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A Study on a Situation Awareness Model for Navigators in Congested Waters

T. Endoo, C. Nishizaki & O. Tadatsugi
University of Marine Science and Technology, Tokyo, Japan

ABSTRACT: In recent years, most maritime accidents have been caused by deficiencies in navigators’ situational awareness. Previous studies have evaluated the navigators' situation awareness (SA) through the application of the Situation Awareness Global Assessment Technique (SAGAT) in ship maneuvering simulations. Researchers have developed collision avoidance support systems and collision risk assessment models to mitigate maritime accidents. However, existing models often apply conventional weight parameters for collision risk factors, which may not be appropriate for navigators with different experience levels. To refine these weight parameter sets tailored to each navigator level, based on each navigator's significant SA, derived from experimental navigators' situation awareness measurement. In addition, grid search-based weight aggregation was employed to systematically refine the weight distributions, optimize the impact of collision risk factors, and ensure improved model accuracy. The results demonstrate that the proposed weight parameters improve the detection rate of significant targets according to navigator’s experience level in congested waters.

1 INTRODUCTION

Improper lookouts by navigators have been identified as a primary cause of frequent maritime accidents. Failure to maintain a proper lookout has been identified as a major cause of ship collisions, and is considered a situational awareness error by navigators. Grech et al. analyzed maritime accident reports and found that 71% of human errors were related to SA [1]. SA is a critical factor in risk assessment. Endsley proposed a situational awareness global assessment technique (SAGAT) [2] to measure the SA of an aircraft pilot in a cockpit. Okazaki proposed a method that could be measured by the SAGAT to measure the SA of a ship navigator's SA in pilot training using a ship maneuvering simulator [3]. An analytical method for maritime accident analysis that uses a bridge simulator to identify the critical factors contributing to navigational watchkeeping and to assess a navigator's decision-making processes has been proposed [4], [5].

To reduce the number of maritime accidents, researchers have developed ship support systems to provide information for ship collision avoidance. However, the effectiveness of such systems may vary depending on the navigator's level of experience. Specifically, the information provided may be insufficient for less experienced navigators, whereas it may be overly detailed for highly experienced navigators, potentially affecting decision-making efficiency. Ship collision risk modeling and risk analysis have recently become the focus of several studies [6]. One of the ship collision risk models is the collision risk index (CRI), which is a computational tool used to reflect the risk of collision based on dynamic navigational factors such as the DCPA, TCPA, relative distance, relative bearing, and velocity ratio between two ships through fuzzy inference to evaluate the probability and severity of collision risk with multiple ships [6]. In addition, the SA model is a cognitive process by which navigators perceive critical environments and current risks, and project future states to support effective decision-making [7]. Consequently, the collision risk and SA models are interdependent, as an accurate SA enables navigators to interpret and make decisions regarding collision risks, while the collision risk model provides a real-time risk indicator that supports the perception of risk and projects the future state of the SA. By integrating the SA model into the collision risk model, collision risk recognition can be made more compatible with the actual decision-making of navigators to improve the applicability of CRI models across different navigator experience levels.

However, the existing CRI models typically rely on fixed-weight parameters for risk factors, which may not align with the decision-making strategies of navigators with different expertise levels. Thus, an optimized weighting approach is required. Traditionally, a grid search has been employed in machine learning for hyperparameter tuning by systematically exploring a predefined set of parameter values to identify the optimal configuration [8]. In this study, we adapted the grid search approach by applying it to weight aggregation rather than to hyperparameter tuning. This method systematically evaluates different combinations of weight parameters and identifies the optimal set that best aligns with the SA patterns of the navigators. This adaptation ensures that the collision risk model accurately reflects the decision-making of navigators across various ranks, thereby improving its effectiveness in real-world maritime operations.

2 NAVIGATOR SITUATIONAL AWARENESS

This study focuses on ship navigation in congested waters, where vessel density and collision risks are significantly higher than those in the open sea. In addition, navigators operating under such conditions require advanced practical skills, knowledge, situational awareness, and decision-making to encounter a multiple-target ship scenario. To systematically evaluate navigators' SA, decision-making processes, and risk prioritization strategies under congested water conditions. The SA measurements and risk prioritization of the navigators were conducted during the simulated experimental scenario, and the adapted SAGAT was applied using a radar-plotting chart. In addition, experiments were conducted at the National Maritime Research Institute in a bridge simulator, which contains general navigational equipment such as radar, ECDIS, compass, binoculars, and a steering control unit.

2.1 *SAGAT*

The SAGAT is an effective technique for measuring SA in simulation experiments. The Originally developed and proposed by Endsley to measure aircraft pilots' SA in simulator cockpits, and procedural standards for the SAGAT were established [2]. An adapted SAGAT modifies the original SAGAT measurement method and procedural standard to measure the SA of a ship navigator in a ship maneuvering bridge simulator [3].

During the experiment, the SAGAT was used to measure the SA. The experiment was interrupted immediately. In addition, the simulator screen temporarily turned black while the subject answered questions to measure the recognized situation. After completion of the questionnaire, the simulations were resumed. However, if the simulation is interrupted for an excessive duration, experimental continuity decreases. Therefore, interruption exceeding two minutes were found to negatively affect experimental continuity. However, it is difficult to keep the questions answered within two minutes by oral answers. Additionally, there are ambiguities in oral answers regarding recognized targets in a congested sea area, particularly expressing their positions [4].

