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RESEARCH ON MULTI VESSEL COLLISION AVOIDANCE IN NARROW WATERS BASED ON ALLIANCE GAMES

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Abstract. *To tackle the challenge of implementing automatic collision avoidance for multiple vessels in narrow waters, this study integrates alliance games with the dynamic collision avoidance systems of ships, adhering to the International Rules for Collision Avoidance at Sea (COLREGs). We introduce a theoretical framework that utilizes alliance games to mitigate the risk of maritime collisions, specifically targeting scenarios where ships navigate in close proximity to each other in confined waterways. The framework's application is aimed at facilitating automated decision-making processes for collision avoidance. Our findings indicate that the incorporation of alliance games significantly enhances the ability to manage collision risks and achieves automated collision avoidance in narrow water environments.*
Keywords: Alliance game, Narrow waters, Multi vessel collision avoidance, Equilibrium

1. **Introduction.** In narrow waters, the operational range for ship collision avoidance is severely limited due to geographical constraints and dense ship traffic. This makes the collision avoidance techniques for ships significantly different from those used in open water environments. Collision avoidance decisions must consider not only changes in direction but also variable speeds [1]. Particularly in busy port waters, where the distribution of ships is relatively dense and the navigation dynamics of target vessels are variable, it is also necessary to consider the influence of nearby static obstacles such as reefs and small boats [2]. The coupling problem of dynamic and static obstacles under multiple constraints makes the research on automatic collision avoidance algorithms extremely complex, and there is relatively little research on related automatic collision avoidance algorithms. Common methods include the Vector Field Histogram (VFH) [3,4], improved vector histogram algorithms [5], rolling window methods [6,7], artificial potential field methods [8,9], and velocity obstacle methods [10,11]. However, when encountering a large and dense number of ships, some theories and algorithms may not even be able to obtain feasible solutions within an acceptable time. This study aims to improve safety and efficiency in narrow waterway navigation by developing a sophisticated collision avoidance system based on alliance game theory. It seeks to overcome current methodological limitations and bridge the gaps in automated, real-time decision-making for scenarios with multiple vessels.

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This paper is organized as follows. Section 1 reviews the literature. Section 2 introduces the methods to evaluate dynamic collision hazard level and describes our modeling framework. Section 3 shows our results under multi ship alliance game. Section 4 further constructs game model for encounter situations. Section 5 simulates the multi ship collision avoidance game in the encounter scenario based on the electronic chart platform and ship motion simulator system. Section 6 concludes the paper with a summary of results.

1.1. **Knowledge status.** Research on multi-vessel collision avoidance in waterways has advanced. The latest progress in multi ship collision avoidance research mainly focuses on four aspects: multi ship encounter situation recognition, collision risk assessment, collision avoidance path planning, and collision avoidance decision-making methods.

Firstly, multi ship encounter situation recognition. The 1972 International Maritime Collision Avoidance Regulations (COLREG) did not clearly define the responsibility for multiple ship encounters and collision avoidance. Therefore, ocean autonomous surface vessels (MASS) and maritime vessels with autonomous navigation capabilities face the problem of identifying complex multiple ship encounters and making corresponding collision avoidance decisions. In order to identify multi ship encounter situations and improve navigation safety, Zhu et al. proposed a model that can mine multi ship encounter situations from Automatic Identification System (AIS) data, analyze the spatiotemporal process of encounters, and make collision avoidance decisions. This method overcomes the problem that traditional collision risk assessment methods are only applicable to differences between two ships and ship perception. Compared with traditional artificial potential field methods, this method has fewer turns and smoother trajectories [12]. Lyu et al. used the velocity obstacle algorithm to visualize and identify the dangers of multiple ship encounters, and proposed a simplified method for classifying ship encounter situations in multiple clusters [13]. Gao et al. identified multi ship encounter trajectory data by cross matching two ship encounter data and proposed a Spatiotemporal Edge and Node Attention Graph Convolutional Network (ST-ENAGCN) with graph convolution units and Long Short-Term Memory (LSTM) units to achieve graph structure learning of human experience in multi ship encounter situations. This study supports autonomous navigation of MASS clusters under Human-Machine Hybrid (HMH) conditions [14].

Secondly, collision risk assessment. With the rapid development of maritime transportation, the number of ships involved in multi ship encounter scenarios is also increasing, and the complexity and risks of navigation will increase exponentially. At this time, collision risk assessment and prediction are crucial for the safety management of maritime transportation. In terms of collision risk assessment, the latest research methods mainly include fuzzy logic multi ship collision risk assessment model [15], quantitative visualization multi ship collision assessment [16], spatiotemporal coupled ship collision risk assessment model [17], collision probability calculation method based on Monte Carlo simulation [18]. Some scholars have also combined risk perception with path planning, using risk perception A* algorithm and other methods to find the optimal route for ships [19,20].

Thirdly, collision avoidance path planning. In terms of collision avoidance path planning research, due to the involvement of multiple dynamic factors, some methods such as dynamic clustering analysis and adversarial training are used to simplify calculations and improve the time efficiency of path planning. Yu et al. proposed a dynamic path planning method based on Dynamic Clustering Analysis (DCA) to address the high computation time problem of path planning in the case of multiple ship encounters and the impact of target ship motion changes on path planning. This method dynamically clusters target ships with similar attributes into a group of ships, reducing the number of computational targets and improving the efficiency of path planning [21]. [22] proposed a Risk Aware trajectory prediction framework based on the Generative Adversarial Network (RAGAN) architecture. RAGAN utilizes GAN to learn potential collision avoidance interaction patterns in multi ship encounters. Through adversarial training, RAGAN continuously improves its ability to generate accurate and safe ship trajectories. However, traditional prediction methods often overlook the intricate spatiotemporal interactions and inherent collision avoidance maneuvers that occur during multiple ship encounters, resulting in insufficient accuracy in predicting interaction trajectories.

