Advances in Reliability, Safety and Security, Part 3 – Kołowrocki, Dąbrowska (eds.)
© 2024 Polish Safety and Reliability Association, Gdynia, ISBN 978-83-68136-15-9 (printed), ISBN 978-83-68136-02-9 (electronic)

Advances in Reliability, Safety and Security

ESREL 2024
Monograph Book Series

Fuzzy-Logic Based Human-Machine Shared Control Method For Maritime Autonomous Surface Ships

Tong Xia[a,b,c], Yamin Huang[a,b,d], Linying Chen[a,b,e],
Yuanqiao Wen[a,b,d,f], Liang Huang[a,b,d]

[a]*State Key Laboratory of Maritime Technology and Safety, Wuhan University of Technology, Wuhan, PR China*
[b]*National Engieering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan, PR China*
[c]*School of Transportation and Logistics Engineering, Wuhan University of Technology, Wuhan, PR China*
[d]*Intelligent Transport Systems Research Center, Wuhan University of Technology, Wuhan, PR China*
[e]*School of Navigation, Wuhan University of Technology, Wuhan, PR China*
[f]*Sanya Science and Education Innovation Park, Wuhan University of Technology, Sanya 57200, China*

Abstract

In recent years, Maritime Autonomous Surface Ships (MASS) have been one of research hotspots in the field of shipping. However, fully autonomous ships are unlikely to be addressed quickly due to the restrictions of technology. Thus, focuses have on the remote control technology which applies to L2 and L3 class MASS according to IMO. Shared control that combines the advantages of human and machine is a classic scheme of remote control and has emerged as a key method for realizing remote MASS in practice. At present, there is much research about human-machine shared control in autonomous vehicle but less in autonomous ships. This paper proposes a shared control method based on fuzzy logic which is effective in dealing with the uncertainty and fuzziness of the factors in ship safety. A shared control framework is proposed to fuse the control commands from autonomous system (machine) and human operators (human). According to the guideline for remote control ships from major classification societies, the control permission should switch from the machine to the human when the encountering some specific scenarios which are sensitive area navigation scenario, nominal scenario without obstacles, and encountering scenario. After analysing these scenarios, three key factors are chosen as the input variables of fuzzy-logic based arbitrator, namely channel deviation, relative velocity, and distance to obstacles, and fuzzy rules are developed. Based on the rule, weight (human operator or machine) would change dynamically according to the current navigation environment. Besides, the method's characteristics of scenario superposition and combination contribute to its excellent adaptability. To demonstrate the proposed method, one simulation test which sets up with a controlled ship navigating along a specified route, avoiding unidentified obstacles and passing through bridge areas is employed. To avoid the obstacles, the controlled ship has to deviate from the channel. The weight of human operator changes under the combined action of relative velocity and channel deviation. When one of the two factors decreases and the others increase, the varying rate of weights slows down. And when controlled ship is about to navigate through the bridge, fuzzy-logic based arbitrator raise the driving weight of human operator to ensure the navigation safety. The result reveals the potential of the proposed method in enhancing the safety of the MASS with human in control loop.

Keywords: MASS, human in loop, shared control, weight switching

1. Introduction

The development of the Maritime Autonomous Surface ships (MASS) becomes a hot technical trend as the research on autonomous control technologies has entered a new stage. International Maritime Organization (IMO) defined MASS as ships which can run independently with different degrees of interaction with human operators and divided MASS into four level: L1, L2, L3, and L4. MASS can be used for carrying out various tasks including cargo transportation, ocean monitoring, search and rescue operations, etc., while reducing operating costs (Kurt et al., 2022), environmental pollutions (Burmeister et al., 2014) and accidents/incidents (Ahvenjärvi, 2016). Due to the uncertainties on the safety and reliability of the autonomous systems, the fully autonomous surface ships are still on its way to maritime practices, while the MASS with human-in-the-loop is attracting more and more attention from both the academy and industry, specifically, L2 and L3 MASS.

In L2 and L3, the machine is sharing the control of the ships with the human operators, in which human and machine can both gain benefit from each other. The machine would help the human operators to handle some simple scenarios, which reduces the workload of human; on the other hand, the human can handle the ship when the scenario is too complex for machine to find a feasible and rule-compliant solution. Thus, many studies are focusing on the cooperation and collaboration between the human and machine. Lang et al. (2023) propose a shared control method which offers control signal from autonomous arbitrator as the supplementary of human operators' instruction for autonomous vehicles (AV); A game-based authority allocation strategy for shared control is designed by Li et al. (2019) and Xu et al. (2022) conduct a study about control measures and applications of shared control architecture (SCA) in aviation. Abundant research is carried on in the field of AV and aviation, however, it is still in its infancy in maritime shipping.

