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COLREGs-Compliant Unmanned Surface Vehicles Collision Avoidance Based on Multi-Objective Genetic Algorithm

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ABSTRACT Autonomous ships or Unmanned Surface Vehicles (USV) collision avoidance and path planning problems among multi-vessels are investigated in this paper. Firstly, a modified fuzzy dynamic risk of collision model based on time and space collision risk index is proposed, which is much closer to real ship applications. Then, the fitness functions based on the risk of collision, navigational economy, International Regulations for Preventing Collisions at Sea 1972 (COLREGs) and collision avoidance timing are established respectively to ensure the rationality of ship collision avoidance decisions. Moreover, path planning with global search capability is realized by the multi-objective decision theory combined with a genetic algorithm. The practicability and rationality of the recommended trajectory are guaranteed. Meanwhile, the problem of the non-inferior solution can be addressed by adapting the weight method and the constraint method and the optimized solution of the decision-making system can be achieved finally. Simulation results are further presented to validate the effectiveness of the proposed path planning and collision avoidance methods.

INDEX TERMS Genetic algorithms, automatic collision avoidance, risk of collision, multi-objective decision making.

I. INTRODUCTION

In recent years, with the rapid development of Artificial Intelligence (AI) technology [1], [2], many intelligent algorithms, such as genetic algorithms, expert intelligence systems [3], [4], neural network algorithms [5]–[7], and fuzzy logic algorithms [8], [9] are widely used in the automation research of automobiles and aerial vehicle [10]. On the other side, the revolution of navigation technology also promoted the development of ship automation and ship intelligence technology, and the Maritime Autonomous Surface Ships (MASS) or the Unmanned Surface Vehicles (USV) have become a popular research topic [11]–[13].

Automatic collision avoidance is one of the key technologies to realize autonomous navigation. It will significantly

reduce the probability of collision accidents caused by human error and achieve active prevention [14], [15].

Intelligent expert system based approaches were applied to research ship avoidance collision in [16], [17]. Neural network-based ships collision avoidance problems were studied in [18], [19]. A fuzzy logic-based decision-making system for collision avoidance of ocean navigation could be found in [20], [21]. However, as pointed out in [22], intelligent expert system, neural networks and fuzzy logic-based ship collision avoidance algorithms have their own merits and shortcomings. For example, intelligent expert system approaches have a high professional level and excellent reliability but they are difficult to make creative answers to unexpected situations [16], while during a multi-vessels encounter situation, sometimes ships will involve in an emergency situation. Neural network methods can identify the nonlinear and complex ship motion model, but their effects are highly dependent on training evolutionary learning data [16].

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In addition, the fuzzy logic algorithm has strong fault-tolerant ability, and is robust to the system controlled object, environment change and condition change, but the control accuracy depends heavily on the prior knowledge of expert database, the problem of multi-objective matching during emergency situation still cannot be solved well [20], [21].

Recently, the genetic algorithm based ship path planning and collision avoidance have been studied extensively [23]–[27].

Genetic algorithm is a computational model that simulates the natural selection of Darwin's biological evolution theory and the biological evolution process of genetic mechanisms. It is a method to search for the optimal solution by simulating the natural evolution process [25]. In addition, it has been revealed in [22] that the genetic algorithm can be used to model the ship's trajectory planning and collision avoidance during a multi-vessel encounter situation. Moreover, the weakness of the above-mentioned algorithms can be overcome. Hence, it is of great significance to research ship path planning and collision avoidance based on the genetic algorithm. Chien-Chou Shih [28] *et al.* proposed a genetic-based approach to path-planning of the autonomous underwater glider. Wenyu Cai [29] *et al.* used genetic algorithms to solve the multi-traveler problem with Euclidean distance as a cost function when studying underwater unmanned ship path planning. Nevertheless, both [28] and [29] are not focusing on the path planning of the surface vehicle.

Based on big data analysis, the genetic algorithm was used to realize the intelligent avoidance of shipwreck in [30], but no emergency situation or unforeseen scenarios are considered. Based on the genetic algorithms, Yang Long [31] *et al.* proposed a new initial population method to create a better initial population quality, and designed adaptive crossover probability and mutation probability. However, this method uses the grid method to construct the navigation environment, the size and number of grids will directly affect the algorithm's operation speed and the effectiveness of collision avoidance decisions, meanwhile the grid method is challenging to apply to multi-vessels collision avoidance in complex waters. In [32], the branch-and-bound method and genetic algorithms were adopted to solve the task of optimal safe ship trajectory in a collision situation. However, the index factors of the shipping risk model were not fully considered. In [33], the trajectory planning was addressed to achieve multi-vessel collision avoidance based on the Genetic Algorithm and Nonlinear Programming, but the simulation only applies to open-sea, and can not achieve good collision avoidance effect in dense navigable waters.

In this brief, COLREGs-compliant multi-vessels collision avoidance based on the multi-objective genetic algorithm is investigated and the typical situation simulation of multi-vessel are presented.

As to the risk decision model of ship collision avoidance, the traditional risk model based on the risk of space collision index and time collision index will “over-maximize” the calculated risk of ship collision to some extent, and it is

easy to cause uncoordinated actions when making collision avoidance decisions. Therefore, a modified fuzzy dynamic risk of the collision model is proposed, which is much more in line with the actual situation. Then, the fitness functions based on the risk of collision, navigational economy and collision avoidance timing are established respectively. Combined with the author's actual ship working experience, it is worth mentioning that International Regulations for Preventing Collisions at Sea (COLREGS) are also considered to ensure the rationality of ship collision avoidance decisions. While due to the contradiction of each objective function, the optimal solution of each objective function cannot be achieved simultaneously. In view of this, the weight method and constraint method are considered comprehensively according to the characteristics of each objective function. Based on the multi-objective genetic algorithm, path planning with global search capability and collision avoidance can be realized. Both the practicability and rationality of the recommended trajectory are guaranteed. Finally, simulation results are shown to demonstrate the effectiveness of the proposed path planning and collision avoidance methods.

