IAMU 2021 Research Project
(No. 20210103)

Evaluation of Sharp-Lookout Skills Using Performance Assessment toward Developing Automatic Target Avoiding System

By

Tokyo University of Marine Science and Technology, Japan

August 2022

IAMU
International Association of Maritime Universities

This report is published as part of the 2021 Research Project in the 2021 Capacity Building Project of International Association of Maritime Universities, which is fully supported by The Nippon Foundation.

Editorial

IAMU Academic Affairs Committee (AAC)

Head of Committee :	Professor Dr. Adam Weintrit Rector, Gdynia Maritime University (GMU)
Editorial committee :	Adam Przybylowski (GMU) Avtandil Gegenava (BSMA) Christian Matthews (LJMU)
Contractor :	Atsusi Horiuchi
Research Coordinator :	Jun Kayano

Published by the International Association of Maritime Universities (IAMU) Secretariat
Meiwa Building 8F, 1-15-10 Toranomon, Minato-ku,
Tokyo 105-0001, JAPAN
TEL : 81-3-6257-1812 E-mail : info@iamu-edu.org URL : http://www.iamu-edu.org

ISBN978-4-907408-36-7

IAMU 2021 Research Project

(No. 20210103)

Evaluation of Sharp-Lookout Skills Using Performance Assessment toward Developing Automatic Target Avoiding System

By

Tokyo University of Marine Science and Technology, Japan

Contractor : Atsusi Horiuchi
Research Coordinator : Jun Kayano
Research Partner : Momoko Kitada, WMU
Samuel R. Pecota, CSUM

Evaluation of Sharp-Lookout Skills Using Performance Assessment toward Developing Automatic Target Avoiding System

Jun Kayano
Associate Professor, Tokyo University of Marine Science and Technology, kayano@kaiyodai.ac.jp
Momoko Kitada
Associate Professor, World Maritime University, mk@wmu.se
Samuel R. Pecota
Director, California Maritime Academy, Specota@csum.edu

Abstract

In this study, we aimed to develop an algorithm of new target avoiding system based on the characteristics of professional lookout skills. Firstly, we constructed an algorithm for searching collision avoidance route by using PSO with OZT as collision risk index. The simulation experiments were carried out and the effectiveness of the proposed algorithm was verified. However, in other simulation experiment for the proposed algorithm applying to all the ships, ships collided or closed to collide to each other because this algorithm calculates the collision avoidance route only where the other ships would not change their behaviors. To improve the algorithm, we tried to identify the characteristics of experienced navigators' lookout skill. Before that, we administered an online questionnaire among experienced deck officers and less experienced ones to understand sociotechnical barriers to the newly proposed system to assist decision-making of deck officers on watch. Next, to visualize the characteristics of experienced navigators' lookout skills, based on the results of simulation experiment by using Eye-tracker, we compared the line-of-sight data of skilled ship navigators with the ship maneuvering behavior and considered quantitative data on the 'point-of-sight' and 'time-of-sight' before and after acting for each ship maneuvering. We also measured low frequency/high frequency (LF/HF) values by the heart rate variability to show mental workload. Finally, we focused on the experienced navigators' skills of predicting future behavior of the other ships. In consideration of uncertainty of the other ships' future behaviors, we calculated not only OZT but also potential OZT. SVM was also applied to predict the other ship's behavior as well as to search for collision avoidance route. Though the simulation experiments, the effectiveness of the proposed algorithm was verified.

Keyword: *Automatic Collision Avoidance, Lookout Skill, Obstacle Zone by Target*

1. Introduction

In recent years, development of Maritime Autonomous Surface Ships (MASS) has attracted great attention along with improvement of Global Navigation Satellite System (GNSS) position accuracy, communications infrastructure, computer technology and so on. Autonomy of ship maneuvering leads to safety enhancement by reducing human error, optimization of ship maneuvering, burden reduction of navigator's mental workload and so on.

To avoid collisions with other ships is one of the main jobs of navigators. There are three steps in the process of decision making. The first step is information collection. The second step is information processing, where all collected information would be processed and analysed by the team on duty at bridge to recognize about the own ship current situation. The third step is the decision of own ship action [1]. Most navigators have collected information by using Distance of Closest Point of Approach (DCPA) and Time to Closest Point of Approach (TCPA) calculated by Automatic Radar Plotting Aid (ARPA) and so on and changing rate of relative bearing to the target ship. Then they have analysed the navigational situations and made behavioural decisions to avoid collision. Their critical decisions are highly subjective and can lead to error and potentially, to ship collision. Human error accounts for about 80–85% of all marine accidents [2].

To reduce such human errors, various research of constructing collision avoidance algorithms have been carried out. Imazu et al. (2002) [3] proposed the Obstacle Zone by Target (OZT), the visually expressing method of the collision risk zone in accordance with the situation of encountering the other ship and ships' speeds. Kayano et al. (2010) [4] improved OZT by applying Kalman Filter to. Sawada et al. (2021) [5] constructed the automatic collision avoidance algorithm based on the OZT by using reinforcement learning. There also some research proposing Velocity Obstacle (VO) models. This model was firstly developed in the field of robot motion planning [6]. Kuwata et al. (2013) [7] proposed the collision avoidance algorithm complied with Convention on the International Regulations for Preventing Collisions at Sea, 1972 (COLREG) rules by applying VO algorithm to ships. Huang et al. (2018) [8] constructed the VO model for collision avoidance against multiple other ships. Zhang et al. (2021) [9] proposed the VO model -based collision avoidance algorithm complied with COLREG rules by using scenario-based numerical simulation. As noted above, various collision avoidance algorithms were developed and some attempts to constructing automatic collision avoidance algorithms by applying rule-based or machine learning- based algorithm were also confirmed. However, Zhang et al. (2021) pointed out the problem that automatic collision avoidance algorithms tend to think much or little of COLREG rules. Some previous researches don't consider the change of the other ship's behaviour. It also confirmed that human's decision-making procedure needs to be reflected in the algorithm.

On a practical level, navigators avoid collisions with other ships mainly based on their experience. Experienced navigators normally have little trouble identifying collision threats. Therefore, identifying the characteristics of experienced navigators' lookout skill will certainly lead to a reduction in sea accidents.

In this study, we aim to develop an algorithm of new target avoiding system based on the characteristics of professional lookout skills. we evaluated the characteristics of sharp-lookout skills using visual information and so on. We used OZT as an index to estimate collision risks when constructing the automatic collision avoidance algorithm.

2. Route Search Algorithm by using OZT and PSO

In this study, collision avoidance route is searched by using Particle Swarm Optimization (PSO) with OZT as collision risk index.

To judge collision risk with the other ship, it needs some sort of methods to evaluate it. As one of such methods, Hasegawa et. al (2012) [10] used DCPA and TCPA as parameters to determine collision risk value, which were acquired by using fuzzy reasoning. Fuzzy reasoning can reflect regulations and navigator's manoeuvring knowledge on evaluation of collision risk. Although this method responds to multiple other ships one-by-one basis, it cannot do all together. On the other hand, OZT can express the collision risks with all ships around the own ship simultaneously.

In this chapter, we explained overview of OZT and PSO, and how to use them in this study.

2.1 Overview of OZT

OZT is a method of visually expressing areas in which there is a high possibility of colliding with obstacles such as other ships. The existence of OZT or not is calculated based on the time to reach the target ship to a calculation point and the probability that the own ship changed its course to the point and the ship reaches to the point at the time. If a navigator maneuvered a ship to avoid all OZTs, the ship would not face any collisions.

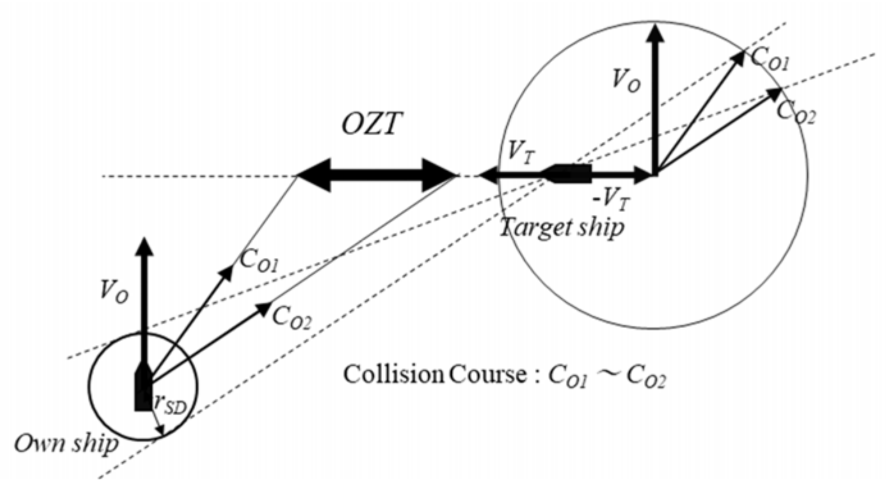


Fig.2.1 Obtaining the OZT

OZT is taken from the following procedures.

1) The collision course C_O of the own ship that may collide with the target ship in the future is calculated by the following equations, where d is the angle between the own ship and the target ship, A_Z is the azimuth angle of the target ship, C_T is the course of the target ship, V_T is the speed of the target ship, Vo is the speed of the own ship, and r_{SD} is the safety passing distance between the own ship and the target ship.

$$\alpha = \sin^{-1}\{r_{SD}/d\} \tag{2.1}$$

$$N = V_T/V_O \tag{2.2}$$

$$C_O = A_Z \pm \alpha - \sin^{-1}\{N \sin(A_Z \pm \alpha - C_T)\} \tag{2.3}$$

2) Shift the collision course (C_{O1} and C_{O2}) to the own ship. and find the zone which part of the course line of the target ship cut out by these collision courses. This zone is OZT.

In Fig.2.2, there are 2 vessels around the own ship. No.1 target ship is a crossing vessel. Its value of DCPA is 0NM and its value of TCPA is 30minutes. No.2 target ship is a same course vessel. Its value of DCPA is 1.2NM and its value of TCPA is 49minutes. As for values of DCPA and TCPA, No.1 target ship is smaller than No.2 target ship. Therefore, only judging from these values might lead to a conclusion that the risk to collide with No.1 target ship is high and the risk to collide with No.2 target ship is not so much. In this figure, OZTs are shown as the areas filled with white. As for OZT, compared to No.1target ship, No.2 target ship is closer to the own ship and cover a wider area. In this way, OZT enable navigators to understand easily they have to change their courses to avoid No.2 target ship first. Furthermore, it is difficult to know how degree the own ship has to alter her course only from the information of DCPA and TCPA because they show just the distance when the own ship approaches to the target ship closest and the time until then. On the other hand, the distribution of OZT shows the own ship has to alter her course large enough to avoid collision at this time. OZT tells what kind of behavior makes the own ship possible to avoid collision safely and effectively because it shows truly risk zone for collision precisely.

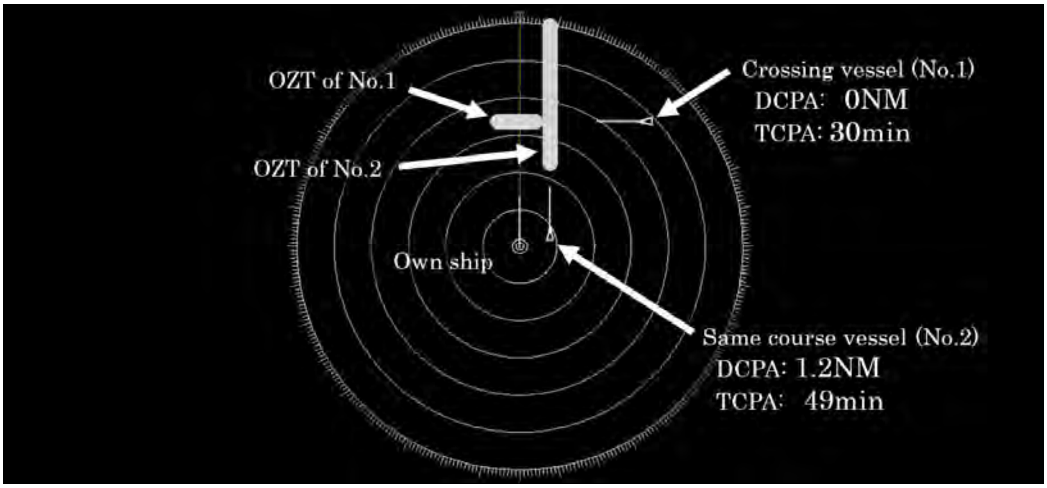


Fig.2.2 Conceptual image of OZT

2.2 Overview of Particle Swarm Optimization (PSO)

PSO, one of metaheuristics, was initially proposed by Kennedy and Eberhart in 1995 [11] and has drawn much attention in recent years with its advantages, such as its simplicity of the algorithm, its wide range of applications and its high global searching ability. In this method, social behavior of bird flocking and fish schooling is applied to search method. Particles spread in the solution space interact and move to find a better solution. It also solves non-linear optimization problems effectively.

PSO is a method that particle swarm simulating animal flocking search in a solution space sharing information. That is, assume we have n particles sharing the potion coordinate $x_i(i = 1 \sim n)$ in the space within the range shown in Fig. 2.3, particle i retains the information of potion x_i and velocity v_i . Potion x_i expresses solution of the problem. At time step t, potion x_i (t) and velocity v_i (t) of particle i are updated using equation (2.4) and (2.5).

$$\boldsymbol{v_i(t) = wv_i(t-1) + c_1r_1(p_i - x_i\,(t)) + c_2r_2(g - x_i(t))} \tag{2.4}$$
$$\boldsymbol{x_i(t+1) = x_i(t) + v_i(t)} \tag{2.5}$$

where r_1 and r_2 are random numbers, constants w, c_1 and c_2 are parameters to the PSO algorithm, and p_i is the position that gives the best value ever explored by particle i (*pbest*) and g is that explored by all the particles (*gbest*). The positions of p_i and g are updated when that of particle i is updated. This process is repeated a certain number of times to find a better g. As shown in Fig.2.4, each particle's new positioning $x_i(t+1)$ is composed of 1) vector approaching to *gbest*, 2) vector approaching to *pbest*, and 3) inertia vector.

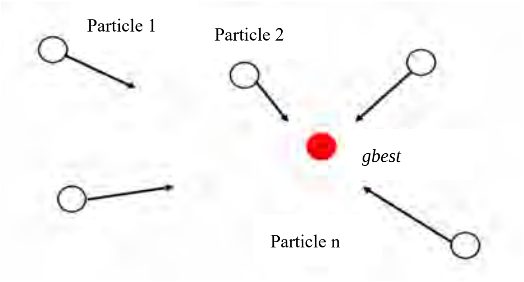


Fig. 2.3 Search method in PSO

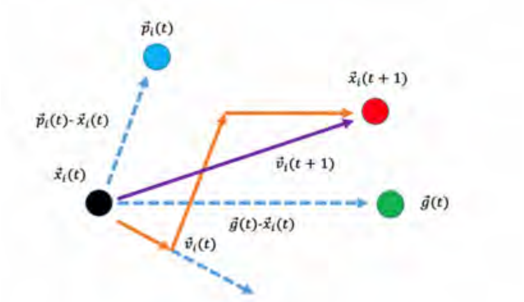


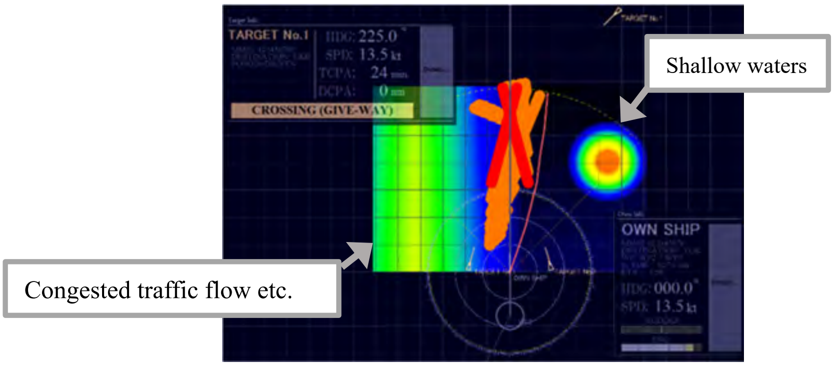
Fig.2.4 Search point updates in PSO

2.3 Generation of ship trajectory by using OZT and PSO

In generation of ship trajectory by using OZT and PSO, the algorithm selects the collision avoidance route not passing through OZT with the information acquired by AIS, radar and so on (positioning, route, and speed of own ship as well as the other ships). Also, it can show risk area and select appropriate route by setting various areas, not limited to OZT, where navigators want to avoid. The procedure of route search is as follows.

Step 1 Show collision risk in areas

OZT is calculated from the information obtained by AIS, etc,. In addition, as shown in Fig. 2.5, the areas such as shallow waters, congested traffic flow and prohibited area for navigation are set.



Shallow waters

Congested traffic flow etc.

Fig. 2.5 Image of risk area setting

Step 2 Create multiple lines setting particles as waypoints

As shown in Fig.2.6, multiple route candidates are set by connecting several particles as waypoints.

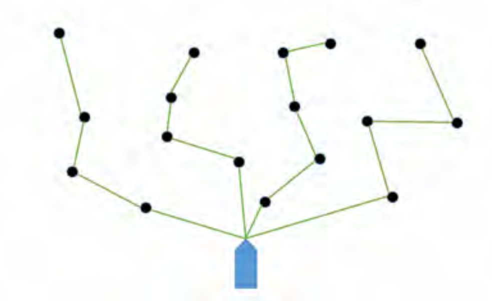


Fig.2.6 Setting routes by using particles

Step 3 Number and positioning of particles in search space

Particles are located randomly in search space. In this study, the length of search space is set for 30 minutes by reference to Imazu’s previous study [12].

Step 4 Considering characters and rules of ships

Because values for movement direction and distance are set randomly, particles sometimes move to unrealistic positions, such as in risk area and rear of the own ship. It results in selecting inappropriate routes, for example, the ship doesn’t head to a destination, or the altering course angle is unnecessarily large. Then the following evaluations are carried out.

1) impose heavier penalty to the route passing through risk area for collision, grounding and so on.
2) impose penalty according to the distance between the route’s final point and the destination.
3) impose penalty on the route proceeding to the opposite direction from the destination (rear of the own ship)
4) impose penalty according to its degree when the course is altered from second times

Step 5 Calculating positioning and velocity of each particle

Save the evaluate value and its waypoint positioning of *gbest* as well as *pbest*. Then calculate the positioning and velocity of waypoint (particle) at next step by equation (2.4) and (2.5).

Step 6 Creating routes
Adopt the highest evaluated route among the routes obtained by testing repeatedly Step 4 and Step 5 enough times.

3. Verification of the algorithm by using OZT and PSO

To verify the effectiveness of the algorithm proposed in the previous chapter, the simulation experiments were carried out. In the simulation experiments, the Fist Order Nomoto Equation of the form was used [13]. The sea area is set wide, and the influence of disturbance is not made account.

We used Imazu Problem as scenario of the experiments [14]. Imazu problem is a kind of a set of benchmark scenarios for difficult encounter situations and is sometimes used for evaluating collision avoidance algorithm. The encounter situations in which multiple ships are mutually related are very complicated. However, Imazu indicated that they were composed of combinations of encounter relationships between two ships, which were divided into the following two categories.

Category 1: In this situation, there exists collision risk between two ships. They are divided into three situations, i.e., head-on situation, crossing situation and overtaking situation.

Category 2: In this situation, there doesn't exist collision risk between two ships as long as they keep their course and speed, but if either ship changes its course or speed, it has to consider the other ship. Ships pass at relatively close distance.

In these encounter situations, the positional relationship between two ships can be determined by setting their speed, their course difference, and the time to collision. Imazu also pointed out that it was enough to evaluate collision avoidance algorithm in the encounter situations with up to four ships because in the dangerous encounter situations in the open sea, the situations in which less than four ships (including the own ship) were related constitute 99.1 % of all. Imazu created the stylized scenarios in the encounter situations with up to four ships. Imazu problem consists of 42 scenarios separated in 2 phases. In Phase1, the problem is easy of the first, but gradually become difficult. The problems in Phase 2 are quite difficult.

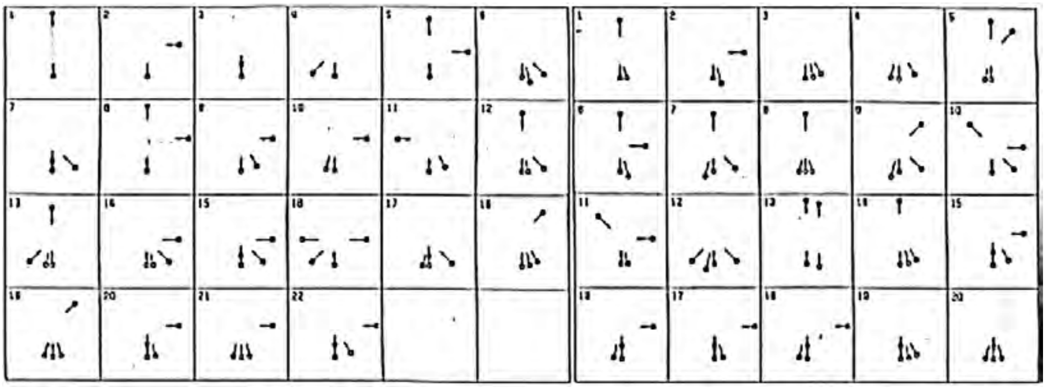


Fig.3.1 Imazu Problem

Firstly, we applied the proposed algorithm to No.1 ship only and carried out the simulation experiment. The simulation results are shown in Appendix (Fig.A.1-Fig. A.42).

As can be seen from these figures, ship avoids colliding with other ships safely (Evidently, there exist black-out areas, the areas of collision, in some cases. However, there didn't occur any collision within

30 minutes set as the length of search space). However, in this experiment, because the proposed algorithm was applied to No.1 ship only, the other ships did not change their behaviors. Then we carried out other simulation experiments when the proposed algorithm would be applied to all the ships. The results are shown in Appendix (Fig.A.43-84). Among them, the results that the ships collided or closed to collide to each other within 30 minutes from the start of the experiment are shown from Fig. 3.2 to Fig.3.17. As mentioned before, the black-out area shows the area the ships collided or closed to collide to each other. Such collision risk occurred because this algorithm calculates the collision avoidance route only where the other ships would not change their behaviors. On the other hand, at practical level, experienced navigators normally have little trouble identifying collision threats. Therefore, identifying the characteristics of experienced navigators' lookout skill will certainly lead to a reduction in sea accidents.