Fourthly, collision avoidance decision-making methods. The research on multi ship collision avoidance decision-making mainly applies deep reinforcement learning technology [23,24]. In situations where multiple ships encounter each other, only by collaborating and jointly planning collision avoidance strategies can collision risks be effectively reduced. Multi intelligent deep reinforcement learning methods gradually generate intelligence through the interaction between intelligent agents and the environment, simulating human environmental adaptability. This is an effective way to develop collaborative, safe, and practical multi ship intelligent collision avoidance strategies, which have been widely applied in the field of multi ship collision avoidance decision-making [25,26]. In multi ship encounter scenarios, the trial-and-error learning iteration speed of reinforcement learning is very slow. In response to this issue, [28] and [6] developed a novel intelligent collision avoidance algorithm based on Approximate Representation Reinforcement Learning (AR-RL) to achieve collision avoidance capability for autonomous surface vessels (MASS) in continuous state space environments involving interactive learning.

These collision avoidance techniques that perform well in open waters, such as dynamic windows, deep learning, and artificial potential field methods, have limited effectiveness in narrow waterways. This limitation stems from insufficient consideration of unique environmental constraints, such as variable vessel and obstacle sizes, speed variations, and precise positioning and speed data. In addition, these methods often underestimate the impact of environmental factors such as wind, ocean currents, and wave surges, as well as the importance of ship maneuverability in collision avoidance. The suboptimal design of multi ship collision avoidance strategies leads to poor coordination between ships, further exacerbating this problem.

1.2. Research objectives.

Since the concept of "e-Navigation" was proposed by the International Maritime Organization in 2006, the use of internal and external communication networks on ships has enabled the collection, integration, and display of shipshore information, and the continuous advancement of related technologies for information exchange between ships, ships and shore, and shore to shore. Based on the increasingly sophisticated shipshore information technology and the development trend of future ship intelligence, we can assume that the game formed by the encounter of multiple ships in narrow waters is an alliance cooperation game under complete information.

The purpose of this study is to introduce alliance game into the dynamic collision avoidance system of ships, propose a theoretical framework based on alliance game to resolve the "collision danger" of multiple ships in narrow waters, and achieve the goal of automatic collision avoidance of multiple ships.

1.3. Innovation points.

This study integrates the theory of coalition games into the dynamic collision avoidance system for ships, offering an innovative solution to the problem of multiple ship collisions in narrow waters. The research team has developed a theoretical framework based on coalition games, which effectively addresses the collision risks of multiple ships in narrow waters and automates collision avoidance decision-making. The outcomes of this study not only highlight the significance of theoretical innovation but also represent a substantial advancement in the field of maritime navigation safety.

2. Dynamic Collision Hazard Level.

According to international practice, a narrow waterway can be referred to as a navigable waterway if its width is within 2 nautical miles. When intelligent ships navigate in narrow waters, the control system needs to independently complete functions such as trajectory planning and collision avoidance. During this process, the ship's navigation needs to meet various constraint conditions to avoid dynamic and static obstacles.

2.1. Analysis of constraints on narrow waters characteristics.

1) Static constraints: static obstacles such as water depth in the waterway, islands, reefs, shore bridges, and stationary ships in the anchorage.

2) Maneuverability constraints: the number of ships encountering situations, ship quality indicators (speed, acceleration, angular velocity, angular acceleration, tonnage, minimum turning radius, maximum rudder angle), relative position and relative velocity between ships, etc.

3) Real-time constraint: Ships need to perceive and monitor the navigation environment in real time, plan the navigation trajectory in real time, and avoid obstacles.

4) Dynamic constraints: Disturbance constraints such as wind, waves, and currents in narrow water areas.

2.2. The risk degree of collision.

The risk degree of collision refers to the likelihood of collision between ships based on factors such as their relative position and motion. Usually, the risk-degree of collision of ships is comprehensively evaluated using the Distance to the Closest Point of Approach (DCPA) and the Time to Closest Point of Approach (TCPA). DCPA refers to the minimum passing distance between the vessel and the target. The smaller the value of DCPA, the greater the likelihood of collision. TCPA refers to the time from the target to the point of closest encounter (CPA). The smaller the value of TCPA, the higher the likelihood of collision. The usual calculation formula is as follows:

$$T_{CPA} = \begin{cases} 0, & \text{if } \|v_A - v_B\| \le \varepsilon \\ \dfrac{(P_A - P_B) * (v_A - v_B)}{\|v_A - v_B\|^2}, & \text{otherwise} \end{cases} \tag{1}$$

$$D_{CPA} = \|(P_A + v_A T_{CPA}) - (P_B + v_B T_{CPA})\| \tag{2}$$

Here, v_A represents the speed of the vessel, v_B represents the speed of the obstacle ship, P_A represents the location of the vessel, and P_B represents the position of the obstacle ship.

For the convenience of research, it is assumed that all ships can freely exchange the following information: static information such as captain, ship width, ship name, type, and call sign, voyage information such as ship cargo type and destination, dynamic information such as real-time heading, speed, and position, driving style action strategy, and safety encounter parameters. Another commonly used method for calculating the risk-degree of collision is the weighting method proposed by Kearon [29]:

$$\rho = (aD_{CPA})^2 + (bT_{CPA})^2 \tag{3}$$

In the above equation, a and b represent the weighted values, which are experimental data obtained from statistical analysis. The smaller the value of collision risk ρ, the more dangerous the ship is, and the greater the possibility of collision with incoming ships.