To make the process of takeover smooth and safe, Abbink et al. (2012) propose a haptic shared control with fixed authority by introducing a new parameter named level of haptic authority (LoHA); A shared authority mod is employed to transfer control authority from an humans' trust in automated driving system (ADS) to a human driver (Saito, et al., 2018); Tian et al. (2020) take steering angles into shared control structure to ensure lateral path tracking effect and utilize fuzzy-logic to determine the authority allocation of steering angle. Clearly, the method of associating changes in shared control weights with influencing factors has been shown to achieve real-time authority switching in the field of vehicle autonomous driving, as evidenced by numerous studies. Few studies about dynamic shared control weight of ships have been done. And the existing researches about AV mainly consider the control weight arbitration scheme in terms of the functions that the controller needs to perform such as lane keeping and path tracking instead of scenarios, which is not suitable for maritime.

Fuzzy logic with the feature of model-free is well-explored and widely used in many fields of research. In the maritime field, Das et al. (2022) utilize fuzzy logic to describe imprecise cost parameter in ship scheduling problem; A fuzzy logic-based approach is design to alert dangerous factors in bridge area (Wu B. et al., 2019; Bakdi et al., 2022) use fuzzy logic to encode COLREGs to make it executable for MASS. It shows that fuzzy logic has a strong vitality in reflecting the decision process of human, which is also suitable for arbitrating the control among human and machine.

In brief, shared control scheme with fuzzy-logic is effective in human-machine collaboration and is a key method of developing MASSs, however, lack of practice in autonomous ships. To fill the gap, this paper is concerned with the shared control method of L2 and L3 class MASSs. Considering the switching scenarios, this paper proposes a fuzzy-logic based shared control system framework to realize real-time integration of human-machine decision-making. A knowledge and rule based fuzzy-logic shared control arbitrator for dynamic human-machine driving weights throughout the navigation process has been designed. In brief, the main contributions are below:

- the framework for switching controls between the machine and the human operators in RCC is proposed;
- three types of scenarios are summarized as the typical driving weight switching scenarios;
- a fuzzy-logic share control scheme is proposed, which dynamically assigns the weights of human/machine based on three key parameters, namely distance-to-target l, channel deviation d_{off} and relative velocity v_r.

The structure of the paper is addressed as follows: the introduction is presented in Section 1, followed by Section 2 that shows the framework of shared control system; Section 3 shows the design flow of the fuzzy-logic based arbitrator; The experiment design and analysis of simulation results are addressed in Section 4; Conclusion is discussed in Section 5.

2. Methodology

2.1. Assumptions

There are many ways to achieve remote control function in MASS, and the role of human operators and machine are different from one to another. To simplify the problem, we consider a remote control system in MASS meeting the following assumptions:

Assumption 1: Perfect communication conditions. The communication conditions between the controlled ship and the human operators from RCC is good. Thus, the command from the human do not have delay.

Assumption 2: Autonomous tracking.The machine on board ship can track the defined trajectory. Thus, the ship could control the ship to handle some simple tasks without interventions from human operators.

Assumption 3: Remote manual mode. The MASS is continuously controlled by human operators on shore RCC, i.e: the human operators would send commands on rudders and propellers to the ship.

Assumption 4: Human always right. This paper assumes that the level of human intelligence surpasses that of intelligent navigation systems. Thus, the shared control system tends to hand over the authority to human when facing complex situations.

2.2. Shared control architecture

Direct shared control fuses command from human operator and autonomous navigation system (ANS) at the operation level, which may cause extra workload of human operator when human and machine sailing intentions are in consistent. Thus, this paper adopts an indirect shared control architecture that fuses control instructions from autonomous navigation system and human operator at decision-making layer instead of operational layer. By introducing a weight parameter λ that changes timely as the sailing environment changing, the fuzzy-logic shared control weight arbitration determines fusion instruction by following the formla:

$$U_s = \lambda U_h + (1-\lambda)U_a \tag{1}$$

where U_s is the shared control command; U_h is human operator's control command; U_a is ANS's control command; and λ is real-time driving weight. According to the value of λ, shared control can be divided into three stages:

- fully autonomous control stage ($\lambda = 0$); at this stage, MASSs fully follow the decision made by ANS;
- pure human operator control stage ($\lambda = 1$); at this stage, human operators gain complete control privileges and operate MASSs based on driving experience and sensor information;
- shared control stage ($\lambda \in (0,1)$); at this stage, human operators and ANSs work collaboratively to determine the fused command.

