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A Path Planning Method for Ship Collision Avoidance Considering Spatial–Temporal Interaction Effects

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Abstract: Efficient and reliable path planning is crucial for smart ships when avoiding collisions with static and dynamic obstacles in complex marine environments. This research proposes a novel path planning method based on the fast marching method to specifically assist with safe navigation for autonomous ships. At the very beginning, a unified representation is specially produced to describe the path planning space based on the parametric fast marching speed function. In addition, the spatial–temporal interaction effects of dynamic obstacles are considered and integrated into the construction of planning space. Subsequently, a path optimization strategy is put forward based on the trajectory prediction of dynamic objects. Particularly, the effectiveness of the method has been validated and evaluated through a number of simulations, which proves that such a method is practical in narrow and crowded waterways.

Keywords: path planning; collision avoidance; fast marching (FM) method; spatial–temporal interaction effects; autonomous ships

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1. Introduction

Marine transportation has rapidly grown in recent years, and cross-national trade has become more and more frequent. In this context, the maritime transportation industry has substantially facilitated the development of the global economy, while ship intelligence is widely expected to play a central role in improving efficiency [1,2]. However, with the increasing demand for maritime traffic, the marine environment has become more complex and crowded, which significantly increases the risk of marine traffic accidents. In the meantime, authoritative maritime accident investigations elaborate that human failures cause about 80% of marine accidents [3,4]. Most intelligent decision-making tools for ships were designed to limit the occurrence of maritime traffic accidents and ensure navigation safety. In particular, the ability to plan a reasonable path while providing emergency decision making is an essential guarantee in ship driving, which is regarded as a core competency of ship intelligence. On this occasion, collision avoidance is also a critical research field for many maritime experts and scholars [5,6].

In this paper, the fast marching (FM) method is chosen due to its good performance in both situation modeling and path planning [7,8], and the collision avoidance problem for ships in complex restricted waters is considered. In general, both static and dynamic obstacles are included in complex restricted waters, which is significantly different from that in open waters [9,10]. The presence of static obstacles (such as shorelines, islands, etc.) and the limitation of water depth significantly reduce the navigable area. In this situation, the collision avoidance solutions in open waters may lead to a potential risk of conflicting with shorelines or shallows. Frequently used path planning algorithms generate solutions only according to the current situation, which is quite different from human navigators. An experienced ship navigator always makes appropriate decisions in navigation based on reasonable anticipations and inferences. Therefore, it is vital to consider the evolution of the navigational situation when providing collision avoidance paths. The real challenge is to accurately model such evolution.

To address these issues, a novel collision avoidance path planning method based on FM was proposed, which considers spatial–temporal interaction effects. At the same time, a novel model was introduced to simulate the situation anticipation of human navigators. The main contribution of the proposed path planning method for autonomous ships are as follows: (1) the FM method is used to create a unified obstacle representation model that is specifically designed to describe the path planning space in complex waters; (2) the spatial–temporal interaction effects of dynamic obstacles are considered and integrated into the construction of planning space; and (3) a path optimization technique based on the trajectory prediction of dynamic objects is put forward for improved flexibility.

The rest of this paper is organized as follows. In Section 2, typical path planning algorithms are reviewed and analyzed. Section 3 describes the flow chart of the path planning approach and the detail of path planning and optimization. Several simulations are conducted in Section 4 to validate the proposed approach. Section 5 concludes this paper and discusses future research.

2. Literature Review

With the development of the shipping industry, more and more academics have focused on the path planning of autonomous ships. Currently, path planning algorithms for ships can be classified into three categories: traditional algorithms, bionic intelligence–based algorithms, and machine learning–based algorithms.

The A*, velocity obstacle (VO) and artificial potential field (APF) algorithms are the most common traditional path planning methods. He et al. [11] devised a dynamic path planning method for collision avoidance based on the A* algorithm and ship navigation rules. The results of the experiments reveal that the method may provide more reasonable paths in complex scenarios to trade-off navigation risk and economic efficiency. However, the planned routes are rarely smooth enough for ships to follow. Zhang et al. [12] combined the VO algorithm and the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) to create a path planning method that allows ships to operate safely in a dynamic environment. The simulation results indicate that the method is capable of giving a deterministic and effective path for collision avoidance in a variety of encounter situations. Nonetheless, in some circumstances, the VO may generate a local minimum solution. Petres et al. [13] used the APF algorithm to construct a virtual gravitational field to steer the ship to the target waypoint in a complex navigation environment. Zhu et al. [14] proposed a novel path planning algorithm for ship automatic collision avoidance based on a modified APF method considering the constraints of both the COLREGs and the motion characteristics of the ship. Experimental results reveal that the proposed method is accurate and reliable, and satisfies the demands of engineering applications. Despite the fact that the APF has the advantages of simple algorithm structure and high computational efficiency, it is easy to fall into local minimum and target point oscillation.

The genetic algorithm (GA), ant colony optimization (ACO) algorithm and particle swarm optimization (PSO) algorithm are examples of bionic intelligence–based path planning methods. Ning et al. [15] developed a global search path planning technique by merging the multi-objective decision theory with the GA. Experimental results demonstrate that the path planning strategy is quite effective at collision avoidance. Lyridis [16] developed an improved ACO with fuzzy logic to deal with local path planning of unmanned surface vehicles (USVs) by taking into account wind, current, wave, and dynamic obstacles. Experiments reveal that the modified algorithm achieves a faster convergence speed. Zhao et al. [17] demonstrated a hybrid multi-criteria ship routing method based on an improved PSO algorithm. The strategy tries to optimize the meteorological risk, fuel consumption, and navigation time associated with a ship. Experiments show that the route planning algorithm can create a number of possible paths while ensuring safety, environmental friendliness, and economic viability. It serves as a resource for captains and shipping companies when deciding on a route. Kang et al. [18] adopted the PSO algorithm to produce the shortest path from the start point to the goal point. Simulation results show that the algorithm is capable of obtaining a COLREGs-compliant and practical navigation path for all four traffic scenarios. However, such bionic intelligence algorithms typically require more prior information and a considerable amount of calculation, which leads to issues such as long calculation time and local minimum; therefore, they are primarily utilized in auxiliary decision-making systems rather than autonomous navigation systems.

