The following publication Wu, B., Cheng, T., Yip, T. L., & Wang, Y. (2020). Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes. Ocean Engineering, 197, 106909 is available at https://doi.org/j.oceaneng.2019.106909.

Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes

Bing Wu[1, 2 *], Huibin Tian[1,3], Tsz Leung Yip[2], Min Xie[4]

[1.] *Intelligent Transport Systems Research Centre (ITSC), Wuhan University of Technology, Wuhan, China, 430063*;
[2.] *Department of Logistics and Maritime Studies, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong;*
[3.] *National Engineering Research Centre for Water Transport Safety (WTSC), Wuhan University of Technology, Wuhan, China;*
[4.] *Department of Systems Engineering and Engineering Management, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong.*

*Corresponding author. Email: bing.wu@whut.edu.cn

Abstract: This paper proposes a fuzzy logic-based approach for intelligent decision-making for navigation strategy selection in the inland traffic separation scheme. The dynamic characteristics of navigation process, including free navigation, ship following and ship overtaking, are further analysed. The proposed model can be implemented in the decision support system for safe navigation or be included in the process of autonomous navigation. The decision-making model is achieved from the perception-anticipation-inference-strategy perspective, and the dynamic features of ships (i.e. speed, distance and traffic flow) are comprehensively considered in the modelling process. From the results of both scenarios for overtaking and following, the proposed approach can be used for intelligent strategy selection.

Key words: fuzzy logic, intelligent decision-making, navigation strategy, perception-anticipation-inference-strategy

1 Introduction

The safety of autonomous ships has attracted much attention recently, and several studies have been focused on this topic. Wróbel et al. (2018a) introduced the System-Theoretic Process Analysis based method for safety analysis design recommendations' elaboration of autonomous ships, and the uncertainty of hardware, software, liveware have been evaluated. In the continuous work, they (Wróbel et al., 2018b) have further analysed the safety of remotely-controlled merchant ships. Thieme et al. (2018) analysed 64 existing ship risk models by using developed criteria for the applicability assessment of autonomous ships. Ramos et al. (2019) focused on the human tasks in the onshore control centre of autonomous ships, and concluded that the humans could be safety barrier for ship collision avoidance.

As the navigation accidents (i.e. collision and grounding) accounts approximately 85% of the maritime accidents (Wróbel et al., 2017), the majority of existing studies focused on such accidents (Wu et al., 2017; Erol et al., 2018) especially the collision avoidance (Perera et al., 2015; Polvara et al., 2018; He et al., 2017; Li et al., 2019; Huang et al., 2018; Huang et al., 2019). From the previous studies (Statheros et al., Ozturk & Cicek 2019; Chen et al., 2019), the concepts, technologies and different risk analysis methods have been summarised. The obstacle avoidance approaches have been widely used recently (Polvara et al., 2017; Huang et al., 2018; Huang et al., 2019), and the COLREG rules (He et al., 2017; Perera et al., 2015; Lyu & Yin 2019), which should be obeyed for ship navigation, are considered and incorporated in the modelling process. Moreover, in the open sea area, as there are many ships navigating in the restricted area from different directions, the encounter scenarios of multiple ships (Li et al., 2019; Zhang et al., 2015; Shen et al., 2019) is also a hot topic for ship-ship collision avoidance.

Another perspective of ship collision avoidance is to derive the ship behaviours by using Automatic Identification System (AIS) data (Zhang et al., 2017; Zhang et al., 2016; Fang et al., 2018; Kim et al., 2017; Wu et al., 2018; Zhang et al., 2018). The data processing is first carried out for noise elimination and data interpolation (Wang et al., 2013; Qu et al., 2011). Then, the linear regression method (Mou et al., 2009), logistic regression method (Kim et al., 2017), fuzzy logic (Zaman et al., 2014), ship domain (Hansen et al., 2013) and some modelling methods are introduced to derive the ship behaviour (Xiao et al., 2015), near miss (Zhang et al., 2016), or marine traffic pattern (Silveira et al., 2013). By introducing this AIS based method, the collision risk can be finally be derived.