In this study, the adapted SAGAT was used to measure navigator SA. In addition, we adapted a method in which subjects filled in the recognized targets on the radar plotting chart. This method was proposed as an evaluation method for pilot marine trainees [9]. We set the interruption time to one minute to enable the subjects to answer questions based on radar-screen information using radar-plotting charts. Figure 1 illustrates the radar plotting chart, in which the subjects marked the recognized targets used in the experiment.

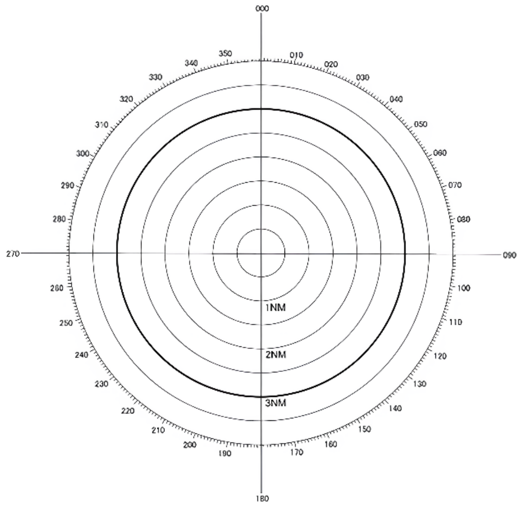

Figure 1. Example of RADAR plotting chart for SAGAT.

2.2 *Result of the previous study on SA.*

In a previous study by Nishizaki [4], the SA and risk priority measurements of navigators were conducted using SAGAT in scenarios involving multiple target ships in congested waters. A previous study used a bridge simulator equipped with general navigational equipment. In addition, four participants had previously participated in a real-world ship in the captain position. The results of the four captains' SA from a previous study are presented in Table 1.

2.3 *Comparison of evaluation risk area and experimental results*

Nakamura and Nishizaki proposed a method for evaluating the safety of an automatic collision avoidance system capable of evaluating risk areas such as danger, caution, attention, and safety [10], [4]. The evaluation method aims to ensure compliance with the maritime rules of the road (COLREGs), which contain three encounter situations: crossing, head-on, and the same way. In addition, the evaluation method was based on the relationship between the rate of change in the bearing and the relative distance. The evaluation risk area method can potentially identify risk targets and categorize them into risk categories such as danger, caution, attention, and safety. In congested waters, there are so many target ships that it is difficult to recognize all those requiring attention. According to the results of the captains' SA in a previous study compared with the evaluation risk area method, as illustrated in Table 1. In the table, the first column and first row indicate the ship ID and SAGAT measurement time, respectively, and the fourth to last rows indicate the ships recognized by the subjects. The total number of recognized ships at each measurement time point is indicated in the third row. The lighter-grey-highlighted cells indicate ships recognized by more than half of the subjects and were significant recognition targets in the study. Grey highlighted cells represents ships captured by the evaluation risk area method, and dark highlighted cells indicate ships captured by more than half of the subjects and the evaluation risk area method.

Table 1. Result of the captains' SA in the previous study [4].

Exp. min	1 (7 min)				2 (12 min)				3 (17 min)				4 (22 min)			
Sub.	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
Ship	2	5	5	6	2	8	6	5	2	7	7	7	2	7	6	7
1				O												
2				O				O	O	O		O		O	O	O
3		O			O	O	O	O	O	O	O	O	O	O	O	O
4						O	O			O	O					
5		O	O													
6										O		O				O
7				O												
8	O	O	O	O			O									
9			O	O		O	O	O			O	O				
10						O				O	O	O		O	O	O
11																
12								O								
13																
14			O									O				
15														O		O
16						O										
17		O														
18						O										
19	O	O	O		O	O	O			O	O			O	O	
20														O	O	O
21																
22																
23										O	O		O	O	O	O
24			O	O		O	O	O			O	O				

2.4 *Concept of the proposed method.*

The recognized risk targets for navigators vary depending on the level of the navigator. The capability to recognize collision risk targets varies among navigators at different levels with varying knowledge, experience, and skills, as is evident from the results of the captains' SA, which illustrates the target recognition patterns in Table 1. In addition, navigational safety relies on the recognition of surrounding ships, particularly in multiple encounter situations. Navigators are tasked with assessing RADAR, automatic identification system (AIS) data, and visualized lookouts. Humans have limitations in recognizing collision risk targets in congested waters. Consequently, the proposed concept gathers the SA of the navigators from the previous study and the current study, which were conducted at the captain's level and officer's level, respectively, to optimize the collision risk model. On the one hand, the collision risk model and the evaluation risk area method have the potential to evaluate the collision risk of surrounding target ships. However, the evidence from the evaluation risk area method, illustrated in Table 1, indicates that the capability may not capture all significant target ships that the subjects identified. Therefore, the proposed concept involves weight optimization in the collision risk model by adapted grid-search weight optimization based on the gathered SAs of the navigators.

3 COLLISION RISK MODEL

3.1 *Outline*

The proposed method aims to enhance the CRI by optimizing its weight parameters to identify the target recognition more effectively based on each navigator's SA result. In a previous study, Nishizaki proposed a model of the evaluation risk area method, such as the attention area, to evaluate the target ships that navigators pay attention to through a simulated experiment in congested water and situation awareness measurements. The proposed method contains three components. First, CRI is the main formula used to evaluate target risk levels. The collision risk index is formulated as fuzzy interference using multiple navigational factors, such as DCPA, TCPA, relative distance, relative bearing, and velocity ratio [6]. Second, we adapted the grid search technique to generate weight combinations to optimize the importance of each factor using the recorded simulated experimental data and navigator SA results. Third, the optimal weight combination was placed into the collision risk index model to assess the risk targets and compare the identified risk targets with the navigator's SA. In addition, the evaluation was based on classification performance metrics to determine how well the optimized weight combination related to the navigator's significant targets.