2.3. Fuzzy-logic based shared control system framework

To take full advantage of the operational capabilities of ANS and human operator and ensure the navigation safety, a fuzzy-logic based shared control system is introduced to coordinate control command as it is shown in Figure 1. Human and autonomous navigation system input control commands u_h and u_a to the shared control system based on their respective desired trajectories r_h and r_a, respectively. Then, weight λ which is determined by an embedded arbitrator based on fuzzy-logic is utilized to the shared control law to synthesize the shared command u_s.

The proposed arbitrator is composed of three parts: a fuzzification interface, a inference engine, and a defuzzification interface. Fuzzification interface determines membership degrees of each actual input transmitted by the sensors from autonomous system and maps them to corresponding fuzzy input, which imitates the fuzzy judgement made by human at current situation. Inference engine utilizes an embedded fuzzy rule base to convert fuzzy inputs into fuzzy outputs which are transmitted to defuzzification interface and turn to actual outputs. The framework of the proposed fuzzy-logic based shared control system is shown in the following figure.

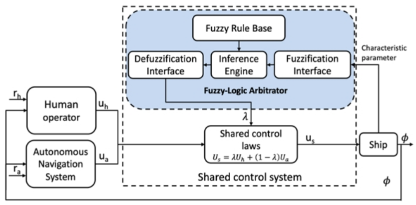

Fig. 1. The architecture of the proposed remote system.

3. Design of fuzzy-logic based arbitrator

The fuzzy-logic is introduced to determine dynamic driving weight λ which is the parametner fusing human and machine commands. To complete the design of the entire arbitrator, this paper defines several scenarios in which the control should change, and the characteristic parameters of each switching scenarios are defined as the actual input of the fuzzy-logic based arbitrator; subsequently, the fuzzification interface of the fuzzy arbitrator takes in the actual inputs and converts them into fuzzy inputs; the inference engine maps the fuzzy inputs to corresponding fuzzy outputs through a fuzzy rule base; finally, the defuzzification interface converts the fuzzy outputs into actual outputs. In order to make the shared control arbitrator universal in the application scenario, this paper chooses three characteristic parameters for representative scenarios and designs fuzzy rules individually.

3.1. Definition of the switching scenarios and characteristic parameters

In the whole takeover process, weight arbitrator is of great responsibility to assume control in dynamic traffic scenario accurately (SAE, 2014) and keep the whole process smoothly. That means the key of realizing dynamic shared control is not only detecting the switching scenario and timing, but also allowing the weight changing according to dynamic scenario. Generally speaking, there are two types of method for defining switching scenarios. One is data-based research methods such as machine learning and the other is rule-based research methods. However, lack of autonomous navigation data limits the usage of data-based method in MASS. Thus, this paper intends to define switching scenarios and select the characteristic parameters by referring to the existing guildlines published by major classification societies. Some researchers (Zhang et al., 2023) aim to divide switching scenario according to relevant regulation on autonomous ships issued by major classification societies. Another vital part after determining switching scenario is identifying scenario feature and extracting characteristic parameters, which will impact control effect directly.

Based on previous studies and regulations on autonomous ships, three types of key switching indicators based on three representative scenarios are summarized, namely sensitive area navigation scenario, nominal scenario without obstacles, and encountering scenario.

(1) Distance-to-target l

In many autonomous ship related guidelines, the switching of control is encouraged when the ship is sailing into sensitive areas, such as bridge areas, docklands, narrow channel, etc. (BV, 2019), (CCS, 2023), (KR, 2022), (RS, 2020). Thus, a parameters distance-to-target l is introduced to help the ship switch the control from the machine to the human when the ship approaches to the sensitive area. Distance-to-target l is defined as:

$$l = min\|p - \alpha_{Area}\|_2 \tag{2}$$

where p is the position vector of the controlled ship; α_{Area} is the boundary of the sensitive areas. The parameters are demonstrated in Figure 2.

(2) Channel deviation d_{off}

In normal cases, the controlled ship would follow the inputted path with certain control errors. As a result, the trajectory of the ship would bounded in an area around the path. However, in some special cases, the ship would deviate from the area by various factors and the control the ship would better swtich back to human operators. For instance, the environmental disturbance is larger than the expectation and exceeds the designed working conditions of the machine (BV, 2019; KR, 2022); the human operators decide to depart from the original path. To help the machine return its control back to human operators, another key factors deviation d_{off} is introduced and formulated as:

$$d_{off} = \frac{|l_{AB} \times l_{AX}|}{\|l_{AB}\|} \tag{3}$$

where l_{AB} is the vector from waypoint A to waypoint B; l_{AX} is the vector from waypoint A to controlled ship. The parameters are demonstrated in Figure 2.

