Development of AI-based Automatic Collision Avoidance System and Evaluation by Actual Ship Experiment

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1. INTRODUCTION

Accompanying the growth of the global economy, the volume of maritime transport is constantly increasing, and improvement of navigational safety in overcrowded ports and congested sea areas has become a major challenge for marine transportation. Because many ship collisions are caused by human factors, it is essentially difficult to completely prevent collisions at sea as long as navigation is performed by human crews. As an additional problem, since Japan is rapidly becoming a "super-aged society," it is likely to become difficult to secure a stable supply of seafarers for domestic shipping in the near future. Considering the difficulty of a fundamental solution to the problems of collisions caused by human factors and shortages of seafarers, technological innovation through cooperation among industry, government agencies and academia are indispensable.

To address this situation, in the Maritime Bureau of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT), a study was carried out in the Maritime Innovation Subcommittee of the Marine Subcommittee, Council for Transport Policy, and a draft roadmap was drawn up targeting practical application of maritime autonomous surface ships (MASS) by 2025. Development and demonstration of technologies for MASS utilizing artificial intelligence (AI) technology, etc. is scheduled for the period from 2020 to 2025. In fact, accelerated moves in the development of automatic navigation systems, not limited to "cognition" assistance in manoeuvring, but also extending to "judgment" and "action" are considered likely in the future, as seen in the development of the Nippon Foundation's Unmanned Ship Project MEGURI 2040, which began in 2020.

Self-driving technologies are being developed for automobiles preconditioned on the existence roadways and other infrastructure. However, the traffic flows of ships at sea are considerably more complex than automotive traffic because ships can basically sail anywhere, and large and small ships with different speeds and manoeuvring performance may coexist in the same waters, and unlike air traffic control systems, ships are not given instructions concerning the ship's route and speed or separation from other ships in marine traffic control. Thus, the key to realizing an automatic navigation technology is how the individual ships themselves can judge the risk of collision foreseeing future conditions and carry out appropriate evasive manoeuvring to avoid collisions, that is, collision avoidance. In order to be a successful means of transportation in the face of global competition, MASS vessels must not only avoid collisions with other ships and obstacles, but must also arrive at their destinations efficiently. Although mere extensions of existing technology do not offer an easy solution to this difficult problem, AI has great latent potential, as AI technologies continue to display capabilities that could surpass those of human beings in various fields.

The purposes of this research are to develop AI for automatic collision avoidance which will be a key technology to a navigation support system for domestic vessels and to conduct a verification experiment in congested waters using an actual ship, with the aim of realizing an automatic navigation technology, which is indispensable for realizing MASS. The individual challenges and implementation items for achieving these purposes were set as shown below. The following chapters present detailed descriptions of each of these items.

(1) Development of automatic collision avoidance AI
(2) Development of AI-based automatic collision avoidance system for use in actual ship experiment
(3) Risk evaluation of AI-based automatic collision avoidance system
(4) Evaluation of automatic collision avoidance AI by simulator experiment
(5) Evaluation of AI-based automatic collision avoidance system by actual ship experiment

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2. DEVELOPMENT OF AUTOMATIC COLLISION AVOIDANCE AI

Describing the process of collision risk judgment and selection of evasive actions in congested waters in clear, universal terms is not an easy task. In particular, virtually no teaching data are available for learning correct and erroneous manoeuvring techniques under a condition of an impending collision. Machine learning is an effective technique from this viewpoint because the machine itself is made to perform evaluations and tuning, and reinforcement learning is especially suitable in action selection problems in which the target of "collision avoidance" is clearly given. In reinforcement learning, intelligence is reinforced by repeating a process of speculative search and evaluation. Although the agent in reinforcement learning learns an action policy that maximizes the expected value of cumulative future rewards, Q-learning is one type of reinforcement learning, in which the agent learns the value of actions based on the results of actually performing those actions. While Q-learning itself is not new, highly accurate estimation of the value of actions that change complexly with respect to states is now possible by approximating the action value function Q by deep learning, and realizing the selection of the optimum action from which the largest cumulative reward can be expected. The learning technique which combines reinforcement learning and deep learning is called "deep reinforcement learning". DeepMind applied deep Q-learning [1] (also called "deep Q-network") to Atari games and attracted immediate attention by enabling operation that exceeded the scores of human players. The AI technology for automatic collision avoidance developed in the present research is a further development of the results of research [2] on automatic collision avoidance of multiple ships applying deep Q-learning.