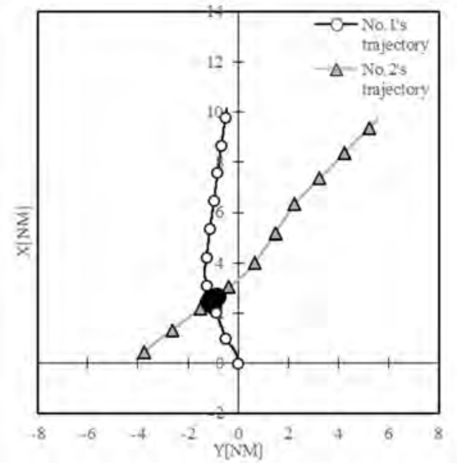


Fig. 3.2 Simulation result (Phase 1, No. 4)

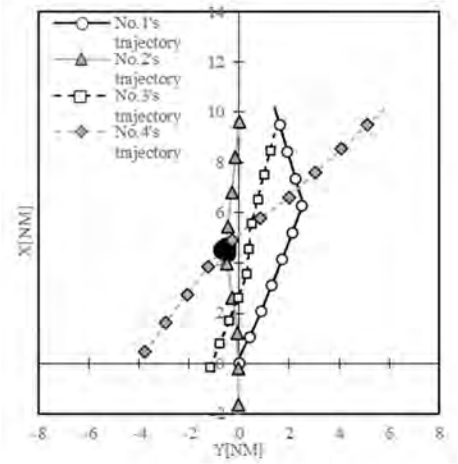


Fig. 3.3 Simulation result (Phase 1, No. 13)

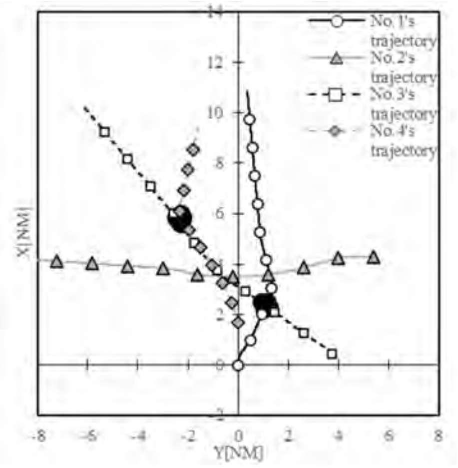


Fig. 3.4 Simulation result (Phase 1, No. 15)

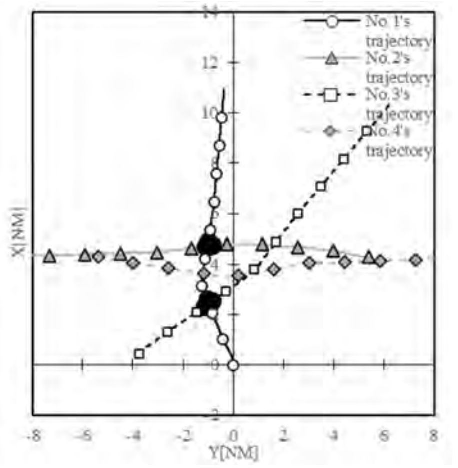


Fig. 3.5 Simulation result (Phase 1, No. 16)

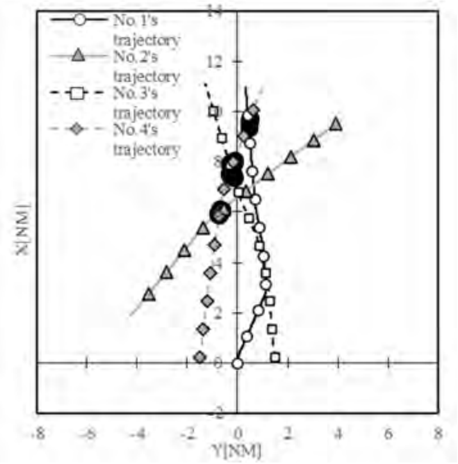


Fig. 3.6 Simulation result (Phase 1, No. 19)

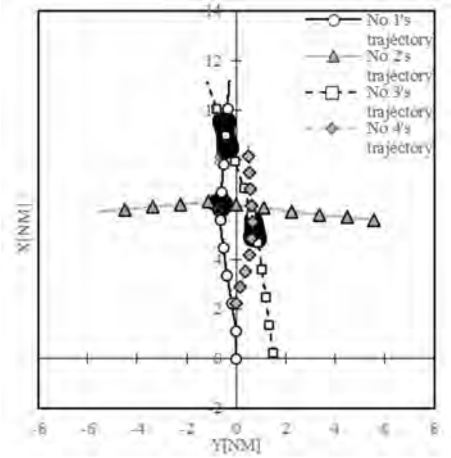


Fig. 3.7 Simulation result (Phase 1, No. 20)

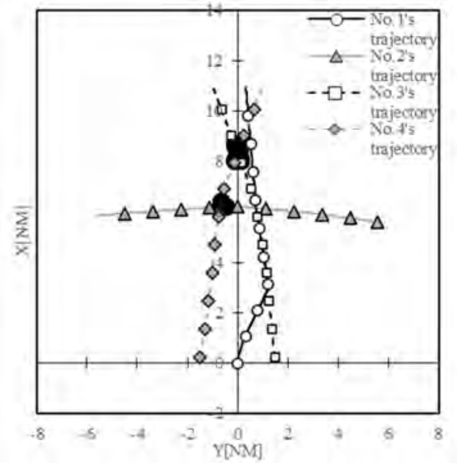


Fig.3.8 Simulation result (Phase 1, No. 21)

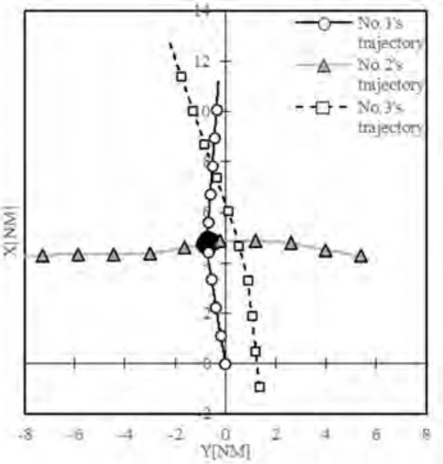


Fig. 3.9 Simulation result (Phase 2, No. 2)

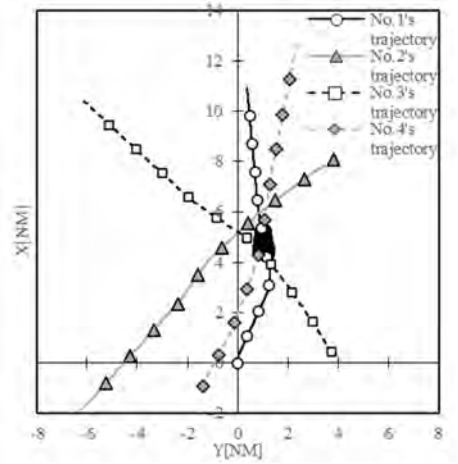


Fig. 3.10 Simulation result (Phase 2, No. 9)

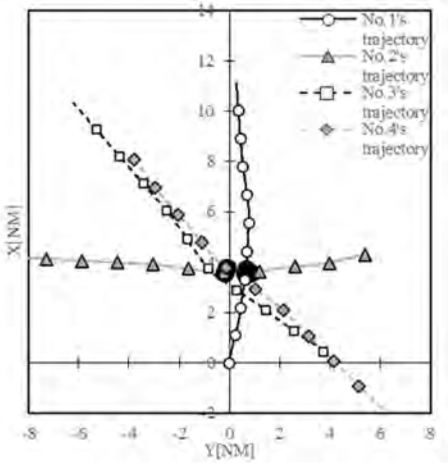


Fig. 3.11 Simulation result (Phase 2, No. 10)

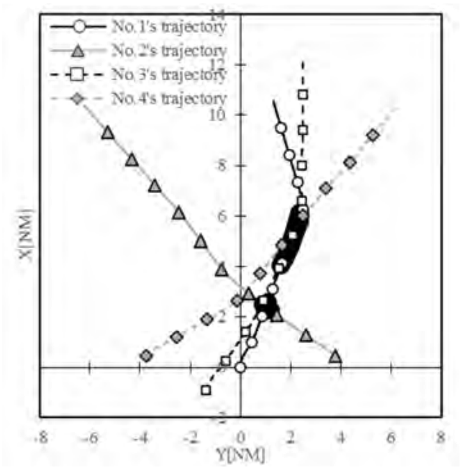


Fig. 3.12 Simulation result (Phase 2, No. 12)

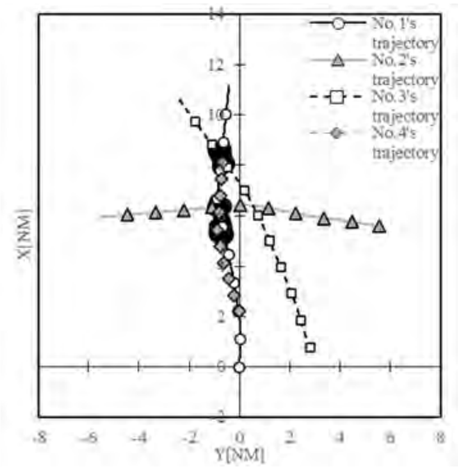


Fig. 3.13 Simulation result (Phase 2, No. 15)

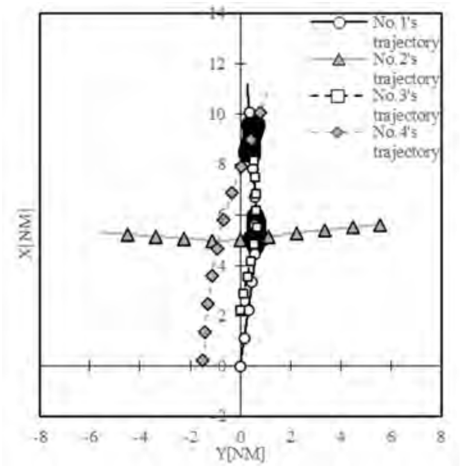


Fig. 3.14 Simulation result (Phase 2, No. 16)

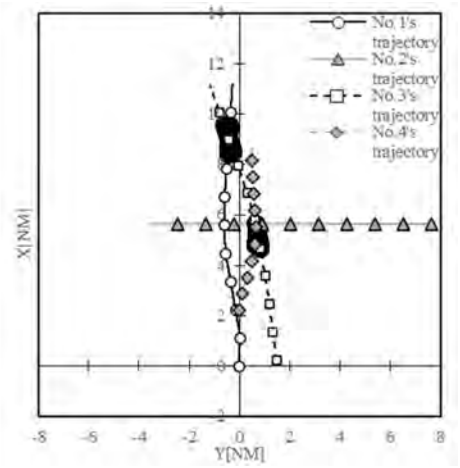


Fig. 3.15 Simulation result (Phase 2, No. 17)

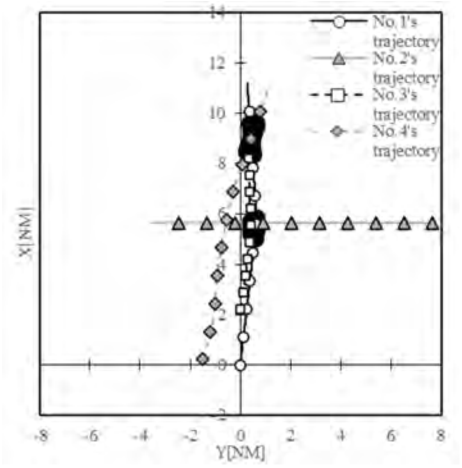


Fig. 3.16 Simulation result (Phase 2, No. 18)

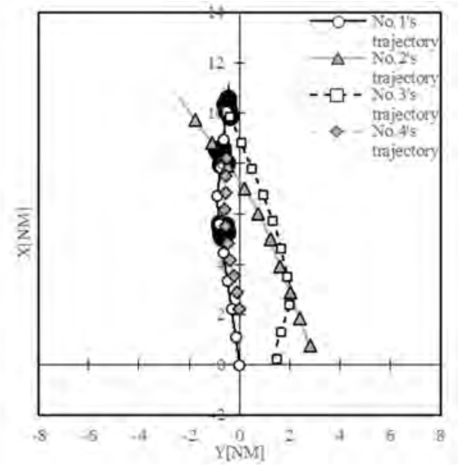


Fig.3.17 Simulation result (Phase 2, No. 19)

4. Trust in a new sociotechnical system - deck officers' perspectives

The adoption of technology requires various factors to consider in order to be fully adopted, such as economic benefit, regulation and governance, social acceptance, knowledge and skills, labour market dynamics, and technology feasibility [15]. A growing interest in sociotechnical systems within the maritime context questions how collaboration and interaction between seafarers and onboard decision support systems take place [16,17]. In this Chapter, we consider how our proposed algorithm and its operator support system are currently perceived by mariners with various sea experiences and examine the human element of technological support to sharp lookout tasks in future operation of ships.

4.1 Trust in the proposed system

To understand sociotechnical barriers to the newly proposed system to assist decision-making of deck officers on watch, an online questionnaire was administered among experienced deck officers (incl. Captains and senior officers) and less experienced ones (incl. junior officers and cadets) to evaluate their trust in such technologies. We asked the participants to what degree they can trust in the new proposed system. Before asking this question, the description of the new system was explained:

"The latest research has developed an algorithm of a new target avoiding system based on the characteristics of professional lookout skills, which has been proven to be reliable. Suppose that this new system has been installed on your bridge to assist your navigation. If a new system indicates danger of collision to a ship which you do not perceive as danger, what is the degree of your trust in the new system?"

The data were collected through SurveyMonkey between November and December 2021. In total, 198 valid responses[1] from the online questionnaire were obtained for analysis. Sixty-one percent (n=120) of respondents had more than 10 years of seafaring experience, 13 percent (n=25) for 5-9 years, 7 percent (n=14) for 3-4 years, 10 percent (n=19) for 1-2 years, and 10 percent (n=20) for less than one year. Half of the respondents were Captains (n=99) and the rest were Chief Officer/1st Officer (n=19, 10 percent), 2nd officer (n=22, 11 percent), 3rd or 4th Officer (n=14, 7 percent), Deck cadet (n=34, 17 percent), and others (n=10, 5 percent). The responses largely came from Indians (n=135, 68 percent) and Filipinos (n=28, 14 percent), followed by only one respondent from each of the following countries: Gabon, Georgia, Iraq, Ivory State, Japan, Nigeria, Pakistan, South Korea, Sri Lanka, Timor-Leste, and no answers (n=2). The majority were men (n=172, 87 percent), 25 were women (13 percent) and one preferred not to say. Participants have work experiences on various ships, such as oil tanker (n=119, 60 percent), general cargo ship (n=72, 36 percent), container ship (n=57, 29 percent), bulk carrier (n=49, 25 percent), chemical tanker (n=37, 19 percent), gas tanker (n=24, 12 percent), car carrier (n=15, 8 percent), Ro-Ro ship (n=13, 7 percent), ferry/cruise/passenger ship (n=12, 6 percent), and offshore supply vessel (n=10, 5 percent) among others[2].

4.2 Why/Why not trust the system?

More than a half of the respondents (n=111, 56 percent) responded positively to their trust in the algorithm-based system for collision avoidance while one third (n=61, 31 percent) was neutral and the remaining 13% of respondents (n=26) showed negative (Fig. 4.1). To follow up their responses, we asked them to provide the reason(s) why they trust or distrust the system.

---

[1] Out of 200 responses recorded, two were data errors.

[2] Many participants indicated more than one type of ship with their sea experience, therefore the sum of all ship types goes beyond the total number of participants.

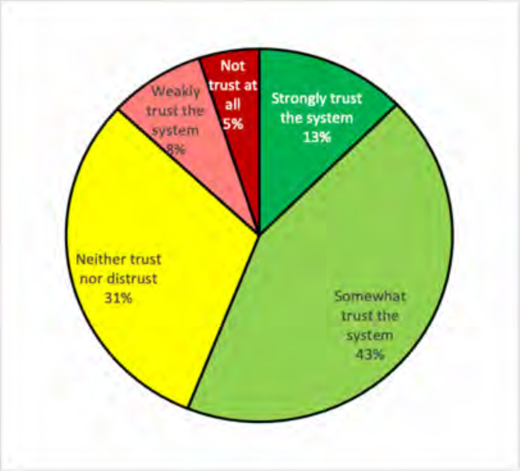


Fig. 4.1 Trust in the system (All responses, n=198)

Those who strongly trust the system (13 percent) raised two justifications. First, they accept and appreciate its scientifically proven and data-driven system, verified after testing. Some mentioned that "*I trust the system, because they did not install that kind of equipment if it's not tested by the professionals, and yet the new generation now will provide a lot of equipment or system that can help with our work.*", "*Because algorithms are data based*", and "*We must innovate new systems by using the latest technology to enhance overall efficiency. Use of the latest technology is always better and beneficial for the entire maritime industry.*" Second, they want to be on the safe side by trusting a new system and some stated that "*Because it gives me an alert to crosscheck myself*", "*That is a layer of safety by which I can avoid a possible collision or a near miss. Nothing wrong to trust the system if that trust is not going to cause any harm*", and "*Having a proactive approach is always admired*".

The most selected answer by the participants was "somewhat trust the system" (43 percent). They identified the main reason why they cannot fully trust the system is because of errors, flaws, and glitches which are often reported in technical systems in general. Some mentioned that "*These are prone to errors since there will be chances of technical glitches.*" and "*There can be flaws in any system, that's why you just can't fully trust or rely on it.*" Others admitted human errors in ship operations, saying that "*Humans are prone to making more errors than machines.*" and "*Because it may have a setting that detects a danger in collision that the human can't. There's always human error, that's why we should always double check.*"

Those participants who responded neutral (31 percent) showed caution in trusting a new system as they were prone to emphasize the importance of human intervention and experience during lookout. Some stated that "*Even with the use of technologically advanced machinery and equipment, we still need to make sure that look out will be performed in the most delicate manner in order to avoid risk of collision.*" and "*Machinery can malfunction but visual lookout and experience will be more accurate.*"

Some participants responded "*weakly trust the system*" (8 percent) and they were trusting humans more than machines, for example, saying that "*Machines are not reliable. Humans are the first source of reliability.*" and "*I always give priority to what I visually see and identify clearly.*" Further, those who mentioned that they do "not trust at all" showed a strong belief and approach in navigation, stating that "*I am a man of conventional approach, no aids can substitute a watchkeeper and his skills are the ultimate measure.*" and "*We are not supposed to trust any system. We have to trust only us.*"

The following sections present the analysis of participants' responses to their trust in the proposed system with variables such as sea experience, rank, ship type, and gender.

4.3 Trust by sea experience

It is observable in Fig. 4.2 that deck officers who have sea-going experience between 1-4 years (combined 1-2 years with 3-4 years) are the group trusting the system the most. Approximately, 64 percent of deck officers with 1-4 year seafaring experience trust the system. On the other hand, deck officers with 5-9 years of experience appeared to be the least trusting in the system (36 percent, combined strongly trust with somewhat trust). Most experienced (more than 10 years) and least experienced (less than 1 year) showed the same tendency of trusting in the system, about a half of them said that they trust in the system. Distrust in the system was found among the least experienced ones (mostly deck cadets) (20 percent) and those with 5-9 years of seafaring experience (16 percent) more than the other groups (7-12 percent).

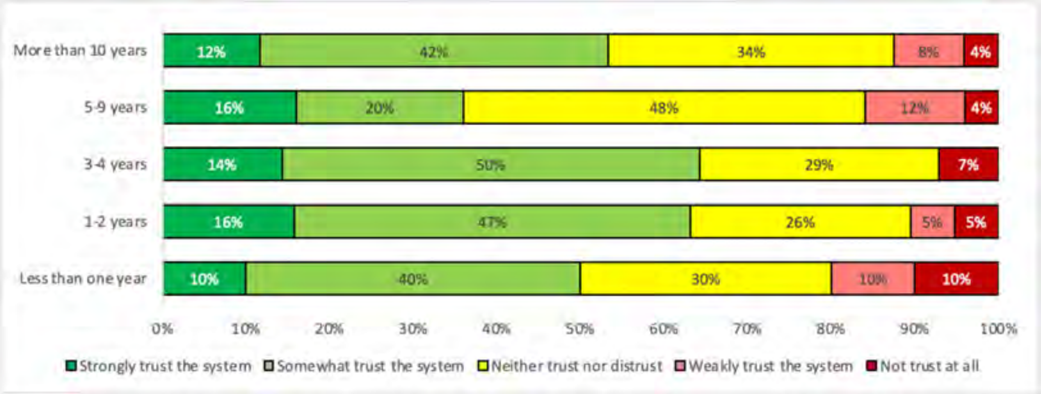


Fig. 4.2 Trust in the system by sea-going experience

4.4 Trust by rank

The data in Fig. 4.3 shows a clear tendency with junior deck officers (3rd or 4th officers) who trust in the system to support navigational operations compared to the other groups. Sixty-five percent of junior deck officers trust in the system, 36 percent of them responded with neither trust or distrust, and none said that they do not trust. The respondents categorized as "Others" include those who used to work on board but are currently shore-based, such as working as managers in the office, being a superintendent or harbour pilot. This group of "Others" responded positively to their trust in the system.

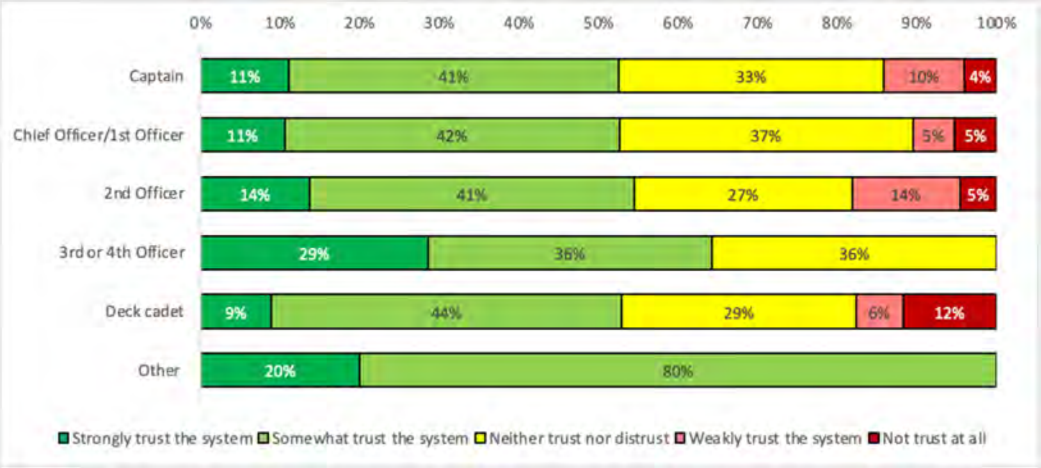


Fig. 4.3 Trust in the system by rank

4.5 Trust by ship type

In this section, five top ship types were selected from the list of indicated ship types on which the participants have worked. In Fig. 4.4, deck officers' trust in the algorithm-based system for collision avoidance were nearly the same for those who experienced on cargo ships, such as bulk carriers, container ships, general cargo vessels and tankers (e.g., oil, gas, and chemical). However, there is a tendency for deck officers on ferry/passenger/cruise ships to trust the system compared to cargo ships. While those on ferry/passenger/cruise ships acknowledge possible errors and failures in the system, similar to those on cargo ships, it may be possible to assume that deck officers on ferry/passenger/cruise ships might have a different sense of responsibility over passengers' lives on top of cargoes.

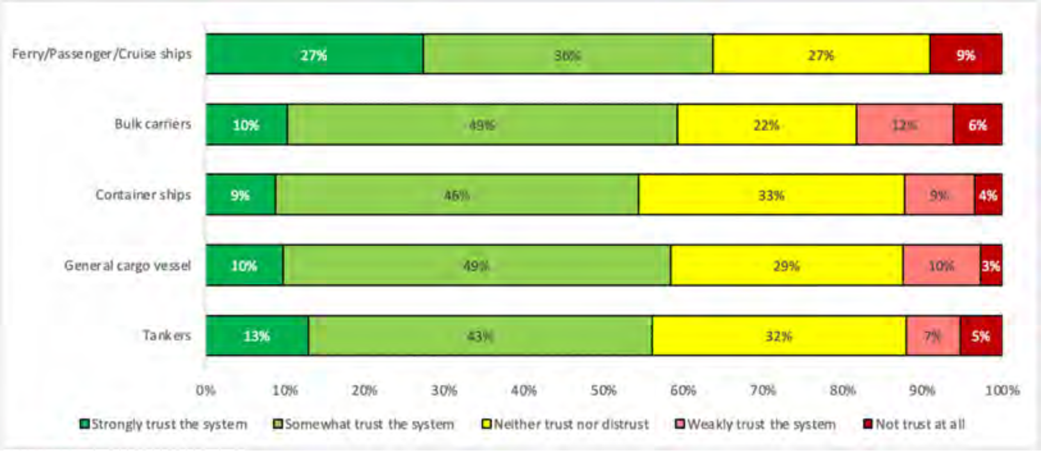


Fig. 4.4 Trust in the system by ship type

4.6 Trust by gender

The degree of trust in the system was also analyzed by gender. Fig. 4.5 shows their responses (n=197) by men (n=172, 87 percent) and women (n=25, 13 percent), and one response from "preferred not to say" was not included in this figure. Though the sample size for women was small, there is an indication that women deck officers in our sample trust less than their male counterparts. The reasons for trust/distrust show a tendency of cautious approach towards newly introduced technologies and they generally believe in their responsibility over judgements and actions rather than trusting machine-made decisions.