Reinforcement learning (RL) based path planning algorithms are the most prevalent form of machine learning–based path planning methods. Chen et al. [19] proposed a Q-learning–based path planning and maneuvering approach for unmanned cargo ships. This method can achieve the best behavioral strategy through training and learning. However, this solution cannot solve the problem of high-dimensional space, and a large q-table may result in slow convergence. Zhou et al. [20] suggested a deep reinforcement learning (DRL) based path planning method for USVs integrating the motion model and collision risk assessment mechanism. The algorithm was tested in both virtual and physical environments. Zhang et al. [21] offered a hierarchical DRL autonomous navigation decision model to implement ship path planning in the port environment. The experimental findings show that the DRL algorithm may significantly improve the safety of ships and the ability of obstacle avoidance. Woo et al. [22] proposed a DRL-based decision-making algorithm to realize the path planning of collision avoidance. A visual grid map representation and a COLREGs-based reward function were specially designed for the approach. Despite the DRL's excellent learning ability and stability, the disparity between the training world and the real world makes the DRL-based solutions challenging to apply.

In summary, although there are numerous path planning methods, few of them can provide appropriate solutions for collision avoidance in complex restricted waters. On the one hand, a unified planning space representation model, which is the fundament of path planning algorithms, needs to be established in advance for both static (shorelines, islands, etc.) and dynamic (target ships or TSs) obstacles. On the other hand, the trajectory prediction of the moving object needs to be further investigated to acquire a path optimization strategy. In order to address the above issues, this research constructs a unified representation model by configuring different FM speed functions for static and dynamic obstacles, and then formulates a path optimization strategy with the help of trajectory prediction. Through the above improving measures, the proposed method can provide a collision-free path, while ensuring the safety and economy of autonomous ships in complex scenarios.

3. A Proposed Approach

This research proposes a novel path planning approach for ship collision avoidance considering spatial–temporal interaction effects. To elaborate the approach in detail, this section describes how it works while planning a path. First of all, the flow chart of the suggested method is introduced in detail. Secondly, in order to describe the situation of navigation scenarios, the planning space representation is designed for both static and dynamic obstacles. Eventually, a path planning approach is put forward with an optimization scheme.

3.1. Flow Chart of the Approach

The flow chart of the discussed method and its algorithmic presentation is shown in Figure 1. There are five main steps in the proposed method as follows:

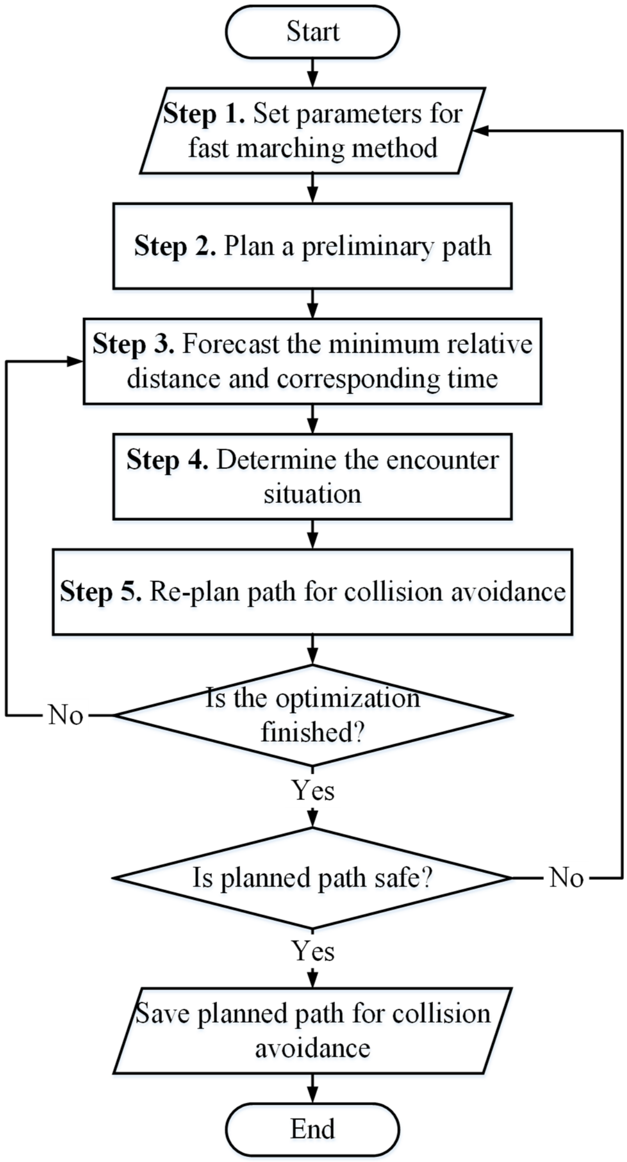


Figure 1. The flow chart of the proposed path planning approach.

Step 1 is to set the FM method parameters, which is the basis of planning space representation.

Step 2 is to plan a preliminary path. In this step, the route is scheduled based on an initial representation of the planning space and used to predict the own ship's (OS's) trajectory.

Step 3 is to forecast the minimum relative distance and the corresponding time. In this procedure, the accuracy of the trajectory prediction of the own ship (OS) and TSs directly affects the efficiency of path planning results.

Step 4 is to determine the encounter situation, which is the foundation for path optimization.

Step 5 is to re-plan the path for collision avoidance.

After that, if the planned path cannot be further optimized and is safe enough, it will be applied for collision avoidance. Otherwise, it is necessary to go back to Step 3 or Step 1 for the path planning updating process.

3.2. Planning Space Representation

Safety is always one of the priority issues for ships in path planning problems. In order to generate safe trajectories, it is necessary to correctly represent the environment in which the path planning algorithm executes, which is especially crucial for ship navigation in complex environments. A suitable safety distance between the OS and obstacles (static and dynamic) during the entire voyage should always be maintained. This section describes the FM-based planning space representation for static and dynamic obstacles.

3.2.1. Fast Marching (FM) Method

The FM method was first proposed by Sethian [23] to solve the eikonal equation by using a single-pass algorithm. The eikonal equation is defined as follows:

$$|\nabla U(\boldsymbol{p})|W(\boldsymbol{p}) = 1, \quad (1)$$

where $\boldsymbol{p}$ represents the point in metric space, i.e., $\boldsymbol{p} = (x, y)$ in 2D space and $\boldsymbol{p} = (x, y, z)$ in 3D space. $U(\boldsymbol{p})$ denotes the travel time of interface front at point $\boldsymbol{p}$, whereas $W(\boldsymbol{p})$ indicates the local propagating speed at point $\boldsymbol{p}$.