The research in this article is limited to narrow waters, we combine the environmental constraints of narrow water bodies and multi ship encounter scenarios, considering DCPA and TCPA, and design dynamic formulas for three indicators as follows:

$$T_{CPA_i}(t) = \begin{cases} 0, \text{ if } \|v_i(t) - v_j(t)\| \le \varepsilon \\ \min \left\{ \dfrac{(P_i(t) - P_j(t)) * (v_i(t) - v_j(t))}{\|v_i(t) - v_j(t)\|^2}, j = 1, 2, \ldots, n, j \ne i; \right. \\ \left. \dfrac{(P_i(t) - P_l(t)) * v_i(t)}{\|v_i(t)\|^2}, l = l_1, l_2, \ldots, l_m \right\}, \text{ otherwise} \end{cases} \tag{4}$$

$$D_{CPA_i}(t) = \min \left\{ P_l(t), \left\| [P_i(t) + v_i(t) T_{CPA_i}(t)] - \left(P_j(t) + v_j(t) T_{CPA_j}(t)\right) \right\|, \right. \\ \left. j = 1, 2, \ldots, n, j \ne i; l = l_1, l_2, \ldots, l_m \right\} \tag{5}$$

$$\rho_i(t) = \left(a_i \frac{D_i(0)}{D_{CPA_i}(t)}\right)^2 + \left(b_i \frac{T_i(0)}{T_{CPA_i}(t)}\right)^2 \tag{6}$$

Here, when $P_l(t)$ represents $T = t$, the distance between the static obstacle and the position of ship i, $l = l_1, l_2, \ldots, l_m$, weighted value a_i, b_i can be pre-set based on the maneuverability and type of the ship itself, and $a_i \le 0.5$, $b_i \le 0.5$.

$D_i(0)$, $T_i(0)$ are the thresholds for the closest encounter distance and closest encounter time of ship i, which can be determined based on factors such as the ship type, ship area, navigation safety field, wave velocity, and navigation experience. Each vessel in the encounter scenario can calculate its own collision risk at any time based on the navigation data of each vessel.

Formulas (4), (5), and (6) that consider characteristic constraints can more accurately express the characteristics of narrow water area collision avoidance games and also make corresponding collision avoidance algorithms more accurate.

According to Formula (6), the higher the value of $\rho_i(t)$, the greater the risk of collision.

3. **Multi Ship Alliance Game.**

Head-on situation is the most common scenario where multiple ships encounter each other in narrow waters. According to COLREGs, the sea level can be divided into 5 encounter areas based on the orientation of the target ship relative to the center ship (or center ship), as shown in Figure 1. The ships in Zone A and Zone D form a head-on situation, where ships in Zone A are sailing in the same direction, and the ships coming from the opposite side of Zone D are also sailing in the same direction.

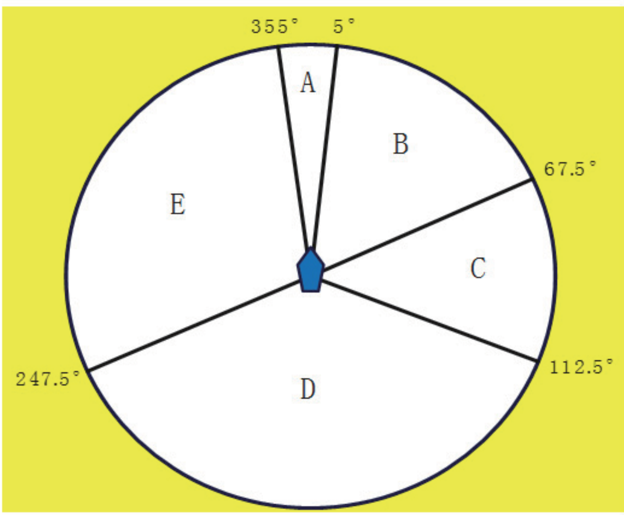

FIGURE 1. Classification of multiple ship encounter situations

The collision avoidance game formed by multiple ships encountering situations in narrow waters has the characteristics of multiple uncertainties and conflicts. The collision avoidance action needs to take account of the overall interests of other ships in the same area.

Alliance game theory allows ships to adopt cooperative strategies and make real-time adjustments to collision avoidance actions, thereby enhancing safety and efficiency in narrow waterways. We considered an alliance composed of ships with the same interests and objectives in the same region.

Definition 3.1. *Let the collection of ships in Zone D be* $S_D = \{1, 2, \ldots, k\}$*, and the collection of ships in Zone A be* $S_A = \{k+1, k+2, \ldots, n\}$*. The ships in Zone D and Zone A form a head-on situation, and collection of participating ships* $N = S_A \cup S_D = \{1, 2, \ldots, n\}$*. The subset* S *of* N *is called a Union of* N*. A total of* n *players can form* 2^n *alliances (Sometimes, the empty set* $\emptyset$ *is also considered as an alliance).*

In a multi-ship encounter scenario, each ship in each area can be regarded as a regional alliance, and any subset of the ship set in each regional alliance can also be regarded as a suballiance of that regional alliance.

Definition 3.2. *The maximum utility of alliance* S *is called as its characteristic function, note it as function* $v(S)$*, where set* $N = \{1, 2, \ldots, n\}$*,* $S \subset N$*. Regulations:* $v(\emptyset) = 0$*. The characteristic function* v *on* N *is a real valued function defined on* 2^N*.*

The characteristic function $v(S)$ is the maximum benefit that can be guaranteed by the actions of an alliance S independent of the alliance $N - S$, which can be obtained through the following methods: the players in alliance S form an alliance to strive for the maximum benefit of S, and once the alliance is formed, the players in alliance S no longer care about their special interests.