Collision risk judgments are made by using a ship "bumper" [3], which is the exclusion zone around a ship. Although different bumper model sizes have been proposed corresponding to the degree of congestion of the waters, in this research, we introduced a "double bumper" combining an inner bumper for congested waters and an outer bumper for open seas. The optimum action for avoiding collisions can be learned by setting a negative reward for intrusion of another ship into the bumper. As the neural network input, information concerning the ship itself, the bumper area, information on other nearby ships, etc. is given in grayscale imagery. Since learning is performed on a simulation base, a manoeuvring motion model for steering is necessary. Here, a first-order KT model was used so that learning is possible provided that the results of the zig-zag test in a sea trial are available. If deep reinforcement learning is applied to manoeuvring for berthing and unberthing, it appears to be necessary to construct a manoeuvring motion model for low speed region based on captive model tests or CFDs (Computational Fluid Dynamics). However, modelling with this degree of precision is not necessary for collision avoidance problems.

When a certain condition has been given in deep Q-learning, a NN which estimates the cumulative reward over the future in case selectable actions are taken is constructed through a very large number of collision avoidance simulations. The available actions in this research are three types, sailing straight, turning to port or turning to starboard, to enable the human evaluation of the judgments by AI in the actual ship experiment. An automatic collision avoidance manoeuvring system that can perform navigation to the destination and collision judgment and danger avoidance without human involvement is realized by combining a general-purpose autopilot and AI that avoids entry of other ships into the bumper of the own ships or drives other ships out of the own ship bumper, which is obtained as a result of deep Q-learning. The actual degree of collision risk changes dynamically depending on the relative relationship with other ships. However, in the present condition, in which there are no precedents for automatic collision avoidance by AI, risk evaluation based on only static elements was adopted, and the highest priority was given to enabling real-time evaluation of the quality of AI manoeuvring by personnel onboard the ship. Moreover, it is also necessary to perform collision avoidance well in advance so as not to threaten other ships. Therefore, although the ship used in the verification experiment was the "Fukae Maru" (training ship of the Graduate School of Maritime Sciences, Kobe University), the value of the largest ship which might possibly be encountered in Osaka Bay was used as the ship length for determining the bumper size in the AI. This data was obtained through an analysis of ship Automatic Identification System (AIS) data for 1 year.

3. DEVELOPMENT OF AI-BASED AUTOMATIC COLLISION AVOIDANCE SYSTEM FOR USE IN ACTUAL SHIP EXPERIMENT

The Kobe University training ship "Fukae Maru" is used in the automatic collision avoidance experiments in actual waters. In addition to broadcasting GPS, gyrocompass, GPS compass, AIS, radar, etc. data in an on-board LAN, the ship is already equipped with an autopilot system [4] utilizing external signals. In implementation of the AI-based automatic collision avoidance system, a sub-PC and a main PC were installed. The sub-PC receives and decodes sensor information, performs databasing, generates information by time difference and monitors received and transmitted signals, while the main PC contains the AI program, which outputs the optimum action based on input data on an arbitrary number of other ships and obstacles in order from the nearest ship to the own ship from the database. Figure 1 shows a block diagram of the system configuration. Although AIS and radar TT data are used in detection of other ships and obstacles, this system does not require collation and matching of information such as the ship position and speed vector, which are obtained from multiple sensors. In the automatic collision avoidance system implemented in this project, UDP communication via the on-board LAN is performed between the PCs and the existing autopilot, and autopilot sails the ship on the optimum course instructed by the AI.

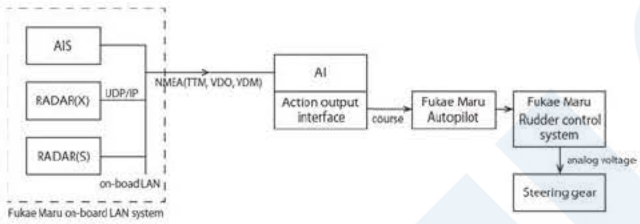

Figure 1 Block diagram of AI-based automatic collision avoidance system

Switching to the automatic collision avoidance mode and setting of way points are performed via the user interface in Fig. 2. The screen displays the own ship, other ships and obstacles, the bumper zone, the target course, etc. The specifications and layout were decided with the cooperation of licensed mariners to enable operability comparable to that of radar and inputting with the minimum mouse operation. Because the NN is a nonlinear statistical filter, it is difficult to display the relationship between inputs and outputs to human operators. Therefore, the interface makes it possible to distinguish whether the course instructions provided by AI at each time-step are the normal sailing mode or the collision avoidance mode. Because the double bumper is always displayed on the screen, the quality of AI-based collision avoidance manoeuvring can be judged easily by on-board personnel, based on whether other ships or obstacles will enter the bumper zone or not.