The FM method calculates the value at every point in accordance with a strategy that is similar to the Dijkstra algorithm [24]. In addition, the FM method is usually applied on a grid map with three categories of points: (1) Far points, which denote the points at which the interface front has not yet arrived, and whose travel times are not yet computed; (2) Trial points, which represent the points at which the front will arrive soon, and whose travel times have already been calculated but may be updated in later computations; and (3) Accepted points, which indicate the points that the front has already passed, and whose travel times will not be changed.

Starting from the original Accepted point, the travel times of the points on the grid map are iteratively calculated. In the beginning, all points of the grid map are marked as Far points and infinity travel times, and the start point is marked as the Accepted point, whose arrival time is set to zero. During each iteration, points adjacent to the Accepted point are marked as Trial points, and travel times of these points are calculated. After that, the Trial point with the shortest travel time will be marked as the Accepted point, and a new iteration begins. This strategy is based on the fact that the travel time U at any point only depends on the neighboring points. In fact, such neighboring points generally have smaller values. The specific calculation process refers to [7,8].

In this research, the FM method is used to model the planning space with different local propagating speed function $W(\boldsymbol{p})$.

3.2.2. Static Obstacle Representation

There are numerous static obstacles in offshore and inland waters, including shorelines, islands, buoys, etc., which reduce the collision-free area and threaten the navigation safety of ships. Therefore, it is of great essence to model the risk of static obstacles. Considering the same distribution of risk surrounding static obstacles, when applying the FM method to static obstacle representation, the speed function $W(\boldsymbol{p})$ is generally set to a constant value (e.g., $W(\boldsymbol{p})$ equals 1). Furthermore, different safety distance thresholds can be configured according to different application scenarios. As shown in Figure 2a, it is the binary map, which includes static obstacles such as coastlines and several islands. Figure 2b is an example of the static obstacle representation called M_s whose distance threshold d is 100 m. The dark color denotes a high level of risk, and the light represents a low level of risk. Once the distance threshold is determined, the representation of static obstacles at time t is constant, i.e., $M_s(t) = M_s$.

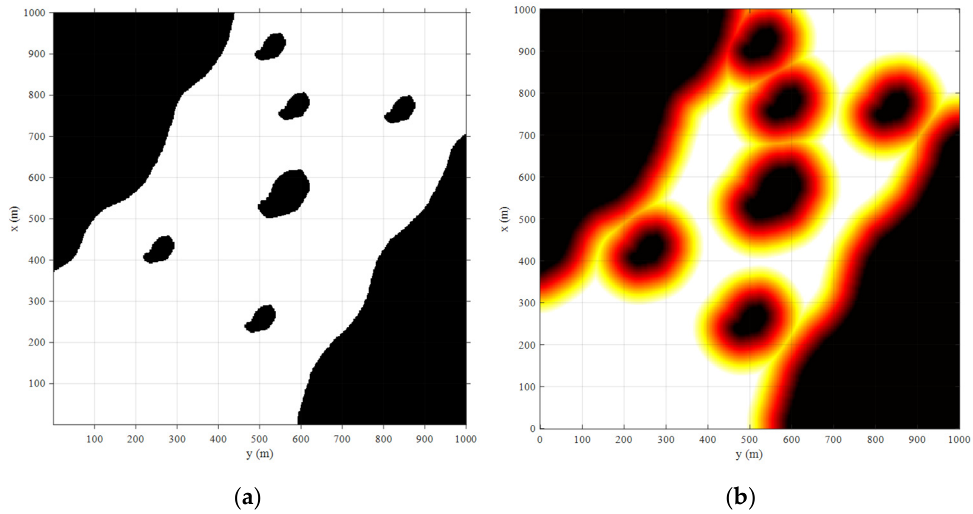


Figure 2. The binary map and a representation of the static scenario (d = 100 m). (**a**) The binary map, (**b**) The static obstacle representation.

3.2.3. Dynamic Obstacle Representation

The representation of dynamic obstacles in the path planning space has been of great interest. In order to ensure the consistency of planning space, the FM method is also adopted to represent the dynamic obstacles in this research. However, constant speed functions are not suitable considering the fact that different directions around dynamic obstacles have different risk distributions. Therefore, a specific speed function has been devised as illustrated in Figure 3. α is the angle relative to the course of a dynamic obstacle, and $W(\boldsymbol{p})$ is the speed function of the FM method used for dynamic obstacles, which is defined as follows:

$$\left.\begin{array}{c} W(\boldsymbol{p}) = \rho \\ \frac{(cos\alpha)^2}{a} + \frac{(sin\alpha)^2}{b} = \frac{1}{\rho^2} \end{array}\right\}, \tag{2}$$

where the values of a and b depend on α. There are four different cases: Case 1, $\alpha \in (0, 0.5\pi]$, a and b are set to r_1 and r_2, respectively; Case 2, $\alpha \in (0.5\pi, \pi]$, a is equal to r_3 and b is equal to r_2; Case 3, $\alpha \in (\pi, 1.5\pi]$, a and b are, respectively, r_3 and r_4; Case 4, $\alpha \in (1.5\pi, 2.0\pi]$, a equals to r_1, and the corresponding b equals r_4. In addition, the safety distance thresholds in the four directions of the bow, starboard, stern, and port are denoted with d_1, d_2, d_3, and d_4, respectively, and meet the following conditions:

$$\frac{d_1}{r_1} = \frac{d_2}{r_2} = \frac{d_3}{r_3} = \frac{d_4}{r_4}. \tag{3}$$

Based on the above model, the representations called M_d of dynamic obstacles are easy to be modeled. As shown in Figure 4, the representation of a dynamic obstacle is modeled with different configurations. Figure 4a shows the representation with a configuration that r_1, r_2, r_3, and r_4 are set to 4.0, 1.0, 1.0, and 1.0, respectively, and the corresponding safety distance thresholds d_1, d_2, d_3, and d_4 are 200 m, 50 m, 50 m, and 50 m. As for Figure 4b, the parameter r_2 and distance threshold d_2 are changed to 1.5 and 75 m. The choice of the above parameters is partially inspired by the work in [25].

The representation of dynamic obstacles at time t is labeled with $M_d(t)$. Different from static obstacles, the representation of dynamic obstacles varies over time, which means that $M_d(t_1)$ is usually not equal to $M_d(t_2)$ when $t_1 \neq t_2$.