Only by considering the overall interests of other ships in the same region and alliance can narrow water vessels effectively avoid collisions and ultimately pass through this narrow water area smoothly. Therefore, the following theorem is proposed.

Theorem 3.1. *Let* v *be the characteristic function on the multi-ship set* N*. Alliance game* $\Gamma = [N, v] = [\{S_1, S_2, \ldots, S_m\}, v]$*, then there is the super additivity: For* $\forall S_i$*,* $S_j \subset N, S_i \cap S_j = \emptyset$*, it has*

$$v(S_i \cup S_j) \geq v(S_i) + v(S_j) \tag{7}$$

Inequality (7) indicates that the characteristic function of the multi ship alliance game has super additivity.

Definition 3.3. *Multi vessel alliance game* $\Gamma = [N, v]$*, assign a real value parameter* $x_j^{(i)}$ *to participant* $k_{m_j}^{(i)}$ *in any alliance* $S_j = \left\{k_1^{(i)}, k_2^{(i)}, \ldots, k_{m_j}^{(i)}\right\}$ *of* N*, forming an* m_j*-dimensional vector*

$$x^{(i)} = \left(x_1^{(i)}, x_2^{(i)}, \ldots, x_{m_j}^{(i)}\right) \tag{8}$$

and meet

$$x_j^{(i)} \geq v\left(\left\{k_j^{(i)}\right\}\right), \quad j = 1, 2, \ldots, m_i \tag{9}$$

Then $x^{(i)}$ *is called to be an allocation scheme for alliance* S_i*.*

Definition 3.4. *The degree of dissatisfaction of a ship alliance with a certain allocation, expressed as the word 'Excess',*

$$e(x, S) = v(S) - \sum_{j \in S} x_j \tag{10}$$

'Excess' is equal to the difference between the value of the alliance and the value allocated to everyone in the alliance. The smaller the exception, the lower the level of dissatisfaction.

Definition 3.5. *The vector composed of all excesses in a ship game, arranged in non-increasing order, is called $O(x)$.*

4. **Game Model for Encounter Situations.** Based on alliance games and collision avoidance rules, we will discuss the intelligent collision avoidance problem of multiple ships in narrow waters.

Encounter situation refers to a situation where two motorized ships meet in opposite or nearly opposite directions, posing a risk of collision. When a ship observes another ship ahead or near the front (within a 3° to 5° range on each side of the bow) and can see the other ship's fore and aft mast lights in a straight line or nearly so, and/or two side lights at night, or can make out the shape of the other ship during the day, it indicates a specific encounter situation. Due to the limitations of navigable water width and navigation rules, the traffic flow in narrow waterways is relatively single, and frequent encounters are mostly overtaking and encountering. The relative speed during overtaking is small, and the overtaking process often takes a long time, resulting in accidents when the ship is overtaking in narrow waterways due to the long-term effect of ship-to-ship effects. According to Article 9, Paragraph 4 of the Rules, "Ships shall not cross narrow waterways or waterways if such crossing would hinder the safe passage of ships that can only navigate in such waterways or waterways". Therefore, the following text only discusses the situation where large ships encounter multiple ships in narrow waterways, as shown in Figure 2.

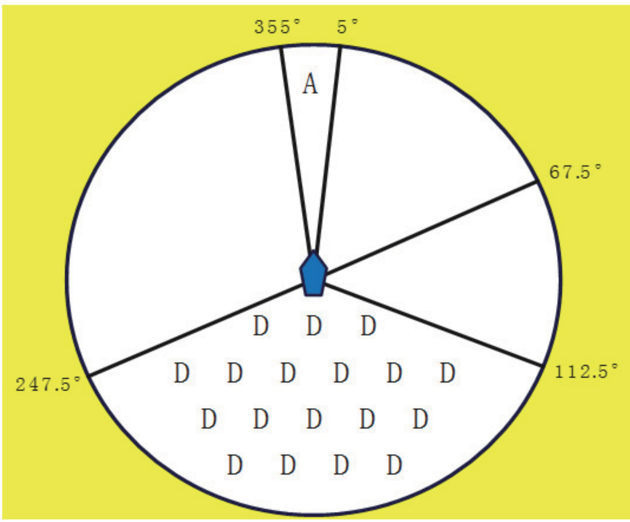

FIGURE 2. The situation of encountering ships

Most modern ships are large or ultralarge, and their motion inertia is significant. Based on the experience of navigation practice and the International Rules for the Avoidance of Collisions at Sea (COLREGs), significant avoidance actions should be taken in situations to ensure the effectiveness of avoidance actions. At the same time, the dynamic collision avoidance game of ships is a sequential game, in which players play games in order at different times and make decisions alternately. To avoid the expansion space of the game being too complex, we only consider turning for collision avoidance, while limiting the upper and lower limits of turning left and right to 30°, and using turning 10° as a strategy and strategy set $A = \{0°, 10°, 20°, 30°\}$, $v(S_j) = \sum_{j\in S} v(j)$.