Fig. 4.5 Trust in the system by gender

4.7 Consideration

Chapter 4 reported on the results of an online questionnaire from 198 deck officers about their degree of trust in the algorithm-based system for collision avoidance. More than a half of the respondents responded positively to their trust in such a system because of its scientifically proven technology and merits of using such navigational aids for crosscheck while others were more cautious about trusting a system because of technical errors, flaws and glitches though human errors can occur as well. Those who responded negatively showed an attitude of trusting human decisions more than machines.

These different responses were also investigated by variables, such as sea experience, rank, ship type, and gender. For ship experience, deck officers who have 1-4 years of seafaring experience generally showed more positively to the system than other groups with less than 1 year or more than 5 years of experience. By rank, 3rd or 4th officers tended to trust in a system more than other ranks. Those who are currently shore-based as managers in the office, superintendents or harbour pilots were also supportive to the idea of using navigational aid systems to increase safety. By ship type, it is observable that those who experienced on board ferry/passenger/cruise ships were more likely to trust in a system than officers on cargo ships. Finally, there was a gender difference among respondents. Women tended to have less trust in such a system than men though further investigation would be needed to confirm such differences.

The limitation of this analysis is that the majority of participants come from India (n=135, 68 percent) and the Philippines (n=28, 14 percent), therefore the results are not representational and may reflect their cultural beliefs. Similar sampling issues also apply when looking at the data by sea experience, rank, ship type and gender. Some categories of groups were small in their sample size.

The result shows that there is a need for establishing a dialogue between developers and seafarers and listening to how they operate ships and when they want technical support through a system. It is evident that seafarers feel highly responsible for safe navigation and their trust in the proposed system can increase if machine errors are reduced but increase its accuracy through further research and data collection from navigating officers. There is also an opportunity of training for deck officers regardless of their lengths of sea-going experiences, to increase their knowledge and skills in technological support to their lookout and navigation.

5. Characteristics of professional sharp-lookout skill

Regarding maritime transportation, compared to other means of transportation such as cars and railroads, the ship traffic has no such thing as defined roads or rails, and they have to identify and avoid ships and obstacles in all directions 360 degrees. This situation is extremely complicated, and that actions to be taken by seafarers are not stipulated clearly by ship-related laws and regulations, and it is largely left to the skills, *kansei*, and customs comes from onboard experience of seafarers that called ‘Seamanship’.

Therefore, to realize practical automated operation technology, it is necessary to analyze the behavior of experienced navigators and understand the basis for making ship maneuvering decisions with good seamanship. The most important thing when making a ship maneuvering decision is the ‘Lookout’, and the most important is the visual sense, which is said to occupy 80-90 % of the information to keep safe navigation.

There are various studies [18,19] on behavior for the ship’s maneuverer and lookout; however, most of them are confirmed by oral questions or questionnaire and not measured by quantitative data. We think the ship maneuverer needs more time to make a decision and take an action for avoiding the target in comparison with other transportation because ships transportation is mixed with a lot of kind of vessel at the same sea areas with good seamanship under the laws [20], and then maybe they cannot objectively grasp and understand all actions for other ships.

Therefore, if it is possible to measure the lookout skills of experienced navigators and visualize them, it can be utilized for the development of an automatically operated ship system and an operation support system.

In this study, we aim to visualize “professional sharp lookout” that is basis for important skill and *kansei* for safe navigation. In this chapter, we firstly compared the line-of-sight data of skilled ship navigators with the ship maneuvering behavior, and considered quantitative data on the ‘point-of-sight’ and ‘time-of-sight’ before and after acting for each ship maneuvering. Next, we clarified another characteristic of experienced navigator’s lookout skill from a previous experiment.

5.1 Simulator-based experiment

5.1.1 Term

We define a term below:

(1) “Point-of-Sight”

The fixation points more than 0.1 seconds continuatively.

The previous study [21] defines more than 165 (msec) continuatively on less than 10 (deg/sec), but we use the fixation point with 0.1 seconds accuracy.

(2) “Time-of-Sight”

The staying time of a fixation point.

5.1.2 Outline

This experiment was carried out by using a ship maneuvering simulator. The subjects wear eye-mark (EMR-9, nac image technology co. [22]), and to operate the ship as usual. The eye-mark and subject condition with eye-mark shows in Fig. 5.1, and image of data and analysis software in Fig. 5.2. The date and time of the experiment is for 3 days and the same time, 13:00-17:00, for each date considering subject’s circadian rhythms. The scenario is set to about 40 minutes in consideration of subjects’ workload and battery capacity. That is, it is an appropriate length of time for the subject to keep normal state during they wear eye-mark, and to avoid target ship.

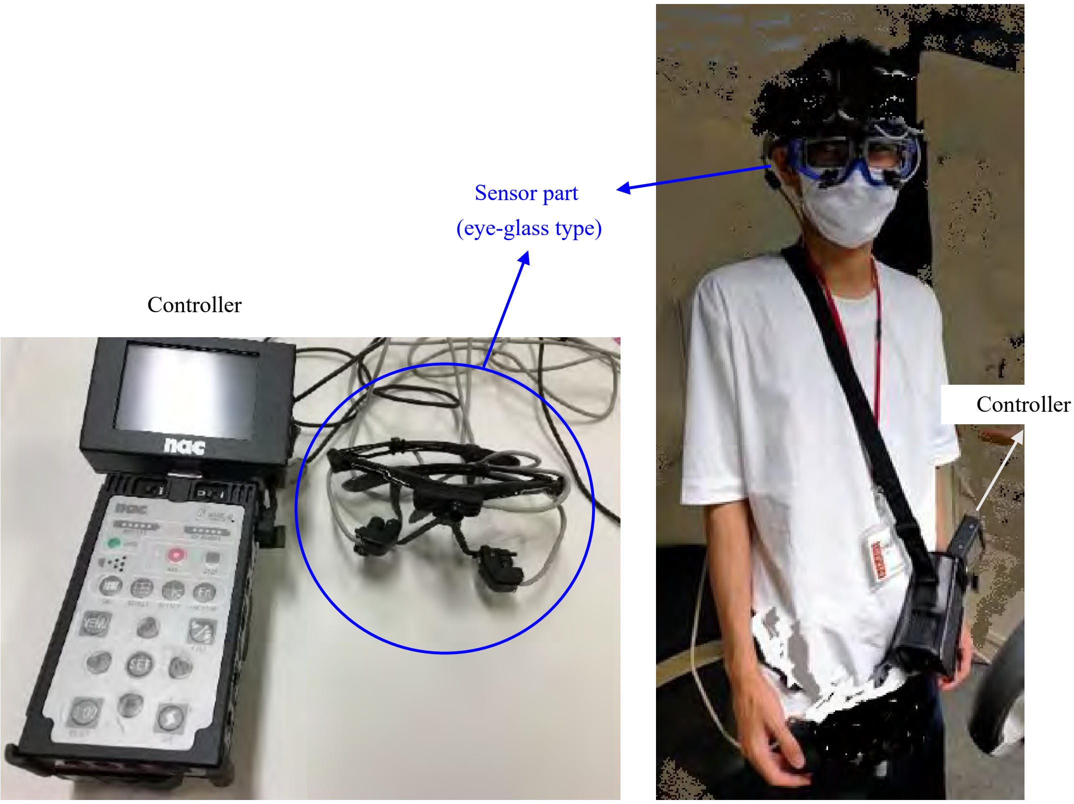


Fig. 5.1 Eye-mark (EMR-9) and image of wearing eye-mark

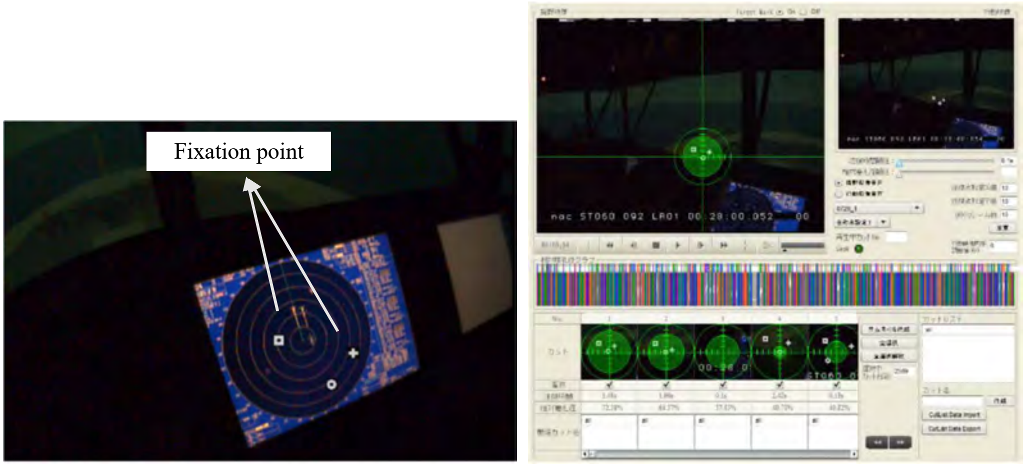


Fig. 5.2 Image of a fixation point by eye-mark (EMR-9) and analysis software

In addition, before the start of the experiment, a familiar maneuvering was carried out for about 10 minutes with measuring attached device.

5.1.3 Scenario

As shown in Fig. 5.3, the scenario is own ship vs. 3 target ships crossing from right side. The own ship must take an action to avoid target ships under the rule on the open sea.

In this scenario, being aware of the automatic ship maneuvering system, the condition is that own ship's speed does not change, and the ship is avoided only by operating the rudder without using radio communication (VHF) with the other ships. In addition, the navigation is based on visual information including binocular-, radar- information, and information obtained only from navigational instruments such as gyro compass and log speed, and the ECDIS is not used.

The own ship's initial speed is 12.3 (kn), course <000> north. There are 3 target ships from 6 to 13 (nm). The visible range is 6 (nm) with binocular.

In this study, 2 subjects passed through between target no.2 and no.3, and 1 subject passed behind all targets.

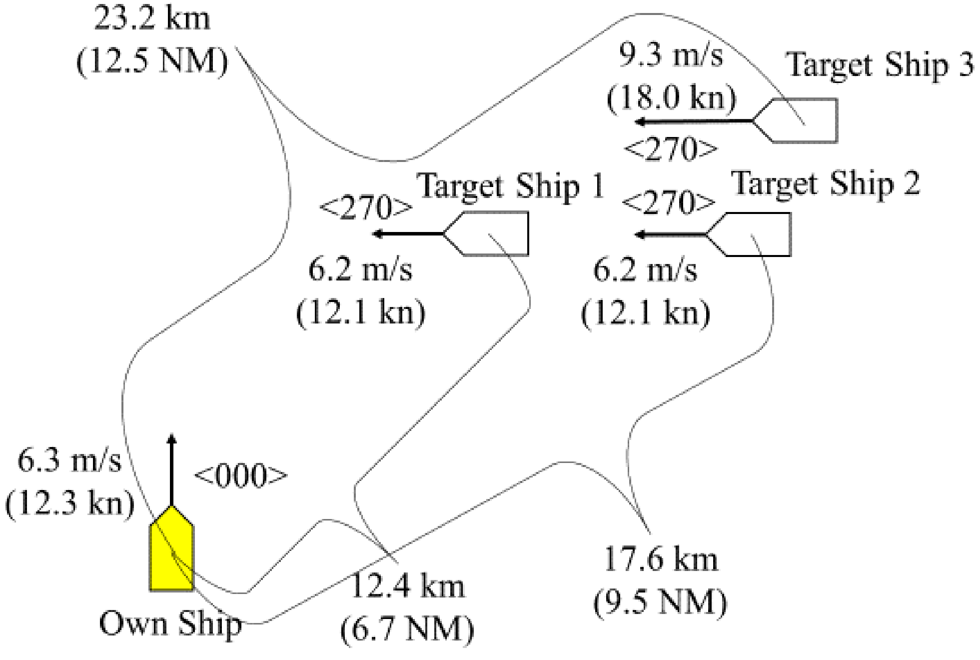


Fig. 5.3 Scenario

5.1.4 Subject

In this study, a subject is an experienced captain of Training Ship in Japan. 2 of three have more than 2 years onboard experience of M/V training ship as captain. Of course, they have enough knowledges and skills for simulator system and simulator-based experiment.

This research was approved by ethic committee of Tokyo University of Marine Science and Technology (TUMSAT) in Japan on 2 June 2021. We explained about the experiment, and 3 subjects (male) agreed to join in this study.

5.2 Evaluation

The evaluation of their line-of-sight and behavior was made by using video data with voice and line-of-sight data by eye-mark, and compare with them, and then we picked up the time-of-sight by radar, binocular, compass for their lookout.

5.2.1 Behavior

We picked up the time for events is below:

(1) Starting time and ending time of the experiment.
(2) Time on walking around in a bridge to do the lookout, radar observation, etc.
(3) Time using radar including recognition of target ship on the radar indicator.
(4) Time on target recognition, explanation on ships maneuver, steering order, etc.
(5) Time on measuring direction of target ship (bearing) using gyro compass.
(6) Time on target recognition and lookout by binoculars.
(7) Others.

5.3 Results

5.3.1 Characteristics of lookout using Radar, Binocular, Compass

We show the characteristics of time-of-sight by radar, binocular, and compass for lookout respectively.

(1) Radar

The time-of-sight for radar is that they stand in front of radar and observe it to check the target and get information. We show the result of time-of-sight by radar in Fig. 5.4. In Fig. 5.4, the data number of x-axis is numbering for time series when the subject does lookout by radar.

From Fig. 5.4, we can confirm 2 characteristics: the one is the time-of-sight for the target ship on radar is 15 to 30 seconds to read target information, and the time decreases for multiple checking to the same target as ‘I’, ‘II’, ‘III’. The other is less than 5 seconds observation time appears after checking the detail information (box).

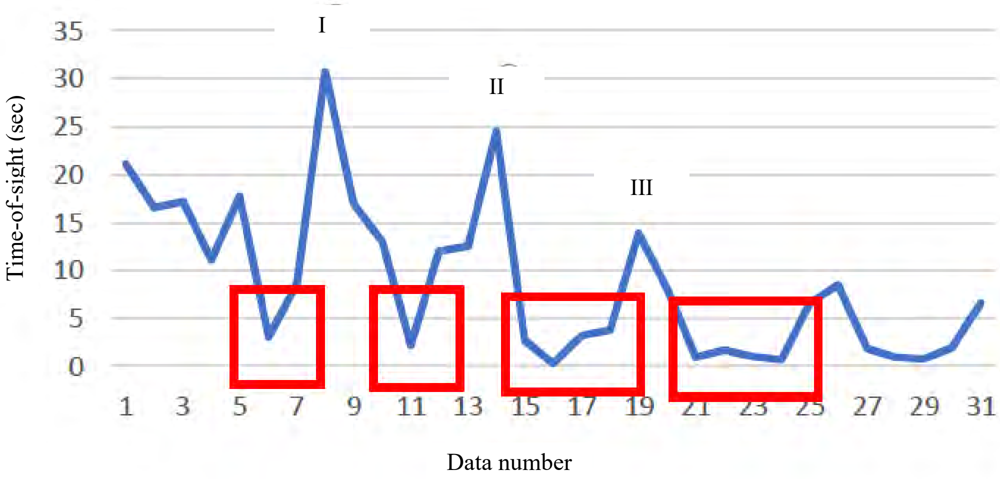


Fig. 5.4. Radar observation

Regarding radar observation, operator needs long time first to understand a target ship's detailed information, after understanding they check the changing of target with short time repetition.

(2) Binocular

The time-of-sight by binocular is that they look the target by binocular and take down the binocular. We have two kinds of lookout by binocular. The one is lookout for around the own ship, the other is lookout for interesting target. We show the result of time-of-sight by binocular in Fig. 5.5. In Fig. 5.5, the data number of x-axis is numbering for time series when the subject does lookout by binoculars.
From Fig. 5.5, we confirmed the time-of-sight by binocular is about from 10 to 20 seconds for lookout.

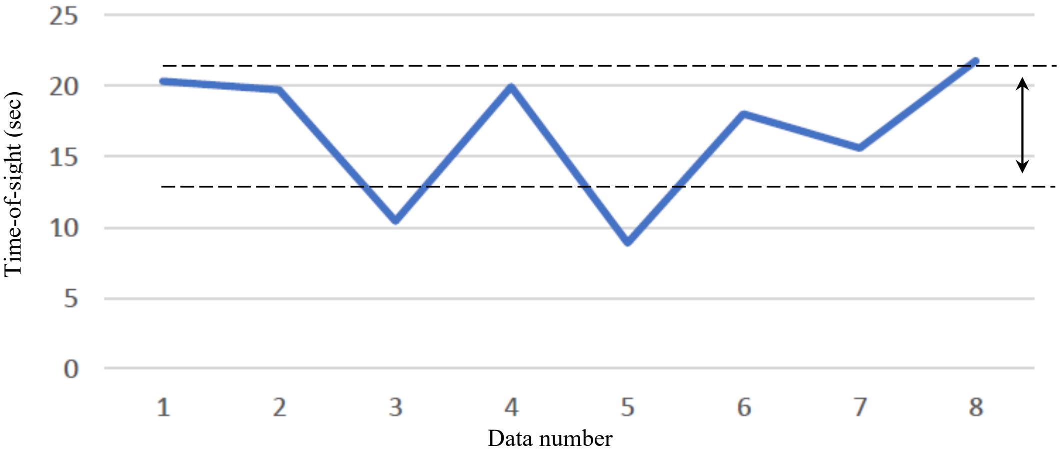


Fig. 5.5. Lookout by binocular

Regarding lookout by binocular, operator needs more than 10 seconds to understand target situation for keep safe navigation.

(3) Compass

The time-of-sight by compass is during time when they measure the bearing of target ship by compass, and from watching the compass card and target in front of the compass stand to leaving line-of-sight from the compass card. We show the result of time-of-sight by compass in Fig. 5.6. In Fig. 5.6, the data number of x-axis is numbering for time series when the subject checks target ship bearing by compass.

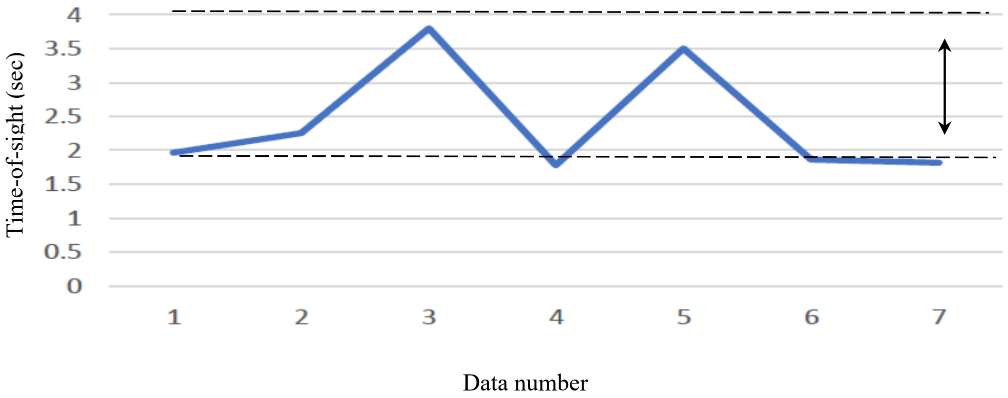


Fig. 5.6. Measurement of target ship bearing

From Fig. 5.6, we can confirm the time-of-sight by compass is about from 2 to 4 seconds.
Regarding measurement of target bearing by compass, operator recognizes in seconds to understand target situation for keep safe navigation.

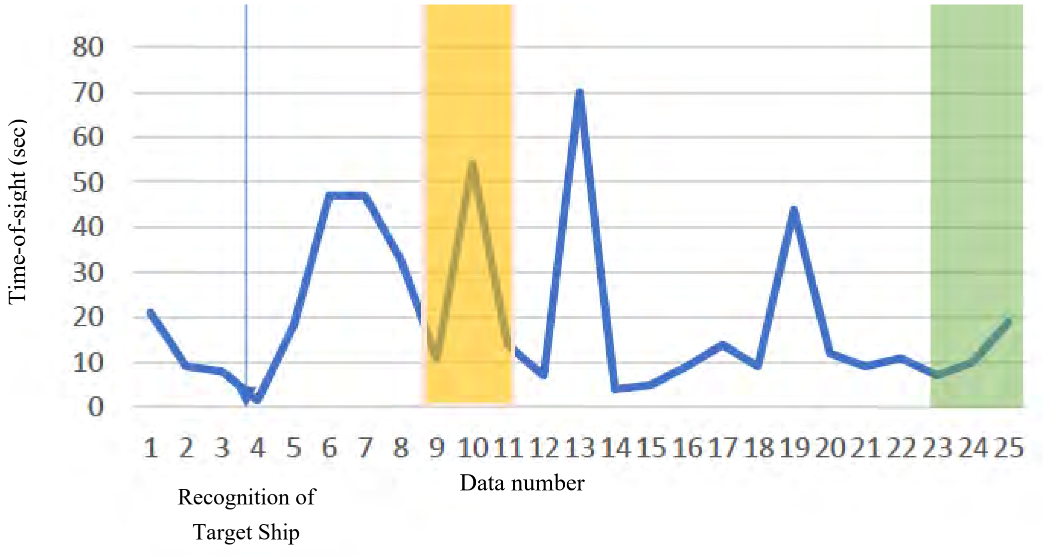
5.3.2 The results of lookout for ship maneuver

We show the results of time-of-sight by radar, binocular, and compass for lookout during ship maneuvering respectively.

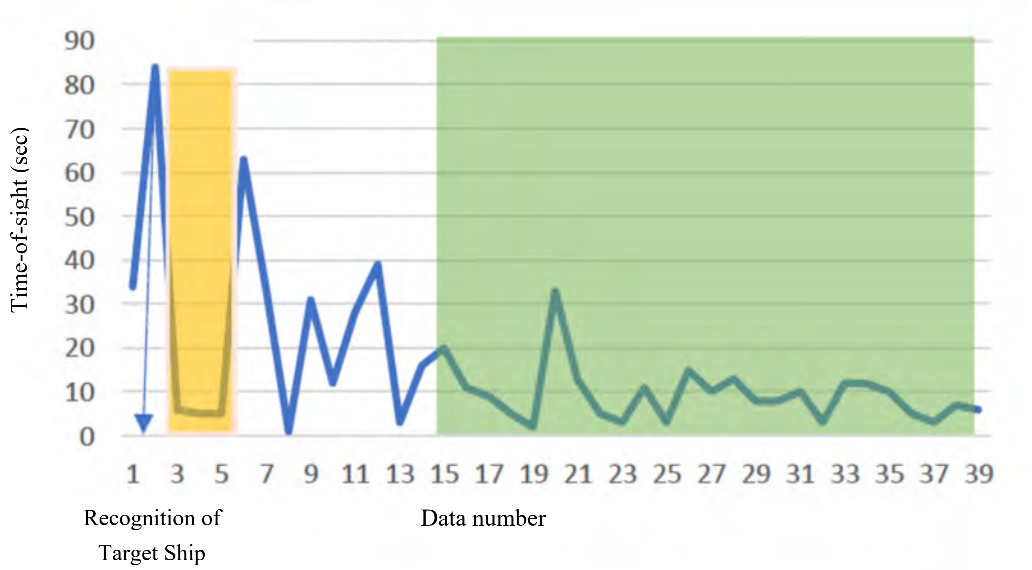
(1) Radar

We show the results of time-of-sight by radar during ship maneuvering in Fig. 5.7. In Fig. 5.7, the data number of x-axis is numbering for time series when the subject does lookout by radar for ship maneuver. In Fig. 5.7, the first surrounded section shows that subjects took actions of target avoidance, and the second surrounded section shows that subjects returned heading back to her course line.
From Fig. 5.7, after subjects recognized the target ship, we can confirm long time-of-sight before order to change course for collision avoidance. Also, time-of-sight tended to shorten as time passed. This tendency is the same as both subjects A and B.