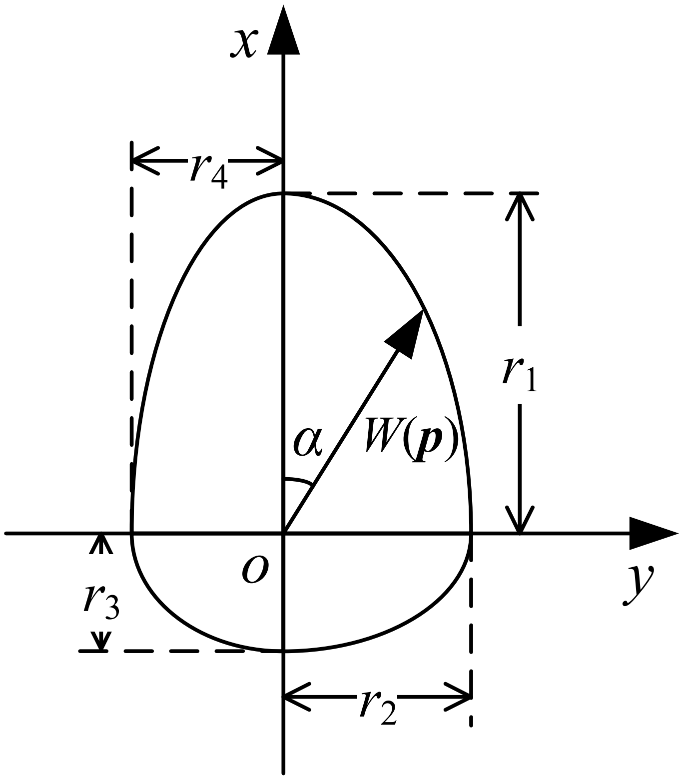


Figure 3. The speed function of the FM method designed for dynamic obstacles.

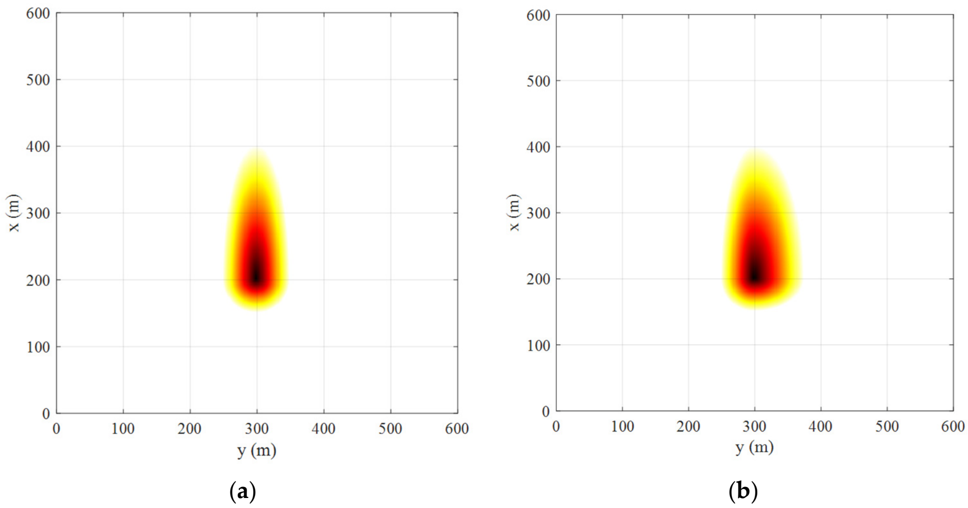


Figure 4. The representation of a dynamic obstacle with different configurations. (**a**) $r_2 = 1.0$ and $d_2 = 50$ m, (**b**) $r_2 = 1.5$ and $d_2 = 75$ m.

3.3. Path Planning Approach

In this section, the proposed path planning method is detailed in-depth. Firstly, the trajectories of OS and target ship (TS) are predicted. Then, a preliminary path is produced. Finally, an iterative calculation is performed to obtain a better path.

3.3.1. Trajectory Prediction of OS and TS

The trajectory prediction of OS is based on the assumption that OS travels along the path at a constant speed. It should be noted that the path points are parameterized with arc length from the start point [26]. Then, a path can be denoted with $P(s)$, where $P(s)$ is a point on the path and the corresponding s is the arc length of the path between the current and the start points. Hence, the trajectory of OS can be characterized as follows:

$$\boldsymbol{p_{os}}(t) = P(v_{os}t), \tag{4}$$

where $\boldsymbol{p_{os}}(t)$ is the predicted position of OS at time t, and v_{os} indicates the velocity of OS. When $t = 0$, $\boldsymbol{p_{os}}(0)$ equals $P(0)$, which means that the OS is located at the start point of the current path.

In addition, the trajectory prediction of TS is also significant for collision avoidance [27,28]. The most basic and widely used method for predicting the trajectory of TS is based on the premise that the TS maintains its velocity and ignores external environmental disturbances [27]. In this work, such a trajectory prediction method is adopted. Therefore, the trajectory of TS based on the position of TS at time t_1 can be defined as follows:

$$\boldsymbol{p_{ts}}(t) = \boldsymbol{p_{ts}}(t_1) + v_{ts}(t - t_1), \tag{5}$$

where $\boldsymbol{p_{ts}}(t)$ denotes the predicted position of TS at time t, and $\boldsymbol{p_{ts}}(t_1)$ indicates the known position of TS at time t_1. v_{ts} is the velocity of TS.

It is worth noting that the external environmental disturbances and the collision avoidance intentions are not included in the present trajectory prediction methods. However, once a new trajectory prediction method is achieved, it can directly replace the current method without any additional effort.

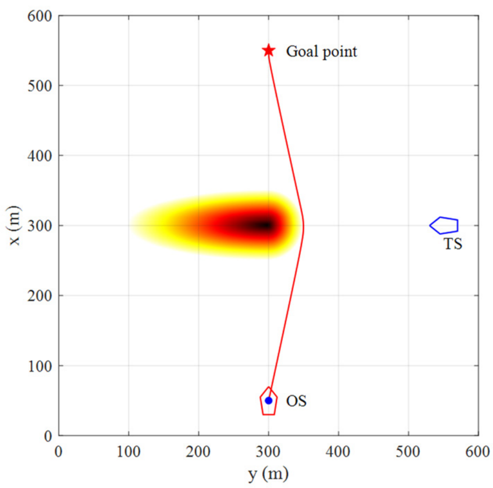
3.3.2. Preliminary Planning

The path planning approach can be divided into three steps. The first step is to compute the planning space representation M_e. Based on the M_e, in step two, the FM method is executed from the start point to generate a joint potential field, namely, the travel time map [8]. The last step is to produce the path based on the joint potential field by applying a gradient descent algorithm.