Position of vessel i at time t: $P_i(x_i(t), y_i(t))$, velocity and heading angle $v_i(t)$, $\varphi_i(t)$, and

$$\dot{x}_i(t) = v_i(t)\cos\varphi_i(t), \tag{11}$$
$$\dot{y}_i(t) = v_i(t)\sin\varphi_i(t), \tag{12}$$
$$\dot{\theta}_i(t) = \omega_i(t), \tag{13}$$
$$\dot{v}_i(t) = a_i(t), \quad (i = 1, 2, \ldots, n) \tag{14}$$

This game constitutes an alliance potential game, and the profit function of the alliance is the potential function

$$p : S \to \mathbb{R} \tag{15}$$

satisfy

$$U_i\left(\hat{s}_i, s_{-i}\right) - U_n(s_i, s_{-i}) = p\left(\hat{s}_i, s_{-i}\right) - p(s_i, s_{-i}), \quad \forall i \in N \tag{16}$$

Here, $\hat{s}_i$ represents a strategy that is different from s_i, while s_{-i} represents a strategy for other users in the system.

Definition 4.1. *According to Formula (6), $\rho_i(t) = \left(a_i \frac{D_i(0)}{D_{CPA_i}(t)}\right)^2 + \left(b_i \frac{T_i(0)}{T_{CPA_i}(t)}\right)^2$, the maximum collision risk of ship D_j relative to all target ships in alliance S_A*

$$\rho_{S_A}^{(j)}(t) = \max\left\{\rho_i^{(j)}(t), i = k+1, k+2, \ldots, n\right\}, \quad j = 1, 2, \ldots, k \tag{17}$$

is defined as the risk-degree of collision of D_j relative to alliance S_A.

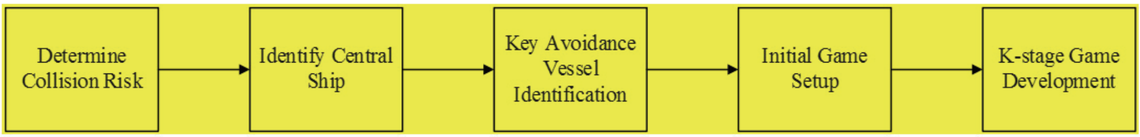

Figure 3. Flowchart of the alliance game

Game model steps:

1) Determine the collision risk of ship D_j relative to alliance S_A, denoted as $\rho_{S_A}^{(j)}(t)$;
2) Determine the center ship $D_{m^*_{(1)}}$:

   Let $\max\left\{\rho_{S_A}^{(j)}(t), j = 1, 2, \ldots, k\right\} = \rho^*_{S_A}(t)$, and when $t = T_1$, the risk-degree of collision of $D_{m^*_{(1)}}$ reaches the critical value $\rho(0)$ for taking avoidance actions, $\rho_{S_A}^{m^*_{(1)}}(T_1) = \rho^*_{S_A}(T_1)$, where $D_{m^*_{(1)}}$ is the center ship.
3) Determine the key avoidance vessel $A_{(1)^*}$

   The key avoidance vessel in Alliance S_A, is the vessel $A_{(1)^*}$ that with the highest collision risk for $D_{m^*_{(1)}}$ when $t = T_1$.
4) Initial game

   In this first stage of the potential game, $D_{m^*_{(1)}}$ taking action relative to $A_{(1)^*}$, the policy space of $D_{m^*_{(1)}}$ is $\left\{s_{m^*_{(1)}}(T_1), s_{\hat{m}^*_{(1)}}(T_1)\right\}$.

   If $D_{m^*_{(1)}}$ takes action $s_{m^*_{(1)}}(T_1)$, the collision avoidance is successful. If participant $D_{m^*_{(1)}}$ takes action $s_{\hat{m}^*_{(1)}}(T_1)$, collision avoidance fails and the game is over, here, $m^*_{(1)} \in \{1, 2, \ldots, k\}$, $s_{m^*_{(1)}}(T_1)$: The action strategy of a significant right turn adopted by $D_{m^*_{(1)}}$ relative to $A_{(1)^*}$, when $t = T_1$. $s_{\hat{m}^*_{(1)}}(T_1)$: Action strategy different from $s_{m^*_{(1)}}(T_1)$, which is adopted by $D_{m^*_{(1)}}$.

5) K-stage game

The first stage of the game will be over if participant $D_{m^*_{(1)}}$ adopts strategy $s_1(T_1)$. At this point, alliance S_A and $S_D - D_{m^*_{(1)}} = S_D^{(2)}$ form a new encounter situation and engage in the second stage of the game.

Assuming that the risk-degree of collision of $D_{m^*_{(2)}}$ in alliance $S_D^{(2)}$ reaches a critical value $\rho(0)$ when $t = T_2$, the central ship $D_{m^*_{(2)}}$ takes action to avoid the key avoidance ship $A_{(2)^*}$ in alliance S_A. If $D_{m^*_{(2)}}$ takes action $s_{m^*_{(2)}}(T_2)$, the collision avoidance is successful. If $D_{m^*_{(2)}}$ takes strategy $s_{\hat{m^*_{(2)}}}(T_2)$, the collision avoidance fails and the game is over.

If $D_{m^*_{(j)}}$ consistently selects strategy $s_{m^*_{(j)}}(T_j)$ for all j less than $k-1$, a new encounter situation arises between S_A and $S_D - D_{m^*_{(k-1)}} = S_D^{(k)}$, and the kth stage game will be played when $j = k$. If $D_{m^*_{(k)}}$ takes action $s_{\hat{m^*_{(k)}}}(T_k)$, the collision avoidance fails, and the game will be over. If $D_{m^*_{(k)}}$ takes action $s_{m^*_{(k)}}(T_k)$, to avoid $A_{(k)^*}$, the collision avoidance will be successful, allowing all participants of Alliance S_D to pass through the narrow channel. Therefore, it has the following.