(3) Relative velocity v_r

Although there are many algorithms have been proposed to help ship collision avoidance, the human operators are still required to monitors the process of collision avoiandce since the collision avoidance systems have not been tested and the systems might provide controversial solutions that might be safe but rule-incompliant. Thus, in this paper, approaching ratio to dangers is considered and relative velocity v_r is used as key indicator, which can be calculated by (4). In the future, as the machine intelligence improving, the machine might handle more complicated scenarios and the torelence to the dangers would be increased. In that case, we might need another indicators.

$$V_r = \|v_1 - v_2\| \tag{4}$$

where v_1 and v_2 represent the velocity vector of the controlled ship and the obstacle. The parameters are demonstrated in Figure 2.

In summary, during navigation in obstacle-free regular areas, the channel deviation d_{off} serves as an indicator for detecting abnormal ship navigation behavior and influences the weight. As the ship enters sensitive areas, changes in weight will be influenced by the distance-to-target l. When encountering obstacles, the relative velocity v_r, representing the degree of danger, and the channel deviation, representing the effectiveness of collision avoidance measures, jointly influence the weight. In real navigaiton environment, the ship might encoutner the mentioned scenarios one-by-one, but in more general case, the ship might face to the mixed scenarios, such as Figure 2. In such case, the arbitrator computes driving weights individually for each of the three scenarios. In order to ensure navigational safety, the highest weight derived from these calculations is chosen as the current control weight and transmitted to the vessel.

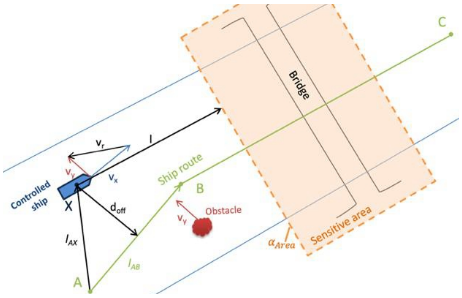

Fig. 2. Membership function graph of output *weight*.

3.2. Selection of fuzzy membership functions

Fuzzy membership functions are tools that transfer actual values to fuzzy values mutually following the lead of fuzzy rule base. Considering the different feature among three types of scenarios, this paper designs three sets of fuzzy membership functions and fuzzy rules. This section provides detailed explanations of the design process with formulas and diagrams for three scenarios. It is noteworthy that the parameter values of the fuzzy membership functions depend on the actual navigation environment and operator preferences. The parameter values presented in this section are for reference only, and adjustments can be made according to the actual situation in practical applications. Trapezoidal, triangular and gaussian fuzzy membership functions are employed for input and output variables, and formulated as:

$$f_n(x\,; a, b, c, d) = \begin{cases} 0, x \le a \\ \frac{x-a}{b-a}, a \le x \le b \\ 1, b \le x \le c \\ \frac{d-x}{d-c}, c \le x \le d \\ 0, d \le x \end{cases} \tag{5}$$

$$f_n(\mathrm{x}\,; e, f, g) = \begin{cases} 0, \mathrm{x} \le e \\ \frac{\mathrm{x}-e}{f-e}, e \le \mathrm{x} \le f \\ \frac{g-\mathrm{x}}{g-f}, f \le \mathrm{x} \le g \\ 0, g \le \mathrm{x} \end{cases} \tag{6}$$

$$f_n(x, \sigma, \mu) = e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{7}$$

where n represents the fuzzy set corresponding to the input/output, f_n is the computed fuzzy input/output value, x represents the actual input value of scene characteristic parameters or the fuzzy output value of weights, and a, b, c, etc., are parameters of the fuzzy membership functions, which vary depending on the specific navigation environment and driver preferences.

In sensitive area navigation scenario, the input variable region considering the motion characteristic and operational characteristics of ships for distance-to-target l spans [0,500] meters, while the output variable weight ranges from [0,1]. The fuzzy sets for distance-to-target l and driving weight are categorized as {danger, normal, safe} and {S, N, D}, respectively, reflecting a descending order of security levels from high to low. Trapezoidal and triangular fuzzy membership functions expressed by (5) and (6) are employed for the input variable and gaussian functions expressed by (7) are employed for the output variable, which are shown in Figure 3.

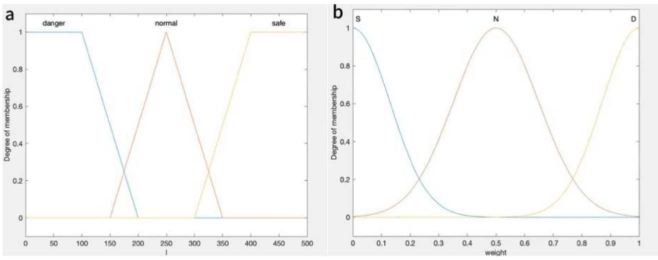

Fig. 3. (a) membership function of input *l*; (b) Membership function of output ***weight***.