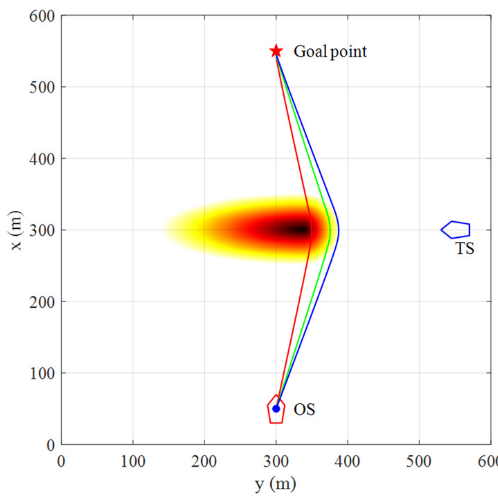
Based upon the representation of static and dynamic obstacles mentioned above, the preliminary planning space representation $M_e(t_0)$ at time t_0 can be calculated as follows:

$$M_e(t_0) = \min(M_s(t_0), M_d(t_0)) = \min(M_s, M_d(t_0)). \tag{6}$$

Then, the preliminary path P_{t_0} can be produced according to $M_e(t_0)$. As shown in Figure 5a, the solid red line is the preliminary path planned in a crossing scenario.



(a)



(b)

Figure 5. The preliminary path and the path optimization process of the proposed approach. (**a**) The preliminary path, (**b**) The path optimization process.

3.3.3. Path Optimization

Since the path is generated based on the position of dynamic obstacles at the current moment, there may still be a potential risk for the OS navigating along this path. Hence, a path optimization method needs to be specified for the safety of the OS. The proposed path optimization scheme can be summed up in the following steps:

Step 1 is to predict the trajectories $\boldsymbol{p_{os}}$ and $\boldsymbol{p_{ts}}$ based on Equations (4) and (5) and path P_{t_1}.

Step 2 is to calculate the minimum relative distance d_{min} and the corresponding time t_2 based on the trajectories of OS and TS.

Step 3 is to forecast the position $\boldsymbol{p_{ts}}(t_2)$ at time t_2 of TS with Equation (5).

Step 4 is to update the dynamic obstacle representation $M_d(t_2)$ based on $\boldsymbol{p_{ts}}(t_2)$ and regenerate the planning space representation $M_e(t_2)$ with Equation (6).

Step 5 is to plan the new path P_{t_2} for collision avoidance.

The proposed path optimization is an iterative process. The iteration will be finished when the minimum relative distance d_{min} converges to the maximum and meets the safety requirements of OS. Otherwise, it is necessary to reconfigure the parameters of the FM method and re-execute the path planning algorithm.

Figure 5b shows the path optimization process. The three iteratively generated paths P_{t_0}, P_{t_1}, and P_{t_2} are denoted by the solid red, solid green, and solid blue lines, respectively.

4. A Case Study

In order to validate the performance of the suggested path planning method, this section builds up a simulation environment to run the validation. Both simple and complex scenarios are contained in the simulated environment. The planned path, the collision avoidance trajectories, and the relative distance between OS and TSs are presented for each test.

4.1. Test Cases with a Single Dynamic Obstacle

Test cases with a single dynamic obstacle involving three different scenarios, head-on, overtaking, and crossing, were conducted in this section. All the mentioned cases are the most basic ship encounter situations. Furthermore, the research on the three basic cases is of great significance for ship collision avoidance in complex scenarios.

4.1.1. Head-On

This case includes the OS and one TS, creating a two-ship encounter situation of head-on as viewed from the OS's perspective. The OS had an initial position at $(50,\ 300)$ m, a velocity of 2.0 m/s, and an initial course of 0°. The TS's corresponding initial position, velocity, and course were set to $(550,\ 300)$ m, 2.0 m/s, and 180°, respectively.

According to COLREGs rule 14 [29], in the case of a head-on encounter, each ship should alter its course to starboard to pass on the port side of the other. Therefore, both the OS and the TS are give-way vessels in this case. Throughout the path planning progress, it was assumed that the speed and course of TS remain the same (treated the TS as a stand-on vessel) when predicting the trajectory of TS. A configuration where r_1, r_2, r_3, and r_4 were set to 4.0, 1.5, 1.0, and 1.0, respectively, for the planning space representation, was adopted in this case. Parameter r_2 for starboard is larger than parameter r_4 for port, promoting a situation where the OS and TS pass on the port side of the other according to COLREGs rule 14 [29]. The corresponding safety distance thresholds d_1, d_2, d_3, and d_4 were 200 m, 75 m, 50 m, and 50 m, respectively.

Figure 6a shows the path planning results of the proposed approach from the OS's perspective for this case, and Figure 6b shows the predicted collision avoidance trajectories of the head-on scenario. According to the trajectories, the shortest relative distance between the OS and the TS is 50.17 m. As shown in Figure 7, the relative distance is indicated with a filled circle red line. It can be inferred that safety is guaranteed when the OS navigates along the planned path, even if the TS takes no action.

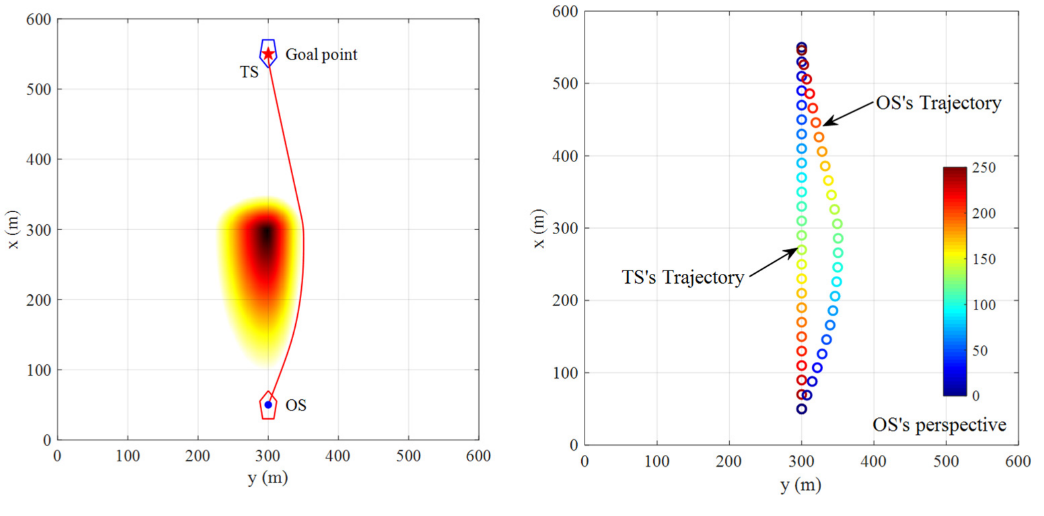


Figure 6. The path planning results and the collision avoidance trajectories in the head-on scenario. (**a**) The path planning results, (**b**) The collision avoidance trajectories.