Compare with the existing research on ship path planning and collision avoidance, the main contributions of this study are as follows.

First, based on the author's actual ship working experience, a modified fuzzy dynamic risk of the collision model is applied, which is more suitable for navigation practice. Meanwhile, COLREGs are also well-considered. In [34], combined with the modified rapidly-exploring random tree (RRT) algorithm and modified dynamic window (DW) algorithm, a parallel trajectory planning algorithm was proposed. However, both [34] and [22] can not reflect the risk of collision (ROC) between ships, even though ROC is not clearly defined in COLREGs, it is an important index to measure the navigation safety of ships. In [14], COLREGs-constrained ships path planning was addressed based on the modified artificial potential fields, it can achieve real-time collision avoidance, but the decision model mainly relies on the single factor of the distance between ships.

In [35], a distributed coordination for collision avoidance of multiple ships are discussed, but its compatibility with COLREGs and the ROC indicators should be further addressed. In this case, a comprehensive ROC model is more necessary.

Second, the fitness functions based on ROC, navigational economy and collision avoidance timing and COLREGs are established respectively. Compared with the selection of fitness function in previous literature, such as [14], [22], [31], and [32], the fitness functions in this brief is more practicality and rationality.

Third, a multi-objective decision theory-based genetic algorithm is adopted. While in [14], the path planning was based on the artificial potential field method, the problem of optimal local solution cannot be solved well. In [35], the rudder angles and the corresponding operation time for rudder steering were used as the optimization strategy to find

the collision avoidance plan. However, the practicality of the recommended route remains to be further verified.

The remainder of this paper is organized as follows. Ships collision avoidance process is introduced in Section II. In Section III, the main result of a multi-objective decision theory-based genetic algorithm is presented. The effectiveness of the proposed algorithm is validated by simulation in Section IV. This brief ends with conclusions drawn in Section V.

II. OVERVIEW OF SHIP COLLISION AVOIDANCE PROCESS

A. DIVISION OF SHIP COLLISION AVOIDANCE PHASE AND SAFETY DOMAIN

Collision prevention is an incredibly complicated process, which requires a thorough study of the entire process and every single section. COLREGs merely makes qualitative stipulations on every part, while quantitative studies are necessary to build a mathematical model for every section [36]. As is shown in Figure 1, the decision-making process of vessel collision avoidance mainly includes the following aspects.

field and put forward various models. For the convenience of the system application, this brief adopts the SDA model based on the ship domain that was proposed by Goodwin [37]. The region of the ship’s safety domain is shown in figure 2.

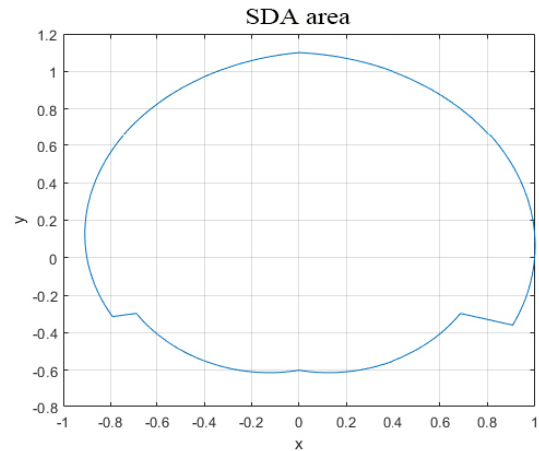


FIGURE 2. The region of the ship safety domain.

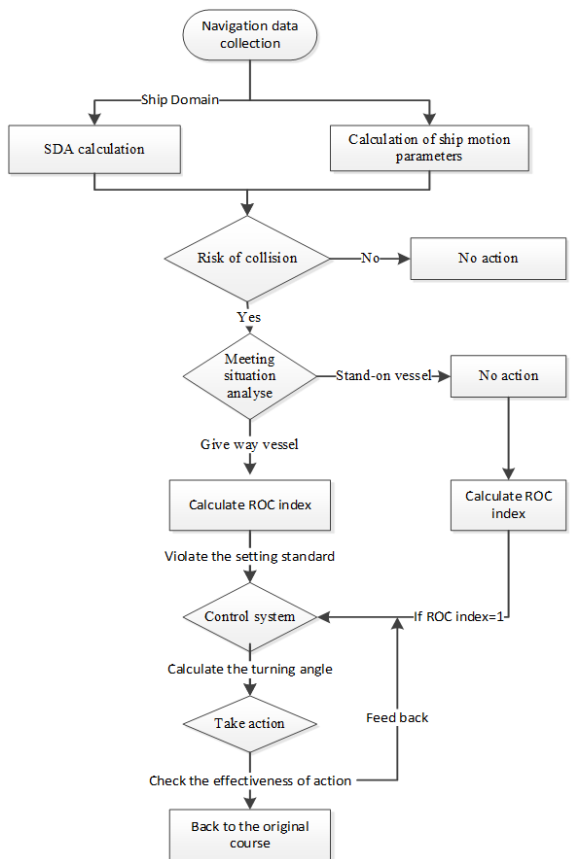


FIGURE 1. Flow chart of ship collision avoidance decision.