In encountering scenario, the input variable region for channel deviation d_{off} spans [0,900] meters and relative speed v_r spans [0,10] knots, while the output variable weight ranges from [0,1]. The fuzzy sets for channel deviation d_{off} and relative speed v_r are categorized as {slight, medium, severe} and {slow, medium_speed, fast}, respectively, reflecting a descending order of degrees from high to low. [S, MS, M, MD, D] is the fuzzy set for output ***weight.*** Trapezoidal, Gaussian and triangular fuzzy membership functions are employed for the input variables which is shown in Figure 4 (a) and Figure 4 (b), whereas triangular functions are adopted for the output variables, which is shown in Figure 4 (c).

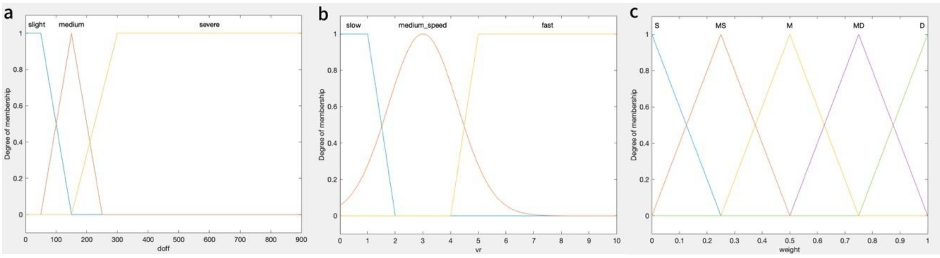

Fig. 4. (a) membership function of input d_{off} ; (b)membership function of input v_r; (c) Membership function of output ***weight.***

In nominal scenario without obstacles, the input variable region for channel deviation d_{off} spans [0,900] meters, while the output variable weight ranges from [0,1]. The fuzzy sets for channel deviation d_{off} and weight are categorized as {slight, medium, severe} and {S, N, D}. Trapezoidal and triangular fuzzy membership are applied to input variable and output variable, which is shown in Figure 5.

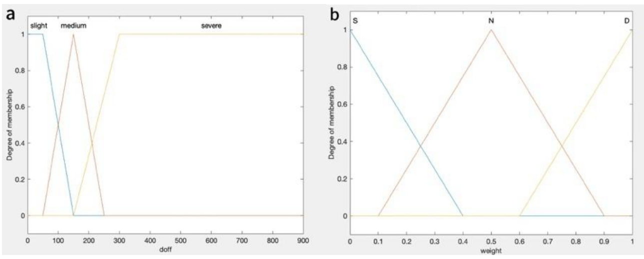

Fig. 5. (a) membership function of input d_{off}; (b) Membership function of output ***weight.***

3.3. Establishment of the fuzzy rule base

Fuzzy rules based on expert knowledge and experience is a collection of all mapping relationships between fuzzy inputs and fuzzy outputs. When autonomous ships gradually enter sensitive areas, the interaction between ships and the environment becomes more complex, resulting in increased operational difficulty. To ensure safe and efficient navigation decisions, it is necessary to increase the weight of human operator in these contexts. A ship trajectory that deviates from specific channel is regarded as abnormal trajectory. Therefore, when the degree of deviation keeps rising, it is necessary to increase the driving weight to draw the human operator's attention to anomalies. Fuzzy rule bases for sensitive area scenario and nominal scenario are shown in Table 1.

Table 1. Fuzzy rules table for sensitive area navigation scenario and nominal scenario without obstacles.

Fuzzy input		Weight
Distance-to-target l	Safe	S
	Normal	N
	Danger	D
Channel deviation d_{off}	Slight	S
	Medium	N
	Severe	D

As for encountering scenario, nine rules are included. When v_r is high and d_{off} is small, it indicates that the current situation warrants the attention of human operator but is not extremely urgent. Therefore, the driving weight should increase at a relatively slow rate; when v_r and d_{off} are at a high level simultaneously, it indicates that the behaviour of avoiding obstacles is performing, however, not efficient enough. Driving weight should be handed over to human operators quickly; when v_r is slow while d_{off} is large, collision measures work so the driving weight should increase at a slow rate to make sure the whole process safe; when v_r is slow and d_{off} is small, it means the current situation is generally safe, and the formulation of navigation decisions can primarily be handled by the autonomous navigation system. Fuzzy rule base for encountering scenario is shown in Table 2.