Switching from normal operation to AI manoeuvring in the actual ship experiment is performed by switching from hand control to remote control by a rotary switch based on the judgment of ship's captain. Automatic collision avoidance by AI is started by pushing the transmission button from the interface on the main PC, and if the captain judges that a dangerous condition exists, it is possible to return immediately to hand control simply by switching the same rotary switch.

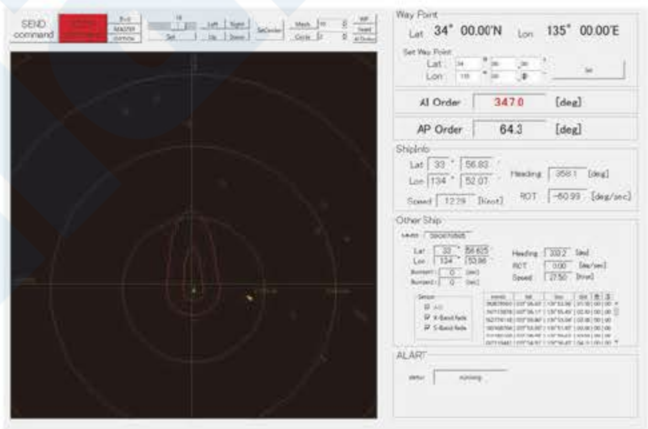

Figure 2 User interface of AI-based automatic collision avoidance system

4. RISK EVALUATION OF AI-BASED AUTOMATIC COLLISION AVOIDANCE SYSTEM

4.1 Overview of FMEA

In this research, Failure Mode and Effects Analysis (FMEA) was adopted as a method for risk evaluation. The target of FMEA is the demonstration equipment of the AI-based automatic collision avoidance system. The purpose of this analysis is to clarify whether the functions required in the system can be achieved inconceivable failure modes or operation becomes unsafe and whether alternative measures have been taken in case operation becomes unsafe, and to verify logically whether deficiencies have not been included in the system configuration and design in advance.

Figure 3 shows the configuration of the on-board system of the Fukae Maru. Information on the own ship and its surroundings collected by AI-PC2 (sub-PC) is transmitted to AI-PC1 (main PC), and AI-PC1 outputs the optimum heading based on that information. Autopilot controls the ship's rudder according to the heading order from AI-PC1. Since the target system of the FMEA is limited to only the demonstration equipment of the AI-based automatic collision avoidance, functions used in normal operation are excluded from the FMEA. Accordingly, the target of the FMEA is the newly added equipment and the equipment that have information communication between AI-PC1 and PC2.

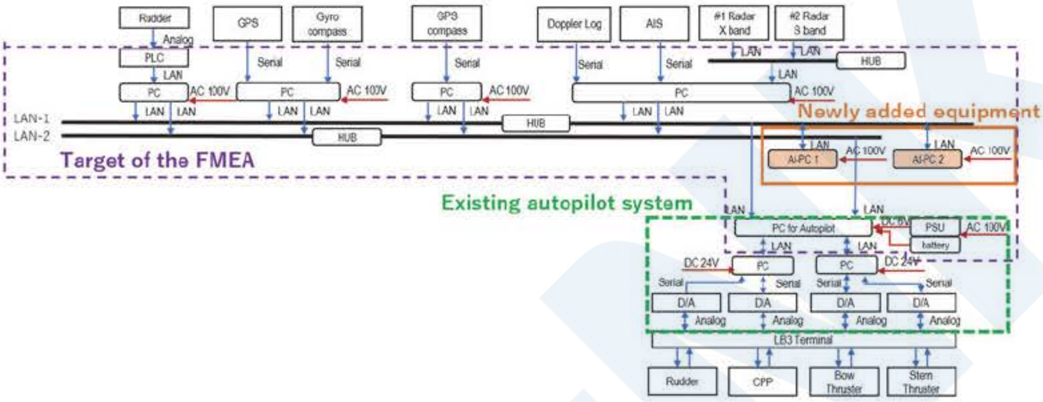

Figure 3 Configuration of on-board system

This FMEA is focused on AI control ON mode because, in the case of AI control OFF mode, the system is regarded as a normal operation by disconnecting the communication line between the current system and the AI system. However, the failures that affect normal operation are in the scope of this analysis. The top failure events are as described below.