Regarding radar observation for ship maneuvering, in all subjects, there was a tendency to have a long-term time-of-sight (50-90 (sec)) between after recognizing the crossing ship and taking actions of target avoidance. We think subjects simulate and estimate the avoidance methods with radar information before taking actions. Also, time-of-sight by radar becomes short (less than 20 (sec)) as later ship operation.



(Subject A)



(Subject B)

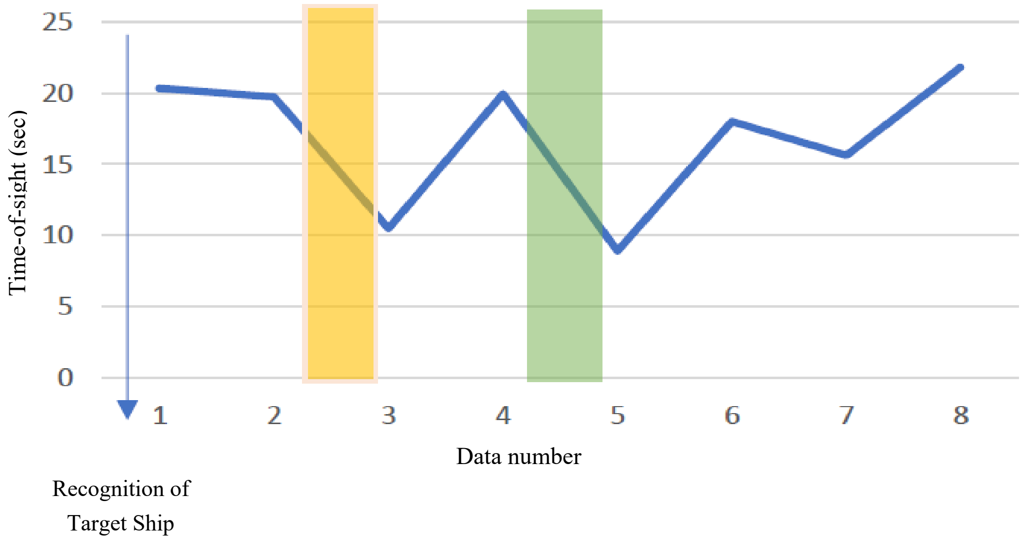
Fig. 5.7 Radar observation

(2) Binocular

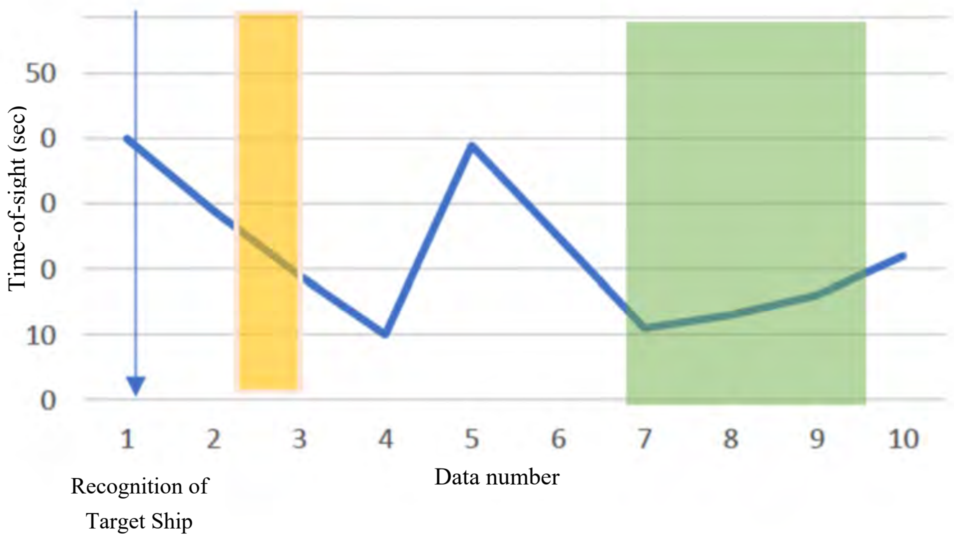
We show the results of time-of-sight by binocular during ship maneuvering in Fig. 5.8. In Fig. 5.8, the data number of x-axis is numbering for time series when the subject does lookout by binoculars for ship maneuver.

In Fig. 5.8, the first surrounded section shows that subjects took actions of target avoidance, and the second surrounded section shows that subjects returned heading back to her course line.

From Fig. 5.8, the time-of-sight by binoculars is from about 10 to 40 seconds, and we can confirm longer time before the operation. Also, they have short time-of-sight by radar after by binocular.



(Subject A)



(Subject B)

Fig. 5.8 Lookout by binocular

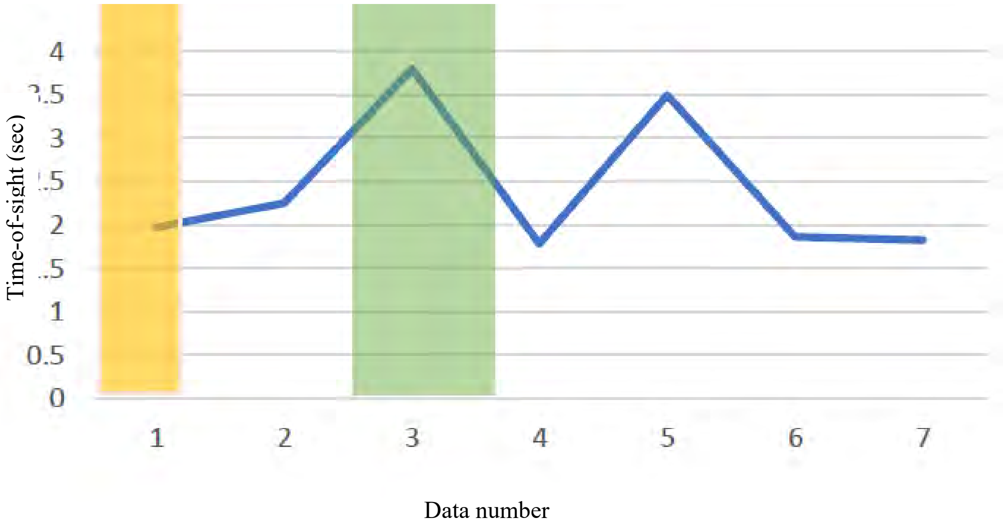
Regarding lookout by binocular during ship maneuvering, it is considered that it takes about 10 to 40 seconds for the recognition of target ships and its confirmation.

(3) Compass

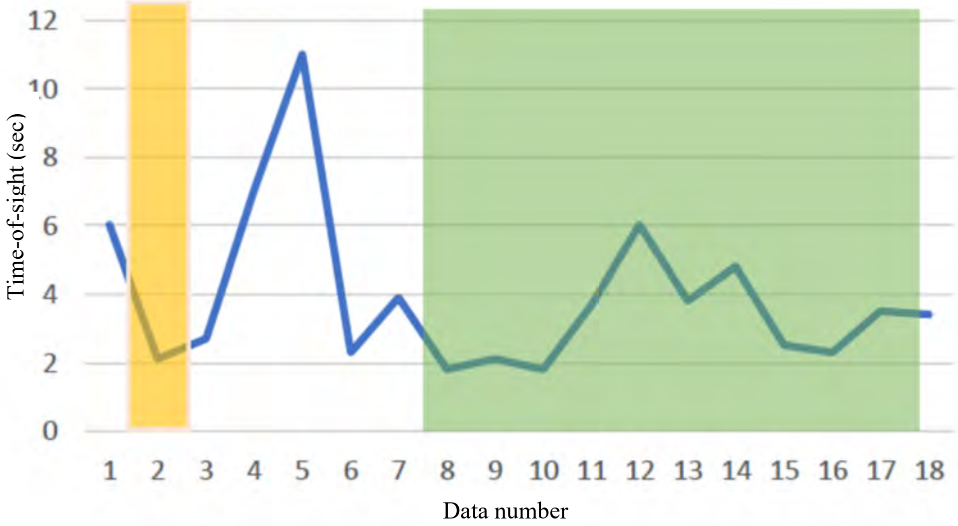
We show the results of time-of-sight by compass during ship maneuvering in Fig. 5.9. In Fig. 5.9, the data number of x-axis is just numbering for time series when the subject checks target ship bearing for ship maneuver.

In Fig. 5.9, the first surrounded section shows that subjects took actions of target avoidance, and the second surrounded section shows that subjects returned heading back to her course line.

From Fig. 5.9, the time-of-sight when they measure the bearing is about 2 to 11 seconds, and there are not remarkable points before and after avoidance of target ship.



(Subject A)



(Subject B)

Fig. 5.9 Measurement of target ship bearing

Regarding measurement of target bearing, it is considered that at least 2 seconds or more time-of-sight is necessary; moreover, more time is required for ships in turns.

As a result, the following findings obtained. Regarding skilled captain's line-of-sight, about time-of-sight by radar, they need a lot of time for its observation to get information, especially when they avoid a target ship, and the time decreases as the maneuvering is going ahead. We can presume that there is some relationship between the time-of-sight by radar and their thinking state. Also, the time-of-sight for the target ship by radar to read target information is more than 15 seconds. About time-of-sight by binocular, they took more than 10 seconds. About time-of-sight by compass to understand the change of target ships bearing, it found that continuous time-of-sight for more than 2 seconds was carried out.

5.4 Mental workload as reference index

Fig. 5.10 shows an example of the measured low frequency/high frequency (LF/HF) values [23] [24] measured by the heart rate variability. Significant responses, defined as increases in the LF/HF as a result of stressful conditions, are indicated in the figure by numbers. Table 5.1 shows the events that were occurring when each significant response was identified in Fig. 5.10. According to Fig. 5.10 and Table 5.1, LF/HF greatly increased in response to events III and IV, when it is likely that stress was being experienced owing to the need for attention to the movements of other ships.

The maneuvering simulator experiments showed that navigator reactions captured by physiological data can be explained in terms of behavior events. Furthermore, behavior analysis using video confirmed that the behaviors associated with experimental scenarios involving multiple ships were difficult to evaluate based solely on biometric data. Therefore, line-of-sight measurement is considered a necessary element. In addition, the results of subject feedback indicated that if the experimental scenarios last about 40 to 50 min with sufficient breaks, the burden on the subject from wearing measuring devices is within tolerances.

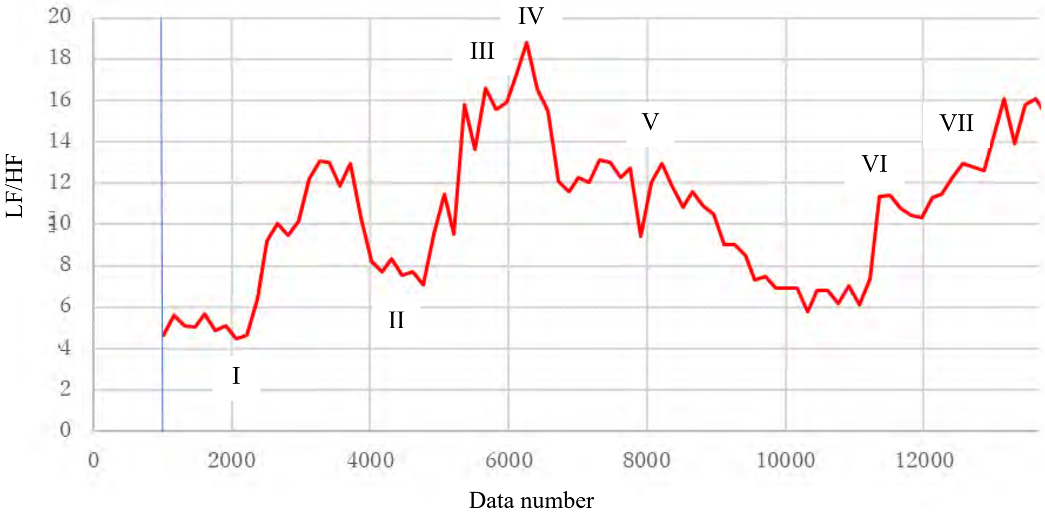


Fig. 5.10. Mental workload for ship maneuvering with a heart rate variability

Table 5.1 Behavioral events

	Event
I	VHF radio communication
II	Radar observation
III	VHF radio communication with target ship
IV	VHF radio communication with target ship
V	Call VHF radio communication from other ship
VI	Radar observation
VII	Radar observation, check the forward fishing boat

As a result, the following findings obtained. The biomedical data is useful to evaluate the skilled operator-level recognition of maneuvering environments and determination of ship maneuvers. Then, the possible quantification of recognition and judgment dynamics was demonstrated according to line-of-sight, and heart rate fluctuations based on the relationship between the various measured data and distance from other vessels, CPA, TCPA, bearing rate, etc. The results of this chapter will be used to inform future experimental design and scenarios that can help to quantify the requirements for Maritime Autonomous Surface Ships (MASS).

5.5 Characteristics of professional sharp-lookout skill clarified by previous experiment

In the previous experiment the authors carried out, to make clear the difference of the characteristics of lookout skill between less experienced navigators and experienced navigators, a ship-handling simulation experiment was carried out. The navigation data of the other ships is shown in Table 5.2.

Table 5.2 Navigation data of the other ships

Other Ship No.	Bearing	Distance	Speed	Heading
1	070°	2.7 NM	12.0 knot	267°, Altered to 257°after 292seconds past from start.
2	153°	2.4 NM	18.0 knot	347°, Altered to 000°after 508seconds past from start.
3	041°	5.9 NM	11.0 knot	270°
4	036°	4.7 NM	10.0 knot	270°
5	330°	3.6 NM	13.0 knot	090°
6	311°	6.5 NM	13.0 knot	090°
7	310°	2.6 NM	9.0 knot	090°
8	318°	2.5 NM	11.0 knot	065°, Altered to 100°after 673seconds past from start.
9	057°	6.8 NM	11.0 knot	270°
10	023°	6.9 NM	8.8 knot	228°
11	012°	6.1 NM	8.0 knot	270°
12	314°	5.9 NM	13.0 knot	090°, Altered to 130°after 425seconds past from start.
13	306°	6.8 NM	12.0 knot	089°
14	347°	2.6 NM	12.0 knot	134°, Altered to 90°after 388seconds past from start.
15	049°	6.0 NM	10.0 knot	312°
16	009°	4.8 NM	10.0 knot	270°
17	024°	2.2 NM	13.5 knot	090°
18	357°	5.5 NM	12.0 knot	181°, Altered to 224°after 210seconds past from start and Altered to 180°after 534seconds past from start.
19	003°	2.2 NM	12.0 knot	000°
20	054°	8.1 NM	11.0 knot	270°
21	312°	0.5 NM	18.0 knot	180°
22	176°	23.3 NM	13.0 knot	000°
23	000°	12.8 NM	16.0 knot	180°
24	055°	6.0 NM	10.0 knot	270°

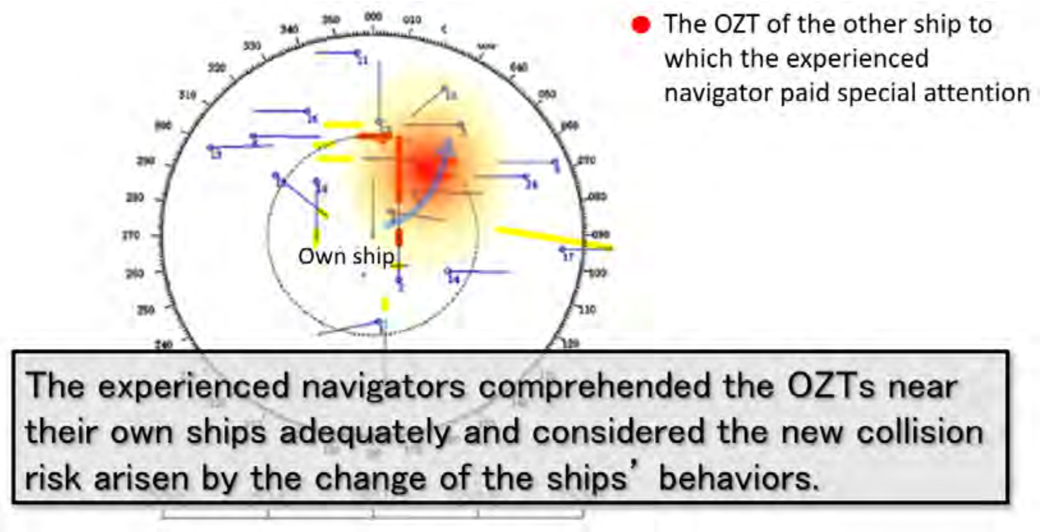
In the previous experiment, the data at time 720 seconds from the start of the simulation was analyzed. The simulation was stopped when 720 seconds were past from the start and the subjects were asked to which ship they paid special attention.

Table 5.3 Values of DCPA and TCPA of the other ships

Other Ship No.	DCPA	TCPA	Inexperienced		Experienced		
			A	B	A	B	C
1	—	—					
2	0.5 NM	8 min	●	●			●
3	0.3 NM	10 min	●	●	●	●	
4	0.4 NM	6 min	●		●	●	
5	1.2 NM	0 min		●		●	
6	0.0 NM	10 min	●	●			●
7	—	—					
8	0.5 NM	0 min		●			
9	1.4 NM	13 min			●	●	●
10	0.2 NM	10 min		●	●		●
11	2.3 NM	12 min			●		
12	1.1 NM	5 min					
13	0.7 NM	12 min	●	●			
14	—	—	●				
15	0.9 NM	29 min					
16	2.5 NM	4 min		●	●		
17	—	—					
18	1.0 NM	2 min		●			
19	—	—	●	●	●	●	
20	1.4 NM	18 min					
21	—	—					
22	0.2 NM	109 min	●				
23	0.1 NM	15 min					
24	1.4 NM	11 min			●	●	●

● was marked in case of the navigator paid special attention to the ship

Table 5.3 shows values of both DCPA and TCPA of the other ships and which ship the navigators paid special attention to. From this figure, it can be seen that even though/ DCPA and TCPA values of the other ships were large, that is, collision risks seemed to be small from these values, experienced navigators in common paid special attention to No.9 and No.24, while all the less experienced navigators did not. By analyzing these data with OZT, it was found that the experienced navigators not only comprehended the OZTs near their own ships adequately but also considered the new collision risk arisen by the change of the ships' behaviors. It means that predicting ships' behaviors is important for collision avoidance safely.



● The OZT of the other ship to which the experienced navigator paid special attention

The experienced navigators comprehended the OZTs near their own ships adequately and considered the new collision risk arisen by the change of the ships' behaviors.

Fig.5.11 The OZT the experienced navigators paid special attention to

6. Improvement of collision avoidance algorithm by using lookout skills of experienced navigators

In this study, to improve collision avoidance algorithm by using lookout skills of experienced navigators, we focused on their skills of predicting future behavior of the other ships.

As explained above, we used Obstacle Zone by Target (OZT) as an index to estimate collision risks when constructing the automatic collision avoidance algorithm. In this study, in consideration of uncertainty of the other ships' future behaviors, we calculated not only OZT but also potential OZT.

Potential OZT appears when the other ships alter its course. SVM was also applied to predict the other ship's behavior as well as to search for collision avoidance route.

6.1. Predicting ship behavior by SVM

Navigators customarily alter its course to starboard to avoid collision. However, altering its course to port is sometimes safer and more efficient and results in due regard to good seamanship. Therefore, it is important to know in which case the ship should alter her course to starboard or port to avoid collision. In this study, SVM was applied to predict the other ship's behavior as well as to search for collision avoidance route.

SVM is one of pattern recognition models by using supervised learning and can be mainly applied to classification and regression. SVM is one of the best mechanical learning models superior to recognition abilities among the currently known methods because it is designed to acquire high-recognition abilities toward untrained data. SVM is a method to configure two classes of pattern classifier by using linear input device. SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. Moreover, the SVM can be used for multidimensional data because the SVM can apply a kernel trick [25]. Therefore, in this study, SVM was applied to predict the other ship's behavior as well as to search for collision avoidance route.

By learning the data obtained by the simulation results and classified for two groups, SVM found the hyperplane between 'altering its course to starboard' and 'altering its course to port' to avoid collision.

The data of the subjects' behaviors to avoid collision in 42 cases of Imazu Problem were classified in two categories; altering its course to starboard and altering its course to port. Then the classified data was feed to SVM as training data and SVM found a hyperplane between altering her course to starboard and altering her course to port.

Examination procedure is explained with Fig.6.1 and Fig.6.2.

In the situation shown in Fig.6.1, OZT exists from bow side to 23 degrees to starboard and the distance from OZT is 4 miles. In this scenario, the subject alters its course to starboard to avoid collision. This result was classified as 'altering its course to starboard' with the record of OZT distribution's degree and its distance. On the other hand, in the situation shown in Fig.6.2, OZT exists too wide to alter its course to starboard to avoid collision. Then the subject altered its course to port to avoid collision. This result was classified as 'altering its course to port'. SVM found a hyperplane by analyzing these classified data as training data.

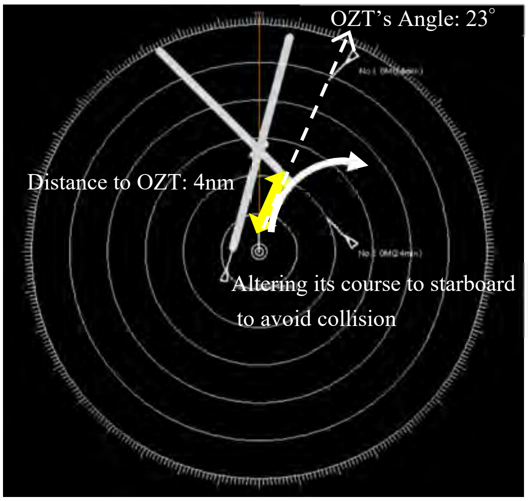


Fig. 6.1 A simulation example for collision avoidance (in the case of altering its course to starboard)

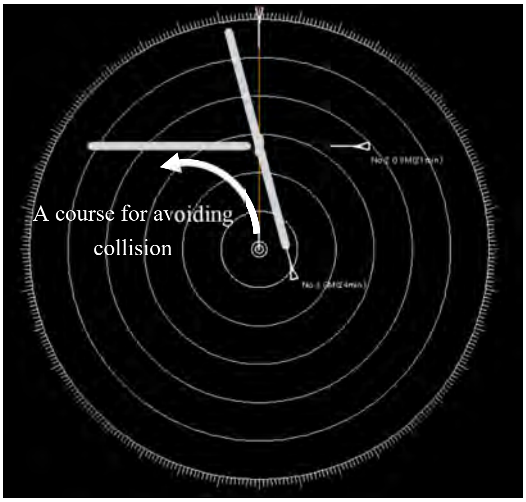


Fig. 6.2 A simulation example for collision avoidance (in the case of altering its course to port)

Fig.6.3 shows training data plotted on X-Y axis. Round dots show ‘altering its course to starboard’ and square dots show ‘altering its course to port’. The distance to the rightmost OZT from own ship is put on the vertical axis and the angle to the right end of the area covered by OZT is put on horizontal axis. SVM made a hyperplane by using these coordinate points as training data. The result is shown in Fig. 6.4.