There is no unified standard for the Safe Distance of Approach (SDA) in COLREGs. The ship domain is a spatial scale surrounding the vessel that the obstacles and other vessels shall keep clear. It is also a vital criterion in assessing the encounter situation. Many experts have studied in this

Based on the revised domain model, when determining the safe encounter distance, the concept of a fuzzy boundary is used to obtain the fuzzy boundary [38], fuzzy boundary = $0.276domain = 0.276SDA$. The time to conduct action by the give-way vessel is determined as follows:

$DCPA$ (Distance to closest point of approach) $\geq SDA$ means a safe encounter situation, no action;

$SDA \geq DCPA \geq SDA - FBD$ (Fuzzy boundary) means that it involves an ROC, but the risk is relatively low; the give-way vessel can take no action.

$DCPA \leq SDA - FBD$ means that it involves an ROC; the give-way vessel should take actions to keep out of the way of the stand-on vessel, make sure that it is finally past and clear and $DCPA \geq SDA$ is restored.

Encounter situation includes every situation, no matter whether the vessels are in sight of one another or not. According to the COLREGs, and considering the general practice of seafarers, the encounter situation can be divided into six regions when the two ships are in sight of one another. As shown in Figure 3, the own ship has the responsibility to keep out of the way of the coming ship in the direction of the F, A, and B areas. The own ship shall alter course to starboard of the coming vessel in F and A areas, and alter course to port of the coming vessel in B area. The own ship is a stand-on vessel to the coming vessel in C, D and E, and shall keep her course and speed. If the own ship finds that the give-way vessel does not take appropriate action in compliance with COLREGs, she may conduct an action to avoid collision by her maneuver alone.

B. RISK OF COLLISION MODEL

1) SPACE COLLISION RISK

Space Collision Risk (SCR) index refers to a measurement of ROC when a possible collision accident exists between the

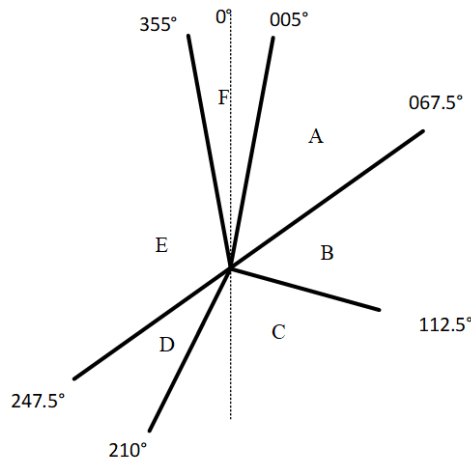


FIGURE 3. Collision avoidance action classification between two ships.

two vessels. Here the SCR is determined by the relationship between $DCPA$ and ship safety encounter area d_1 and ship safety passing distance d_2 . When $|DCPA| < d_1$, it is considered that the ship is involved in a collision situation. At this time, $SCR = 1$; When $|DCPA| > d_2$, that is, $DCPA$ is greater than the safety passing distance of the ship, the ship has no collision risk, $SCR = 0$; when $d_1 \leq |DCPA| \leq d_2$, the range of SCR values varies with $DCPA$ [39]. The subordinated function udt of the space collision risk is shown in equation (1).

$$udt = \begin{cases} 1 & |DCPA| \leq d_1 \\ \left[\frac{d_2 - |DCPA|}{d_2 - d_1} \right]^{3.03} & d_1 \leq |DCPA| \leq d_2 \\ 0 & d_2 \leq |DCPA| \end{cases} \quad (1)$$

2) TIME COLLISION RISK

Time collision risk (TCR) index refers to the temporal urgency degree when a vessel is navigating toward the point of last-minute action.

If the time from the position when the collision avoidance operation is taken to the point of last-minute action is t_1 , then when $TCPA$ (Time to closest point of approach) $< t_1$, the TCR is considered to be 1. Meanwhile, according to common practice and perception of seafarers, if the distance between the two vessels is outside 12 n mile, then the TCR can be set to zero by default. The TCR is reflected in the relationship between $TCPA$, t_1 and t_2 . When $TCPA$ makes “+,” it means that the ship has not passed the Closed Point of Approach (CPA). When $TCPA$ makes “-,” it means that the ship has already passed the CPA [39]. Thus, the subordinated function of the TCR is as shown in equations (2) and (3).

When $TCPA > 0$, the subordinated function of the time collision risk utt is

$$utt = \begin{cases} 1 & TCPA \leq t_1 \\ \left[\frac{t_2 - TCPA}{t_2 - t_1} \right]^{3.03} & t_1 \leq TCPA \leq t_2 \\ 0 & t_2 \leq TCPA \end{cases} \quad (2)$$

When $TCPA \leq 0$, the subordinated function of the time collision risk utt is

$$utt = \begin{cases} 1 & |TCPA| \leq t_1 \\ \left[\frac{t_2 + TCPA}{t_2 - t_1} \right]^{3.03} & t_1 \leq |TCPA| \leq t_2 \\ 0 & t_2 \leq |TCPA| \end{cases} \quad (3)$$

where $t_1 = \frac{\sqrt{D_L^2 - DCPA_{DLMA}^2}}{V_r}$, $t_2 = \frac{\sqrt{12^2 - DCPA^2}}{V_r}$.

D_L indicates the distance between vessels at the last minute action point. $DCPA_{DLMA}$ is the $DCPA$ value of the ship at the last-minute action point. For the sake of safety, in this paper, ROC begins since the two ships are in sight of each other within 12 nautical miles.

3) CALCULATION OF THE LAST MINUTE ACTION POINT

This brief uses the method of [38] to calculate the point of last-minute action. Assume that when own ship is full of rudder turning 090° , the two ships just collided at this time. The K in equation (5) represents the index of the turning ability, and T represents the index of tracing ability.