- Equipment failure
- Loss of signal

The FMEA for equipment failure and loss of signal is designed to be expressed in one sheet. The FMEA was conducted referring to the "Guidelines for Implementation of Failure Mode and Effects Analysis (FMEA)" issued by ClassNK.

4.2 FMEA Test Using Actual System

In the demonstration experiment using a ship, safe navigation and operation are the most important. Therefore, the on-board testing is focused on how to acknowledge the system failure by operators and how to switch the system mode to AI control off based on the FMEA sheet.

In the FMEA, although various failure modes such as power supply failure, component failure, communication failure, wiring failure, and sensor failure are set, the effects of various failures of surrounding devices on AI-PC1 and AI-PC2 can be regarded as communication failures that disrupt signals from the devices concerned. Therefore, the targets of this test are power source anomalies of AI-PC1, AI-PC2, LAN1 HUB, and LAN2 HUB, which are the main communication paths, and communication failures of the two AI-PCs, which are the core elements of the system.

The test results confirmed that this is a design in which the system operator can recognize failures, for example, by notification of the system operator when an abnormality occurs in the equipment. It may be noted that multiple FMEA tests were conducted before reaching this result, and the fact that this testing process can contribute to the implementation of effective measures for design deficiencies and safe test voyages is considered to be one of the benefits of conducting the FMEA.

5. EVALUATION OF AUTOMATIC COLLISION AVOIDANCE AI BY SIMULATOR EXPERIMENT

Before conducting an actual ship experiment using the AI-based automatic collision avoidance system, verification and evaluation by simulator experiments are indispensable. In this research, preliminary safety verifications were carried out by two approaches, namely, quantitative evaluation using a ship handling evaluation tool and qualitative evaluation by licensed mariners using a simulator.

5.1 Quantitative Evaluation Using Ship Handling Evaluation Tool

5.1.1 Ship Handling Evaluation Tool

The main elements for recognition of the risk of collision with another ship by the ship's operator are the relative distance between the two ships, the rate of change in bearing, whether the encounter involves bow crossing or stern crossing, etc. As an index for evaluating the results of collision avoidance manoeuvres, Japan Marine Science Inc. has proposed an evaluation area diagram for risk evaluations in which "Danger," "Caution" and "Safety" areas are defined by using the relative distance between ships and the rate of change in bearing [5]. In this evaluation region diagram, the positional relationship (i.e., the "encounter situation") with other ships and the relationship between the relative distance and relative bearing change rate with other ships are classified into multiple graphs, on which "Caution" and "Danger" areas are set. However, in collision avoidance by the developed automatic collision avoidance AI, collision risk is assessed by using a new evaluation area diagram [6] in which the crossing relationship is classified into ships crossing from starboard and ships crossing from port side from the viewpoint that becoming the "stand-on vessel," as specified in the Act on Preventing Collision at Sea, should be avoided as far as possible.

A point deduction system was proposed for evaluations of manoeuvring results, in which a weighting coefficient of −2 is calculated when the ship enters a "Danger" area, and −1 and 0 are calculated for the "Caution" and "Safety" areas, respectively. Table 1 shows the evaluation formulas and the evaluation areas used in preparing the area diagram.

Table 1 Evaluation formulas and definitions of evaluation areas in preparation of area diagram.