Table 2. Fuzzy rule base table for encountering scenario.

Channel deviation d_{off}	Relative speed v_r		
	Slow	Medium_speed	Fast
Slight	S	MS	M
Medium	MS	M	MD
Severe	M	MD	D

3.4. Defuzzification

Defuzzification is the last step which transfers fuzzy outputs into actual values with fuzzy membership functions. This paper utilizes centroid method which is depicted by formula:

$$\lambda = \frac{\int \lambda_0 f_N(\lambda_0)}{\int f_N(\lambda_0)}, \tag{8}$$

where λ is the actual output value; λ_0 is the fuzzy output value; N is the fuzzy set; $f_N(\lambda_0)$ is the membership function of N set.

The input-output relationships of fuzzy-logic arbitrators in three scenarios under their respective fuzzy rules are illustrated in Figure 6. Since sensitive area navigation scenario and nominal scenario without obstacles are single-input-single-output arbitrators, the relationship diagram is two-dimensional, while encountering scenario, being a two-input-single-output arbitrator, features a three-dimensional relationship diagram.

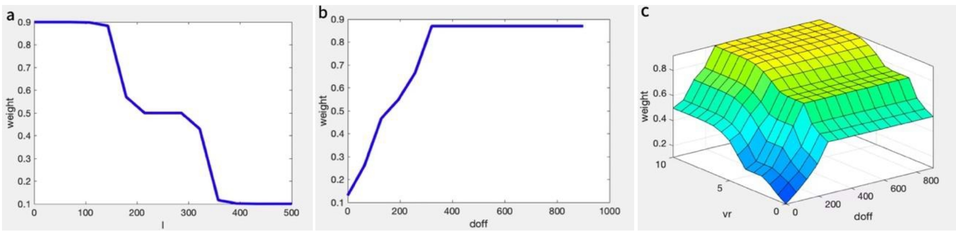

Fig. 6. (a) Input / output surface diagram of sensitive area navigation scenario;
(b) Input / output surface diagram of nominal scenario without obstacles;
(c) input / output surface diagram of encountering scenario.

4. Experiment design and results analysis

4.1. Setup of the experiment

The design rationale of this experiment is to examine the weight variations of the fuzzy-logic based arbitrator under different scenarios: normal ship navigation, encountering obstacles, deviating from the intended route, and traversing sensitive areas. The test is conducted on calm water surfaces with the vessel cruising at a speed of 5 knots. In the experiment, a about 3000-meter route which is represented by green dashed line is established, with a moving obstacle of which the trajectory is denoted by the blue line in Figure 7 (a) traveling perpendicular to the channel. The trajectory of the controlled ship is represented by the red line in Figure 7 (a). And the weight variations resulting from changes in different characteristic parameters will be represented by points of different colors, which is shown in Figure 7 (b).

4.2. Composite scenario experiment

To verify that the weight changes receive the dual effcts of distance-to-target l, relative velocity v_r and channel deviation d_{off}, the experiment simulates a scenario in which a controlled ship of which the trajectory is represented by red line encounters an obstacle while navigating in open waters and takes evasive action. After that, the controlled ship needs to traverse a sensitive area containing a bridge along the route.

The simulation test can be divided into four phases of analysis. The simulated navigation process is shown in Figure 7 (a). In Phase 1, the controlled ship navigates along the predefined route without deviating from the channel. The autonomous navigation system primarily controls the driving authority, and the driving weight remains unchanged. The variation in driving weight during this phase is indicated by red dots. In Phase 2, the controlled ship maneuvers to avoid an obstracle, deviating from the predefined route. As it gradually deviates from the channel and experiences changes in relative velocity with the obstacle, the driving weight progressively increases and then decreases as the avoidance maneuver takes effect. The variation in driving weight during this phase is denoted by green dots. Phase 3 involves the gradual return of the controlled ship to the predefined route. During this process, the driving weight is influenced by the extent of deviation from the channel. When the deviation from the channel is significant, the arbitrator determines that the current decision is insufficiently effective, which makes arbitrator prompts an increase in the driving weight to let human operators take control. The variation in weight during this phase is represented by red dots. In Phase 4, the ship gradually approaches a sensitive area containing a bridge, represented by a black line. The region inside the black dashed line denotes the sensitive area. As the ship enters the sensitive area, the driving weight represented by blue dots begins to increase, reaching its peak when near the bridge, and eventually decreases as the ship moves away. The whole process is shown in Figure 7 (b).