Theorem 4.1. *The alliance S_D in above alliance game has a unique subgame Nash equilibrium in the ith stage*

$$\left\{s_1(T_i), s_2(T_i), \ldots, s_{m^*_{(i)}-1}(T_i), s_{m^*_{(i)}}(T_i), s_{m^*_{(i)}+1}(T_i), \ldots, s_k(T_i)\right\} \tag{18}$$

Here, $s_j(T_i)$ is the action strategy adopted by other ships D_j in alliance $S_D^{(i)}$, except for $D_{m^*_{(i)}}$, to maintain direction and speed, or to reduce speed and maintain direction, $j = 1, 2, \ldots, k$ and $j \neq m^*_{(i)}$.

Theorem 4.2. *The Pareto optimality of the sequential game of alliance S_D in this k-stage:*

$$\left\{s_{m^*_{(1)}}(T_1), s_{m^*_{(2)}}(T_2), \ldots, s_{m^*_{(k)}}(T_k)\right\} \tag{19}$$

Here, $s_{m^*_{(i)}}(T_i)$: The action strategy of a significant right turn adopted by $D_{m^*_{(i)}}$ relative to $A_{(i)^*}$ when $t = T_i$, $s_{\hat{m^*_{(i)}}}(T_i)$: Action strategy different from $s_{m^*_{(1)}}(T_1)$, which is adopted by $D_{m^*_{(i)}}$.

The benefits of alliance S_D, i.e., the potential function

$$p(S_D) = \left\{\sum_{i=k+1}^{n} p(D_i), i = 1, 2, \ldots, k\right\} \tag{20}$$

In this alliance game, each participant adopts the optimal strategy, and no participant can improve their profits by changing their strategy, and there is no way to find it, any participant can increase their profits by changing their strategy, and at this point, the allocation plan of alliance S_D

$$x^{(D)} = \left(x_1^{(D)}, x_2^{(D)}, \ldots, x_k^{(D)}\right), \quad x_j^{(D)} = v\left(\left\{k_j^{(D)}\right\}\right), \quad j = 1, 2, \ldots, k, \tag{21}$$

$$e(x, S_D) = v(S_D) - \sum_{j \in S_D} x_j = 0 \tag{22}$$

The schematic diagram of the extended tree of the alliance game is depicted in Figure 4.

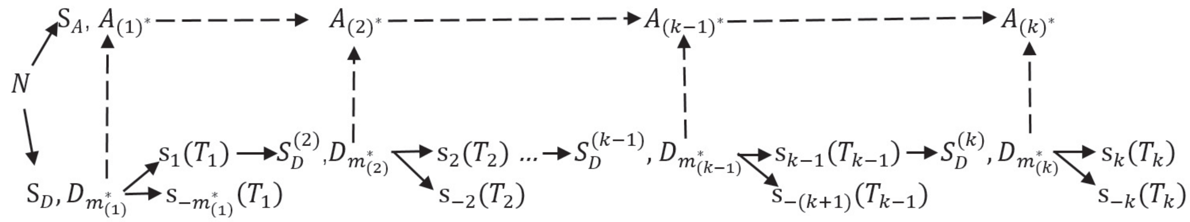

FIGURE 4. Schematic diagram of extended tree for alliance game

N is the root node of the game extension tree, which contains information about the current state, including the position, heading angle, offset, and collision risk of each ship in the two alliances.

5. **Simulation.** The case used in this article is based on the system simulation testing and verification environment of electronic chart platform and ship motion simulator. The electronic chart platform has rich marine geographic information, and the ship motion simulator can convert the decisions generated by collision avoidance algorithms into actual control instructions based on the mathematical model and controller of ship motion, and provide real-time feedback on the ship's motion status information. To verify the feasibility of the evaluation model proposed in this article, the data from the simulation test case was used for calculation. The specific scenario is shown in Figure 5.

Area A contains two target ships, namely Ts1, Ts2, corresponding to "477700203" and "477700204". Area D contains four ships, namely Ts3, Ts4, Ts5, and Ts6, corresponding