From the above analysis, there are some research gaps in the existing studies. First, when introducing the AIS based method, the majority of safe navigation scenarios can be identified. However, from the individual risk perspective, the navigation safety should be focused on the human-like decision-making (Xue et al., 2019) rather than from a macro perspective. Second, the majority of the existing studies focused on the ship-ship collision in open sea area. However, the inland waterway transportation, which accounts for around 55% freight volume in China, deserve much attention for collision avoidance. Third, in the inland traffic separation scheme, the navigation strategy should be more important than the collision avoidance because there are few encounter scenarios (e.g. head on) because the ships should navigate in accordance with the required directions.

Therefore, the motivation of this paper is to select the navigation strategy in the inland TSS from the perspective of human-like decision-making. In the modelling process, the navigation strategy is selected from a comprehensive perspective by considering the ship parameters and dynamic traffic environment, and a four-stage decision-making method is proposed. The remainder of this paper is organised as follows. Section 2 gives some preliminaries on navigation strategy selection in inland TSS, including the fuzzy logic-based method, ship navigation process and four-stage decision-making method. Section 3 proposes the fuzzy logic based decision-making model, and both the typical following and overtaking scenarios are used for application in the Yangtze River. Discussions are carried out in Section 4, and Conclusions are drawn in Section 5.

2 Preliminaries on navigation strategy selection

2.1 Fuzzy logic-based model for decision-making

Fuzzy logic is a widely used method for decision-making (Hao et al., 2016; Goerlandt et al., 2015; Wu et al., 2016; Wu et al., 2018) in transportation systems. This is owing to the advantages of using this method for decision-making and they can be summarised as follows: 1) The ability to describe systems linguistically through rule statements; 2) The ability to deal with imprecision (vagueness and uncertainty of human expressions) fit ideally into decision systems.

Traditionally, there are four significant components of fuzzy inference system (FIS), which are a fuzzification interface, a fuzzy rule base, a fuzzy inference engine, and finally a defuzzification interface, which is shown in Figure 1. The process of developing a FIS is as follows: 1) The crisp input is converted to fuzzy numbers by using fuzzification method. 2) The fuzzy rule base is constructed by using a number of fuzzy IF–THEN rules. 3) The decision-making unit performs the inference operations based on the IF-THEN rules. 4) The defuzzification interface transforms the fuzzy result of the inference into a crisp output.

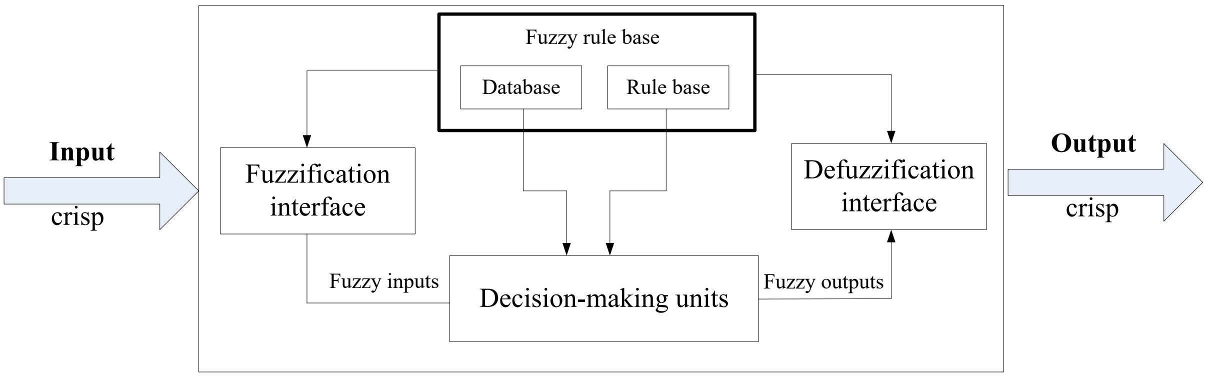


Fig. 1 Generic fuzzy inference system

Specifically, each step can be achieved as follows.