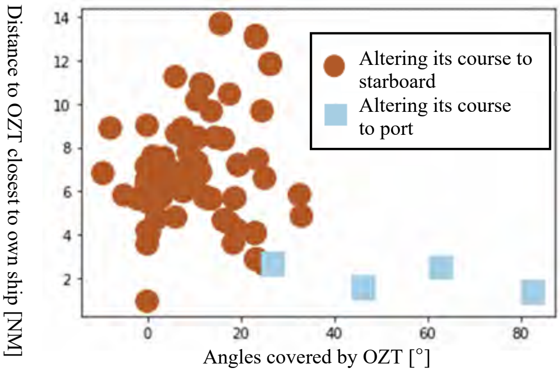


Fig.6.3 Training data plotted on X-Y axis

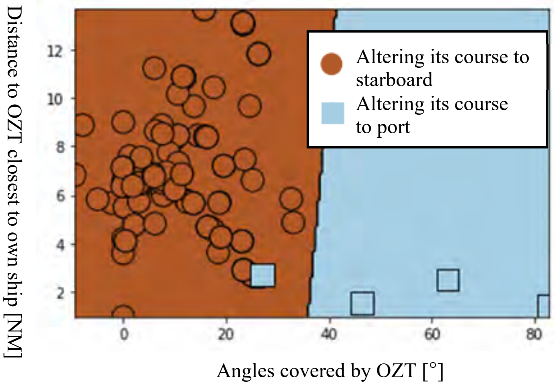


Fig.6.4 Calculation results by SVM

From Fig.6.4, it was found that the hyperplane between 'altering its course to starboard' and 'altering its course to port' was located around 35°. However, several square dots were isolated in the area enclosed with a circle the ship should be 'altering its course to starboard'. In this study, the reason why such isolated square dots ('altering its course to port') existed in the area of 'altering its course to starboard' was considered.

As a result, it was presumed that there exists psychological pressure against 'altering its course to starboard' which cannot be expressed by OZT in the situation. For example, as shown in Fig.6.5, there exists a same course vessel at almost the same speed as the own ship on the starboard.

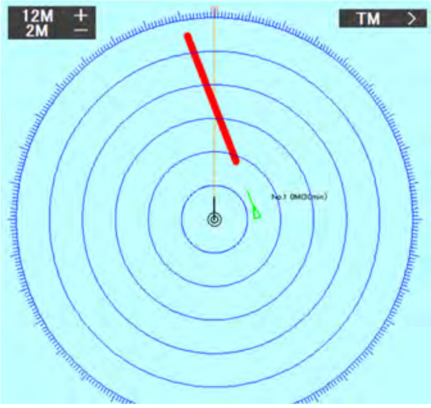


Fig.6.5 Encounter situation with a same course vessel at almost the same speed as the own ship on the starboard

6.2 Outline of collision avoidance algorithm proposed in this study

Based on the maneuvering tendency acquired by the hyperplane, the proposed algorithm searches the collision avoidance route under the following procedures.

1) The algorithm calculates OZTs around the own ship.
2) If OZT exist within 2° to the left and the right from heading, it judges there exists risk of collision and starts calculating the collision avoidance route. If not, it follows the originally planned route.

3) If the own ship will go ahead and be a stand-on ship, it keeps its course. If not, it starts calculating the collision avoidance route.
4) It calculates OZTs around the other ships on the assumption that the other ships were the own ship. And by using distribution of ships and OZTs around the other ships, it predicts future behaviors of the other ships based on maneuvering characteristics of experienced navigators.
5) It calculates potential OZTs by using future behaviors of the other ships acquired in 4).
6) By using PSO, it calculates the effective route that avoids OZTs as well as potential OZTs (and shallow waters, shores and so on, if any).
7) If there doesn’t exist any risk to collide with the other ships, it returns heading back to the originally planned route.

To verify the effectiveness of the proposed algorithm, the simulation experiments in all 42 cases of Imazu Problem were carried out.

6.3 Simulation experiment to verify the effectiveness of the proposed algorithm

The simulation results are shown in Fig.6.6 to Fig.6.21. These figures are presented for comparison with the simulation results in Chapter 3 (Fig.3.2 - Fig 3.7). As shown from Fig. 6.6 to Fig. 6.21, in all cases, not only the own ship but also all ships appropriately avoided to collide with the other ships and the effectiveness of the algorithm was verified.

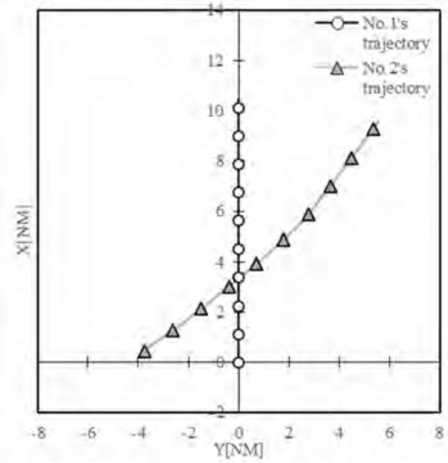


Fig. 6.6 Simulation result (Phase 1, No. 4)

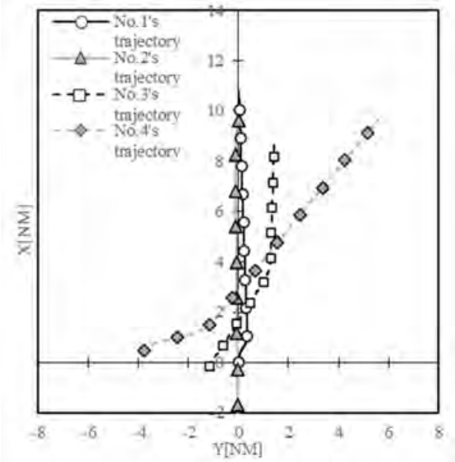


Fig. 6.7 Simulation result (Phase 1, No. 13)

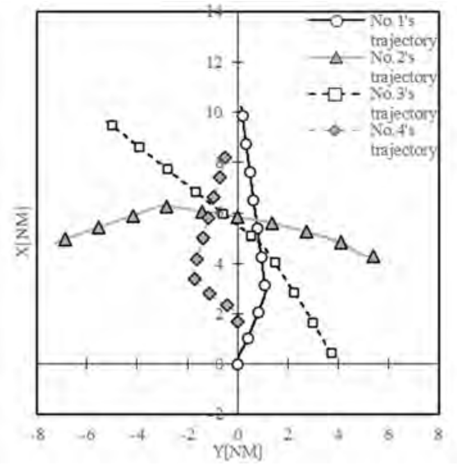


Fig.6.8 Simulation result (Phase 1, No. 15)

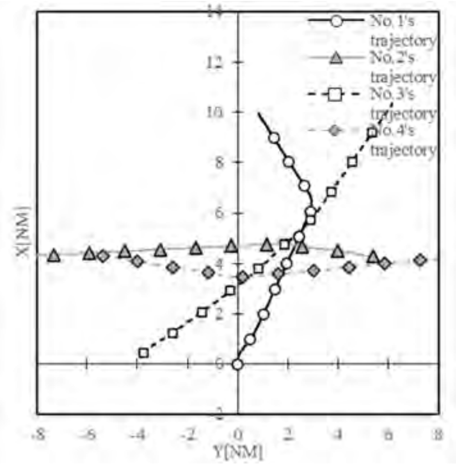


Fig.6.9 Simulation result (Phase 1, No. 16)

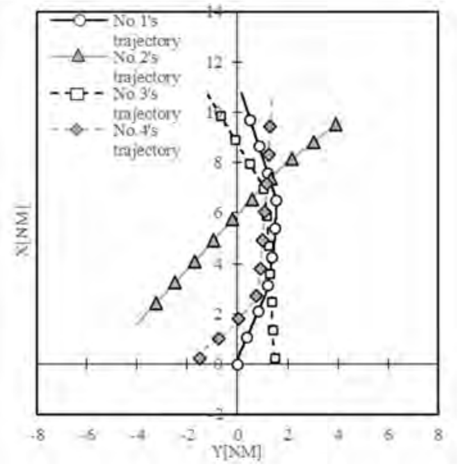


Fig.6.10 Simulation result (Phase 1, No. 19)

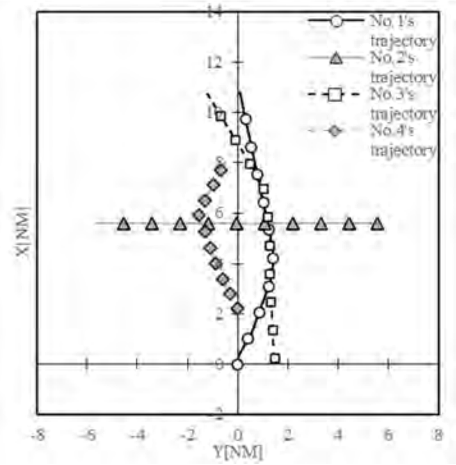


Fig.6.11 Simulation result (Phase 1, No. 20)

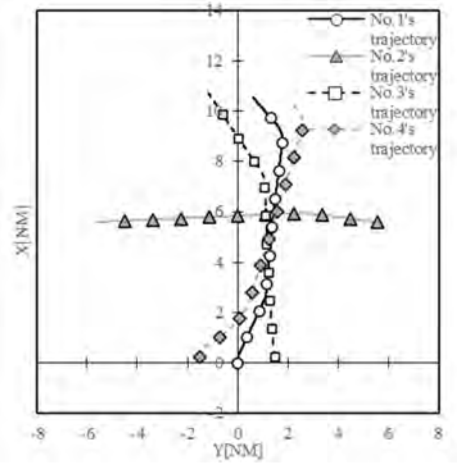


Fig.6.12 Simulation result (Phase 1, No. 21)

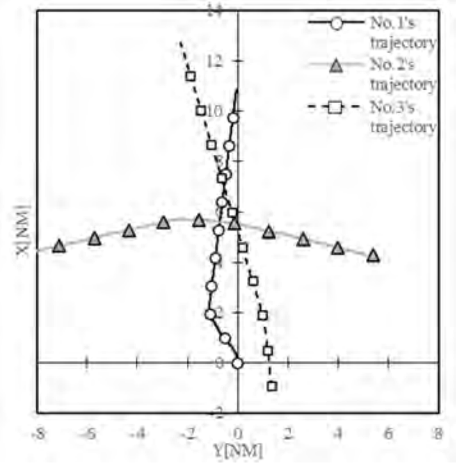


Fig.6.13 Simulation result (Phase 2, No. 2)

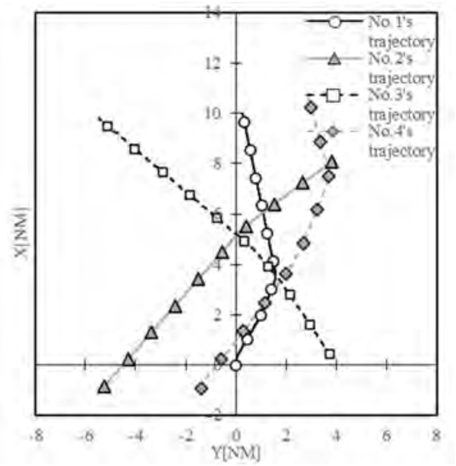


Fig.6.14 Simulation result (Phase 2, No. 9)

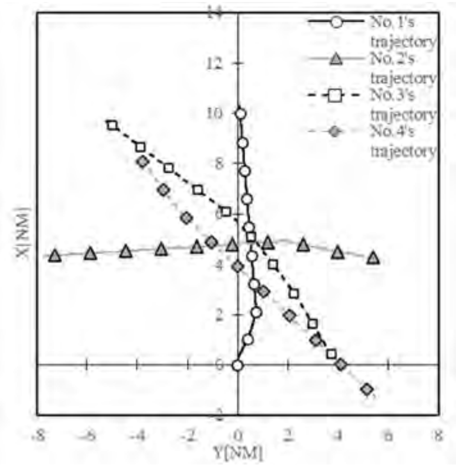


Fig.6.15 Simulation result (Phase 2, No. 10)

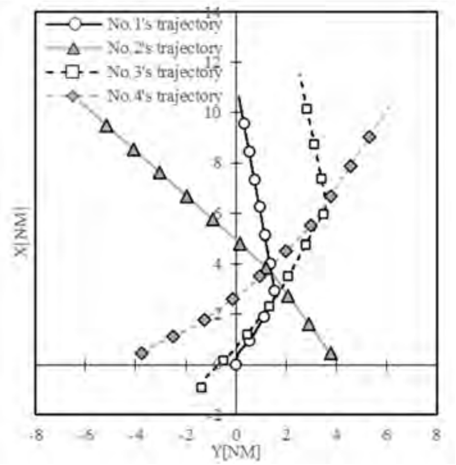


Fig.6.16 Simulation result (Phase 2, No. 12)

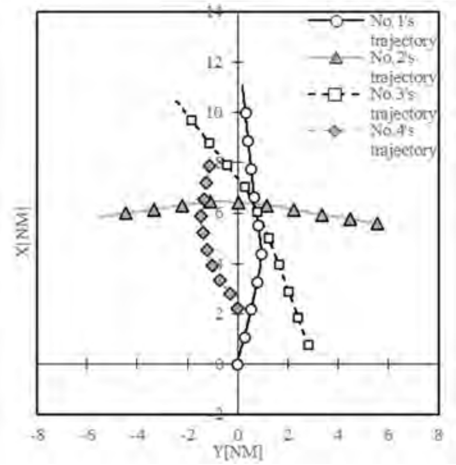


Fig.6.17 Simulation result (Phase 2, No. 15)

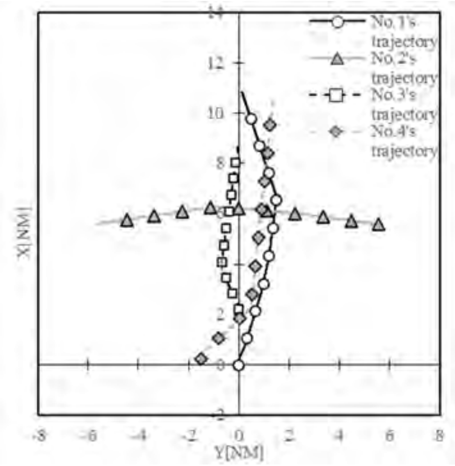


Fig.6.18 Simulation result (Phase 2, No. 16)

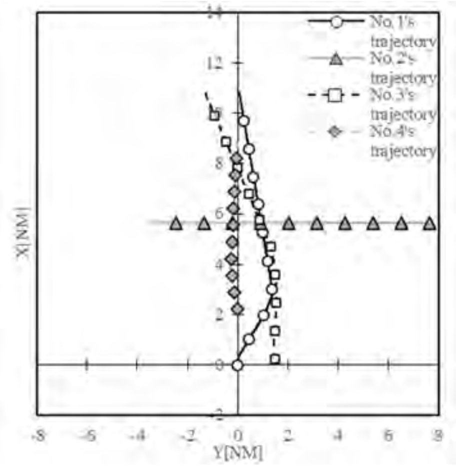


Fig.6.19 Simulation result (Phase 2, No. 17)

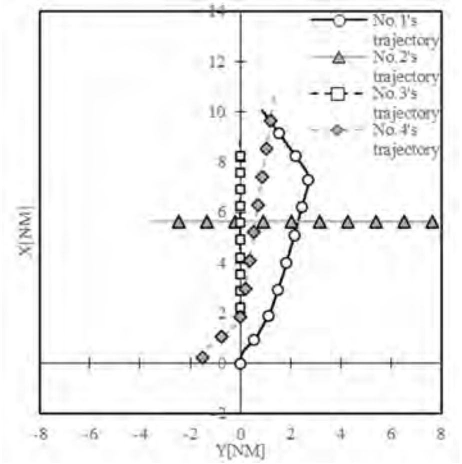


Fig.6.20 Simulation result (Phase 2, No. 18)

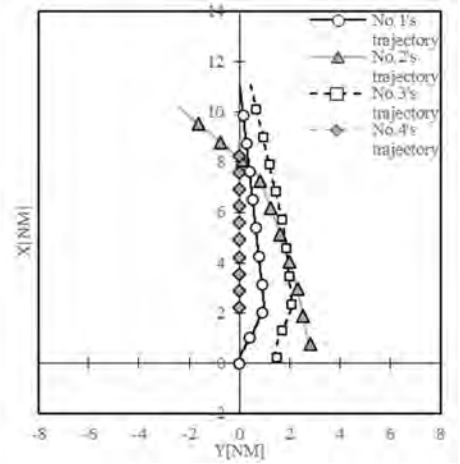


Fig.6.21 Simulation result (Phase 2, No. 19)

The simulation results in the case of Phase 2, No. 12 are shown from Fig. 6.26 to Fig. 6.32. The left figures show the simulation result of the algorithm without predicting ship behavior by SVM (Chapter 3) and the right figures show that of the algorithm with predicting ship behavior by SVM (Chapter 6). In the left figures, the ships collided or closed to collide at the black-out areas. On the other hand, the ships didn't collide at all. OZT distributions at the beginning of the experiment are shown from Fig. 6.22 to 6.25. In these figures, OZTs are shown as the areas filled with white. In the left figures, OZTs are relatively small because the algorithm calculated on the assumption that the other ships keep their courses. On the other hand, OZT in the right figures are wider because the algorithm also take account into the changes of the other ships' behaviors. The wider OZT distribution is, the larger the ship's behavior to avoid collision is. As a result, it leads to secure spaces for the other ship to avoid collision. For example, as shown in the left figure of Fig.6.23, at the experiment of the algorithm without predicting ship behavior by SVM, No.2 target ship altered her course to port in the case of Phase 2, No. 12 because OZT distribution was placed a little bit to the right. On the other hand, at the experiment of the algorithm with predicting ship behavior by SVM, No.2 target ship altered her course to starboard largely because it predicted from the OZT distribution shown in the left figure of Fig.6.23 that the other ships would alter their courses to starboard side to avoid collision. Then, the space for No.1 target ship to avoid collision was secured as shown in Fig.6.29. It can be said that this collision avoidance behavior reflects the way of thinking of the experienced navigators and the effectiveness of the proposed algorithm was verified.

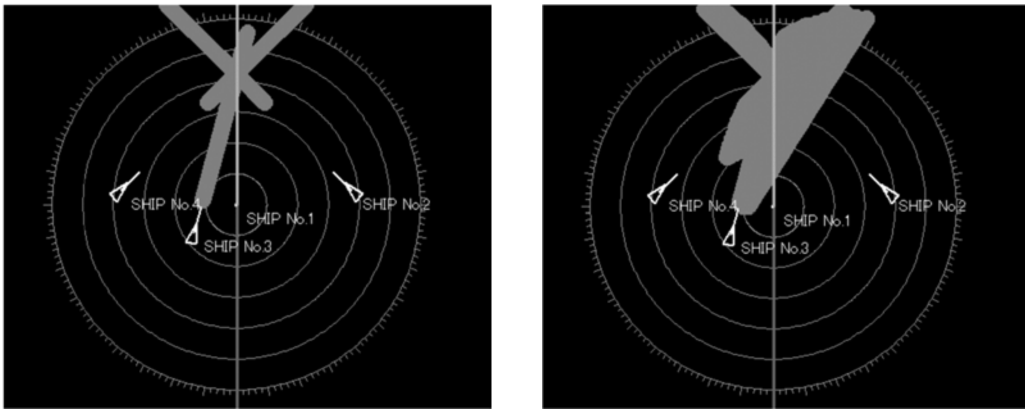


Fig. 6.22 OZT distributions seen from No.1 ship at the beginning of the experiment (Phase 2, No. 12)

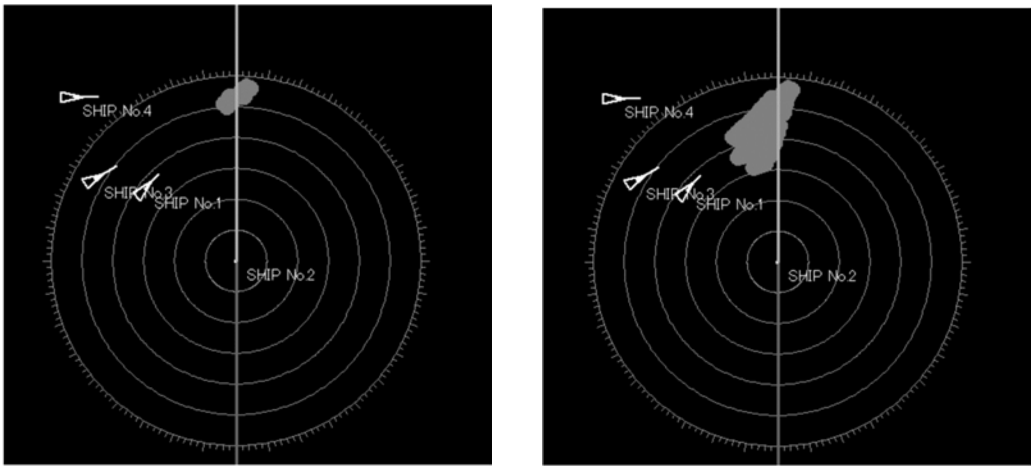


Fig. 6.23 OZT distributions seen from No.2 ship at the beginning of the experiment (Phase 2, No. 12)

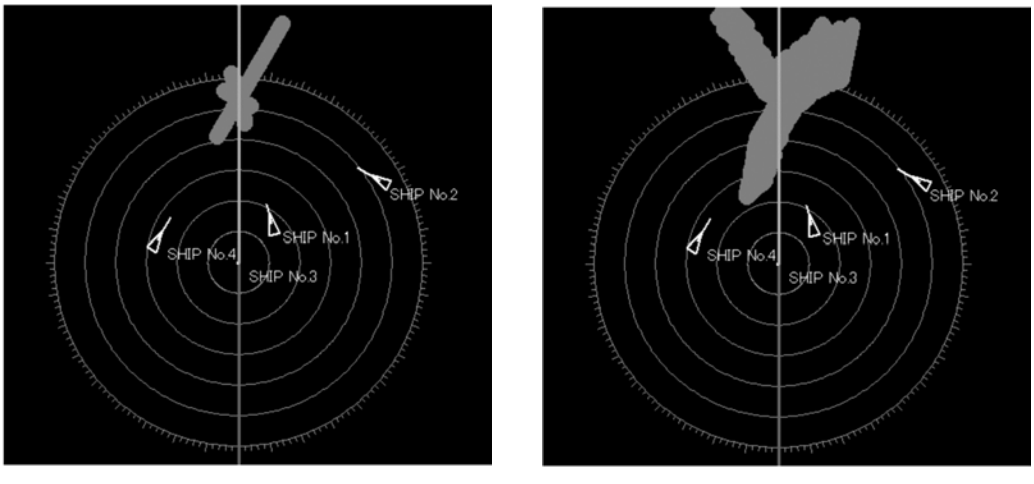


Fig. 6.24 OZT distributions seen from No.3 ship at the beginning of the experiment (Phase 2, No. 12)

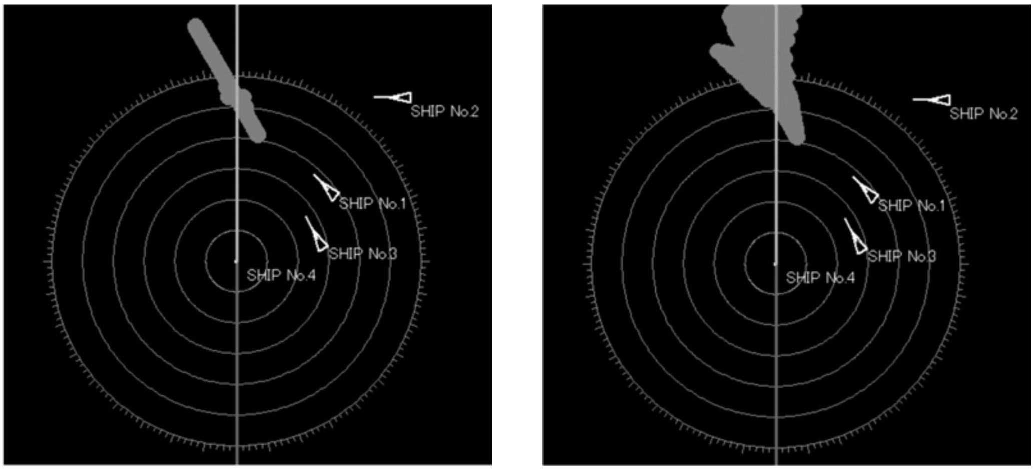


Fig. 6.25 OZT distributions seen from No.4 ship at the beginning of the experiment (Phase 2, No. 12)