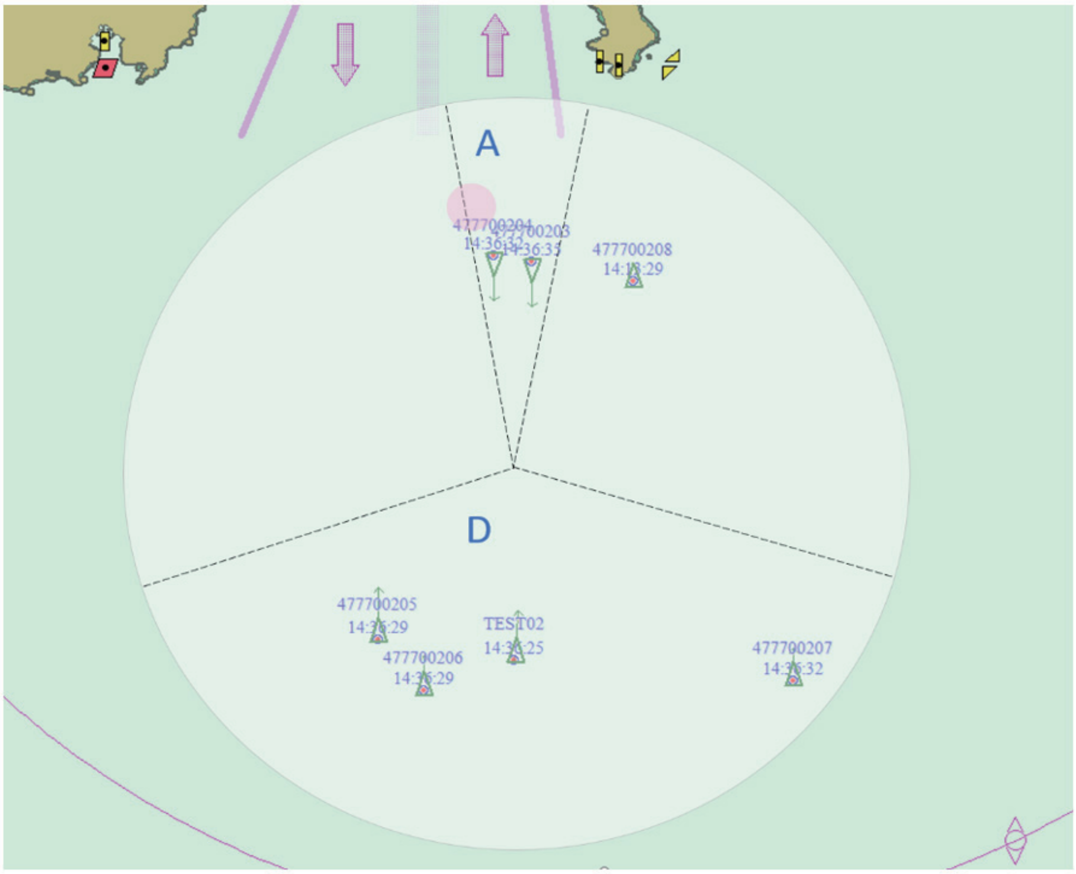

FIGURE 5. Experimental starting diagram

to "477700205", "477700206", "TEST 02", and "477700207", respectively. To consider the impact of static obstacles, set "477700208" as the Ts7 ship in a stationary state and simulate static obstacles.

The specific starting position and heading speed of the target vessel are shown in Table 1 below.

TABLE 1. Experimental starting source data

Vessel	Latitude	Longitude	Heading	Speed
Ts1	38°49′44″N	121°47′41″E	180°	10kt
Ts2	38°49′22″N	121°48′01″E	180°	10kt
Ts3	38°43′46″N	121°45′37″E	000°	14kt
Ts4	38°43′13″N	121°46′14″E	000°	7kt
Ts5	38°43′51″N	121°47′42″E	005°	12kt
Ts6	38°43′29″N	121°52′57″E	000°	6kt
Ts7	38°48′42″N	121°49′42″E	270°	0

According to the experimental simulation scenario and Formula (6), calculate DCPA and TCPA, and select the critical collision risk value $\rho^* = 9.80$. When $T_1 = 7.76$ mins, the collision risk between Ts5 in Alliance D and Ts2 in Alliance A is the highest (see Table 2), and reaches the critical value ρ^*. Therefore, in the first round of the game, Ts5, also known as TEST 02, is the central ship, and Ts2 is the key avoidance ship.

TABLE 2. Risk level between starting vessels

Target ship 1	Target ship 2	DCPA (nm)	TCPA (mins)	ρ (Collision risk)
Ts1	Ts2	0.45	∞	0
Ts1	Ts3	1.61	15.68	1.20
Ts1	Ts4	1.13	11.84	1.11
Ts1	Ts5	0.89	10.26	5.99
Ts1	Ts6	4.12	12.07	2.3
Ts1	Ts7	1.57	8.92	2.96
Ts2	Ts3	1.87	9.21	1.10
Ts2	Ts4	1.39	11.17	3.87
Ts2	Ts5	0.91	7.76	9.80
Ts2	Ts6	3.85	11.36	0.32
Ts2	Ts7	1.31	9.06	5.48

Figure 6 shows the avoidance diagram of the central ship. During the avoidance process, the central ship Ts5 made a decision to turn right 30 degrees to avoid the key avoidance ship Ts2.

Here, due to the fact that the voyage trajectory line of Ts1 and the voyage trajectory line of Ts2 are parallel, their TCPA is equal to ∞ and the collision risk is equal to 0.

Figure 7 shows the variation of the shortest encounter distance and time between the center ship Ts5 and the target ships Ts1 and Ts2 in Alliance A during the avoidance process.

From the line chart, it can be seen that after the center ship Ts5 avoids, the shortest distance it will encounter will significantly increase, and the collision risk with Alliance A will be eliminated. Repeat the above game process until all ships in Alliance D safely avoid the ships in Alliance A and pass through this waterway. The simulation results