The transverse distance of the 090° head changing

$$T_R = 2v_0/(K\delta) \times \sin\left(\frac{\Delta C^2}{2}\right), \quad \delta = 35^\circ \quad (4)$$

Turning time

$$t = T + t_0/2 + \Delta C/(K\delta) \quad t_0 = 30s \quad (5)$$

The longitudinal distance of the 090° head changing

$$A_d = v_0 \times [(T + t_0/2) + \sin\left(\frac{\Delta C}{K\delta}\right)] \quad (6)$$

The ship’s moving distance

$$D_0 = \sqrt{A_d^2 + T_r^2} \quad (7)$$

The moving distance of the target ship within time “t”

$$D_t = v_1 t \quad (8)$$

Use (x_0, y_0) to represent (x'_0, y'_0)

$$\begin{cases} x'_0 = x_0 + A_d \sin c_0 + T_R \cos c_0 \\ y'_0 = y_0 + A_d \cos c_0 + T_R \sin c_0 \end{cases} \quad (9)$$

Use (x_1, y_1) to represent (x'_1, y'_1)

$$\begin{cases} x'_1 = x_1 + D_t \sin c_t \\ y'_1 = y_1 + D_t \cos c_t \end{cases} \quad (10)$$

Establish the relationship between (x_0, y_0) and (x_1, y_1) according to the relationship between (x'_0, y'_0) and (x'_1, y'_1)

$$\begin{cases} x'_0 - x'_1 = (L_0/2 + B_r/2) \sin(c_0 + \Delta c) \\ y'_0 - y'_1 = (L_0/2 + B_r/2) \cos(c_0 + \Delta c) \end{cases} \quad (11)$$

According to formula (9), formula (10), formula (11), the distance between the initial two ships is obtained, which is the distance between vessels at the last-minute action point.

$$D_L = \sqrt{(x_0 - x_t)^2 + (y_0 - y_t)^2} \quad (12)$$

4) SHIP RISK OF COLLISION MODEL

The calculation models of SCR and TCR used in literature [39] are shown as follows:

$$CRI = udt \otimes utt \quad (13)$$

CRI means the index of ROC, the meanings of the above expression are

- (1) if $udt = 0$, then $CRI = 0$
- (2) if $utt = 0$, then $CRI = 0$
- (3) if $udt \neq 0, utt \neq 0$, then $CRI = \max(udt, utt)$

The ROC calculation model in formula (13) can reflect the actual ROC value of ships to a certain extent, but it will also lead to the over-maximization of ROC, which will lead to a big difference between the calculated result of collision avoidance situation of some ships and the actual value, and The original low-risk encounter situation will be miscalculated as a high-risk situation.

When the ship performs the actual avoidance operation, it only needs to ensure that the value of the SCR or TCR is reduced to the safe avoidance threshold, that is, the actions taken are effective to avoid a collision.

For SCR and TCR, only specific avoidance measures need to be taken to ensure that the minimum value is reduced to 0, then it is safe to “avoid” the other ship, and the scope of the avoidance measures at this time is small. Based on this principle, the modified ROC model can be taken as follows:

$$CRI = \min(udt, utt) \quad (14)$$

III. SHIP COLLISION AVOIDANCE BASED ON MULTI-OBJECTIVE GENETIC ALGORITHM

A. MULTI-OBJECTIVE DECISION THEORY

Compared with single-objective decision-making, multi-objective decision-making is more complicated, mainly reflected in incommensurability and contradiction between goals. Incommensurability means that when making multi-objective decisions, each target measurement unit is not uniform; contradiction means that when one method is used to optimize an objective, the performance of other objectives will become worse, it is difficult to make the values of each objective the optimal solution.

These two typical characteristics of multi-objective decision-making make the solution not unique when solving the target optimization. In the case of multi-objective decision making, a series of non-inferior solutions are usually obtained. In this brief, when studying the multi-objective decision-making problem of ship collision avoidance, it requires the minimum collision risk of the ship and the minimum deviation from the original route. Therefore, a scheme that minimizes the value of each objective function is selected for multi-objective decision making.

Let $x = (x_1, x_2, \dots, x_n)^T$ be the n -dimensional vector composed of decision variables. The constraint of the decision variable is $g_i(x)$ representing the i -th constraint.

The objective functions of multi-objective decision are expressed as $f_1(x), f_2(x), \dots, f_p(x)$, respectively. Then the multi-objective decision problem of p objective functions under m constraints can be expressed as:

$$\begin{aligned} \min F(x) &= (f_1(x), f_2(x), \dots, f_p(x)) \\ \text{s.t. } g_i(x) &\leq 0, i = 1, 2, \dots, m \\ lb &\leq x_j \leq ub, j = 1, 2, \dots, n \end{aligned} \quad (15)$$

In equation (15), lb, ub are the lower and upper limits of the decision variable, respectively. Here, as an example, the constraint condition is $g_i(x) \leq 0$ and the actual situation depends on different problems.

The above description is a representation of the multi-objective decision problem. If $X = \{x | g_i(x) \leq 0, i = 1, 2, \dots, n\}$, the mathematical definition of the non-inferior solution can be expressed as:

Let $\bar{x} \in X$, if there is no arbitrary $x \in X$, makes $F(x) \geq F(\bar{x})$, and there is at least one component that makes $f_i(x) \geq f_i(\bar{x})$, then \bar{x} is the non-inferior solution in the multi-objective decision problem.