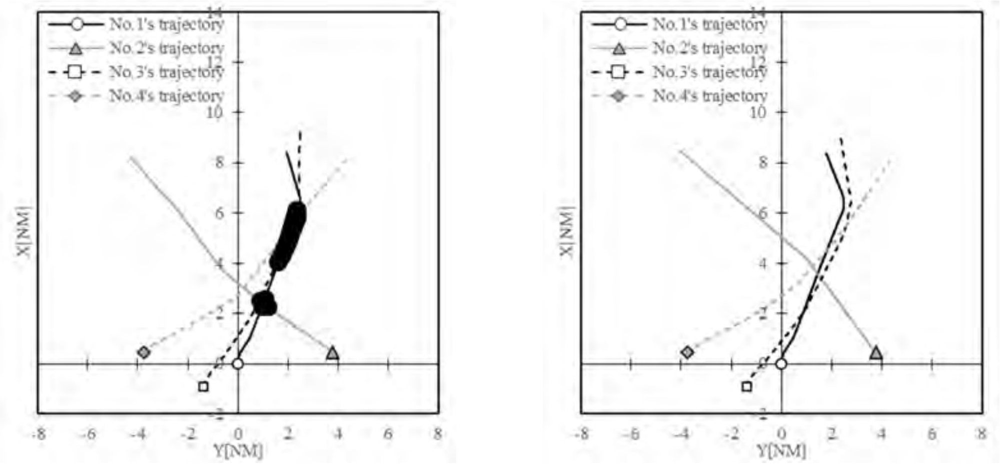


Fig.6.26 Ships' positions at the beginning of the experiment (Phase 2, No.12)

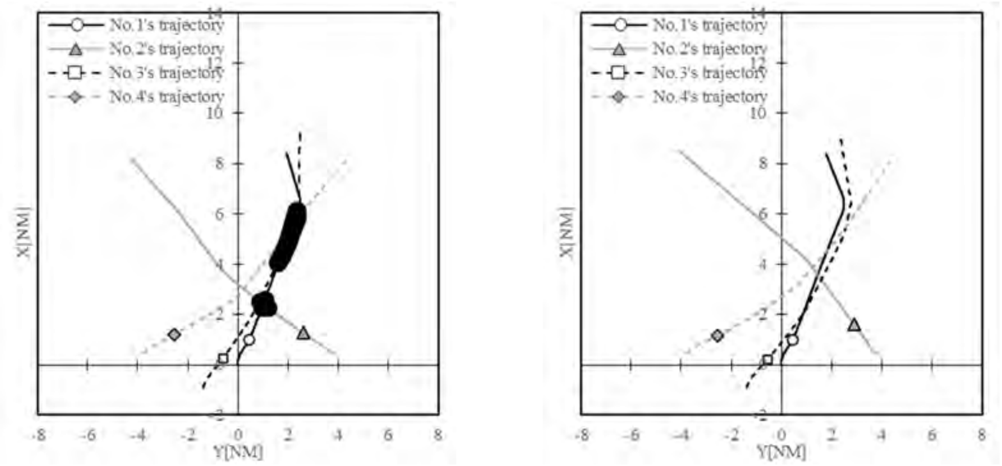


Fig.6.27 Ships' positions at fifth minutes from the start of the experiment (Phase 2, No.12)

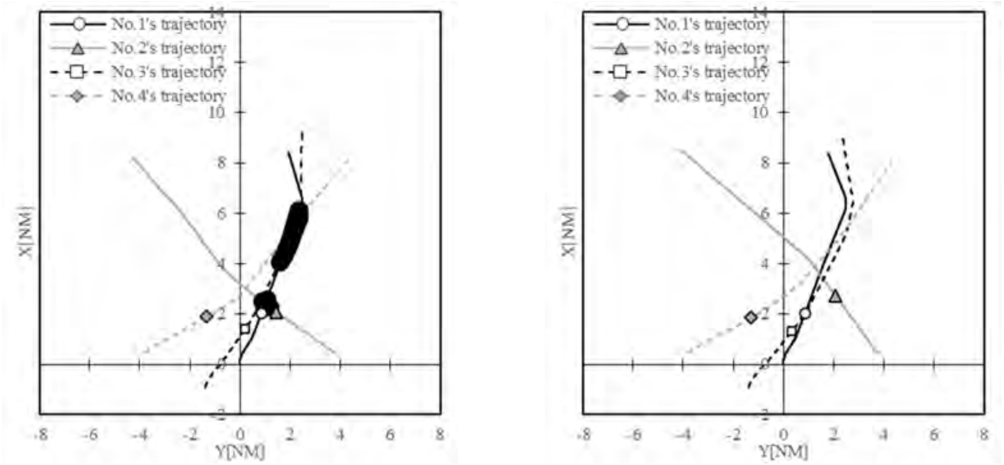


Fig.6.28 Ships' positions at tenth minutes from the start of the experiment (Phase 2, No.12)

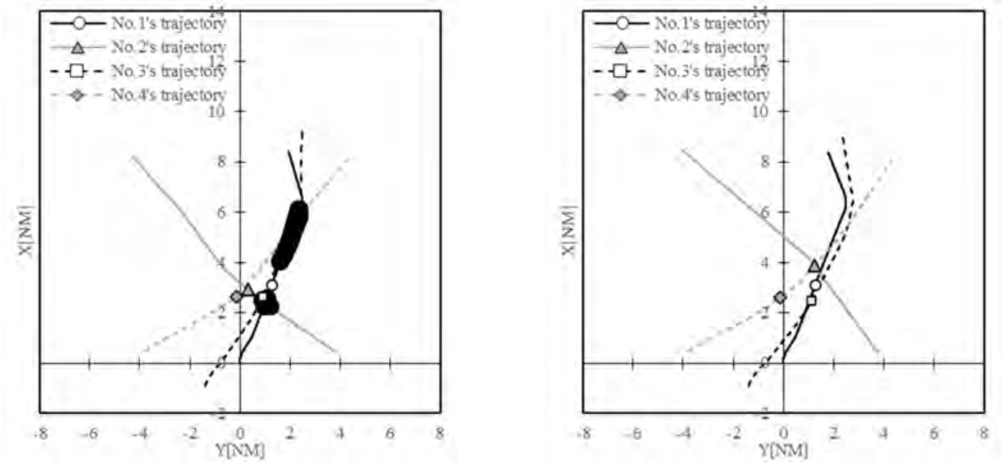


Fig.6.29 Ships' positions at fifteenth minutes from the start of the experiment (Phase 2, No.12)

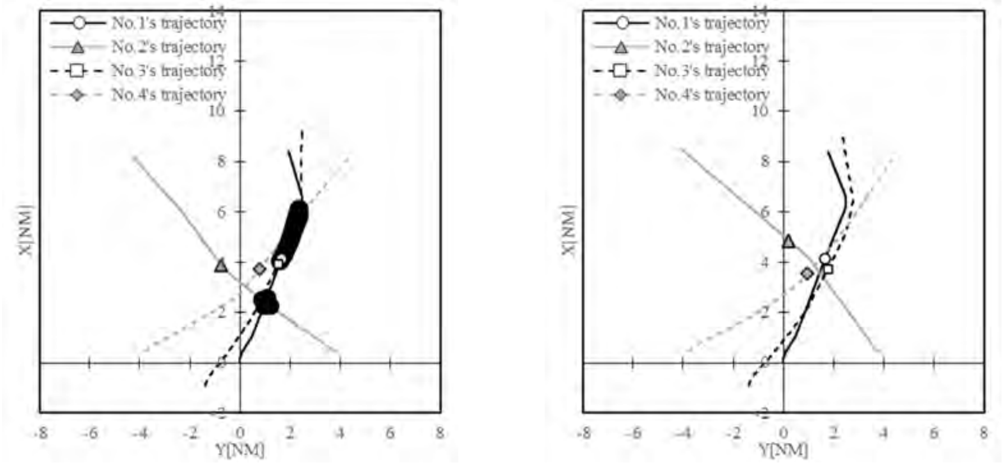


Fig.6.30 Ships' positions at twentieth minutes from the start of the experiment (Phase 2, No.12)

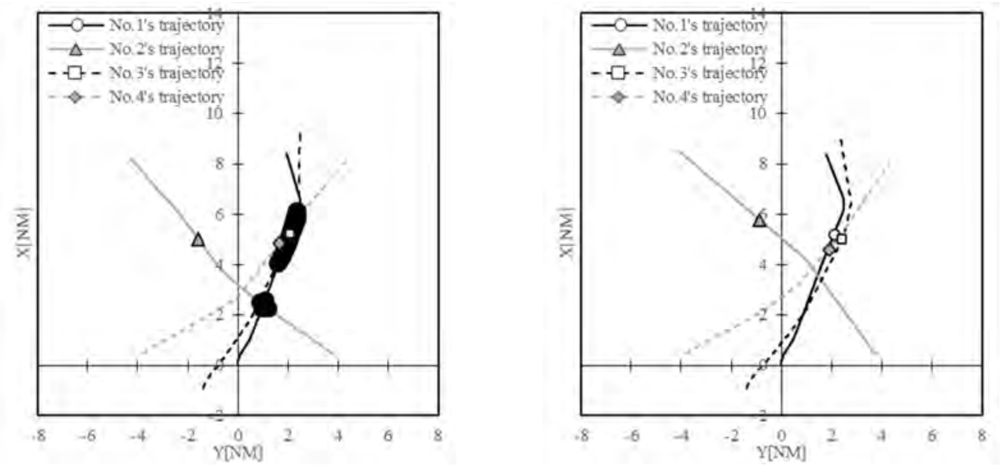


Fig.6.31 Ships' positions at twenty-fifth minutes from the start of the experiment (Phase 2, No.12)

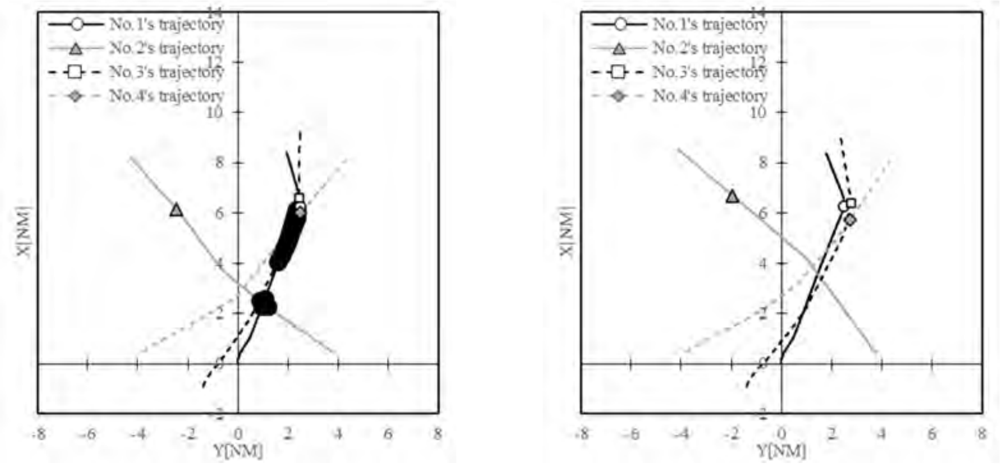


Fig.6.32 Ships' positions at thirtieth minutes from the start of the experiment (Phase 2, No.12)

7.Conclusions, limitations, and future work

In this study, we aimed to develop an algorithm of new target avoiding system based on the characteristics of professional lookout skills.

Firstly, we constructed an algorithm for searching collision avoidance route by using PSO with OZT as collision risk index. The simulation experiments were carried out and the effectiveness of the proposed algorithm was verified. However, in these experiments, it was set as the algorithm was applied to only No.1 ship and the other ships would not change their behaviors. In other simulation experiment for the proposed algorithm applying to all the ships, ships collided or closed to collide to each other because this algorithm calculates the collision avoidance route only where the other ships would not change their behaviors. On the other hand, at practical level, experienced navigators normally have little trouble identifying collision threats. Therefore, identifying the characteristics of experienced navigators' lookout skill will certainly lead to a reduction in sea accidents.

Secondly, we administered an online questionnaire among experienced deck officers and less experienced ones to understand sociotechnical barriers to the newly proposed system to assist decision-making of deck officers on watch. More than a half of the respondents responded positively to their trust in such a system while others were more cautious about trusting a system. Those who responded negatively showed an attitude of trusting human decisions more than machines. The result shows that there is a need for establishing a dialogue between developers and seafarers and listening to how they operate ships and when they want technical support through a system.

To visualize the characteristics of experienced navigators' lookout skills, based on the results of simulation experiment by using Eye-tracker, we compared the line-of-sight data of skilled ship navigators with the ship maneuvering behavior and considered quantitative data on the 'point-of-sight' and 'time-of-sight' before and after acting for each ship maneuvering. We also measured low frequency/high frequency (LF/HF) values by the heart rate variability to show mental workload. The biomedical data is useful to evaluate the skilled operator-level recognition of maneuvering environments and determination of ship maneuvers. However, behavior analysis using video confirmed that the behaviors associated with experimental scenarios involving multiple ships were difficult to evaluate based solely on biometric data. Therefore, line-of-sight measurement is considered a necessary element. Then, the possible quantification of recognition and judgment dynamics was demonstrated according to line-of-sight, and heart rate fluctuations based on the relationship between the various measured data and distance from other vessels, CPA, TCPA, bearing rate, etc.

Next, we clarified another characteristic of experienced navigator's lookout skill from a previous experiment. In the previous experiment, to make clear the difference of the characteristics of lookout skill between less experienced navigators and experienced navigators, a ship-handling simulation experiment was carried out. By analyzing the results with OZT, it was found that the experienced navigators not only comprehended the OZTs near their own ships adequately but also considered the new collision risk arisen by the change of the ships' behaviors. It means that predicting ships' behaviors is important for collision avoidance safely.

To improve collision avoidance algorithm by using lookout skills of experienced navigators, we focused on their skills of predicting future behavior of the other ships. In consideration of uncertainty of the other ships' future behaviors, we calculated not only OZT but also potential OZT. SVM was also applied to predict the other ship's behavior as well as to search for collision avoidance route. Though the simulation experiments, the effectiveness of the proposed algorithm was verified.

The limitations of the proposed algorithm and the means for further development are as follows. Firstly, the proposed algorithm should be improved to deal with conduct in restricted visibility and in restricted ability to manoeuvre. International Maritime Organization (IMO) has recently completed a regulatory scoping exercise on MASS and commenced work on the development of a goal-based instrument regulating its operation. The outline of the draft guidelines for MASS operations proposed by Japan, Russian Federation and United Arab Emirates, safe fallback response is included as a general requirement for MASS [26]. We should take it into consideration. Secondly, more training data should be collected to improve the accuracy of the proposed algorithm. Lastly, the effectiveness of the proposed algorithm should be also verified though actual ship experiments.

Acknowledgement

This research project was supported by Nippon Foundation (Project ID: 2019527479, ID: 2020562841) in section 5 for measuring line-of-sight by eye-tracker. It was supported by a large number of people; the staff of California Maritime Academy, Tokyo University of Maritne Science and Technology, World

Maritime University, and IAMU. We thank Prof. Koji Murai, Tokyo University of Marine Science and Technology, for simulation experiments and analysis in Chapter 5.

References

[1] Hayama Imazu. "Evaluation method of collision risk by using true motion." TransNav: International Journal on Marine Navigation and Safety of Sea Transportation 11.1 (2017).

[2] Clifford Baker and Denise McCafferty, "Accident database review of human element concerns: What do the results mean for classification." *Proc. Int Conf.'Human Factors in Ship Design and Operation, RINA* Feb. 2005.

[3] Hayama Imazu, Junji Fukuto, and Masayoshi Numano. "Obstacle zone by target and its expression." *The Journal of Japan Institute of Navigation* 107 (2002): 191-197.

[4] Jun Kayano, Hayama Imazu, Hitoi Tamaru and Takahiko Fujisaka, “"On the Prediction of Ship's Motion for OZT by Using Kalman Filter." *The Journal of Japan Institute of Navigation* 123 (2010).

[5] Ryohei Sawada, Keiji Sato, and Takahiro Majima. "Automatic ship collision avoidance using deep reinforcement learning with LSTM in continuous action spaces." *Journal of Marine Science and Technology* 26.2 (2021): 509-524.

[6] Paolo Fiorini, and Zvi Shiller. "Motion planning in dynamic environments using velocity obstacles." *The international journal of robotics research* 17.7 (1998): 760-772.

[7] Yoshiaki Kuwata, Michael T. Wolf, Dimitri Zarzhitsky, and Terrance L. Huntsberger, "Safe maritime autonomous navigation with COLREGS, using velocity obstacles." *IEEE Journal of Oceanic Engineering* 39.1 (2013): 110-119.

[8] Huang, Yamin, P. H. A. J. M. Van Gelder, and Yuanqiao Wen. "Velocity obstacle algorithms for collision prevention at sea." *Ocean Engineering* 151 (2018): 308-321.

[9] Wenjin Zhangi, Chengyong Yan, Hongguang Lyu, Pingling Wang, Zongyao Xue, Zehua Li, and Bai Xiao "COLREGS-based path planning for ships at sea using velocity obstacles." *Ieee Access* 9 (2021): 32613-32626.

[10] Kazuhiko Hasegawa, Junji Fukuto, Rina Miyake, and Masahiro Yamazaki, "An intelligent ship handling simulator with automatic collision avoidance function of target ships." Proc. of INSLC 17 (2012).

[11] James Kennedy and Russell Eberhart, “Particle Swarm Optimization”, In *Proceedings of ICNN'95-international conference on neural networks* , (1995) Vol. 4, pp. 1942-1948.

[12] Hayama Imazu and Takeo Koyama, “The Optimization of the Criterion for Collision Avoidance Action-II”, *The Journal of Japan Institute of Navigation*, Vol.72, (1985), pp.23-30

[13] Kensaku Nomoto and Katashi Taguchi, “On Steering Qualities of Ships (2)” , *Journal of the Society of Naval Architects of Japan*, Vol. 101, (1957), pp. 57-66

[14] Hayama Imazu, *Research on collision avoidance maneuvere.*, Ph.D. thesis, The University of Tokyo (1987)

[15] WMU, “*Transport 2040, Automation, Technology, Employment: The Future of Work*”, WMU, (2019).

[16] Christine Chauvin, Jean-Pierre Clostermann, and Jean-Michel Hoc, “Situation Awareness and the Decision-Making Process in a Dynamic Situation: Avoiding Collisions at Sea”, *Journal of Cognitive Engineering and Decision Making*, Vol. 2, (2008), 1-23.

[17] Yemao Man, Margareta Lützhöft, Nicole A. Costa, Monica Lundh, and Scott N. Mackinnon, “Gaps Between Users and Designers: A Usability Study About a Tablet-Based Application Used on Ship Bridges”, *Advances in Human Aspects of Transportation*, (2018), pp 213-224.

[18] Masao Furusho, Masaaki Tomonaga, Tadahiko Fukuda and Shigetoshi Kai, “A Lookout of the Ship's Operator from the Standpoint of Sight-line Displacement”, *The Journal of Japan Institute of Navigation*, Vol.97, (1997), pp.231-239

[19] Masao Furusho, “Visual Perception of the Targets for a Good Lookout at Sea”, *The Journal of Japan Institute of Navigation*, Vol.87, (1992), pp.59-66

[20] Convention on the International Regulations for Preventing Collisions at Sea

[21] Ryoko Fukuda, Minoru Sakuma, Etsuo Nakamura, and Tadahiko Fukuda, “Experimental consideration on the definition of a fixation point”, *The Japanese Journal of Ergonomics*, Vol.32, No.4, (1996), pp.197-204

[22] nac Image Technology inc. HP, https://www.nacinc.jp/ (2022.5.26)

[23] Koji Murai, Chihiro Nishizaki, Jun Kayano, Hitoi Tamaru amd Ruri Shoji,“Quantitative Evaluation of Good Seamanship using Physiological Data to realize Maritime Autonomous Surface Ships,” *Proceedings of 2021 Asia Navigation Conference*, S4-A-2 (2021)

[24] Hiroaki Kobayashi and Shoichi Senda, “A Study on the Measurement of Human Mental Work-load in Ship Handling Using SNS Value”, *The Journal of Japan Institute of Navigation*, Vol. 98, (1998), pp.247-255

[25] B. Scholkopf, C.J.C. Burges, A.J. Smola, *Advances in Kernel Methods-Support Vector Learning*, The MIT Press (1999), B.Scholkopf and A.Smola, *Learning with kernels*, MIT Press (2002)

[26] Japan, Russian Federation and United Arab Emirates, *Outline of the draft guidelines for MASS operations*, presented at Maritime Safety Committee 105th session, IMO (2022)