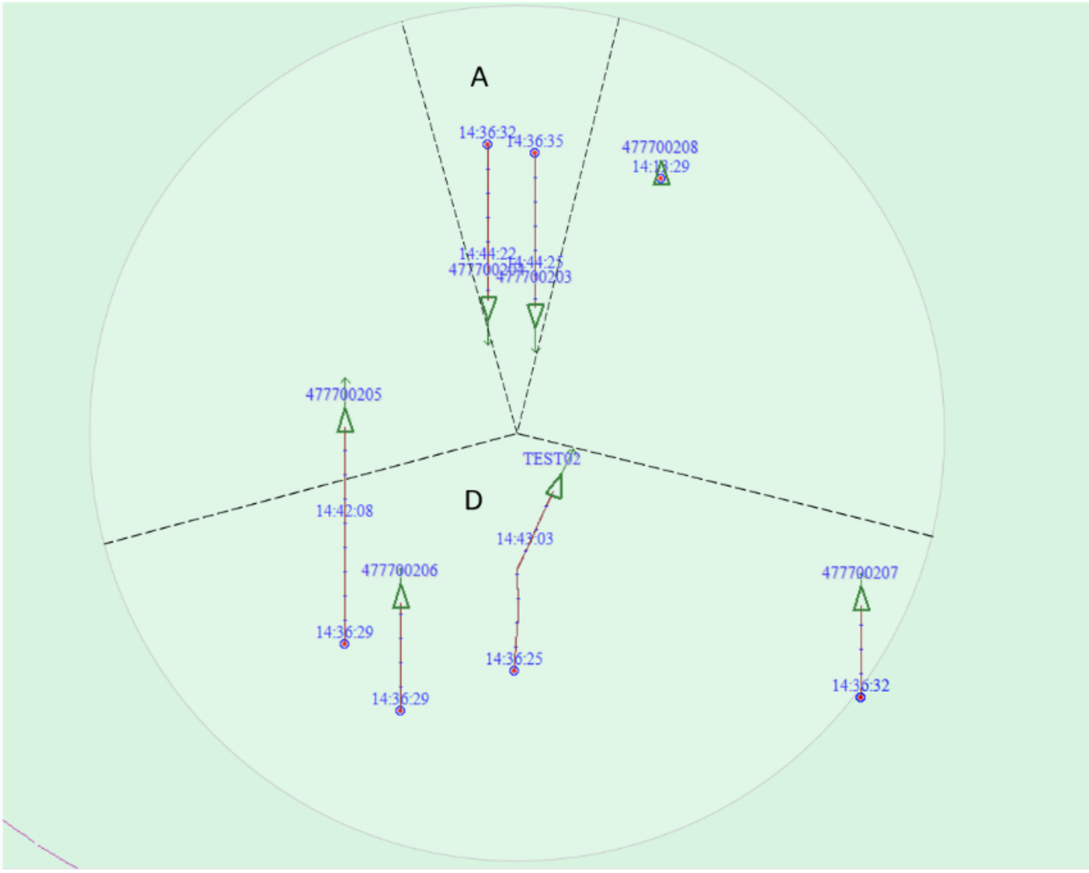

FIGURE 6. The central ship responds with avoidance measures

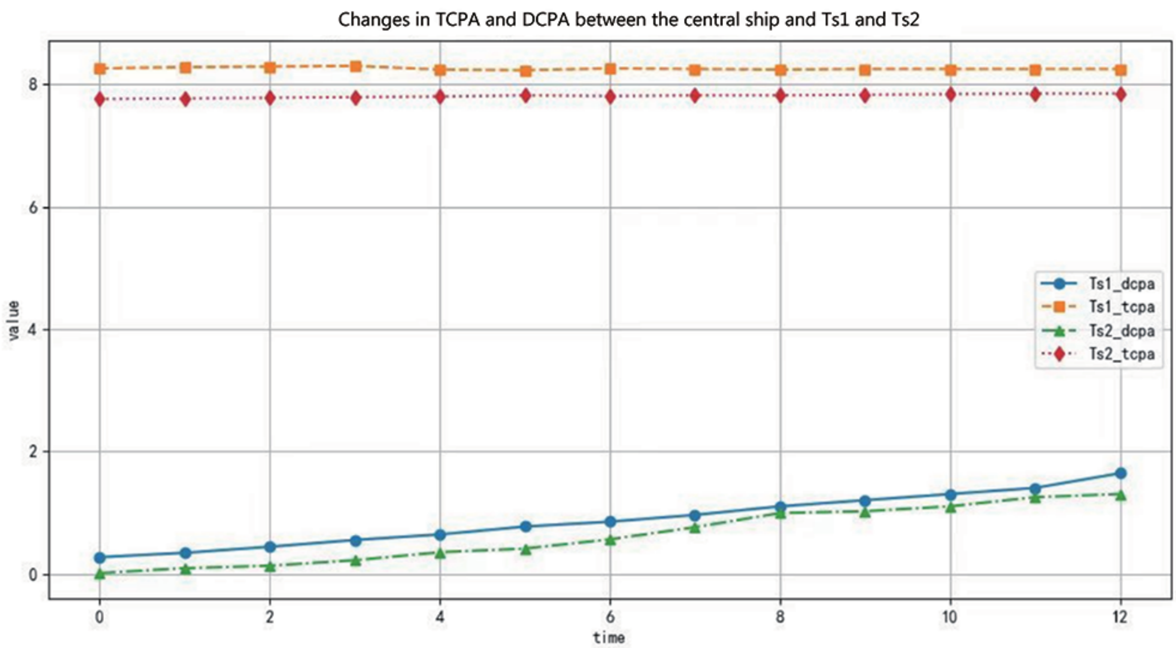

FIGURE 7. Changes in TCPA and DCPA between the central ship and target ships Ts1 and Ts2

demonstrate the feasibility of the proposed alliance game collision avoidance model in this paper.

6. **Summary.** This study applies alliance game theory to the ship collision avoidance decision-making system and propose a dynamic collision avoidance method for ship alliances. The practical utility of the research is demonstrated through several key applications. Firstly, it enables the automatic implementation of collision avoidance tactics in conditions of poor visibility, thereby minimizing human error. Secondly, in congested ports, it facilitates the coordination of multiple vessels' movements, leading to optimized routing and speed, which in turn enhances navigation efficiency. Additionally, this research supplies essential data support and establishes communication standards for the advancement of intelligent shipping and autonomous navigation technologies, propelling the shipping industry towards greater safety, efficiency, and automation. The results of system simulation testing based on electronic chart platform and ship motion simulator have verified the feasibility of the multi ship alliance game method proposed in this study. Looking ahead, future research should delve into the refinement of collision avoidance algorithms and the development of collaborative mechanisms that can adapt to more intricate and ever-changing navigational conditions and ship dynamics. This will contribute to the ongoing enhancement of maritime safety and the optimization of ship traffic management.

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