3.2 *Collision risk index model*

The CRI was defined as the basis for decision-making in collision avoidance to evaluate a target that has the possibility and severity of collision risk. The CRI evaluates the degree of collision risk by comprehensively considering the DCPA, TCPA, relative distance, relative bearing, and velocity ratio between two ships [6]. As illustrated in Figure 2, the DCPA and TCPA can be obtained through geometric calculations of the ship encounter situation, where the dashed line represents the extended line of the relative velocity (V_R). The position coordinates, velocity, and course of the own ship are S_O (x_O,y_O), V_O, and φ_O. The position coordinates, velocity, and course of the target ship were S_T (x_T,y_T), V_T, and φ_T. Additionally, those of D_R, V_R, and φ_R are the relative distance, velocity, and course, respectively. a_T is the azimuth of the target ship, and θ_T is the relative bearing. The equations for DCPA, TCPA, D_R, φ_R, V_R and θ_T are defined in Eqs. (3)-(10) [6].

$$DCPA = D_R \times \sin\left(\varphi_R - a_T - \pi\right) \tag{1}$$

$$TCPA = D_R \times \cos\left(\varphi_R - a_T - \pi\right) / V_R \tag{2}$$

$$D_R = \sqrt{\left(x_T - x_O\right)^2 + \left(y_T - y_O\right)^2} \tag{3}$$

$$\varphi_R = \begin{cases} \tan^{-1}\left(\dfrac{V_{Rx}}{V_{Ry}}\right), & V_{Rx} \geq 0,\ V_{Ry} \geq 0 \\ \tan^{-1}\left(\dfrac{V_{Rx}}{V_{Ry}}\right) + 90°, & V_{Rx} \geq 0,\ V_{Ry} \leq 0 \\ \tan^{-1}\left(\dfrac{V_{Rx}}{V_{Ry}}\right) + 180°, & V_{Rx} \leq 0,\ V_{Ry} \leq 0 \\ \tan^{-1}\left(\dfrac{V_{Rx}}{V_{Ry}}\right) + 270°, & V_{Rx} \leq 0,\ V_{Ry} \geq 0 \end{cases} \tag{4}$$

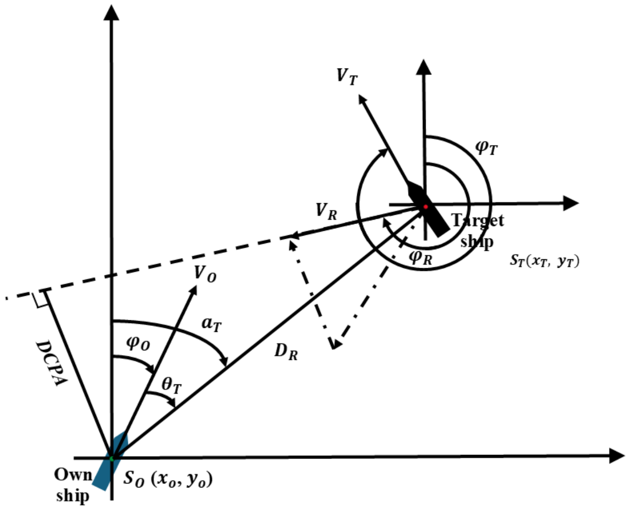

Figure 2. Diagram of the two-ship encounter geometry [6].

$$\begin{cases} V_{Rx} = V_{Tx} - V_{Ox} \\ V_{Ry} = V_{Ty} - V_{Oy} \end{cases} \tag{5}$$

$$\begin{cases} V_{Ox} = V_O \sin\varphi_O \\ V_{Oy} = V_O \cos\varphi_O \end{cases}, \begin{cases} V_{Tx} = V_T \sin\varphi_T \\ V_{Ty} = V_T \cos\varphi_T \end{cases} \tag{6}$$

$$V_R = \sqrt{V_{Rx}{}^2 + V_{Ry}{}^2} \tag{7}$$

$$\theta_T = a_T - \varphi_O \tag{8}$$

The crucial factors (DCPA, TCPA, D_R, θ_T, and V_T/V_O) are considerable for evaluating the collision risk index. However, evaluating these factors is difficult because the relationship between collision risk factors is complex and ambiguous, and each factor has a different impact on the evaluation of the risk of collision depending on the encounter situation. Owing to the complex relationship between collision risk factors, fuzzy synthesis judgment is introduced to express knowledge and experience with ambiguous boundaries [11], [12]. Therefore, this study was conducted to predict the CRI through fuzzy inference according to various encounter situations using membership functions defined as follows [6]:

1. The membership function of DCPA:

$$u_{DCPA} = \begin{cases} 1, & d_1 \geq |DCPA| \\ 0.5 - 0.5\sin\left[\dfrac{\pi}{d_2 - d_1}\left(|DCPA| - \dfrac{d_2 + d_1}{2}\right)\right], & d_1 < |DCPA| \leq d_2 \\ 0, & d_2 < |DCPA| \end{cases} \tag{9}$$

where u_{DCPA} denotes the membership function of the DCPA, d_1 denotes the minimum encounter distance between the two ships, and d_2 denotes the safe encounter distance. d_1 and d_2 are defined as [6].