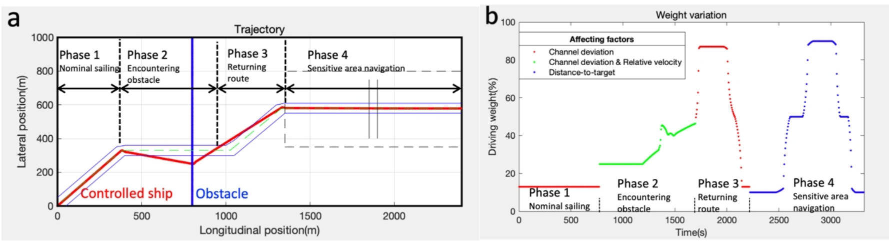

Fig. 7. (a) Trajectory of the controlled ship in conventional area with obstacles; (b) Graph of driving weights.

4.3. Discussion

As the experiment result indicates, the fuzzy-logic based arbitrator realizes the dynamic driving weight assignment due to the present motion state of ship when controlled ship successively sails into three representative scenarios. It is obvious that weight correlates negatively with distance-to-target l. As the controlled ship closes to the sensitive area, weight keeps growing and peaks. It is found that the changes in distance-to-target l can be reflected in the weight in time. The result also indicateds a simultaneous increase and decrease in channel deviation doff, suggesting that lateral displacement of the ship during operation is continuously monitored in real-time. Once it exceeds the normal value, the arbitrator promptly provides feedback in the form of driving weight to alert the human operator. It is observed that the changes in relative velocity and channel deviation are positively correlated with the weight. However, the asynchronous changes between the two alter the rate of weight change.

In addition, it can be observed in Phase 1 that even during normal navigation phases, λ is not equal to 0, indicating that humans still maintain a lower level of weight, which is due to the characteristics of fuzzy logic. This is acceptable because it can enhance human attention during navigation to cope with unexpected situations.

From the experiment, we can conclude the advantages of the proposed methods:

- Real-time. Fuzzy-logic based arbitrator will assign the control of the ship to human and machine with weight that is determined by the motion state of the ship, which means the MASSs with fuzzy-logic based shared control method can achieve full-time and effective dynamic adjustment of driving weight distribution, facilitating real-time interaction for human-machine intelligent decision-making;
- Well-adapted. This paper regards navigation as a process of scenario switching, occurring among three distinctive scenarios, namely sensitive area navigation scenario, nominal scenario without obstacles, and encountering scenario. Thus, the entire navigation process can be abstracted as the concatenation and blending of these three scenaios.

Although the expected functions of the fuzzy-logic based arbitrator is verified by the result of experiment, there are still some problems to be solved reflected by the graph of weight variation:

- Jumps in scenarios transitions. Although achieving smooth weight changes within the same scenario, there are still fluctuations in weight when switching between scenarios. This may be attributed to the different influencing factors between the preceding and subsequent moments. This issue may be addressed by implementing a variation controller during scenario transitions. Once the weight change between consecutive moments exceeds a certain threshold, the controller will enforce a gradual weight adjustment at a certain rate;
- Lack of blending scenario test. In this experiment, the fuzzy rules play a role one by one, without considering the mixed scenario such as ship encountering obstacles in the sensitive area. Although the result has proved the effectiveness in encoutnering the mentioned scenarios one-by-one, experiments involving the simultaneous occurrence of all three scenes have not been conducted.

To summarize, the experiment show the effectiveness of the fuzzy-logic based arbitrator. The trend of changes in characteristic parameters and weight aligns with navigation experience and knowledge, reflecting the real-time dynamic variation characteristic of the fuzzy-logic arbitrator. And the composite scenario experiment has preliminarily proved the good adaptability of this method.

5. Conclusion

Aiming at the gap of control methods for L2 and L3 class MASSs, a fuzzy-logic based arbitrator which determines control command fusion parameters λ for shared control system is designed to achieve real-time weight change in navigation dynamic scenarios. This paper investigates a dynamic driving weight shared control method based on fuzzy logic, which provides a novel measure for real-time interaction of human-machine in decision-making. By referring to the relevant regulations issued by the classification societies, the navigation process is divided into three typical switching scenarios. Distance-to-target l, channel deviation d_{off} and relative speed v_r are selected as the input of fuzzy arbitrator. After analysing the mechanism of these three factors affecting driving weight, fuzzy rule bases are designed. Finally, the effectiveness of the proposed shared control method is verified by the result of three experiments.

