direction was the positive direction of the E-axis, and the upward direction was the positive direction of the N-axis. The experimental area was 30 km long and 20 km wide. The software could arbitrarily set the starting and end points of USV, the shape, size, position of the obstacle. In addition, the simulation experiment could display the navigation parameters of USV in real time and draw the trajectories of USV with smooth curves of red. As shown in Table II, we set the initial parameters of USV as given in the table below. To complete the simulation quickly, factors for accelerating it were set here.

TABLE II
INITIAL PARAMETER LIST FOR USV

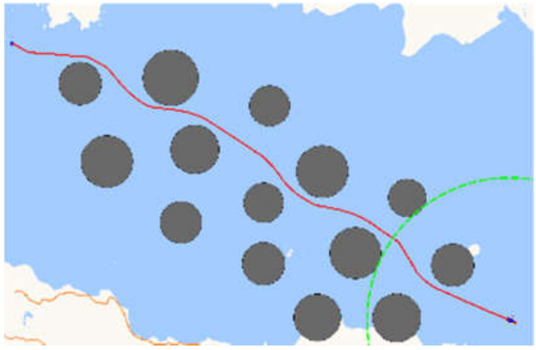
Initial velocity	50 knot
Initial heading	Pointing to the end
Maximum velocity	50 knot
Maximum distance	1000 km
Distance of starting collision avoidance	2.0km
Safe distance	800m
Sailing area	30 km long, 20 km wide

As shown in Fig. 6, in the experiment, USV traveled from the starting point to the end point. When the distance to the obstacles was less than 2 km, the system started collision avoidance and circumvented both sides of the target, and continued to sail toward the end. During the voyage, the distance between USV and obstacles was always kept greater than the minimum safe distance. This meant that collision avoidance was effective.

As shown in Figs. 7, the trend of acceleration and yaw rate were smooth, and there was no emergency acceleration and deceleration or large-angle turns. As shown in Fig. 8, the trend of fitness were optimized for the maximum value. Multiple optimizations were performed in the same state, the fitness of optimization was not changed by much, and the algorithm had a certain stability.



(a) Conventional GA



(b) Improved GA
Fig.6. Simulation effect of collision avoidance planning

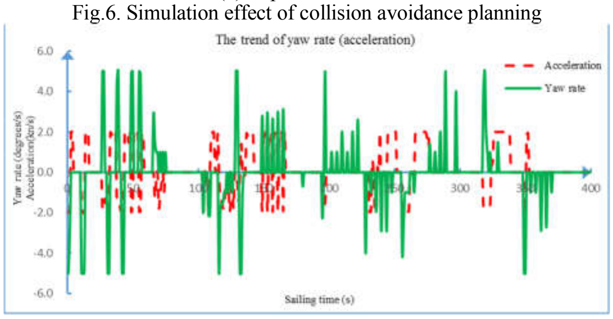


Fig.7. The trend of acceleration and yaw rate

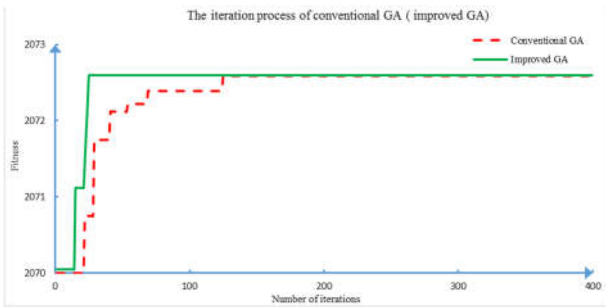


Fig.8. The iteration process

As shown in Table III, compared with the iterative process of the conventional genetic algorithm, the number of iterations were reduced, the speed of convergence clearly improved, premature convergence was slightly improved, and there was no local optimization. We improved the genetic algorithm with a low standard deviation, high success rate, and strong stability. Following the program test, the efficiency of the algorithm was thus high, and its optimization time was adequate for system response.

TABLE III
PARAMETER COMPARISON OF GENETIC ALGORITHM

	Conventional GA	Improved GA
Operation time	160ms	100ms
Success rate	85%	98%
Standard deviation	1.876	0.945
Number of iterations	300-400	200-300

V. CONCLUSION

The most significant contribution of this paper is solving the problem of USV collision avoidance planning in the complex marine environment by using the improved genetic algorithm. For the complex marine environment, we establish models of the USV system. When the USV encounters dynamic obstacles, we divide scenarios involving encounters and design corresponding collision avoidance strategies; and calculate the motion parameters and risk of collision to determine whether to start collision avoidance. Following this, we improve the genetic algorithm through retention, deletion, and replacement, use the analytic hierarchy process to build the fitness, iteratively optimize the acceleration and yaw rate, and calculate the optimal path for collision avoidance for USV.

Finally, we built a USV simulation platform of collision avoidance planning based on the QT software, and designed some typical simulation cases to verify the effectiveness of the proposed collision avoidance planning. The results show that the proposed method can be used to plan the optimal path of collision avoidance for USV in complex environment, and has good stability and smooth trajectories. Compared with the conventional genetic algorithm, the improved algorithm effectively reduces the number of iterations, running time, and standard deviation, and improves the success rate.

ACKNOWLEDGMENT

The authors thank the Automation College of Harbin Engineering University for providing a laboratory learning environment and experimental equipment, and colleagues and students in the laboratory for their assistance.

This work was supported in part by the National Natural Science Foundation of China under Grant 61633008 and Grant 51609046, and in part by the Natural Science Foundation of Heilongjiang Province under Grant F2015035.