$$d_1 = \begin{cases} 1.1 - \dfrac{0.2\theta_T}{\pi}, & 0° \leq \theta_T < 112.5° \\ 1.0 - \dfrac{0.4\theta_T}{\pi}, & 112.5° \leq \theta_T < 180° \\ 1.0 - \dfrac{0.4\left(2\pi - \theta_T\right)}{\pi}, & 180° \leq \theta_T < 247.5° \\ 1.1 - \dfrac{0.2\left(2\pi - \theta_T\right)}{\pi}, & 247.5° \leq \theta_T \leq 360° \end{cases}$$
$$d_2 = 2d_1 \tag{10}$$

2. The membership function of TCPA:

$$u_{TCPA} = \begin{cases} 1, & t_1 \geq |TCPA| \\ \left(\dfrac{t_2 - |TCPA|}{t_2 - t_1}\right)^2, & t_1 < |TCPA| \leq t_2 \\ 0, & t_2 < |TCPA| \end{cases} \tag{11}$$

where u_{TCPA} is the membership function of the TCPA, t_1 represents the ship collision time, and t_2 represents the time taken to start paying attention to the target ship. t_1 and t_2 are expressed as [6].

$$t_1 = \begin{cases} \dfrac{\sqrt{D_1{}^2 - DCPA^2}}{V_R}, & DCPA \leq D_1 \\ \dfrac{\left(D_1 - DCPA\right)}{V_R}, & DCPA > D_1 \end{cases}$$
$$t_2 = \begin{cases} \dfrac{\sqrt{D_2{}^2 - DCPA^2}}{V_R}, & DCPA \leq D_2 \\ \dfrac{\left(D_2 - DCPA\right)}{V_R}, & DCPA > D_2 \end{cases} \tag{12}$$

3. The membership function of D_R [6]:

$$u_{D_R} = \begin{cases} 1, & 0 \leq D_R < D_1 \\ \left(\dfrac{D_2 - D_R}{D_2 - D_1}\right)^2, & D_1 \leq D_R \leq D_2 \\ 0, & D_2 < D_R \end{cases} \tag{13}$$

where u_{DR} is the membership function of the relative distance and D_1 represents the minimum distance to be avoided by the give-way ship. Generally, D_1 is set as 12–14 times the ship length, D_2 represents the safe distance for collision avoidance. D_1 and D_2 are expressed as [6].

$$\begin{aligned} D_1 &= (12-14)L \\ D_2 &= 1.7\times\cos(\theta_T-19°)+\sqrt{4.4+2.89\times\cos^2(\theta_T-19°)} \end{aligned} \tag{14}$$

4. The membership function of θ_T:

$$u_{\theta_T} = 0.5\left[\cos\left(\theta_T-19^{\circ}\right)+\sqrt{\frac{440}{289}+\cos^2\left(\theta_T-19^{\circ}\right)}\right]-\frac{5}{17} \tag{15}$$

where $u_{\theta T}$ is the membership function of relative bearing.

5. The membership function of V_T/V_O :

$$u_{\varepsilon} = \frac{1}{1+\frac{2}{\varepsilon\sqrt{\varepsilon^2+1+2\varepsilon\sin C}}} \tag{16}$$

where u_{ε} is the membership function of relative ratio velocity, ε represents V_T/V_O , $C \in [0°,180°]$ is collision angle. C can be expressed as follows [6].

$$\sin C = \left|\sin\left(\left|\varphi_T-\varphi_O\right|\right)\right| \tag{17}$$

The CRI value between the two ships was calculated based on the membership functions above. The CRI has a value between 0 and 1 for the degree of collision risk by simultaneously reflecting various condition risks. The collision risk value is considered high when f_{CRI} is greater than 0.6 [6]. Therefore, the collision risk model is defined as follows [6]:

$$f_{CRI} = W\cdot U = \left(w_{DCPA}, w_{TCPA}, w_{D_R}, w_{\theta_T}, w_{\varepsilon}\right)\begin{bmatrix} u_{DCPA} \\ u_{TCPA} \\ u_{D_R} \\ u_{\theta_T} \\ u_{\varepsilon} \end{bmatrix} \tag{18}$$

where f_{CRI} is the collision risk function, W is the weight matrix in which each weight belongs to (0,1) and the sum of the weights is 1. w_{DCPA}, w_{TCPA}, w_{DR}, $w_{\theta T}$ and w_{ε} are weight of membership functions, which are usually set as 0.400, 0.367, 0.133, 0.067 and 0.033 accordingly [6]. In addition, U is the membership function matrix.

3.3 *Proposed method*

The collision risk function consists of two components: a weight parameter matrix and membership function matrix. The proposed method focused on w_{DCPA}, w_{TCPA}, w_{DR}, $w_{\theta T}$ and w_{ε} that are typically set to 0.400, 0.367, 0.133, 0.067 and 0.033, respectively. The navigators' SA was obtained in both a previous study involving captains and the current study involving officers. The SAs of the navigators showed that the target recognition patterns of the captains in the previous study and officers in the current study were different, as shown in Table 1. and Table 3. This allows the CRI to identify the target recognition patterns of captains and officers separately. In addition, to determine which parameters place more emphasis, the weight parameters must be optimized separately for each navigator group.