Encounter situation		*Evaluation formula*		*Evaluation*
Head-on/ Crossing from Starboard	Bow Crossing	$\theta < \infty$	$R <$ 185.2 [m]	Danger
		$\theta \leq 4.5 \times 10^5 \cdot R^{-1.7}$	$R <$ 1852.0 [m]	
		$\theta < \infty$	$R <$ 463.0[m]	Caution
		$\theta \leq 15.0 \times 10^5 \cdot R^{-1.7}$	$R <$ 3,426.2[m]	
		Range excluding danger area and caution area		Safety
	Stern Crossing	-		Danger
		$\theta \leq -5.2 \times 10^5 \cdot 170^{-1.7}$	$R <$ 185.2 [m]	Caution
		$\theta \leq 15.0 \times 10^5 \cdot R^{-1.7}$	$R <$ 3,333.6 [m]	
		Range excluding caution area		Safety
Same-way		$\theta < \infty$	$R <$ 277.8[m]	Danger
		$\theta < \infty$	$R <$ 463.0[m]	Caution
		$\theta \leq 15.0 \times 10^5 \cdot R^{-1.7}$	$R <$ 926.0 [m]	
		Range excluding caution area		Safety
Crossing from Port	Bow Crossing	$\theta < \infty$	$R <$ 185.2[m]	Danger
		$\theta \leq 4.5 \times 10^5 \cdot R^{-1.7}$	$R <$ 1852.0[m]	
		$\theta < \infty$	$R <$ 463.0[m]	Caution
		$\theta \leq 15.0 \times 10^5 \cdot R^{-1.7}$	$R <$ 14,816.0 [m]	
		Range excluding danger area and caution area		Safety
	Stern Crossing	$\theta \leq -5.2 \times 10^5 \cdot 170^{-1.7}$	$R <$ 185.2[m]	Caution
		$\theta \leq -5.2 \times 10^5 \cdot R^{-1.7}$	$R <$ 9,260.0[m]	
		Range excluding danger area and caution area		Safety

θ : Rate of change in bearing *(deg./min.)* R: Relative distance *(m)*

Danger	: Unacceptable area
Caution	: The area where own ship commences to avoid or expect another ship to avoid
Safety	: Acceptable area

The area charts were formulated based on approximately 30,000 datapoints in a manoeuvring experiment in which the subjects were the captains and pilots of ocean-going ships [5]. In addition, because the results of a collision avoidance demonstration experiment with a coastal tanker showed the validity of an evaluation area diagram assuming congested waters for a ship with a total length of 50 m or more, this was adopted as a technique for objectively evaluating the results of the automatic collision avoidance by AI in this research.

5.1.2 Evaluation Results of Collision Avoidance Manoeuvring

Using the ship handling evaluation tool described in the previous section, collision avoidance manoeuvring by AI was scored for a total of 39 scenarios simulating traffic flows in actual waters, including typical 1:1 encounter scenarios and scenarios involving encounters with multiple other ships. Examples of the test scenarios and evaluation results are shown in Figs. 4 and 5, and Table 2, respectively. In the top part of Fig. 5, the graph in the upper left is the area diagram for bow crossing by a ship crossing from starboard, that at the lower left is for stern crossing, and that in the upper right is for a same-way ship. Here, the results of manoeuvring in the encounter situation in Fig. 4 are plotted as red dots at 10 sec. intervals based on the relationship between the relative distance and relative bearing change rate with respect to the other ship. The lower part of Fig. 5 is an evaluation area diagram for a ship crossing from port, but in this scenario, there is no ship that fits this description. Table 2 shows the results of scoring of the test scenario in Fig. 4 using the evaluation tool. The fact that the own ship passed a ship crossing from starboard, which crossed in front of the own ship, without entering the Caution or Danger areas, can be read from both the area diagram and the scores.

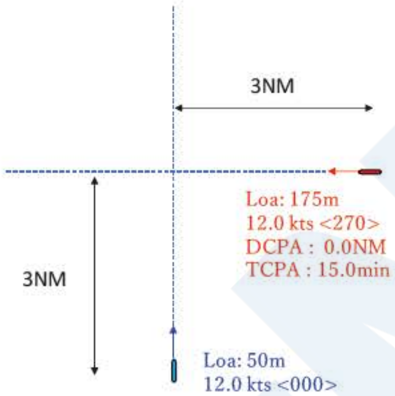

Figure 4 Example of test scenario (1:1 crossing ship)