REFERENCES

[1] J. Wang, W. Gu, J. Zhu, J. Zhang, “An Unmanned Surface Vehicle for multi-mission applications,” *Proc. - Int. Conf. Electron. Comput. Technol.,* Macau, China, pp. 358-361, Feb. 2009, 10.1109/ICECT.2009.136.

[2] J. Larson, M. Bruch, R. Halterman, J. Rogers, R. Webster, “Advances in autonomous obstacle avoidance for unmanned surface vehicles,” in *Assoc. Unmanned Veh. Syst. Int. - Unmanned Syst. North America Conf.*, Washington, D.C., United states, vol. 1, pp. 484-498, Aug. 2007.

[3] P. Tang, R. Zhang, D. Liu, L. Huang, G. Liu, and T. Deng, “Local reactive obstacle avoidance approach for high-speed unmanned surface vehicle,” Ocean Eng., vol. 106, pp. 128-140, Jul. 2015, 10.1016/j.oceaneng.2015.06.055.

[4] B. Richard, L. Yuanchang, S. Rui, “Smoothed A* algorithm for practical unmanned surface vehicle path planning,” Appl. Ocean Res., vol. 83, pp. 9-20, Feb. 2019, 10.1016/j.apor.2018.12.001.

[5] L. Song, Z. Chen, Y. Mao, Z. Dong, Z. Xiang, “Error Mitigation Algorithm Based on Bidirectional Fitting Method for Collision Avoidance of Unmanned Surface Vehicle,” Pol. Marit. Res., vol. 25, no. 4, pp. 13–20, 2018, 10.2478/pomr-2018-0127.

[6] Y. Liu, R. Bucknall, “Path planning algorithm for unmanned surface vehicles formations in a practical maritime environment,” Ocean Eng., vol. 97, pp. 126-144, Mar. 2015, 10.1016/j.oceaneng.2015.01.008.

[7] H. Fukushima, K. Kon, F. Matsuno, “Model predictive formation control using branch-and-bound compatible with collision avoidance problems,” IEEE Trans. Rob., vol. 29, no. 5, pp. 1308-1317, 2013, 10.1109/TRO.2013.2262751.

[8] A. He, X. He, B. Xiao, “Underwater unmanned platform route planning based on improved genetic algorithm,” in Jour. Qingdao Univ, Qingdao, China, 2012, vol. 14, no. 4, pp. 89-92.

[9] G. Li, C. Guo, Y. Li, W. Deng, “Fractional-Order PID Controller of USV Course-Keeping Using Hybrid GA-PSO Algorithm,” Proc. - Int. Symp. Comput. Intell. Des, vol. 2, pp. 506-509, May. 2016, 10.1109/ISCID.2015.134.

[10] Y. Liu, X. Wu, Y. Guo, S. Xie, H. Pu, Y. Peng, “The multiple unmanned surface vehicles cooperative defense based on PM-PSO and GA-PSO in the sophisticated sea environment,” Front. Artif. Intell. Appl., vol. 303, pp. 801-809, 2018, 10.3233/978-1-61499-900-3-801

[11] Y.He, Z. Jia, W. Zhang, Q. Jia, Y. Li, “Layered berthing method and experiment of unmanned surface vehicle based on multiple constraints analysis,” Appl. Ocean Res., vol. 86, pp. 47-60, 2019, 10.1016/j.apor.2019.02.003.

[12] Bye, Robin T, Schaathun, Hans Georg, “A simulation study of evaluation heuristics for tug fleet optimisation algorithms," Commun. Comput. Info. Sci, Jan 10, 2015, vol. 577, pp. 165-190, 10.1007/978-3-319-27680-9_11.

[13] Yamin Huang, Linying Chen, Pengfei Chen, Rudy R. Negenborn, P.H.A.J.M. van Gelder, "Ship collision avoidance methods: State-of-the-art", Safety. Sci., Vol. 121, 2020, pp. 451-473

[14] G. Li, C. Guo, Y. Li, W. Deng, “Fractional-Order PID Controller of USV Course-Keeping Using Hybrid GA-PSO Algorithm,” Proc. - Int. Symp. Comput. Intell. Des, vol. 2, pp. 506-509, May. 2016, 10.1109/ISCID.2015.134.

[15] Bye, Robin T, " A Receding Horizon Genetic Algorithm for Dynamic Resource Allocation: A Case Study on Optimal Positioning of Tugs," *Int. Con. Comp. Intel*, Valencia, SPAIN, Oct 24-26, 2010, vol. 399, pp. 131-147.

[16] Tsou, M., Kao, S., & Su, C. (2010). Decision Support from Genetic Algorithms for Ship Collision Avoidance Route Planning and Alerts. Jour. Navigation, vol. 63, no. 1, pp. 167-182, 10.1017/S037346330999021X.

[17] Shengke Ni, Zhengjiang Liu, Yao Cai, Xin Wang, "Modelling of Ship’s Trajectory Planning in Collision Situations by Hybrid Genetic Algorithm", Pol. Mar. Res. 3 (99) 2018, vol. 25, pp. 14-25, 10.2478/pomr-2018-0092.

[18] X. Zeng, M. Ito and E. Shimizu, "Collision avoidance of moving obstacles for ship with genetic algorithm," Proc. Int. Cat. No.00TH8494, Nagoya, Japan, 2000, pp. 513-518.

[19] Y. Zhao, W. Li, P. Shi, “A real-time collision avoidance learning system for Unmanned Surface Vessels,” Neurocomputing, vol. 182, pp. 255-266, Mar. 2016, 10.1016/j.neucom.2015.12.028

[20] S. Campbell, M. Abu-Tair, W. Naeem, “An automatic COLREGs-compliant obstacle avoidance system for an unmanned surface vehicle,” Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ, vol. 228, no. 2, pp. 108-121, May. 2014, 10.1177/1475090213498229.