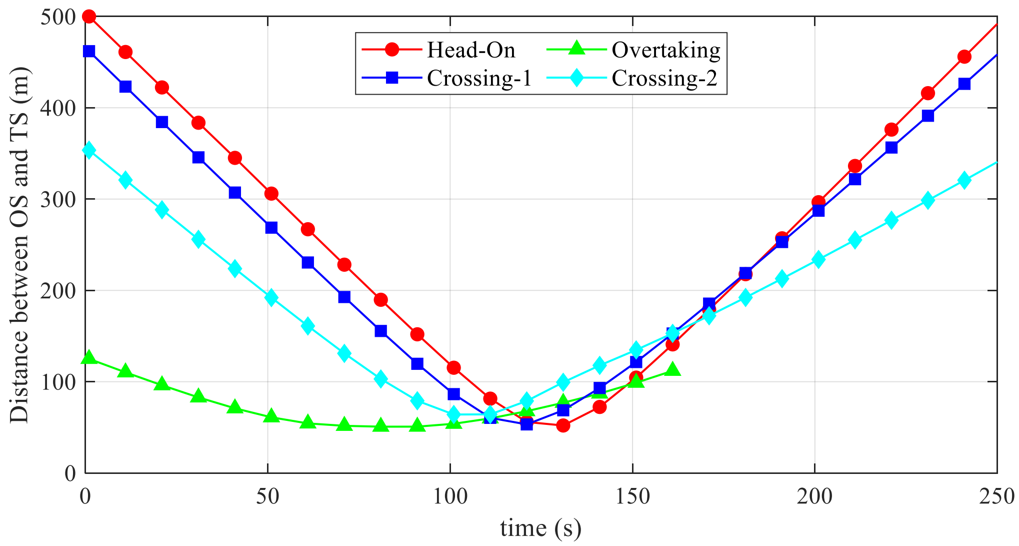


Figure 7. The relative distances between OS and TSs in the single dynamic obstacle scenario.

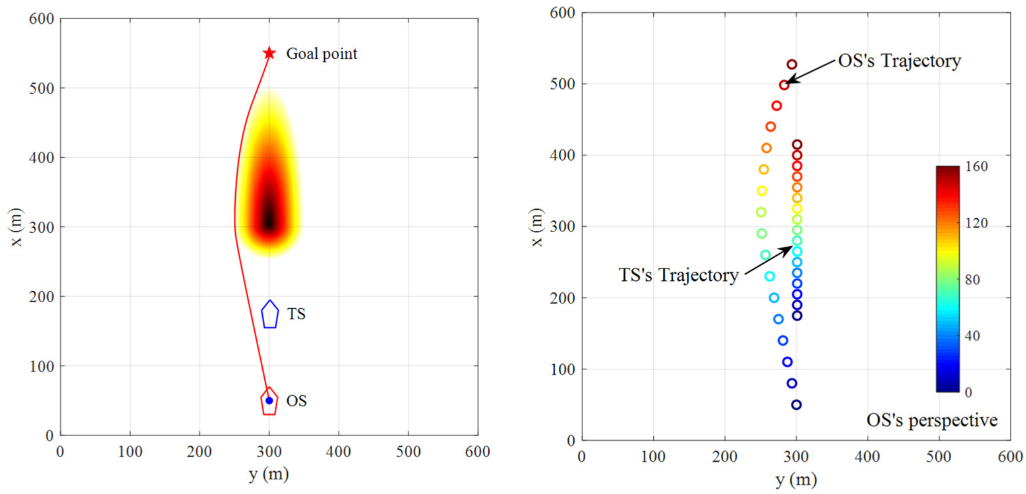
4.1.2. Overtaking

A two-ship encounter situation of overtaking as viewed from the OS's perspective was considered in this case. The OS's initial position, velocity, and course were set to $(50,\ 300)$ m, 3.0 m/s, and 0°, respectively, and the corresponding initial position, velocity, and course of TS were set to $(175,\ 301)$ m, 1.5 m/s, and 0°, respectively. It should be noted that a little offset to the right was added to the position of TS for the uniqueness of the reasonable path.

Under the provisions of COLREGs Rule 13 [29], the OS as a give-way vessel should keep out of the way of TS, whereas the TS as a stand-on vessel should always maintain its course to avoid confusion in this case. Rule 13 [29] does not clarify that a give-way vessel should alter its course to which side (starboard or port) when overtaking a stand-on vessel. Hence, parameters r_1, r_2, r_3, and r_4 were set to 4.0, 1.0, 1.0, and 1.0, and the corresponding safety distance thresholds d_1, d_2, d_3, and d_4 were 200 m, 50 m, 50 m, and 50 m, respectively. The same configuration was adopted for the starboard and port when modeling the space representation.

Figure 8 shows the path planning results and the collision avoidance trajectories in the overtaking scenario. The planned path is indicated with a solid red line, as shown in

Figure 8a. The OS is expected to alter its course to the port side to pass on the TS based on the path. The collision avoidance trajectories of this overtaking scenario are shown in Figure 8b. The relative distance is denoted with a filled triangle green line, as shown in Figure 7, and the shortest distance between OS and TS is 50.49 m. The results demonstrate that collision avoidance can be realized when the OS follows the planned path.



(**a**) (**b**)

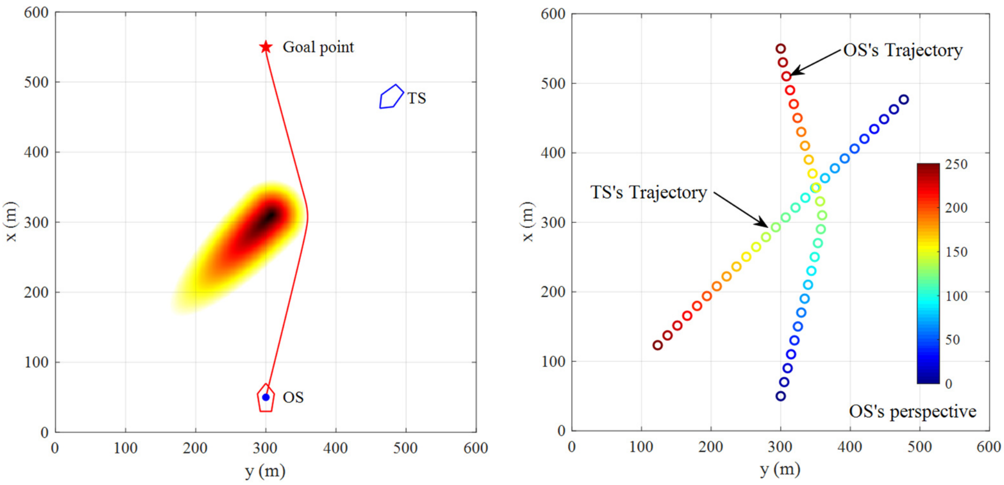
Figure 8. The planning results and the collision avoidance trajectories in the overtaking scenario. (**a**) The path planning results, (**b**) The collision avoidance trajectories.