Appendix

Appendix: Simulation results

Simulation 1: apply the algorithm proposed in Chapter 3 to No.1 ship only

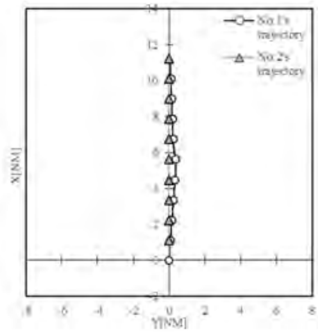


Fig. A.1 Phase 1, No. 1

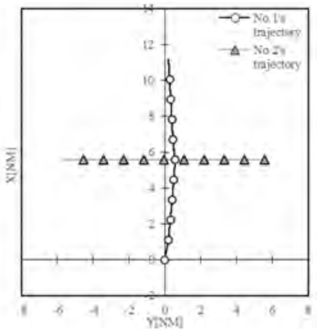


Fig. A.2 Phase 1, No. 2

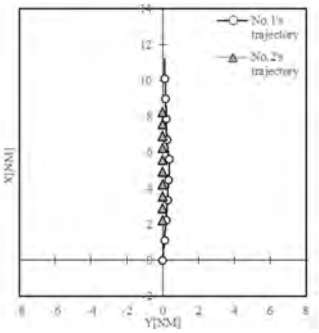


Fig. A.3 Phase 1, No. 3

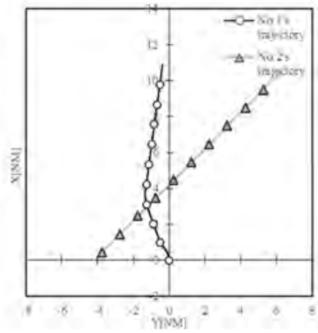


Fig. A.4 Phase 1, No. 4

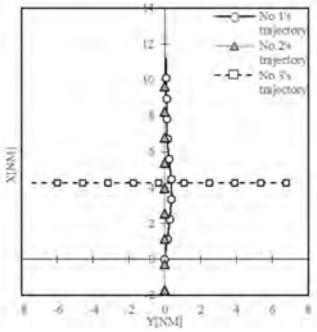


Fig. A.5 Phase 1, No. 5

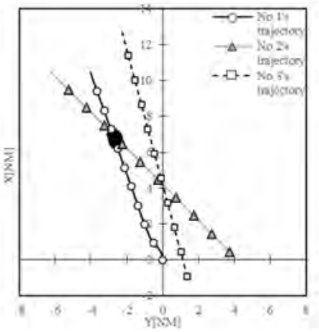


Fig. A.6 Phase 1, No. 6

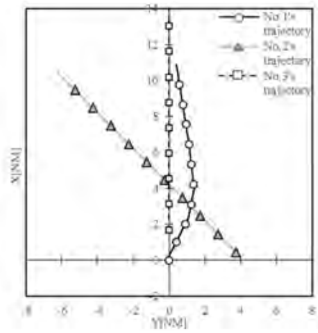


Fig. A.7 Phase 1, No. 7

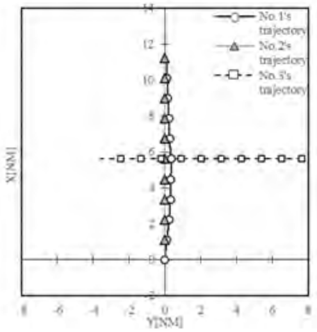


Fig. A.8 Phase 1, No. 8

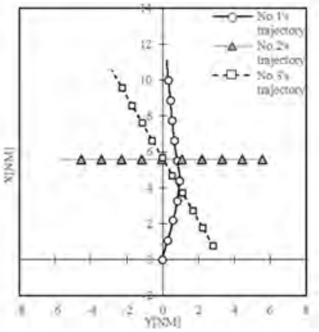


Fig. A.9 Phase 1, No. 9

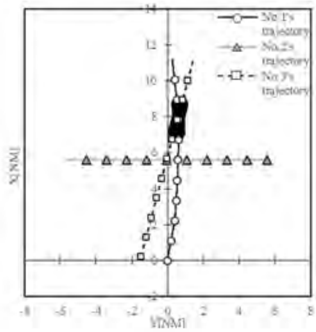


Fig. A.10 Phase 1, No. 10

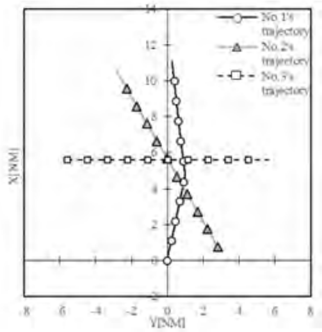


Fig. A.11 Phase 1, No. 11

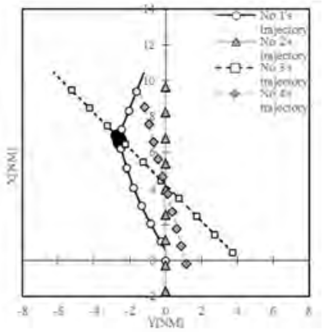


Fig. A.12 Phase 1, No. 12

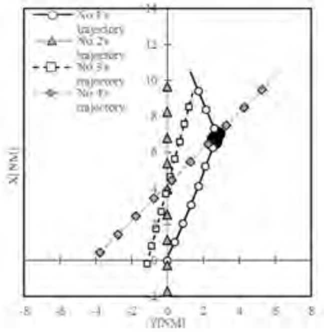


Fig. A.13 Phase 1, No. 13

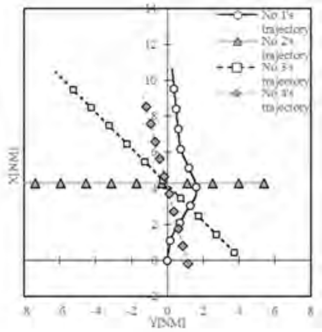


Fig. A.14 Phase 1, No. 14

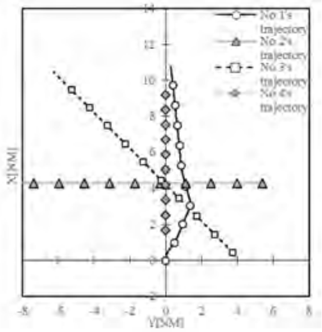


Fig. A.15 Phase 1, No. 15

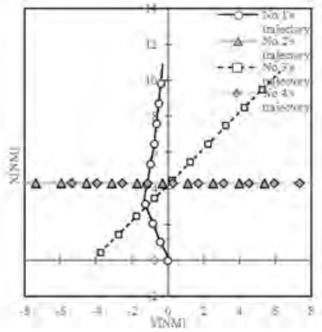


Fig. A.16 Phase 1, No. 16

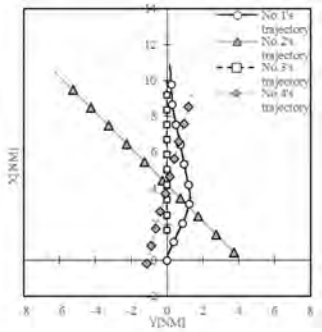


Fig. A.17 Phase 1, No. 17

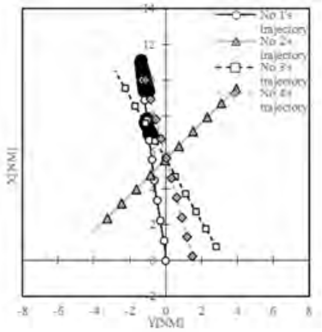


Fig. A.18 Phase 1, No. 18

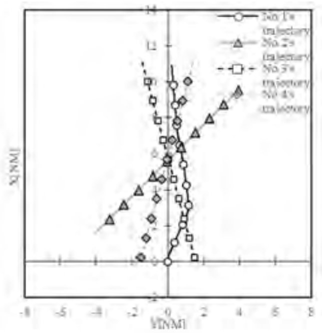


Fig. A.19 Phase 1, No. 19

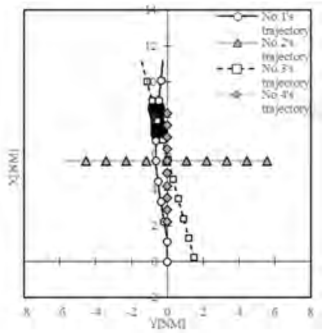


Fig. A.20 Phase 1, No. 20

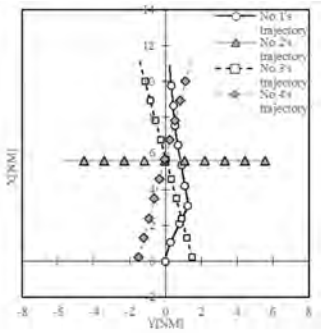


Fig. A.21 Phase 1, No. 21

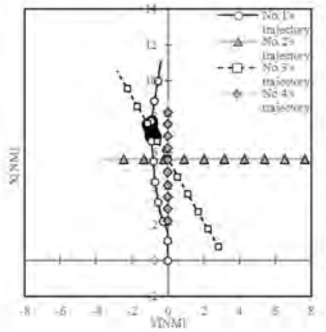


Fig. A.22 Phase 1, No. 22

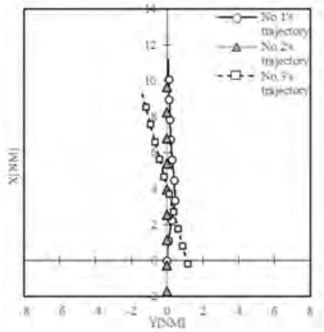


Fig. A.23 Phase 2, No. 1

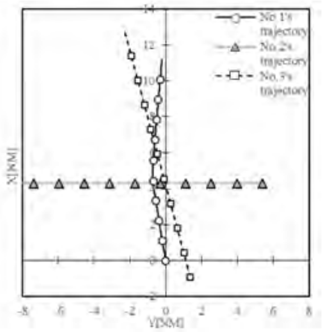


Fig. A.24 Phase 2, No. 2

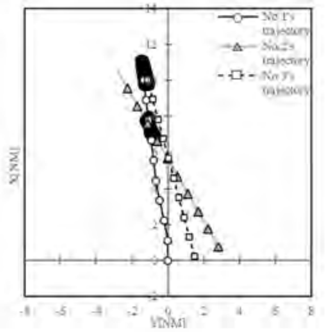


Fig. A.25 Phase 2, No. 3

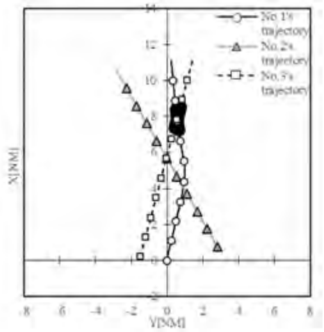


Fig. A.26 Phase 2, No. 4

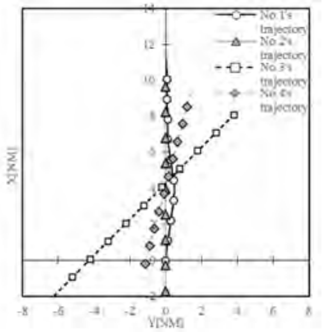


Fig. A.27 Phase 2, No. 5

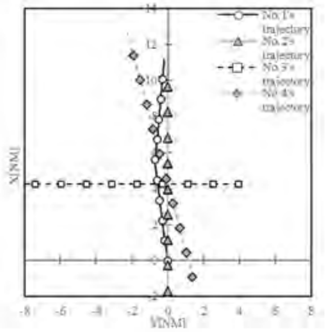


Fig. A.28 Phase 2, No. 6

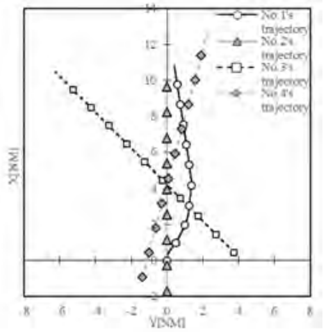


Fig. A.29 Phase 2, No. 7

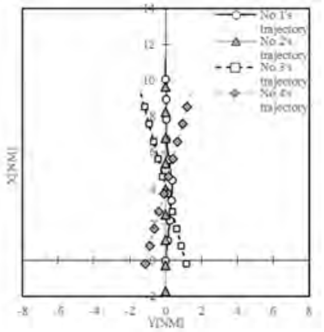


Fig. A.30 Phase 2, No. 8

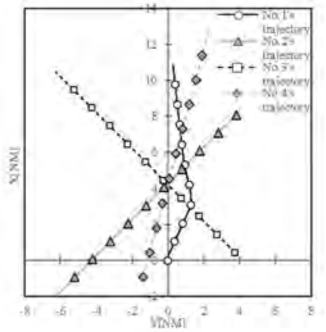


Fig. A.31 Phase 2, No. 9

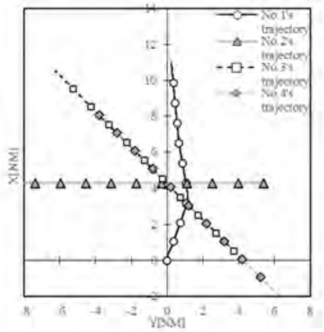


Fig. A.32 Phase 2, No. 10

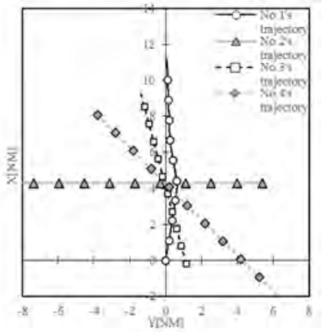


Fig. A.33 Phase 2, No. 11

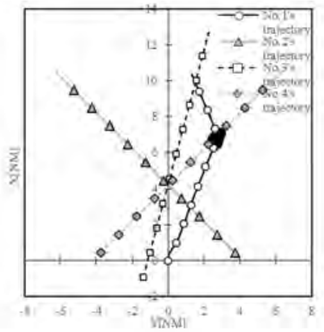


Fig. A.34 Phase 2, No. 12

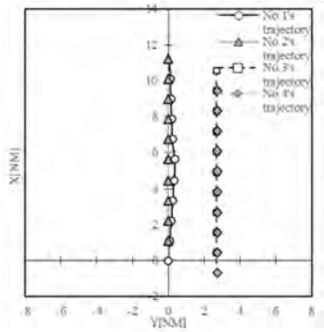


Fig. A.35 Phase 2, No. 13

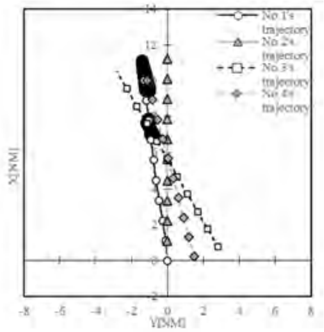


Fig. A.36 Phase 2, No. 14

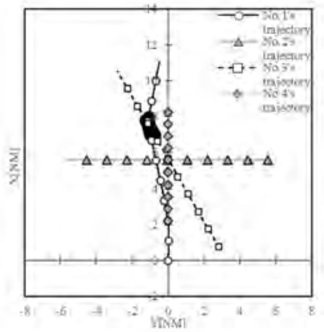


Fig. A.37 Phase 2, No. 15

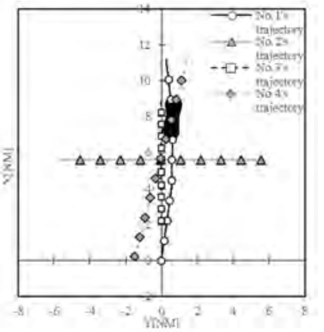


Fig. A.38 Phase 2, No. 16

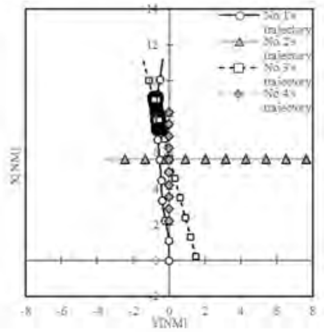


Fig. A.39 Phase 2, No. 17

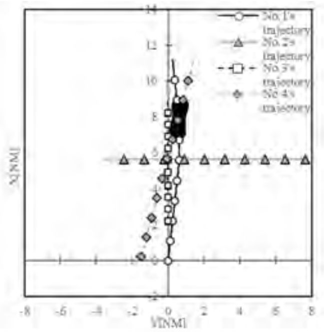


Fig. A.40 Phase 2, No. 18

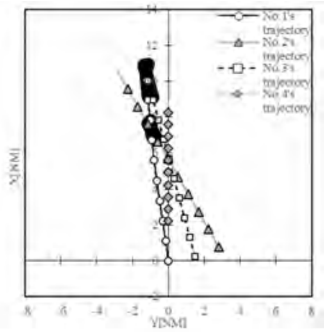


Fig. A.41 Phase 2, No. 19

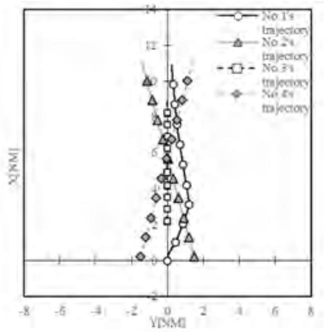


Fig. A.42 Phase 2, No. 20

Simulation 2: apply the algorithm proposed in Chapter 3 to all ships

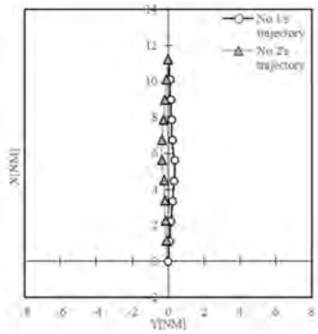


Fig. A.43 Phase 1, No. 1

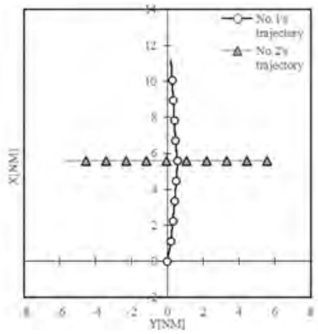


Fig. A.44 Phase 1, No. 2

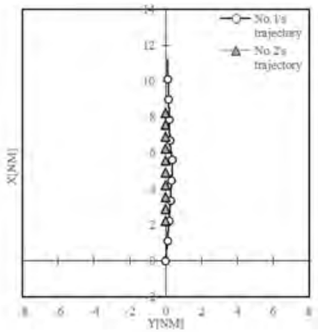


Fig. A.45 Phase 1, No. 3

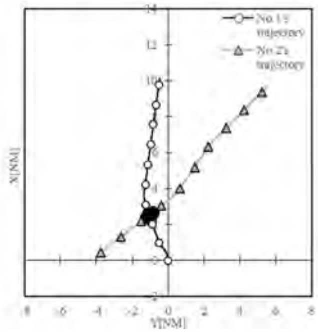


Fig. A.46 Phase 1, No. 4

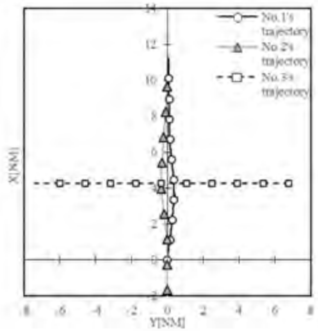


Fig. A.47 Phase 1, No. 5

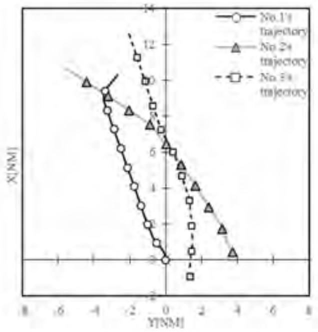


Fig. A.48 Phase 1, No. 6

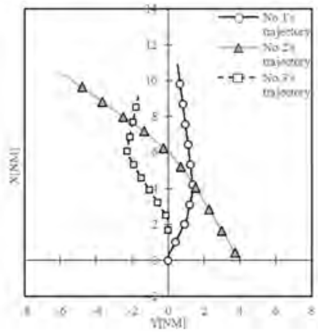


Fig. A.49 Phase 1, No. 7

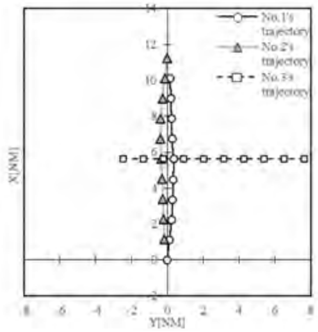


Fig. A.50 Phase 1, No. 8

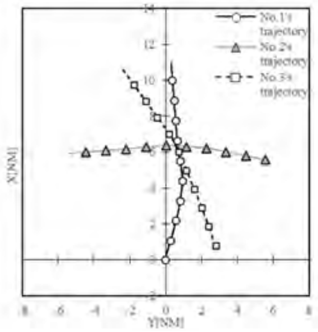


Fig. A.51 Phase 1, No. 9

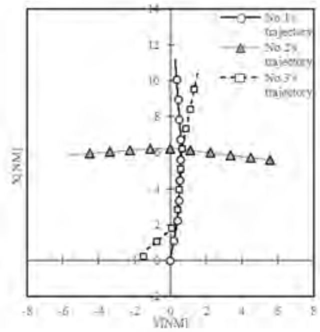


Fig. A.52 Phase 1, No. 10

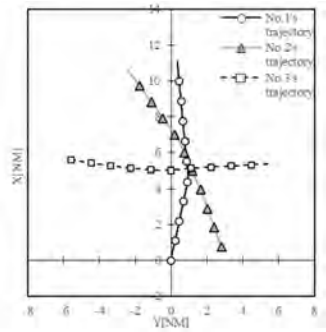


Fig. A.53 Phase 1, No. 11

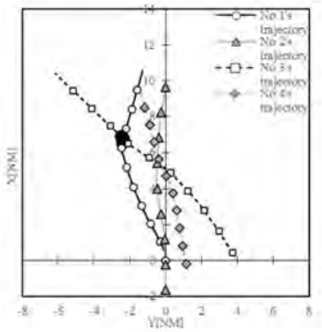


Fig. A.54 Phase 1, No. 12

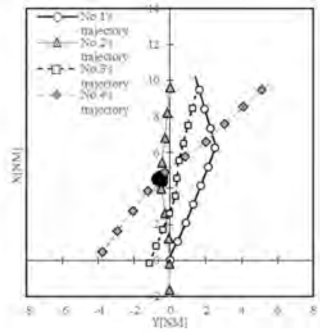


Fig. A.55 Phase 1, No. 13

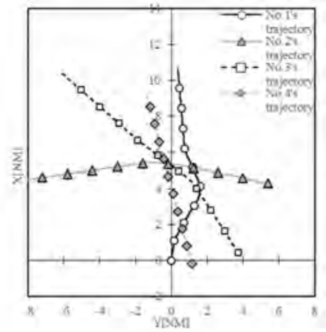


Fig. A.56 Phase 1, No. 14

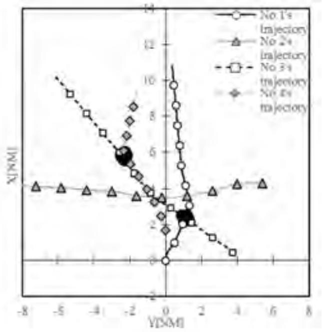


Fig. A.57 Phase 1, No. 15

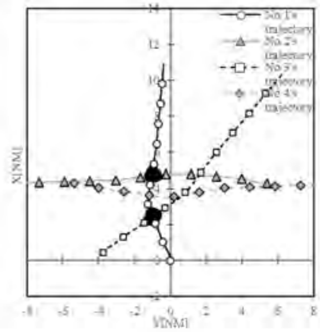


Fig. A.58 Phase 1, No. 16

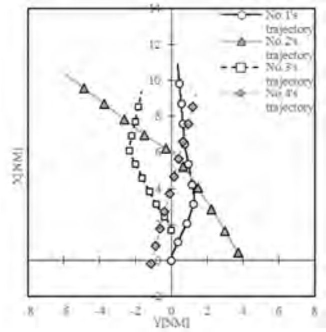


Fig. A.59 Phase 1, No. 17

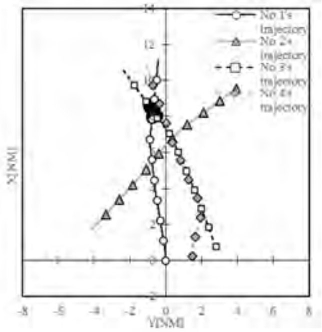


Fig. A.60 Phase 1, No. 18

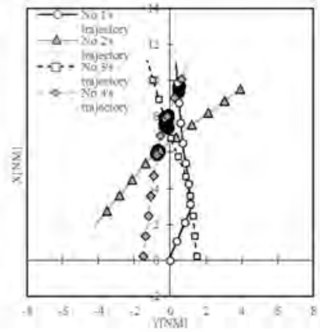


Fig. A.61 Phase 1, No. 19

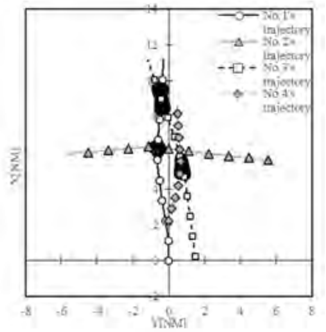


Fig. A.62 Phase 1, No. 20

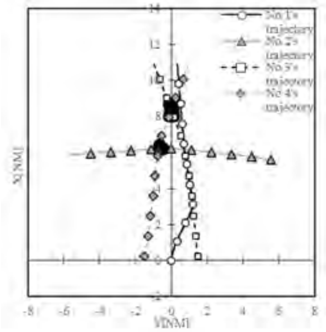


Fig. A.63 Phase 1, No. 21

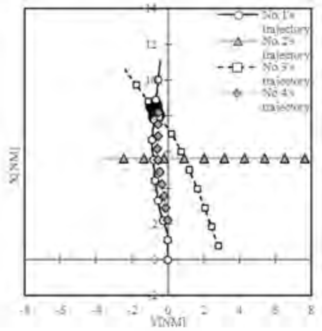


Fig. A.64 Phase 1, No. 22