B. GENETIC ALGORITHM IMPLEMENTATION PROCESS

1) CHROMOSOME CODING

The genetic algorithm is a random search optimization algorithm based on natural selection and biological, genetic mechanism. As to the genetic algorithm, the coding of the chromosome is the initial condition of the initial population generation. By encoding, the parameters of the problem are encoded and expressed as the chromosome of the genetic algorithm. The most widely used methods of chromosome coding are binary coding and real coding. The coding method used in this paper is actual number coding, which does not need to perform the numerical conversion, but directly uses real numbers to represent decision variables, and each chromosome corresponds to a real number vector.

2) INDIVIDUAL FITNESS EVALUATION

In the genetic algorithm, the fitness of the individual is evaluated by establishing a fitness function, and the possibility of the individual inheriting downward is determined. It should be noted that when calculating the probability, the fitness of all individuals is non-negative, then the individuals with high fitness can continue to inherit. The selection of the fitness function mainly includes the following three ways.

- 1) Directly transform the objective function into a fitness function F .

$$F = \begin{cases} f(x) & \text{The objective function is maximized} \\ -f(x) & \text{The objective function is minimized} \end{cases} \quad (16)$$

- 2) Problem of finding the minimum.

$$F = \begin{cases} c_{\max} - f(x) & f(x) < c_{\max} \\ 0 & \text{else} \end{cases} \quad (17)$$

If it is the problem of seeking the maximum value, then

$$F = \begin{cases} f(x) + c_{\min} & f(x) > c_{\min} \\ 0 & \text{else} \end{cases} \quad (18)$$

3) The problem of the objective function being the minimum.

$$F = \begin{cases} \frac{1}{1 + c + f(x)} & c > 0, c + f(x) \geq 0 \\ \frac{1}{1 + c - f(x)} & c > 0, c - f(x) \geq 0 \end{cases} \quad (19)$$

3) BASIC OPERATION OF GENETIC ALGORITHM

The essential operation of the genetic algorithm simulates the process of chromosomes in biological evolution and genetic mechanisms, including selection, crossover, and variation.

The selection operation, also called replication, selects individuals with better performance in the population with a certain probability, and replicates to the next generation for reproduction. The likelihood of the individual being selected is proportional to the individual's fitness value, that is, the fitness value is higher; the greater the probability of being selected. Commonly used selection operations include the roulette method, bidding competition selection, and optimal preservation strategy.

Among them, the roulette method is widely used, and the possibility that an individual is selected as follows.

$$p_i = F_i / \sum_j^N F_j \quad (20)$$

In equation (20), F_i is the fitness value of the individual, and N is the size of the population size.

The crossover operation in the genetic algorithm is exchanged and combined by two chromosomes in the parent. The crossover operation generally has binary coding and real coding. In this brief, the actual coding is used. The method of crossover operation of chromosome a_k , and chromosome a_l at the position j is as follows:

$$\begin{cases} a_{kj} = a_{kj}(1 - b) + a_{lj}b \\ a_{lj} = a_{lj}(1 - b) + a_{kj}b \end{cases} \quad b \text{ is a random number between } [0 \ 1] \quad (21)$$

The operation of mutation is the operation of mutation on a certain point in the chromosome to make it mutate into a better new individual. The method of mutating the j -th gene a_{ij} of the individual i is as follows.

$$a_{ij} = \begin{cases} a_{ij} - (a_{ij} - a_{\max}) * f(g), & r \geq 0.5 \\ a_{ij} - (a_{\min} - a_{ij}) * f(g), & r < 0.5 \end{cases} \quad f(g) = r_2(1 - g/G_{\max})^2 \quad (22)$$

In equation (22), a_{\max} represents the upper bound of the gene a_{ij} , a_{\min} represents the lower bound; whereas in $f(g)$, r_2 represents the random number, g represents the number of iterations of the current algorithm, G_{\max} is the maximum number of iterations, and r is a random number between $[0 \ 1]$.

The population of the genetic algorithm will continue to perform the genetic operations until the algorithm requirements are met.

C. DESCRIPTION OF SHIPS COLLISION AVOIDANCE PROBLEMS

At present, the determination of collision avoidance timing mainly includes the use of the ship domain to determine the collision avoidance timing [40], the use of the threshold value of ROC to determine the collision avoidance timing [41], and the use of data statistics to determine the collision avoidance timing [42].

In this brief, the threshold of ROC is set to determine the avoidance timing during an encounter situation, that is, the threshold $CRI = 0.5$. When the $CRI \geq 0.5$, the own ship begins to take action to avoid a collision, that is, to take early evasive action. The principle of actions taken by the give-way vessel is to minimize the ROC between the vessels.

But if only the path with the least risk of collision is taken, the path will continue to be deflected after the action is taken

However, if only the route with the least risk of collision is taken, the route will continue to deflect after taking action, and the trend toward $CRI = 0$ will be developed, at this time, although it is safe to avoid the other ship, it is an unreasonable avoidance action.

In order to make up for this problem, and also under the premise of ensuring the safety of avoidance, make the ship avoidance route to a lesser extent deviation than the original route is necessary.

In the decision-making process of collision avoidance, not only the safety of the route should be satisfied, but also the economy should be achieved as far as possible. Moreover, the COLREGs should also be met. However, the values of the various objective functions are contradictory. Therefore, how to find the optimal solution of avoidance action in each contradictory objective function becomes the primary problem to be studied in this brief.

D. SELECTION OF FITNESS FUNCTION

1) SEFETY-BASED FITNESS FUNCTION

As was shown in [43], the safety of the ship is the first factor to be considered; that is, during an encounter situation, the give-way vessel should take action to avoid collision within a valid distance. When $CRI = 0$, it indicates that the collision risk of the two ships is 0, and when $CRI = 1$, it suggests that the two ships have the highest collision risk. The CRI reflects the degree of collision risk of the ship in space and time. So the minimum CRI value is required to ensure an effective collision avoidance.