This study adopted a grid search technique, which is typically used to determine the optimal hyperparameters in machine learning [8]. The grid search-based weight aggregation optimization is illustrated in Figure 3. to determine the optimal weight parameter set to compute the collision risk function during maritime navigation. The proposed method systematically explores the weight space to maximize the model performance, ensuring accurate risk classification based on the SA of navigators. We used combinations of weights with up to three decimal places, from 0.0 to 1.0, and differed by 0.001 within each grid. Because the number of possible weight combinations is extremely large, we applied the grid search refinement level technique, which divides the refinement into three levels, starting with a resolution of 0.1, and increasing to 0.01, and 0.001, respectively, with each level of refinement capturing the majority of weights and using them in the next refinement level. Moreover, the weight combinations are constrained to sum to 1.0. The grid search weight aggregation process continues until all possible weight combinations are evaluated. Each combination is applied to the collision risk function to obtain f_{CRI} by using the recorded navigational simulation data. To evaluate the effectiveness of each weight combination, the significant targets of the navigators were used as ground-truth risk targets. The classification of risk or non-risk is under the condition that if f_{CRI} is greater than 0.6, as was set in a previous study [6], the target will be identified as a risk target. In addition to evaluating classification performance, standard evaluation metrics such as the F1-score, precision, recall, and accuracy were applied. Grid search weight aggregation was performed to determine the best weight parameters until all possible combinations were accomplished.

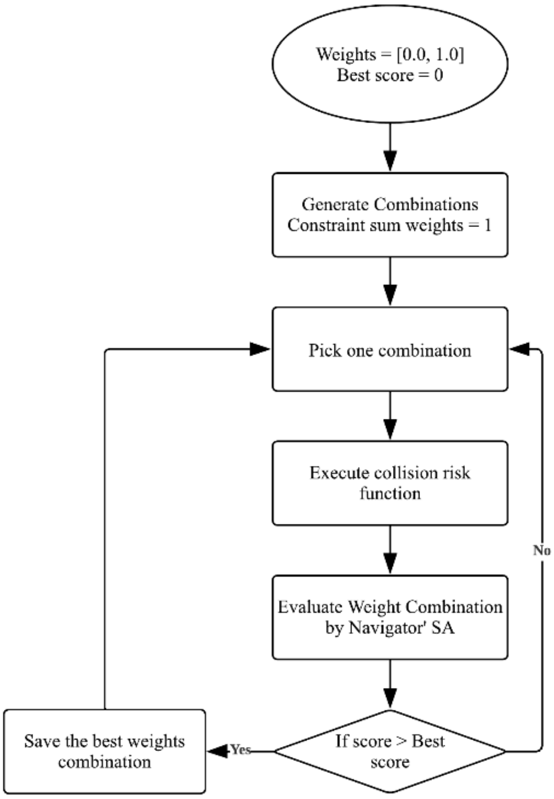

Figure 3. Grid search method for finding the best weights combination.

4 EXPERIMENT

4.1 *Bridge Simulator*

The experimental bridge simulator setup was adapted from a previous study [4], with the same equipment configuration and procedure used to assess the SA of navigators using the SAGAT. The purpose of the simulator experiment was to obtain the SA results of the navigators in watchkeeping, which were measured by the SAGAT. Experiments with the SAGAT were conducted using the full mission bridge simulator of the National Maritime Research Institute. The bridge simulator installed general navigational equipment, such as a compass, binoculars, radar, ECDIS, and a steering stand with a steering wheel. The simulator analysis systems recorded the subjects' responses in the navigational order and encountered situations.

4.2 *Subjects*

In this study, 12 subjects with different onboard experience from those in the previous study were employed. The details of the subjects in previous and current studies are shown in Table 2 [4].

Table 2. Comparison of subjects' details between the previous and current study.

Experimental session	Subject ID	Proficiency
Previous study	Sub.A	Captain
	Sub.B	Captain
	Sub.C	Captain
	Sub.D	Captain
Current study	Sub.E	2/O
	Sub.F	2/O
	Sub.G	Captain
	Sub.H	Captain
	Sub.I	Captain
	Sub.J	Captain
	Sub.K	C/O
	Sub.L	2/O
	Sub.M	2/O
	Sub.N	2/O
	Sub.O	Captain
	Sub.P	2/O

In this study, the subjects' watchkeeping used general navigational equipment including a compass, binoculars, radar, ECDIS, and steering instruments. Furthermore, the participants were instructed to maintain their own simulated ship on a steady course and speed if possible. During the experiment, when the participants perceived an imminent risk of collision, they were instructed to avoid it.

Before the experiment, to conform with ethical standards in human research, we requested all the subjects to fill out informed consent forms for human research, which all subjects accepted and signed to signify their informed consent.

4.3 *Experimental Scenario and Measurement Method for navigators' SA*

According to the navigator was measured using the SAGAT in a previous study [4]. In this study, it was necessary to perform measurements under the same experimental conditions. Therefore, the open sea was applied as the sea area for the experimental scenario, and there were 24 target ships, each having various encounter situations with the simulated own ship of the subjects. Ship route tracking of the ship and target ships is shown in Figure 4. Because the experiment was conducted using different bridge simulators and ship model versions, the ship model was changed from a cargo ship to a container ship with different ship characteristics such as ship speed and ship maneuvering ability. Therefore, to measure the SA of the navigators under the same encounter situations, the own ship speed was decreased, and the measurement times for the SAGAT were adjusted.