(1) Fuzzification. The purpose of fuzzification is to map the inputs from 0 to 1 using a set of input membership functions. In this process, the number of linguistic variables should be defined and the mapping values for each linguistic variable should also be defined.

(2) Fuzzy rule base. Fuzzy rule base is a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output. In fuzzy reasoning, the fuzzy rules are expressed by using IF–THEN scheme to describe the relationships between input variables and output variables. Traditionally, there are two or three input variables for each output variable, and the input variables and output variable are defined as the fuzzy logic boxes. The reason why there should not be many input variables is to reduce the number of fuzzy rules.

(3) Decision-making units. There are two widely used inference methods, which are Mamdani's fuzzy inference method and Takagi–Sugeno fuzzy inference method. The main difference between these two methods is that the Sugeno output membership functions are either linear or constant. However, the Mamdani is intuitive, widespread accepted, and well suited to human input. As this paper focuses on the human like decision-making, the Mamdani method is adopted.

(4) Defuzzification. This step is to aggregate the qualified consequents to derive a crisp output. There are two common techniques for defuzzifying, which are centre of mass and mean of maximum. As the former takes the total output distribution into consideration, this paper uses the former method in order to gain a comprehensive evaluation result of the navigation strategy.

2.2 Ship navigation process within inland TSS

The TSS is a traffic-management route-system ruled by the International Maritime Organization (IMO). Traditionally, there are two lanes in one TSS, and A ship navigating in a traffic-lane should sail in the general direction of that lane. Note that a TSS with several lanes are not considered in this paper. This is because the inland TSS is often width limited, there will not be enough space for several lanes.

As shown in Figure 2, there are often three states for each ship when navigating in the TSS. After joining the TSS, the own ship (OS) may navigate with free navigation with an expected speed. However, if a target ship

(TS) with a lower speed is ahead of her and with high traffic density in the opposite direction, the OS have to reduce her speed to follow the TS, this state is called ship-following; if there is low traffic density in the opposite direction, the OS may use the other lane to overtake the TS, and this process is called ship-overtaking. It can be seen that the ship is changing her states in from one to another according to the navigation situation.

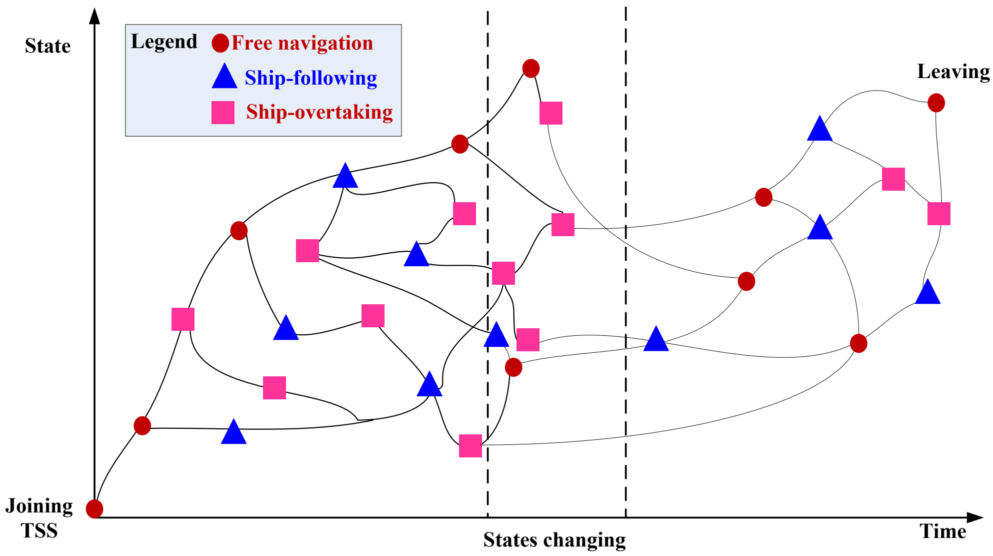


Figure 2 Ship navigation process within inland TSS

Specifically, the characteristics of each state can be summarised as follows.