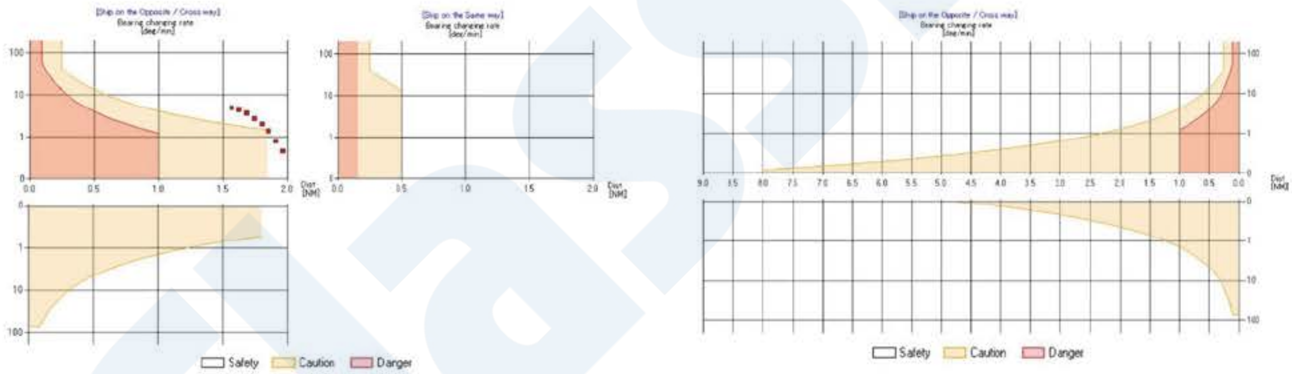

Figure 5 Example of evaluation areas

Table 2 Example of collision avoidance manoeuvring evaluation results

	Safety	Caution	Danger	Total
Sum Counts	917	0	0	917 (a)
Weight Factor	0	-1	-2	-
Sum Score	0	0	0	0 (b)
Total Score	-	-	-	b/a x 100 = 0

Thus, the results of scoring all of the scenarios confirmed that the ship essentially did not enter the "Danger" area and the frequency of entry into the "Caution" area was also kept within the allowable range, according to licensed mariners (as described in the next section), under the condition that deceleration was not allowed. Here, it should be noted that collision avoidance is difficult under these scenarios without changing speed. Further improvement of manoeuvring actions is expected by improvement of the bumper zone and inclusion of speed changes, which are not considered at present in the reinforcement learning.

5.2 Qualitative Evaluation by Licensed Mariners

The persons who participated in the evaluation were 5 licensed mariners (4 captains and 1 first officer) with extensive experience in manoeuvring large ships. The manoeuvring evaluation was conducted by requesting feedback from each subject after observing automatic collision avoidance manoeuvring on a simulator. Under each scenario, the subjects checked the encounter situation from the viewpoint of the own ship, and also checked the encounter situation using arbitrary other ships (large ships), and reported that they had no feelings of unease regarding the movement of the own ship from the viewpoint that "the own ship's movements should not cause anxiety on the other ship, which was being maneuverer by a human operator."

Because the captain of a ship has the authority to make final decisions regarding manoeuvring when conducting the actual ship experiment with the "Fukae Maru," automatic collision avoidance by AI was reproduced on the ship handling simulator and an evaluation was conducted with the cooperation of the crew of the "Fukae Maru", from the viewpoints of the timing of initiation of collision avoidance manoeuvring, the method of collision avoidance and avoidance angle, and timing of return to the original course, etc. with the crew members acting as the evaluators.

In the results of the verification by these evaluators, overall, there was no feeling of discomfort concerning the ship's movement during automatic manoeuvring. However, duly considering the fact that this was for an actual ship experiment in congested waters, problems were identified, as shown in Table 3, and the response measures deemed necessary in an actual ship experiment were taken for each. The actual ship experiment was then carried out after confirming that all of these problems had been solved.

Table 3 Problems of automatic collision avoidance AI in actual ship experiment and response measures

Problem	Solution
Risk of turning to port contrary to COLREGs in case of ships crossing from starboard.	The learning environment was improved, and adjustments were made so that actions apply the COLREGs.
Unsteadiness (wandering) of the bow can be seen (due to turning the rudder to the right, followed by turning back to the left).	The method of giving rewards and algorithm of connection with the autopilot were reviewed to reduce wandering.
Intentions of AI in collision avoidance manoeuvring are unclear.	An interface that shows the bumper and other ships was prepared so that the ship's operator can predict the AI manoeuvring actions.
Experiment may be difficult depending on the environment, such as congestion of surrounding waters, weather, sea conditions, etc.	The environmental conditions were clearly specified in the test proposal.