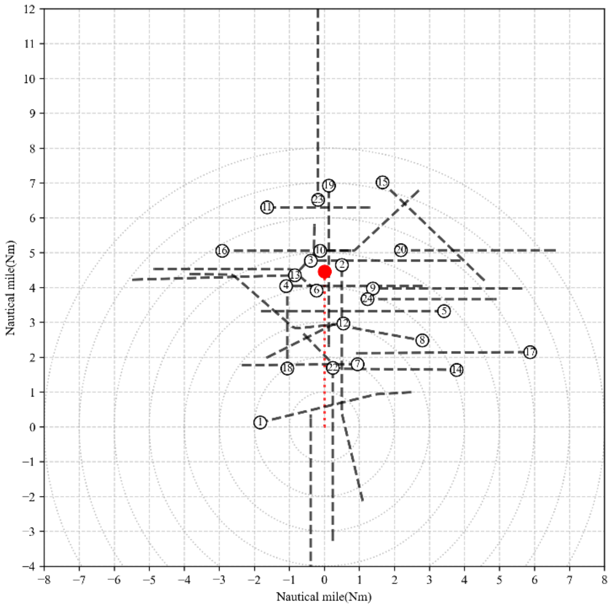

Figure 4. Example tracking of own ship and target ships.

In the current study, the SA of the navigators was measured using the SAGAT under the same experimental conditions as in the previous study. In addition, the scenario spanned approximately 30 min, including the interruption time for the SAGAT, and the experimental scenario was suspended five times after 0, 3, 8, 13, and 22 min. The first measurement was set at the beginning, the second at 3 min, and the third to fifth measurements were conducted every 5 min.

During the interruption time, the navigator's SA was measured by the report that the subjects filled in based on the displayed radar plot chart (Figure 1). The participants filled in the recognized ships and priority rankings in the report. Table 3 illustrates the officers' SA obtained in the current study. In the table, the first column shows the target ship IDs, the second column shows the relationship between the own-ship and target ships, and the initial encounter is mentioned in the second column. In addition, the third column illustrates the result of the SA of the navigators, where the cells marked with a circle represent the recognized targets, and the cells marked with a backslash represent no navigator SA measurements because the navigators performed collision avoidance before the SA measurement time. Moreover, the gray-highlighted cells represented significant target recognition, as assumed in this study, if more than half of the subjects recognized the target.

Table 3. Result of officers' SA.

Exp. min			1 (0 min)												2 (3 min)												3 (8 min)												4 (13 min)												5 (22 min)											
Sub.			E	F	G	H	I	J	K	L	M	N	O	P	E	F	G	H	I	J	K	L	M	N	O	P	E	F	G	H	I	J	K	L	M	N	O	P	E	F	G	H	I	J	K	L	M	N	O	P	E	F	G	H	I	J	K	L	M	N	O	P
Ship	Encounter		5	7	1	3	3	4	5	8	3	6	1	1	7	9	0	5	5	0	0	7	4	0	2	2	6	0	0	7	7	0	0	9	3	0	1	2	4	0	0	7	0	5	0	0	0	0	2	0	6	0	0	0	0	0	6	3	3	0	0	0
1	S to P*1	Cross								O					O	╲			╲	╲	O		╲				╲	╲			╲	╲			╲				╲	╲		╲		╲	╲	╲	╲		╲		╲	╲	╲	╲	╲				╲	╲	╲
2	S	Overtake						O		O							╲	O		╲	╲	O		╲				╲	╲	O		╲	╲	O		╲				╲	╲	O	╲	O	╲	╲	╲	╲	O	╲	O	╲	╲	╲	╲	╲	O	O		╲	╲	╲
3	S to P	Cross		O					O		O				O	╲			╲	╲		O	╲				╲	╲	O	O	╲	╲		O	╲			O	╲	╲	O	╲	O	╲	╲	╲	╲		╲	O	╲	╲	╲	╲	╲				╲	╲	╲
4	S to P	Cross	O						O		O	O			O		╲			╲	╲		O	╲				╲	╲	O	O	╲	╲			╲		O		╲	╲	O	╲	O	╲	╲	╲	╲		╲		╲	╲	╲	╲	╲				╲	╲	╲
5	P to S	Cross		O			O			O							╲		O	╲	╲	O		╲			O	╲	╲	O	O	╲	╲			╲				╲	╲		╲		╲	╲	╲	╲		╲		╲	╲	╲	╲	╲				╲	╲	╲
6	P to S	Cross	O												O	O	╲			╲	╲			╲			O	╲	╲			╲	╲	O		╲			O	╲	╲	O	╲	O	╲	╲	╲	╲		╲		╲	╲	╲	╲	╲	O			╲	╲	╲
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*1 “S” denotes the starboard side and “P” denotes the port side.

5 ANALYSIS

5.1 *Analysis of Weighting Parameters in Collision Risk Model*

In this study, significant recognition targets of captains and officers and simulated navigational data were analyzed by executing a collision risk function through resimulation. This study determined that when the f_{CRI} was > 0.6, it was identified as a significant target. Moreover, the analysis method is a grid-search-based weight parameter optimization, where the sum of weights must equal one. The results of the normalized proposed method for the captain and officer compared to the conventional weight parameters are illustrated in Table 4, where the first row indicates the developed weight set of the captain, the second row indicates the developed weight set of officers, and the third row indicates the conventional weight set proposed in a previous study [6].

Table 4. Normalized Proposed Method Weight Parameters Result for Captain and Officer.