(1) Free navigation. Free navigation means that the ship can navigate as the expected speed of the general direction in that lane. Note that it doesn't mean that the ship can navigate as she wishes (e.g., navigate in the opposite lane), the ship can only navigate with a wanted speed. Note that one condition should be satisfied is that the OS should be far from the TS or the expected speed is lower than TS.

(2) Ship-following. Ship-following means the OS (ship B in Figure 3) follows the TS (ship A) with a safe distance. At three conditions should be satisfied in this scenario: i) The OS is relatively close to TS; ii) The OS keeps away from the TS with at least a safe distance; iii) The speed of OS is approximately equal to the speed of TS. Moreover, another condition may also exist is that the OS cannot overtake the TS because the traffic density

in opposite lane is heavy. As shown in Figure 3, even if the OS intend to overtake the TS, it is impossible and the OS has to reduce the speed to follow the TS.

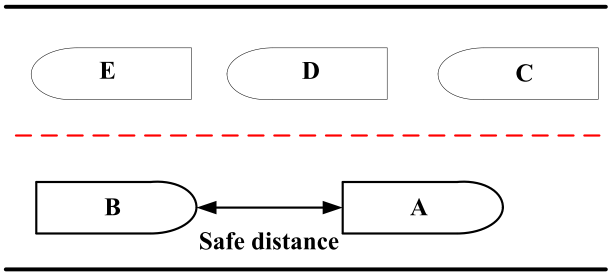


Figure 3 Ship-following scenario within inland TSS

(3) Ship-overtaking. Ship-overtaking means that the OS (ship B in Figure 4) uses the opposite lane to overtake the TS and returns back to the original lane after overtaking. The whole overtaking process is shown in Figure 4. It can be seen that four conditions should be satisfied: i) Before overtaking (i.e. t_0), the OS should keep at least a safe distance and determine that this overtaking operation will not influence the ships navigating in the opposite lane during the whole overtaking process. ii) The speed of OS should be higher than TS (e.g., 2-4 kn), otherwise the overtaking process (i.e. t_1) will take a long time and will significantly influence the ships navigating in the opposite lane. iii) Before changing back to the original lane (i.e. t_i), the OS should keep a safe distance with the ships navigating in the opposite lane. iv) After overtaking (i.e. t_e), the OS will also keep a safe distance with the ship ahead of her (i.e. ship C in Figure 4). Note that when both the overtaking and being overtaken ships are small-sized ships, the overtaking ship don’t need to use the opposite lane but this scenario is not considered in this paper. Another thing should be noted mentioned is that the difference between road and maritime transportation is that the car may not need to return back to the original lane (Balal et al., 2016) but the ship need to return back to original lane.

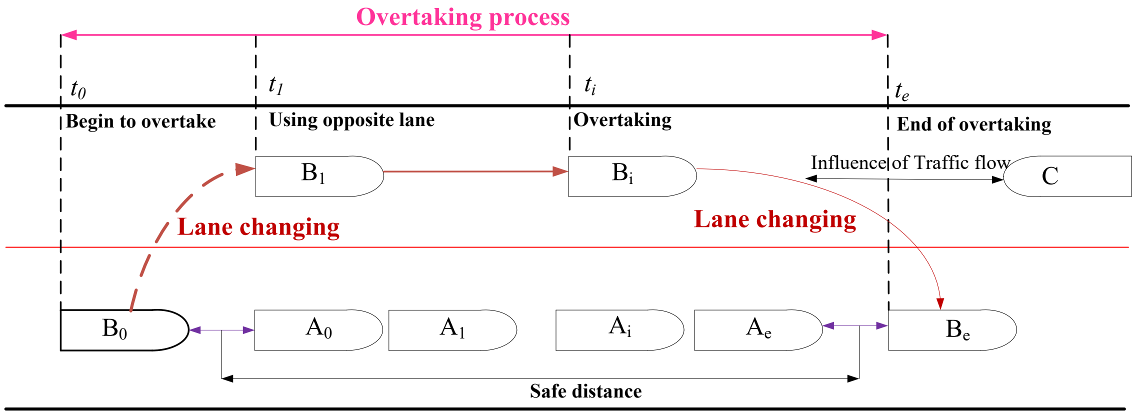


Figure 4 Ship-overtaking scenario within inland TSS

2.3 Dynamic decision-making for navigation strategy

From above analysis, there are three navigation strategies (i.e., free navigation, ship-following and ship-overtaking) when navigating within the inland TSS. For the maned ships, the captain of the OS has to decide which strategy should be adopted. To achieve a human-like intelligent decision-making for navigation strategy selection, the dynamic decision-making process should be analysed.