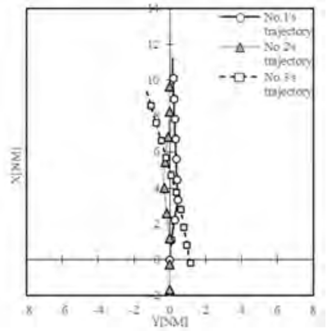


Fig. A.65 Phase 2, No. 1

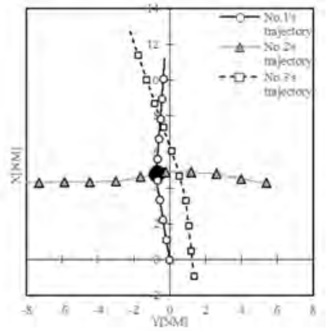


Fig. A.66 Phase 2, No. 2

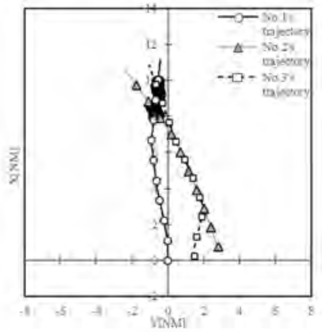


Fig. A.67 Phase 2, No. 3

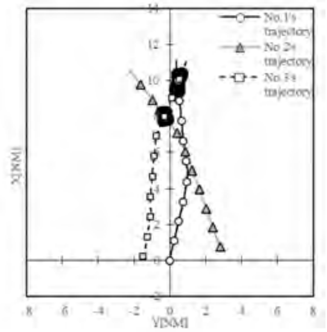


Fig. A.68 Phase 2, No. 4

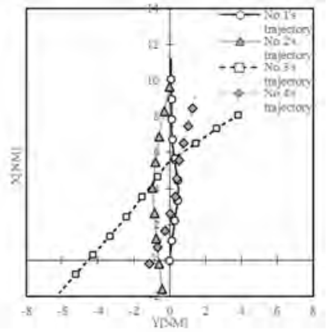


Fig. A.69 Phase 2, No. 5

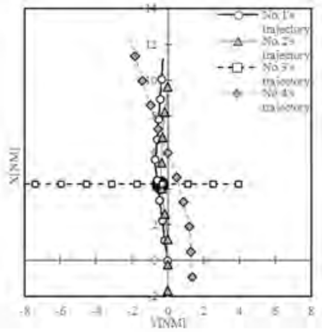


Fig. A.70 Phase 2, No. 6

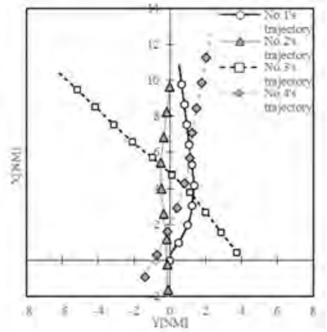


Fig. A.71 Phase 2, No. 7

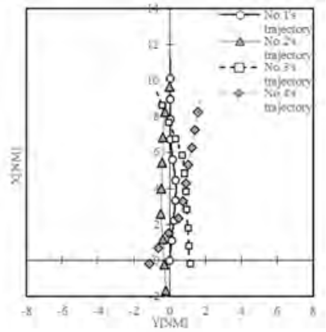


Fig. A.72 Phase 2, No. 8

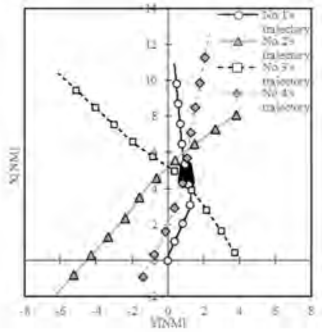


Fig. A.73 Phase 2, No. 9

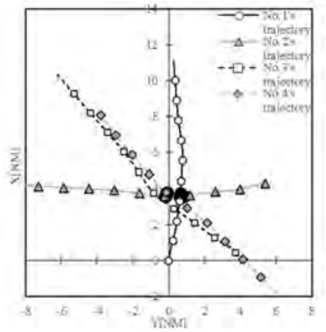


Fig. A.74 Phase 2, No. 10

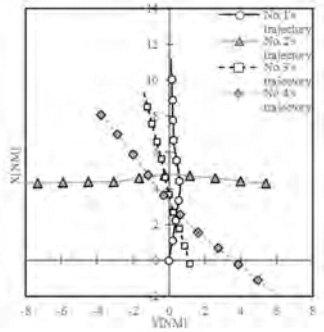


Fig. A.75 Phase 2, No. 11

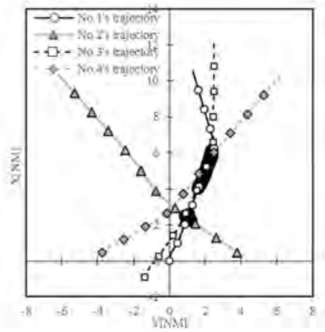


Fig. A.76 Phase 2, No. 12

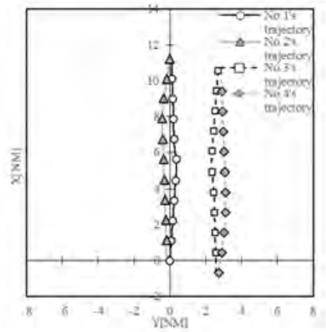


Fig. A.77 Phase 2, No. 13

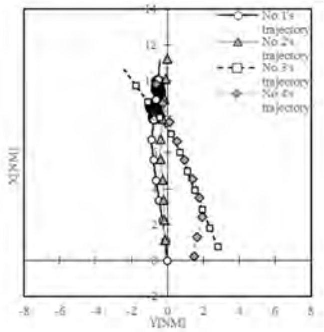


Fig. A.78 Phase 2, No. 14

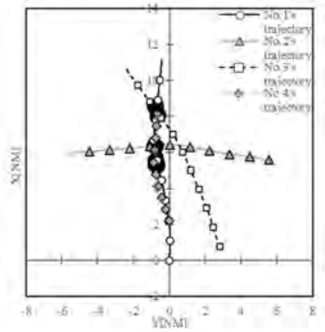


Fig. A.79 Phase 2, No. 15

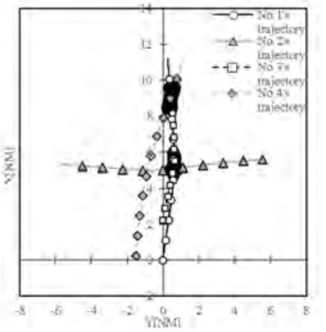


Fig. A.80 Phase 2, No. 16

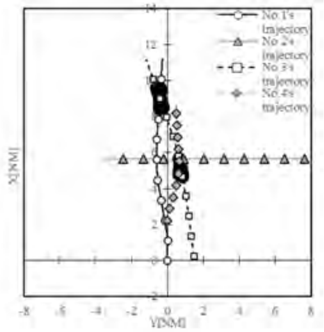


Fig. A.81 Phase 2, No. 17

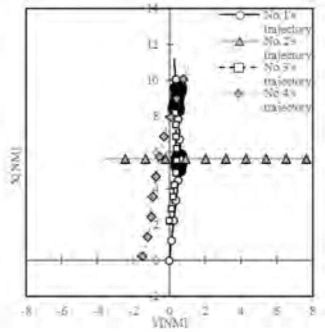


Fig. A.82 Phase 2, No. 18

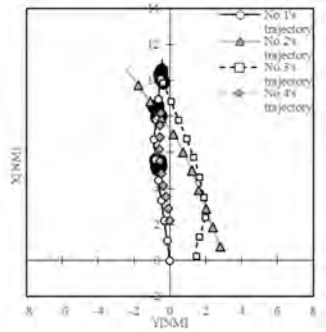


Fig. A.83 Phase 2, No. 19

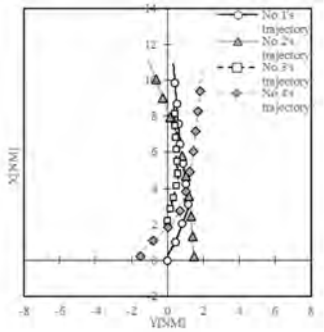


Fig. A.84 Phase 2, No. 20

Simulation 3: apply the algorithm proposed in Chapter 6 to all ships

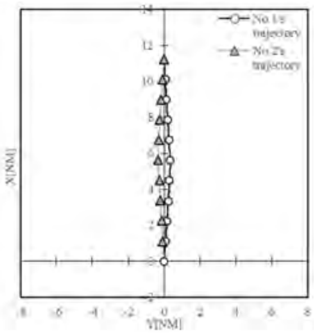


Fig. A.85 Phase 1, No. 1

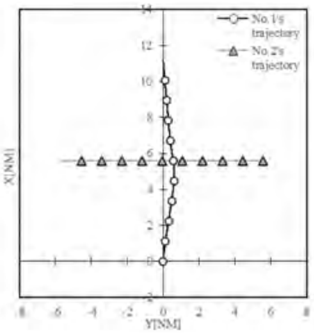


Fig. A.86 Phase 1, No. 2

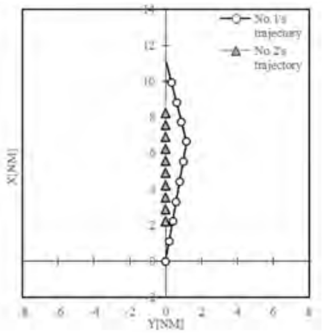


Fig. A.87 Phase 1, No. 3

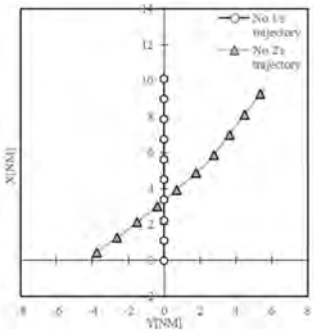


Fig. A.88 Phase 1, No. 4

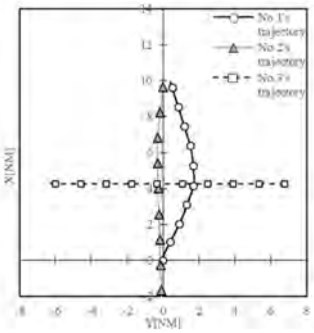


Fig. A.89 Phase 1, No. 5

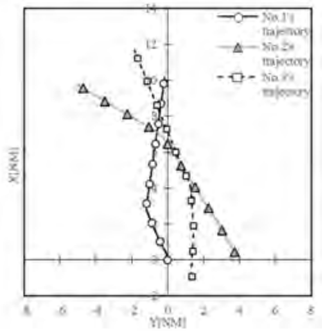


Fig. A.90 Phase 1, No. 6

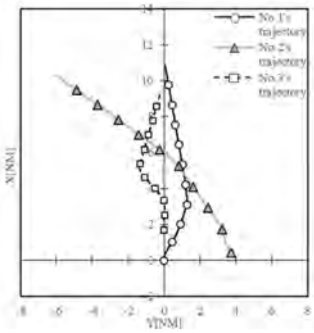


Fig. A.91 Phase 1, No. 7

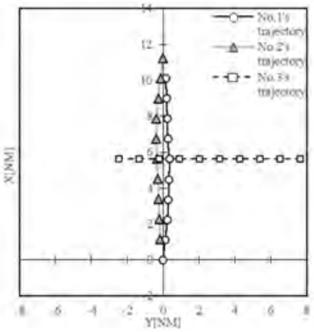


Fig. A.92 Phase 1, No. 8

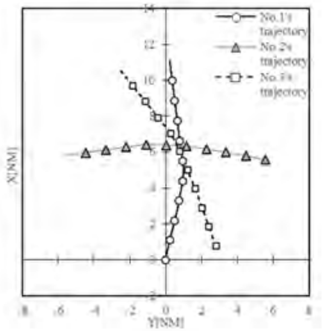


Fig. A.93 Phase 1, No. 9

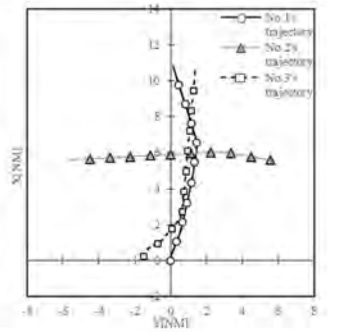


Fig. A.94 Phase 1, No. 10

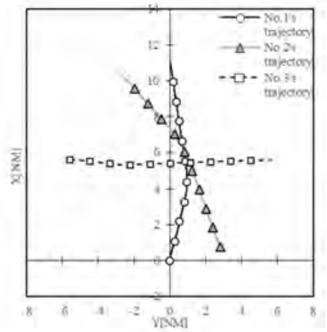


Fig. A.95 Phase 1, No. 11

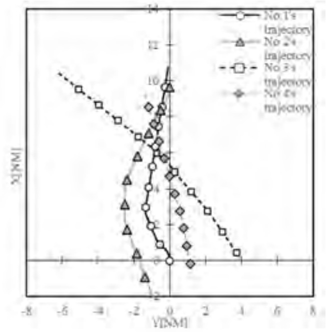


Fig. A.96 Phase 1, No. 12

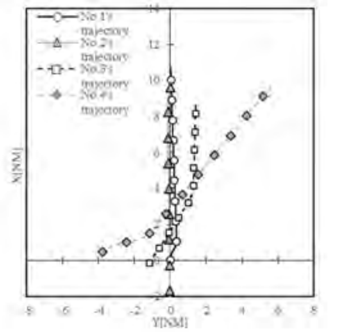


Fig. A.97 Phase 1, No. 13

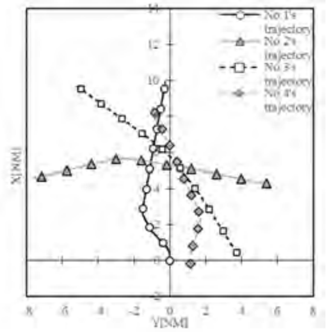


Fig. A.98 Phase 1, No. 14

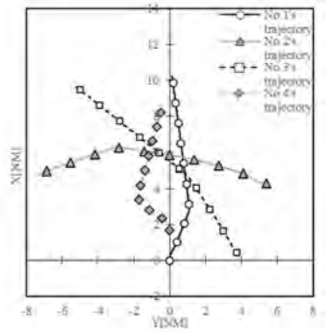


Fig. A.99 Phase 1, No. 15

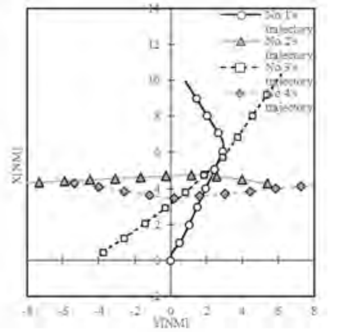


Fig. A.100 Phase 1, No. 16

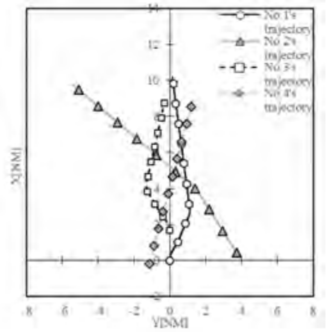


Fig. A.101 Phase 1, No. 17

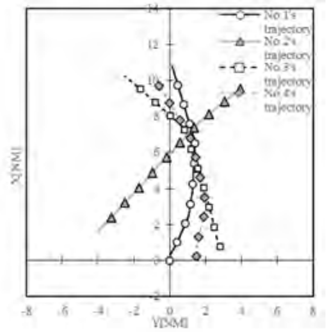


Fig. A.102 Phase 1, No. 18

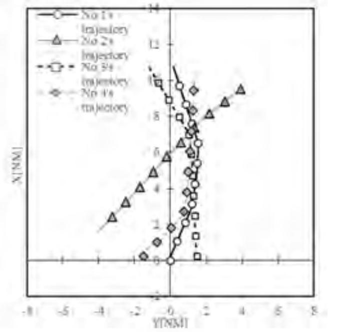


Fig. A.103 Phase 1, No. 19

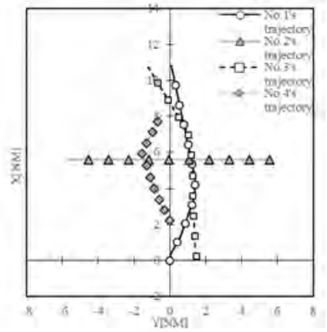


Fig. A.104 Phase 1, No. 20

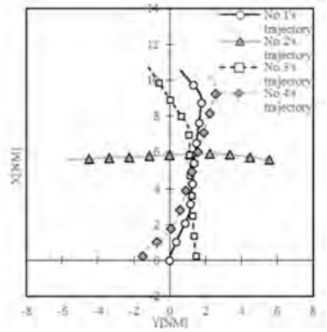


Fig. A.105 Phase 1, No. 21

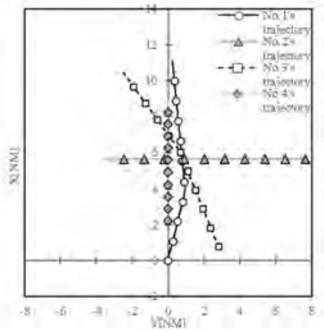


Fig. A.106 Phase 1, No. 22

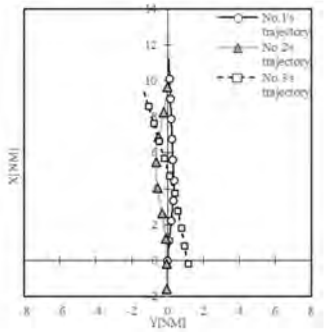


Fig. A.107 Phase 2, No. 1

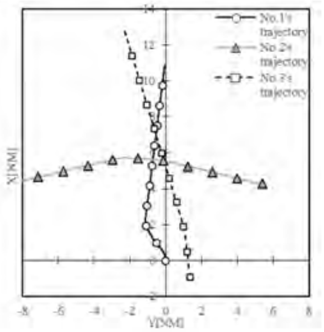


Fig. A.108 Phase 2, No. 2

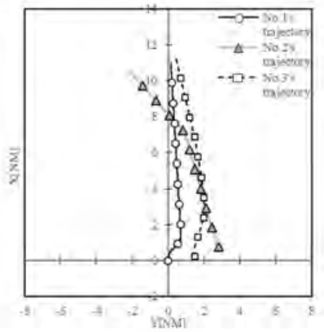


Fig. A.109 Phase 2, No. 3

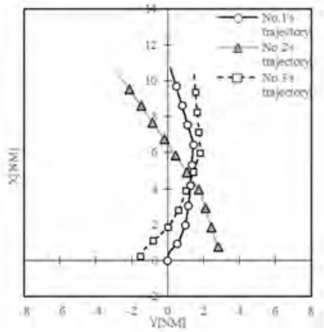


Fig. A.110 Phase 2, No. 4

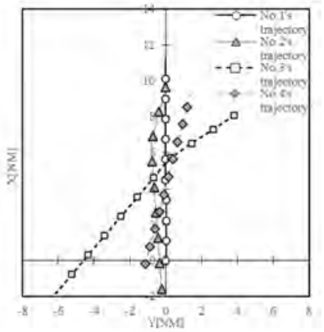


Fig. A.111 Phase 2, No. 5

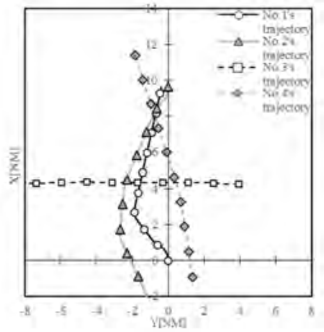


Fig. A.112 Phase 2, No. 6

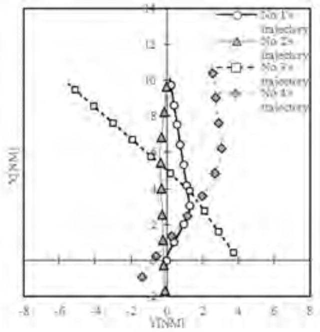


Fig. A.113 Phase 2, No. 7

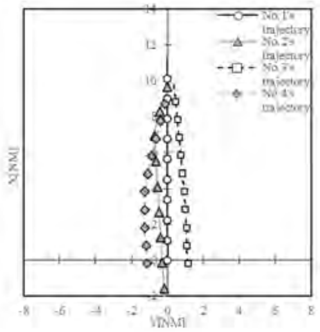


Fig. A.114 Phase 2, No. 8

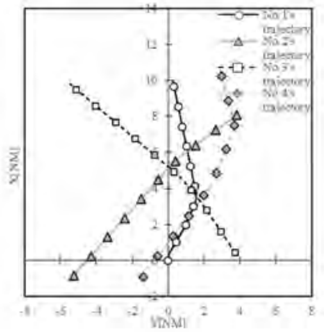


Fig. A.115 Phase 2, No. 9

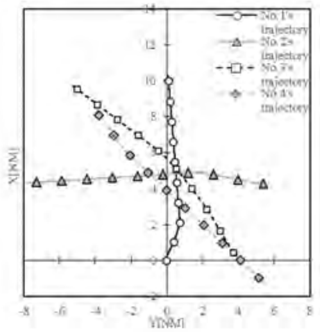


Fig. A.116 Phase 2, No. 10

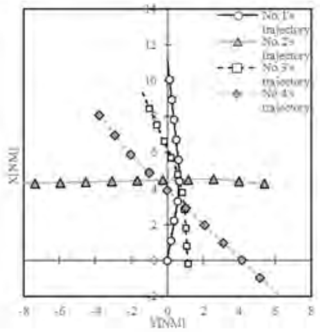


Fig. A.117 Phase 2, No. 11

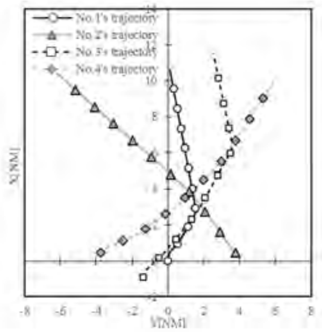


Fig. A.118 Phase 2, No. 12

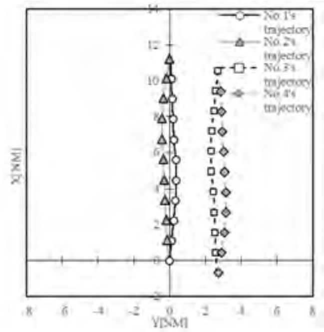


Fig. A.119 Phase 2, No. 13

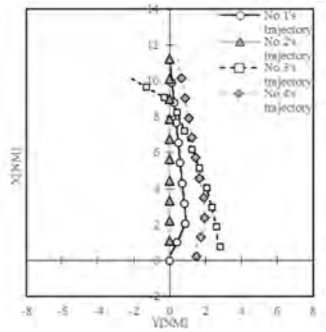


Fig. A.120 Phase 2, No. 14

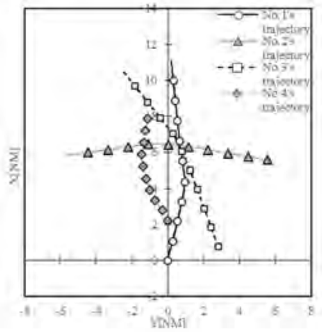


Fig. A.121 Phase 2, No. 15

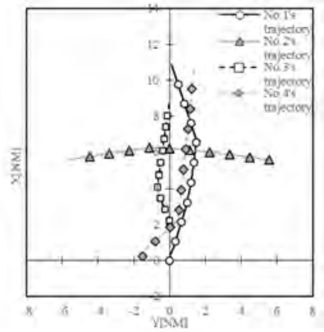


Fig. A.122 Phase 2, No. 16

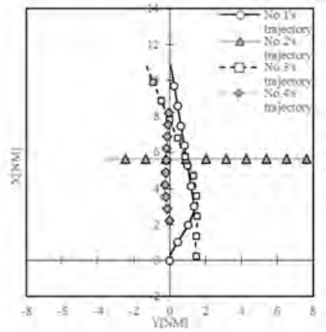


Fig. A.123 Phase 2, No. 17

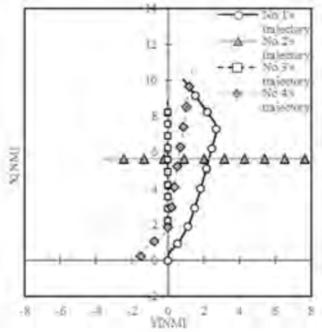


Fig. A.124 Phase 2, No. 18

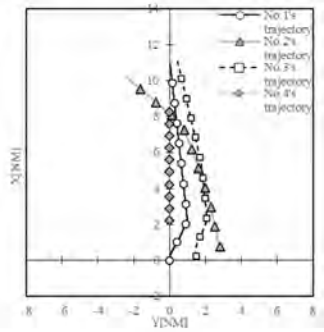


Fig. A.125 Phase 2, No. 19

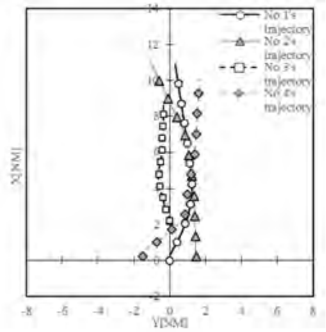


Fig. A.126 Phase 2, No. 20

International Association of Maritime Universities

Meiwa Building 8F, 1-15-10 Toranomon, Minato-ku, Tokyo 105-0001, Japan

Tel : 81-3-6257-1812 E-mail : info@iamu-edu.org URL : http://www.iamu-edu.org

ISBN No. 978-4-907408-36-7