Weights set	Subject	W(DCPA)	W(TCPA)	W(Relative Distance)	W(Relative Bearing)	W(Vo/Vt)
Developed	Captain	0.370	0.190	0.120	0.150	0.170
	Officer	0.246	0.110	0.200	0.333	0.111
Conventional		0.400	0.367	0.133	0.067	0.033

Figure 5 shows the radar chart of the comparison of the normalized proposed method weight parameters on different parameters between the captain and officer, which indicates the distribution of each parameter. In the radar chart, the solid line represents the captain’s optimized weight parameter results and the dashed line represents the officer's optimized weight parameter results. Table 4 presents the normalized weight parameters of the proposed method and shows the distribution of each parameter for the captain and officer. In addition, the developed weight parameter results show the differences in each parameter compared with the conventional weight parameters. Furthermore, the developed weight parameters for the captain and officer illustrate differences in the distribution of the weight parameters.

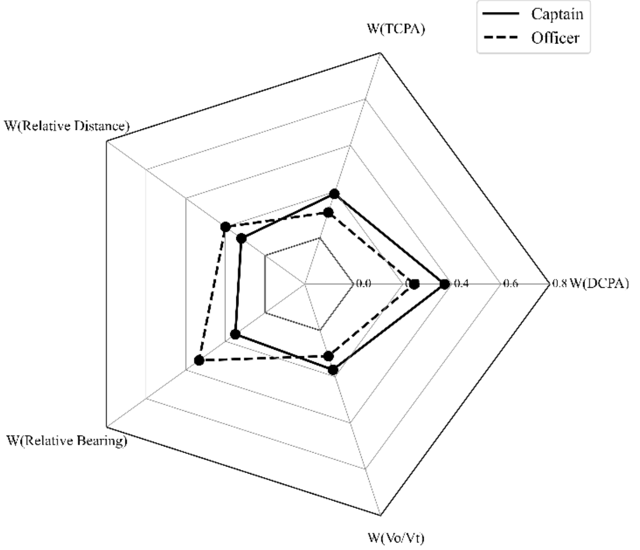


Figure 5. Comparison of normalized proposed method weight parameters on different parameters between Captain and Officer.

Table 5 indicates that the developed weight parameters outperform the conventional weight parameters at both navigator levels. In particular, the developed weight parameters for the captain achieved accuracy, precision, recall, and F1-score higher than those of conventional weights. Similarly, the developed weights for the officer achieve accuracy, precision, recall, and F1-score, which are higher than the conventional weights. In addition, precision measures the proportion of correctly identified positives out of all predicted positives, recall reflects the ability of the weights set to identify all actual positives, and the F1-score is the harmonic means of precision and recall that balances false positives and false negatives. These improvements suggest that the developed weights align better with expert decision-making patterns.

Table 5. Performance comparison between developed weights and original weights for Captain and Officer.

Subject	Weights set	Accuracy	Precision	Recall	F1-score
Captain	Developed	0.875	0.818	0.692	0.750
	Conventional	0.802	0.769	0.385	0.513
Officer	Developed	0.909	0.773	0.680	0.723
	Conventional	0.847	0.615	0.320	0.421

5.2 *Comparison of Weight Parameters Performance Between Proposed Weight Parameters and Conventional Weight Parameters*

Figures 6 and 7 show a comparison of the performance of the developed weight parameters and conventional parameters for the captain and officer, respectively. The vertical axis indicates the number of significant targets identified and the horizontal axis represents the time intervals. The solid line indicates the SA of the navigators; that is the targets selected for more than half of the subjects were considered as significant targets, and the dashed line indicates the targets captured by executing the collision risk function with the developed weight parameters. In addition, the dotted line indicates the significant targets captured by executing the collision risk function using conventional weight parameters. As shown in the figures, the developed weight parameters consistently outperformed conventional parameters. The developed weight parameters achieved recognition of more significant targets throughout the interval time compared to conventional weight parameters, which had lower performance in recognizing the significant target.

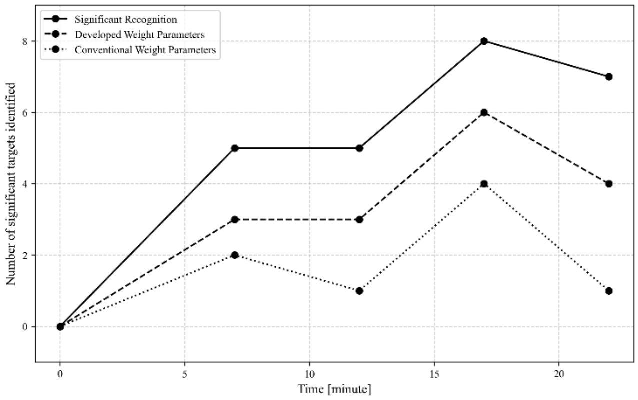


Figure 6. Comparison of performance between developed weight parameters and conventional parameters for the captain.