4.1.3. Crossing

There are two crossing scenarios included in this case, called Crossing-1 and Crossing-2. The same configuration, an initial position at (50, 300) m, a model of 2.0 m/s, and a course of 0°, was chosen for the OS in the two scenarios. In Crossing-1, the TS's initial position and course were set to (477, 477) m and 225°, respectively, and the corresponding original position and course of TS in Crossing-2 were (300, 550) m and 270°. A velocity of 2.0 m/s was adopted for TS in both Crossing-1 and Crossing-2.

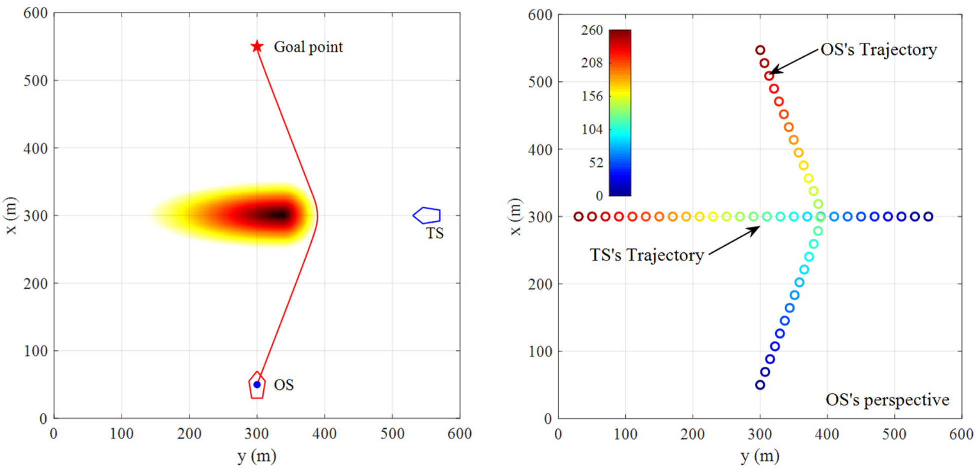
According to the provisions of COLREGs Rule 15 [29], when two vessels are crossing, the vessel that has the other on its starboard should keep out of the way. Therefore, the OS is a give-way vessel in the two crossing scenarios. The same parameters for FM and corresponding safety distance thresholds were selected in this case as in the overtaking scenario.

The simulation results are depicted in Figures 7, 9 and 10. Figures 9a and 10a display the planned path, and Figures 9b and 10b show the collision avoidance trajectories of the two crossing scenarios. Specific quantitative assessments are shown in Figure 7. The relative distances between the OS and the TS in Crossing-1 and Crossing-2 are illustrated by filled square blue and filled diamond cyan lines, respectively. The shortest distances in the two scenarios are 52.60 m and 62.04 m. The results illustrate that a good path planning capability can be achieved with the proposed method.



(**a**) (**b**)

Figure 9. The path planning results and the collision avoidance trajectories in Crossing-1. (**a**) The path planning results, (**b**) The collision avoidance trajectories.



(**a**) (**b**)

Figure 10. The path planning results and the collision avoidance trajectories in Crossing-2. (**a**) The path planning results, (**b**) The collision avoidance trajectories.

4.2. Test Cases in a Complex Scenario

A more complex scenario involving three ships (OS, TS1, and TS2) was considered in this test case. It is a typical offshore water area, where the OS needs to avoid both islands and TSs. As shown in Figure 11a, the encounter scenario size was set to 4 km $\times$ 4 km, where the center was taken as the origin $(0,\ 0)$ m. The initial position of OS was $(-1172.4,\ 0)$ m, and its destination was $(1172.4,\ 620.7)$ m. The velocity and the course of OS were 7.0 m/s and 315°, respectively. Correspondingly, the positions, speeds, and courses of TS1 and TS2 were set to $(115.9,\ 1487)$ m, $(1763, -619.5)$ m, 7.0 m/s, 5.0 m/s, 270°, and 135°, respectively.

In this test case, an assumption was made that the TSs are navigating in the fairways, and the OS tries to cross the fairways. According to COLREGs Rule 9 [29], the OS is required not to impede the TSs. In other words, the OS is a give-way vessel, and the TSs are stand-on vessels. Parameters r_1, r_2, r_3, and r_4 for dynamic obstacles were set to 4.0, 1.0, 1.0, and 1.0, respectively, and the corresponding safety distance thresholds d_1, d_2, d_3, and d_4 were 400 m, 100 m, 100 m, and 100 m. In addition, the safety distance threshold for static obstacles was 200 m in this scenario.