There was also feedback that it may be necessary to reduce speed by using the engine in some manoeuvring situations, rather than manoeuvring to avoid collision by using the rudder. However, this speed reduction option was not provided in this actual ship test. Therefore, it was decided that safety should be ensured by human fallback if the ship encounters situations where speed reduction is necessary.

6. EVALUATION OF AI-BASED AUTOMATIC COLLISION AVOIDANCE SYSTEM BY ACTUAL SHIP EXPERIMENT

A demonstration experiment using the AI-based automatic collision avoidance system was conducted in the congested waters of Osaka Bay over a 3-day period from December 8 to 10, 2020. The waters where the experiment was conducted were southward from Kobe Bay and northward from the Sumoto offing lighted buoy. The safety criteria for conducting the demonstration test of AI manoeuvring were specified as follows:

- Wind speed not exceeding 10 m/s, wave height not exceeding 2 m and visibility of at least 2 miles.
- No abnormalities of the nautical instrument or machinery of the ship itself, or of the functions of AI manoeuvring.
- Judgment by the captain or the mariner on watch duty that congestion and other conditions are suitable for the test.

Figure 6 shows the system for implementation of the actual ship experiment. To ensure safety, the normal watch condition of the ship was maintained, uninterrupted monitoring was conducted by the general supervisor of the test and the engineer responsible for the AI manoeuvring functions, and preparations were made for unexpected events.

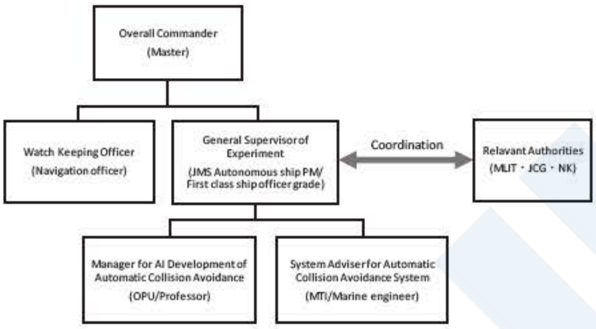

Figure 6 System for implementation of actual ship test

In the actual ship experiment, automatic collision avoidance by AI was conducted for more than 21 encounter situations over the 3-day period. During the experiment, manual manoeuvring was performed so as to create a variety of encounter situations in which a risk of collision would occur. After inputting the latitude and longitude of the way points into the AI-based automatic collision avoidance system, the manual operation was switched to the AI operation mode, and a series of ship manoeuvre until return to the original course was confirmed. Figure 7 shows a photograph of the training ship "Fukae Maru" used in this experiment, Fig. 8 shows an encountering condition during automatic collision avoidance and Fig. 9 shows a photograph of inside the bridge during the experiment.

Figure 7 Training ship "Fukae Maru" used in the verification experiment

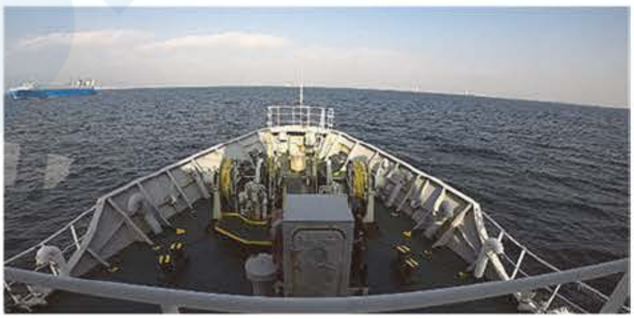

Figure 8 AI-based automatic collision avoidance in Osaka Bay

Figure 9 Condition of inside the bridge during the actual ship experiment

In evaluation of AI-based automatic collision avoidance system, the ship sailed toward the set way points under autopilot, and when the risk of a collision appeared, the capability to properly avoid the collision under the bearing instructions by AI was confirmed. Examples of the experimental results are shown in Figs. 10 and 11. As shown in Fig. 10, in case automatic collision avoidance is initiated from a condition in which another ship is outside the bumper, collision avoidance manoeuvring was performed so that the other ship would not enter the outer "open-water" bumper. The results showed that the ship returned to the original course after the risk of collision with a vessel on an opposite course disappeared. Figure 11 shows a case of initiating automatic collision avoidance from a condition in which other ships are already present inside the bumper. Here, it was confirmed that collision avoidance manoeuvring was carried out so that the other ships did not enter the inner "congested" bumper. The results of this experiment suggested that appropriate collision avoidance manoeuvring corresponding to the degree of congestion is realized by introducing the double bumper, which gives different negative rewards depending on the degree of collision risk.