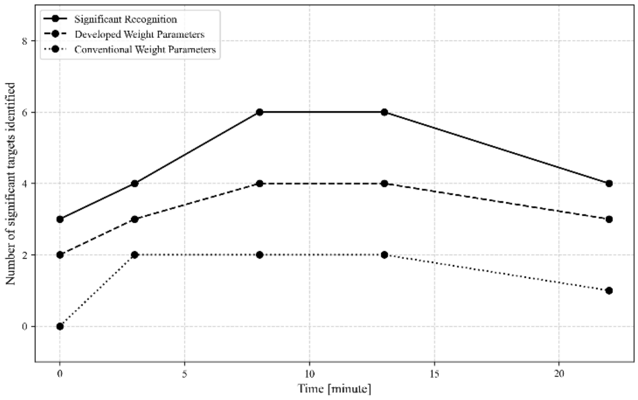
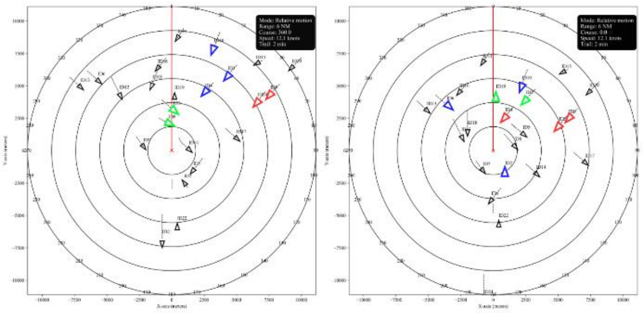


Figure 7. Comparison of performance between developed weight parameters and conventional parameters for officer.

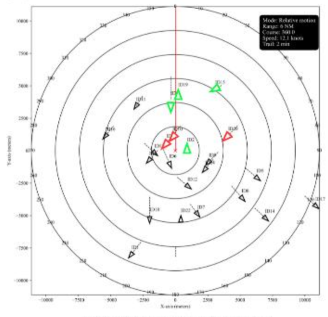
6 CONSIDERATION

Through the officers' simulation experiment using SAGAT and adapted grid-search weight optimization, the study revealed the differences in the weight parameters of navigational risk factors at each navigator level. The analysis of the weighting parameters in the collision risk model illustrates that the developed weight parameters captured significant target ships measured at each navigator level more effectively than the conventional weight parameters. Notably, the results revealed a distinction in emphasis between the two navigator levels. First, captains have more advanced experience, which tends to emphasize higher weights for DCPA, TCPA, and the relative velocity ratio (Vo/Vt), indicating a specific risk-collision strategy. However, officers placed more emphasis on the relative bearing and distance factors. This suggests that officers may rely more on observable target ship positions, whereas captains may focus on the estimated trajectory approach of the target ships.

Moreover, the experimental findings support the hypothesis that situational awareness varies not only in strategies for collision risk assessment but also in emphasis on navigational risk factors across navigator ranks. The analysis of the SA results of the navigators illustrates that the significant recognition between the captain and officer levels was different in the target ship that passed from the port side to the starboard side, and that the relative bearing of the target ship affected the SA of the navigators. Notably, the captains emphasized the target ships, which have a larger relative bearing on the starboard side and the possibility of changing their course across the heading on the starboard side, than the target ships that are closer to their heading. Figure 8 shows the RADAR display at the SAGAT measurement timing in relative motion mode, and the dashed lines represent the trail tracking in two minutes. The RADAR display range was six nautical miles. In addition, the black triangles represent the target ships, and the red and blue triangles represent the target ships that were identified as SA by the captain and officer groups, respectively. Moreover, the green triangles represent the target ships identified as situationally aware by both.



(a) RADAR display at 8 minutes. (b) RADAR display at 13 minutes.



(c) RADAR display at 22 minutes.

Figure 8. RADAR display at SAGAT measurement.

According to a previous study, the rank-order level of navigators mainly focuses on three types of information to decide the priority level of target ships:

the rate of bearing change, distance, and type of encounter situation. In addition, the experimental interview in a previous study illustrated evidence that navigators placed more emphasis on crossing situations from the starboard than on other encounter situations [4]. Similarly, these findings support our findings that the target ships were primarily identified in crossing situations. Furthermore, this study's evidence illustrates that the officers emphasized not only crossing situations from the starboard side but also crossing situations from the port side.

However, the limitation remains in that the officer group was not categorized into official maritime ranks, such as chief, second, or third, which may have led to a mixture of navigator experience levels in SA. In addition, the size of the captains' SA data was limited. To address this limitation, future studies should provide deeper insights into the role of navigator experience. In addition to determining more versatile weights and developing weight parameters, it is necessary to explore the SA data derived from future experiments and combine them with onboard experience.

7 SUMMARY

This study proposes an optimized set of weight parameters for the CRI that is compatible with two levels of navigators to distinguish their varying emphasis on navigational factors in maritime operations.

The experiment was conducted with officers using the SAGAT to measure the SA of navigators. In addition, through resimulation using recorded experimental navigational data and the navigators' SA as the ground truth, grid search-based weight optimization was applied to find the optimal weight parameters. The CRI weight parameters were refined to better capture the significant target ships recognized at each navigator level. The findings demonstrated that the optimized weight parameter configurations could effectively identify risk targets based on the experimental SA data of the navigators. Remarkably, while both the captains and officers recognized some significant target overlap, the variation in the recognition targets indicated that each navigator level emphasized different navigational collision risk factors. These findings suggest that the collision risk model can be developed for specific navigator experiences, thereby improving the risk target recognition model for congested water.

This study has certain limitations. The availability of navigators' situational awareness (SA) data for navigators in both prior and current studies remains limited in terms of quantity. To validate these findings, experiments across different navigator levels are necessary to collect more comprehensive SA data. Additionally, it is necessary to validate the finding that an extended evaluation of more diverse navigator profiles is required. Furthermore, officer-level experiments did not categorize officers into three distinct ranks, although maritime navigation classified ship officers into three levels: third, second, and first officers. Therefore, the officers' target recognition was mixed. Addressing these limitations in future research will provide deeper insights into the role of navigator experience and the diversity of navigator profiles.

ACKNOWLEDGEMENT

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