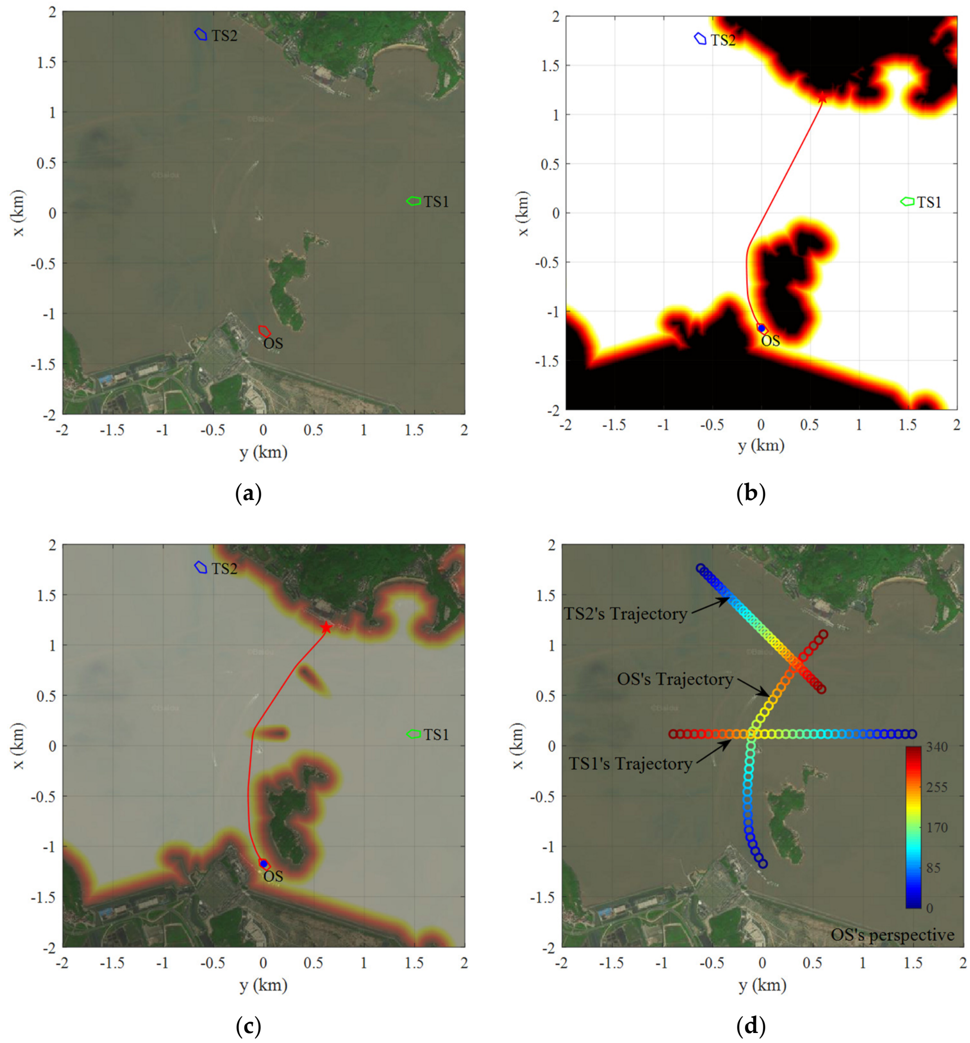


Figure 11. The path planning results and the collision avoidance trajectories in the complex scenario. (**a**) The encounter scenario, (**b**) The preliminary path, (**c**) The path planning results, (**d**) The collision avoidance trajectories.

A preliminary path indicated with a solid red line was generated only based on the static obstacle representation, as shown in Figure 11b. A reasonable path shown in Figure 11c was obtained through path optimization based on the preliminary path. Figure 11d shows the collision avoidance trajectories according to the trajectories' prediction, and a specific quantitative assessment is shown in Figure 12. It is evident that the OS plans to pass by the bow of the TS1. Usually, this is a kind of dangerous navigation behavior. However, a minimum relative distance of 191.65 m can always be maintained between the OS and the TS1 based on the collision avoidance trajectories. According to the above results, the proposed path planning scheme can provide a robust collision avoidance approach by considering spatial–temporal interaction effects.

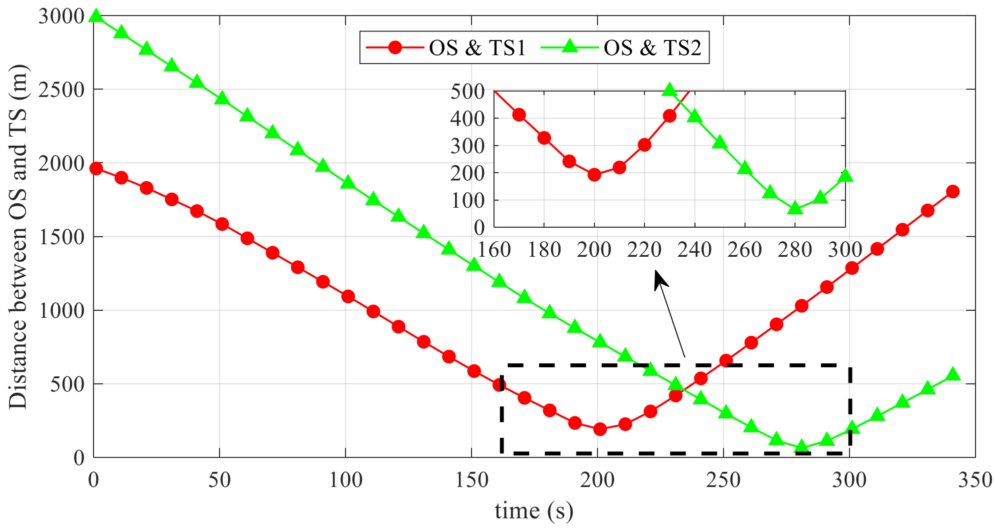


Figure 12. The relative distances between OS and TSs in the complex scenario.

5. Conclusions

In this research, a novel path planning method for ship collision avoidance has been developed using the FM method and trajectory prediction. The introduction of different speed functions for the FM method ensures that the representation of a complex scenario with static and dynamic obstacles can be modelled in a unified space. In addition, a path optimization scheme integrated trajectory prediction has been designed, ensuring that a reasonable collision-free path in complex restricted waters can always be found. Such a path planning strategy can potentially support autonomous ships to undertake missions with improved intelligence.

In terms of future work, one possible improvement is that the navigation rules should be considered more comprehensively. Usually, a collision avoidance decision should be made by adhering to the COLREGs. Only several rules in COLREGs are considered and discussed in our research. Therefore, it is of great significance to consider a complete rule system and establish a corresponding mathematical model. In addition, a more precise and practical rule-constrained trajectory prediction algorithm will considerably improve the performance of the proposed path planning approach.

Another potential improvement is to find an appropriate strategy to configure the parameters of the FM speed function in practical environmental constraints. As discussed previously, the static obstacle has a constant speed function, and the dynamic obstacle has an anisotropic speed function. The key distinction between dynamic and static obstacles is velocity. Hence, it is necessary to take the velocity of obstacles into consideration when selecting parameters for the FM speed function. In practice, the historical data of ship encounters can be a direct clue in the searching of parameters' values.

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Abbreviations

ACO	Ant Colony Optimization
APF	Artificial Potential Field
COLREGs	Convention on the International Regulations for Preventing Collisions at Sea
DRL	Deep Reinforcement Learning
FM	Fast Marching
GA	Genetic Algorithm
OS	Own Ship
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
TS	Target Ship
TSs	Target Ships
USVs	Unmanned Surface Vehicles
VO	Velocity Obstacle

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