According to the thought of switching scenario division, a composite experiment which contains bridge crossing scenario, channel deviation scenario and obstacle avoidance scenario is designed. The relationship between weights and three characteristic parameters, namely distance-to-target l, channel deviation d_{off} and relative velocity v_r, is also demonstrated in the experiment. Specifically, weights increase with decreasing distance, increasing deviation, and increasing relative velocity. In the phase of encountering obstacle, weight is influenced by both channel deviation and relative velocity, which is particularly evident when one increases while the other decreases. In the phase of returning route, weight changes as the degree of channel deviation varies. In the phase of sensitive area navigation, the variation of weight associates with distance-to-target. The synchronization of weight with changes in these three characteristic parameters reflects the dynamic weight issue addressed in this study.

There are many studies that need to be carried out in the follow-up. First, the weight change curve in this study is relatively smooth, however, it can be seen from the experimental result that there is still a need for continued optimization of the fuzzy-logic based arbitrator. Second, navigation is a continuous process. What kind of rules should be applied such as the order of the three fuzzy rules to combine the three generalized scenarios into a personalized navigation scenario still needs to be studied. Finally, the testing effect of the fuzzy logic-based arbiter on the shared control system will be the focus of this study.

Acknowledgements

This work is supported by the Zhejiang Provincial Science and Technology Program through Grant No. 2021C01010, and the National Natural Science Foundation of China (NSFC) through Grant No.52001241, and the Research Program of Sanya City through Grant No. 2022KJCX36.

References

Abbink, D. A., I, Mulder, M., I. 2012. Haptic shared control: smoothly shifting control authority?. Cognition, Technology & Work 14, 19-28.

Ahvenjärvi, S., I. 2016. The human element and autonomous ships. TransNav: International Journal on Marine Navigation and Safety of Sea Transportation 10(3), 517-521.

Bakdi, A., I., Vanem, E., I. 2022. Fullest COLREGs evaluation using fuzzy logic for collaborative decision-making analysis of autonomous ships in complex situations. IEEE Transactions on Intelligent Transportation Systems 23(10), 18433-18445.

Bureau Veritas (BV). 2019. Guidelines for autonomous shipping. BV, Paris.

Burmeister, H. C., I., Bruhn, W., I. 2014. Autonomous unmanned merchant vessel and its contribution towards the e-Navigation implementation: The MUNIN perspective. International Journal of e-Navigation and Maritime Economy 1, 1-13.

China Classification Society (CCS). 2023. Rules for intelligent ships. CCS. Beijing.

Das, M., I., Roy, A., I. 2022. Solving fuzzy dynamic ship routing and scheduling problem through new genetic algorithm. Decision Making: Applications in Management and Engineering 5(2), 329-361.

Hongyan Guo, I., Wanqing Shi, I. 2023. Game-theoretic Human-Machine Shared Steering Control Strategy Under Extreme Conditions. IEEE Transactions on Intelligent Vehicles, 1-15

Korean Register (KR). 2022. Guidance for autonomous ships. KR. Busan.

Kurt, I. Aymelek, I. 2022. Operational and economic advantages of autonomous ships and their perceived impacts on port operations. Maritime Economics & Logistics 24(2), 302-326.

Lang, Y., I., Li, Z., I. 2023. A Shared Control Approach for Autonomous Vehicles via Driver Behaviors Learning. In 2023 IEEE 12th Data Driven Control and Learning Systems Conference (DDCLS), 916-921.

Li, H. M., I., Wang, X. B., I. 2016. Vehicle control strategies analysis based on PID and fuzzy logic control. Procedia engineering 137, 234-243.

Li, M., I., Song, X., I. 2019. Shared control with a novel dynamic authority allocation strategy based on game theory and driving safety field. Mechanical Systems and Signal Processing 124, 199-216.

Russian Maritime Register of Shipping (RS). 2020. Regulations for classification of maritime autonomous and remotely controlled surface ships. RS. St. Petersburg.

SAE On-Road Automated Vehicle Standards Committee. 2014. Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. SAE Standard J 3016, 1.

Saito, T., I, Wada, T., I. 2018. Control authority transfer method for automated-to-manual driving via a shared authority mode. IEEE Transactions on Intelligent Vehicles 3(2), 198-207.

Tian, Y., I, Zhao, Y., I. 2020. The indirect shared steering control under double loop structure of driver and automation. IEEE/CAA Journal of Automatica Sinica 7(5),1403-1416.

Wu, B., I., Yip, T. L., I. 2019. Fuzzy logic based approach for ship-bridge collision alert system. Ocean Engineering, 187, 106152.

XU Shuting, I., TAN Wenqian, I. 2022. Principle and method of shared control system between human pilot and autopilot for aircraft.Flight Dynamics 40(6), 24-31.

Zhang Wenjun, I. Mou Congrui, I. 2023. Control right switching mechanism based on autonomous ship specifications. Journal of Dalian Maritime University 49(4), 1-12. (In Chinese)