In this brief, when planning the collision avoidance path of the ship, considering the actual avoidance process, the ship will not continuously change the heading to perform the avoidance operation. Therefore, this brief divides the collision avoidance path planning into several sub-segments, and each sub-segment the ship is guaranteed to navigate at

a constant speed, and during each sub-segment, the *CRI* of the ship is continuously changing with time. It is required that the ROC in each sub-segment is the smallest, that is, only take the objective function as the maximum value of ROC in the sub-segment, if the maximum value of ROC in the sub-segment is minimized, the value of ROC in the entire segment is small.

Therefore, the fitness function is selected as follows.

$$f_1(x) = \max CRI(V_0, C_0, V_1, C_1, T_r, D) \quad (23)$$

where V_0 is the own ship's speed, C_0 is the ship's heading, V_1 is the target ship's speed, C_1 is the target ship's heading, T_r is the relative bearing, and D is the distance between the ship and the target ship.

2) ECONOMIC-BASED FITNESS FUNCTION

The economic requirement of ship navigation requires that the ship should use the minimum rudder operating range to achieve the best collision avoidance effect during the collision avoidance situation. Therefore, the degree to which a ship deviates from its original course after taking action to avoid a collision can be regarded as the fitness function of the economy. The smaller the degree of deviation from the original route, the better the economic performance of the route is.

The degree to which the collision path deviates from the original course is shown in Figure 4.

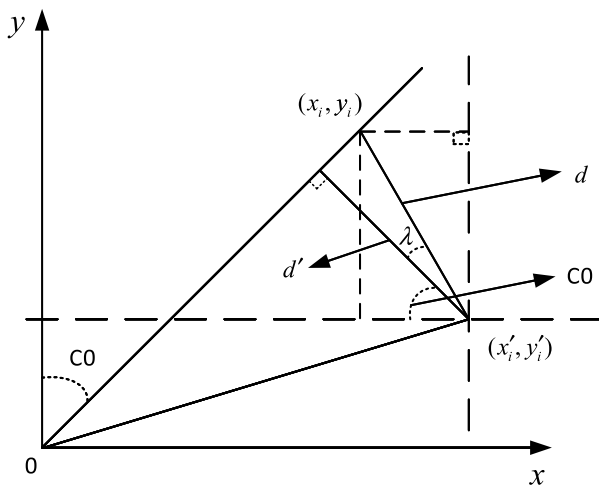


FIGURE 4. The path deviates from the original route.

Set the coordinates of each waypoint of the collision avoidance path: (x'_i, y'_i) . The corresponding position on the original route is: (x_i, y_i) . The distance between the two positions is d , the vertical distance of the ship's steering path point from the original route is d' . In this brief, when the sum of d' of all the segments is the smallest, it is considered that the deviation between the collision path and the original path is minor. $d' = d \cos(\lambda)$, $\lambda = \arctan(|y'_i - y_i| / |x'_i - x_i|) - C_0$, C_0 is the original true course.

Since the ship only considers the steering avoidance measure, the distance on the original route within the same time

interval is equal to the distance after the steering, Therefore, a $\tan(|y'_i - y_i| / |x'_i - x_i|) \geq C_0$ is always true, that is, $\lambda \geq 0$ is always true, and the fitness function can be chosen as

$$f_2(x) = \sum_i^n \sqrt{(x'_i - x_i)^2 + (y'_i - y_i)^2} \times \cos(\arctan(|y'_i - y_i| / |x'_i - x_i|) - C_0) \quad (24)$$

Among them, n means the number of waypoints.

3) FITNESS FUNCTION BASED ON COLLISION AVOIDANCE RULES

When a ship is navigating at sea, the means to avoid a collision can be varied as long as the navigation safety can be guaranteed.

In conditions of excellent visibility and when ships are optically in sight of each other, if two ships are involved in a ROC or cannot guarantee the safe encounter distance, according to COLREGs, the give-way vessel shall conduct early and substantial actions to keep well clear of the other vessel.

Moreover, according to the Rule eight of COLREGs, if the sea-room is sufficient, and the substantial actions are taken in good time and do not lead to another close-quarters situation, then the alteration of course alone may be the most effective action to avoid a close-quarters situation (Commandant, U. C. G., 1999). Thus the autopilot in this dissertation adopted course alteration to avoid a close-quarters situation, but not the acceleration or deceleration maneuvers. So in this brief, the alteration of course is considered as the ship's collision avoidance operation.

In the previous analysis of the situation of the ship's encounter situation, when the relative bearing T_r of a coming vessel is in the A, B, F area, the own ship is the give-way vessel. In other regions, the own ship is a stand-on vessel and should keep course and speed. This brief mainly considers the avoidance action when the ship is a give-way vessel. Therefore, the fitness function when considering the COLREGs is chosen as follows.

$$f_3(x) = \begin{cases} 1 & 000^\circ \leq T_r \leq 112.5^\circ \text{ or } 355^\circ \leq T_r \leq 360^\circ \\ 0 & \text{others} \end{cases} \quad (25)$$

The fitness function $f_3(x)$ can also reflect whether the vessel is a give-way vessel or a stand-on vessel.

4) FITNESS FUNCTION BASED ON AVOIDANCE TIMING

The determination of the occasion for the avoidance of collision is a crucial task. It is of great importance to know how to appropriately and adequately confirm the time of avoiding a collision and take action. Premature actions are of no necessity, while on the other hand, if the actions are taken too late, it may lead the two vessels to fall into a close-quarters situation and uncoordinated actions or even a collision accident. Meanwhile, COLREGs stipulates that avoidance actions should be taken in a "timely" manner. Therefore, the occasion of collision avoidance is a standard to estimate if the action is "timely" enough.