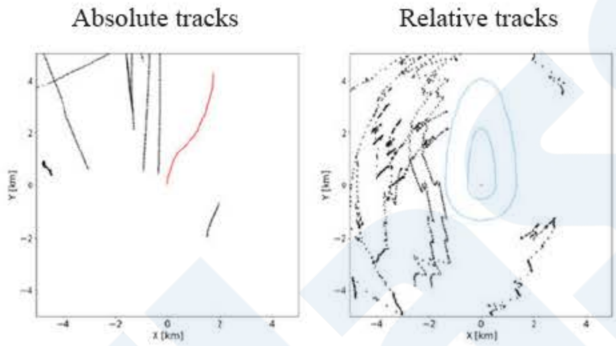

Figure 10 Result of automatic collision avoidance by AI (initiated from condition in which other ships are not present in the bumper)

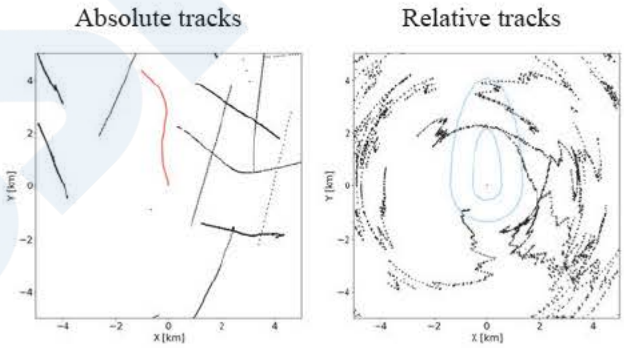

Figure 11 Result of automatic collision avoidance by AI (initiated from condition in which other ships are present in the bumper)

Although this test was conducted in congested waters, where operating fishing boats and buoys are present in addition to general merchant ships, the results confirmed that the ship avoided collisions with other vessels at an appropriate timing under the automatic course control by AI and returned to the original course when the surrounding conditions allowed. In this actual ship experiment, there were time lags of the sensor information till reached to AI and time delay until the rudder was actually operated in response to the course instructions by AI. In addition, there were natural external disturbances, sensor errors and irregularly and frequently changes in the heading exist which do not exist in the simulation. Overall, however, it can be said that the fact that the collision avoidance results obtained in the actual ship test were similar to those in the preliminary verification using the ship handling simulator was an important result.

7. CONCLUSIONS

An automatic collision avoidance system combining an ordinary autopilot and collision avoidance AI based on deep reinforcement learning was developed, and after evaluation using a ship handling simulator, an actual ship test was carried out in Osaka Bay. As a result, an automatic collision avoidance test in congested waters by the course instructions by AI was conducted successfully for the first time. Because manoeuvring results similar to those of the preliminary ship handling simulator experiment were also obtained in the actual ship experiment, it will be possible to proceed with improvement and evaluation of the AI in the future centring mainly on simulation and simulator experiments. On the other hand, for full-scale practical application, it is desirable to strengthen the visualization of AI's manoeuvring instructions, ensure that crew members can understand the intentions of the AI and develop a man-machine interface for approving those intentions. In this research, we used a fixed bumper model in which the degree of collision risk does not change with an encounter situation. However, in actual situations, the risk of collision changes in time. Thanks to the result of successful completion of the automatic collision avoidance experiment using an actual ship, development and introduction of AI that returns an output close to that judged by veteran captains corresponding to dynamically changing collision risk can be expected in the future.

Using the amount of knowledge and experience gained through this actual ship experiment, we will try to realize practical application of an automatic navigation technology at an early date, and contribute to labour-saving and improved safety in coastal navigation by preventing maritime accidents caused by human factors and improving the working environment for seafarers. We hope the success of this actual ship experiment accelerates research and development of marine autonomous surface ships (MASS) in the future.

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