This brief applies the ROC index to determine the occasion of collision avoidance, the risk index and safety index are relative concepts, and the sum of them equals 1. When the risk increases, the degree of safety decreases and vice versa.

The actions should be “timely,” so it is dangerous when the ROC index is equal to or higher than the safety index, and at this moment, vessels should take actions. That is to say, when the ROC index is equal to or higher than 0.5, vessels should conduct actions to avoid a collision, which is precisely the time of collision avoidance for the give-way vessel.

The 2nd item of Rule 17 in COLREGs stipulates that the stand-on vessel shall take action as will best aid collision-avoidance if she finds that the collision cannot be avoided by the action of the give-way vessel alone.

Here, the word “should” is a compulsory demand for the stand-on vessel, so the occasion means that the stand-on vessel should adopt the best way to take action to avoid a collision when the give-way vessel has reached the point of last-minute action but has done nothing. At this time, where $DCPA < SDA$, the ROC index of the stand-on vessel is 1.

Like the fitness function $f_3(x)$, the fitness function of the avoidance timing is used as the judgment of whether and when the ship should adopt the avoidance action. Then its fitness function is chosen as follows.

$$f_4(x) = \begin{cases} 1 & CRI \geq 0.5 \\ 0 & CRI < 0.5 \end{cases} \quad (26)$$

E. MULTI-OBJECTIVE GENETIC ALGORITHM SOLVING METHOD

In this brief, the multi-objective genetic algorithm is addressed to solve the optimal solution for ship collision avoidance decision [44]. The decision variable x is one-dimensional, and x is the vector set of steering amplitude, the other objective functions are the functions about x . The collision avoidance actions required by the COLREGs should be “early,” “largely,” “widely,” and “clearly.”

According to the common practice of seafarers, generally, keep clear of the other vessel with a steering range of not less than 15° and avoid collision with a steering range of not less than 30° . It is best to have a head-turning around 60° so that the course of the two ships can be separated clearly. As the crew usually does not use a large steering range, the steering range is generally concentrated between 20° . To ensure that the simulation experiment can reflect the real situation, in this brief the constraint of x is chosen as $-60^\circ \leq x \leq 60^\circ$.

When the multi-objective genetic algorithm is used to solve the ship collision avoidance decision, the fitness functions $f_1(x), f_2(x)$ play a leading role, $f_3(x), f_4(x)$ are used as the judgment of the ship’s obligation and the steering timing, and also play a role in restraining $f_1(x), f_2(x)$.

Then the optimization problem of the multi-objective genetic algorithm can be described as:

$$\begin{aligned} & \min \{f_1(x), f_2(x)\} \\ & s.t. \quad -60^\circ \leq x \leq 60^\circ \\ & \quad f_3(x) = 1 \text{ or } 0 \\ & \quad f_4(x) = 1 \text{ or } 0 \end{aligned} \quad (27)$$

Therefore, the weighting method can be adopted to process $f_1(x), f_2(x)$ into single-objective decision-making problems and then solve them. That is $\omega_1 f_1(x) + \omega_2 f_2(x)$, and constrained by the $f_3(x), f_4(x)$ function. Therefore, the fitness function of the collision avoidance decision in this paper is taken as:

$$F(x) = \omega_1 f_1(x) + \omega_2 f_2(x), \quad \omega_1 + \omega_2 = 1; \quad (28)$$

$f_3(x), f_4(x)$ are constraints, and the smaller the individual’s fitness value, the better the individual’s performance.

F. MULTI-VESSELS ENCOUNTER PROBLEMS

During the period of navigation at sea, ships will often involve in the multiple encounters situation in dense navigable waters [45]. This brief gives priority to the high ROC situation, and take action to avoid collision of the high-risk vessels first, which means the “key avoidance vessel.”

During the multiple-vessels encounter situation, the safety-based fitness function needs to be improved as follows

If own ship is involved in a situation with two ships, the ROC of each ship is: CRI1, CRI2, and the ROC is also time-varying. The safety-based fitness function of each target ship in each sub-segment is respectively:

$$f_{11}(x) = \max CRI1(V_0, C_0, V_1, C_1, T_{r1}, D_1) \quad (29)$$

$$f_{12}(x) = \max CRI2(V_0, C_0, V_2, C_2, T_{r2}, D_2) \quad (30)$$

Under the premise of giving priority to the “key avoidance vessel”, the total fitness function of the two ships is:

$$f_1(x) = \omega_1 * f_{11}(x) + \omega_2 * f_{12}(x) \quad (31)$$

Among them, the ratio between each CRI and the sum of the total two CRIs is taken as the value of ω , that is, the target ship of each sub-segment which has the highest ROC, then she is the “key avoidance ship” in this segment. The value of ω is shown as follows:

$$\omega_i = \frac{f_{1i}}{f_{11} + f_{12}} * f_{1i} \quad i = 1, 2 \quad (32)$$

IV. MULTI-VESSELS ENCOUNTER SIMULATION EXPERIMENT

In this part, take the full-loaded ocean-going vessel “Yupeng” which belongs to DALIAN MARITIME UNIVERSITY as a simulation example, the course of the own ship $C_0 = 045^\circ$, $V_0 = 14\text{kn}$. Avoidance actions are carried out with excellent visibility. The target ship parameters are shown in Table 1.

TABLE 1. Target ship information table.

Target Ship	V/kn	C/°	Tr/°	D/n mile
Target1	7.5	270	025	8.5
Target2	5	225	000	7.5
Target3	10	180	330	8

In order to verify the effectiveness of the automatic genetic collision avoidance algorithm designed in this paper based on ship collision risk, this paper compares the simulation results with [22]. The simulation results of the multi-vessels encounter situation are shown in Figure 5-8.

Figure 5 shows the optimal path planning of the ship after 100 times iteration. When considering the collision avoidance rules and financial requirements, it can safely and effectively avoid other ships.

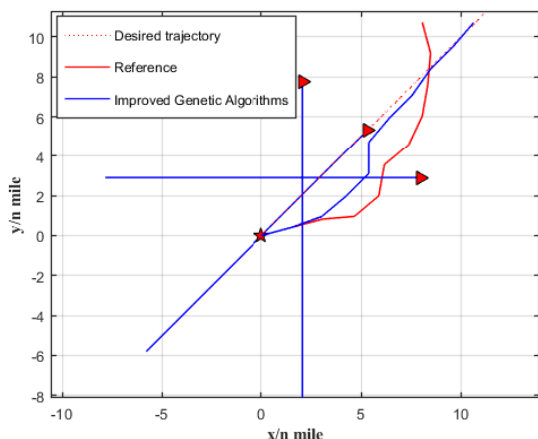


FIGURE 5. The optimal path planning during the multi-vessels encounter situation.

As is shown in Figure 6, the minimum distance between the two ships during the collision avoidance process is more than 1 n miles, keep within safe limits at all times.

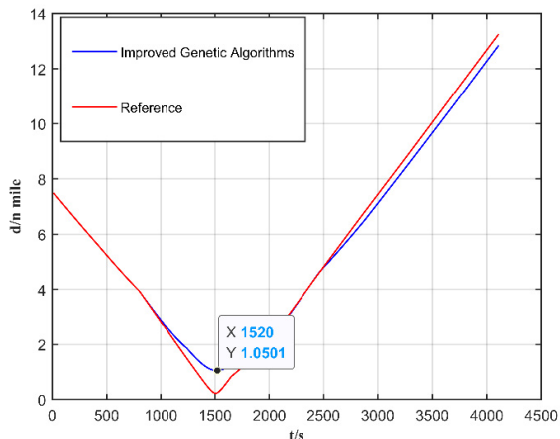


FIGURE 6. The distance between the multiple ships meeting situation.

The dynamic heading information of the own ship is shown in Figure 7. When the ship is involved in a collision situation, when the ROC hits the safety threshold, the ship begins to take action to avoid collision.

The optimization process of the fitness function is shown in Figure 8. When the algorithm comes to the 20 generations, the algorithm tends to be stable, and a better solution to the problem can be obtained. Each time the algorithm performs

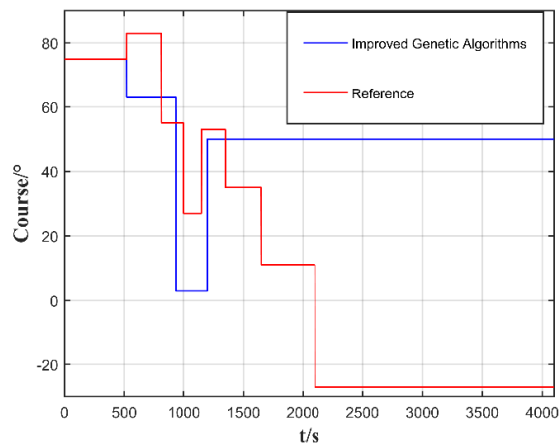


FIGURE 7. The ship's course in multiple ships meeting situation.

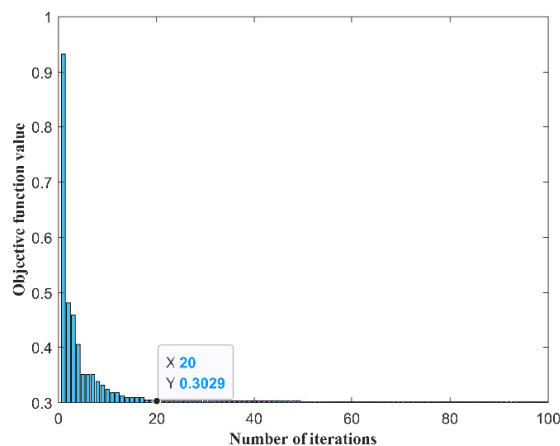


FIGURE 8. Iterative process for multiple ships meeting situation.

an iteration, an avoidance path is generated. After 50 iterations, the algorithm reaches the optimized condition, and the algorithm ends, and the optimal path planning is obtained.

By continuously giving priority to the “key avoidance ship,” the multi-vessels collision avoidance decision model adopted in this brief can deal with the problem of multi-vessels encounter to a certain extent, and ensure that the ship can safely avoid each target ship.

V. CONCLUSION

In this paper, based on the real ship applications, a modified fuzzy dynamic risk of collision model based on time and space collision risk index was addressed.

Then, the fitness functions based on the risk of collision, navigational economy, COLREGs and collision avoidance timing were established to solve the multi-encounter ship collision avoidance decision problems. However, some researches are not considering the COLREGs. By adopting the genetic algorithms to solve the task of optimal safe ship trajectory in a collision situation, [32] not introduced the COLREGs to the shipping risk model.

Combined with the genetic algorithm, multi-objective decision theory was adopted for path planning and collision avoidance. By using the weight method and the constraint method, the problem of the non-inferior solution was solved and achieved an optimality solution of the decision-making system. Simulation results validated the effectiveness of the proposed path planning and collision avoidance algorithm. As vital and exciting research topics, one can aim at path planning and collision avoidance combined with the characteristic of ship rudder servo system of the steering gear.

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