From the analysis of ship-following and ship-overtaking process, before making decisions, the OS has to assess the current situation, anticipate the future situation, make a comprehensive inference and finally make a decision. This process is dynamic as the speed and distance of the other ships may be changed simultaneously. Therefore, a four-stage decision-making process is established as shown in Figure 5 and the detailed explanations are as follows. Note that the fuzzy logic-based method is used in each stage.

(1) Stage 1: Perception. The perception stage is to fuzzify the input variables and to assess the current situation of the OS and TS. In this stage, the ship speed and distance of the OS and TS should be considered to make a comprehensive assessemnt on the current situation.

(2) Stage 2: Anticipation. The perception stage is to assess the future situation of the OS and TS if the OS intends to overtake the TS. The ship speed difference between OS and TS, acceleration of the TS and the traffic flow of the opposite lane should be considered.

(3) Stage 3: Inference. The inference stage is to make a comprehensive consideration on both the current and future situation for the final navigation strategy selection.

(4) Stage 4: Strategy. The strategy stage is to select the best navigation strategy for the OS, and finally, the action can be used.

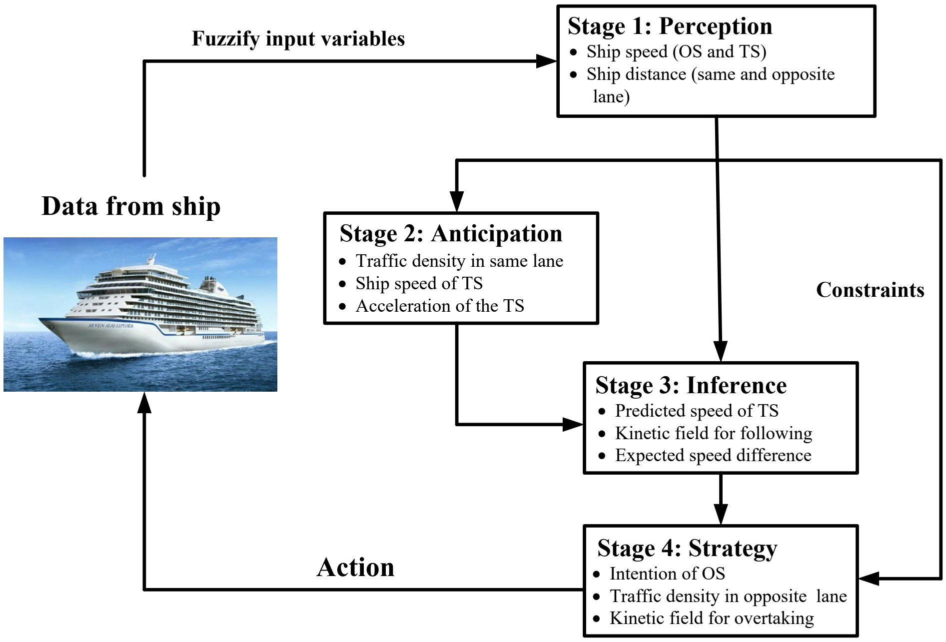


Figure 5 Dynamic decision-making process for navigation strategy

3 Development of intelligent decision-making model for ship navigation strategy

3.1 Establish a dynamic decision-making model

The decision-making model for navigation strategy selection is shown in Figure 6. There are four fuzzy logic based sub-models in this decision-making model. Note that each sub-model is a fuzzy logic-based model, which means all the four sub-models consist of fuzzification (fuzzy membership function, FMF), fuzzy rule base, fuzzy logic box and defuzzification. Moreover, the output for one sub-model maybe the input of another sub-model.

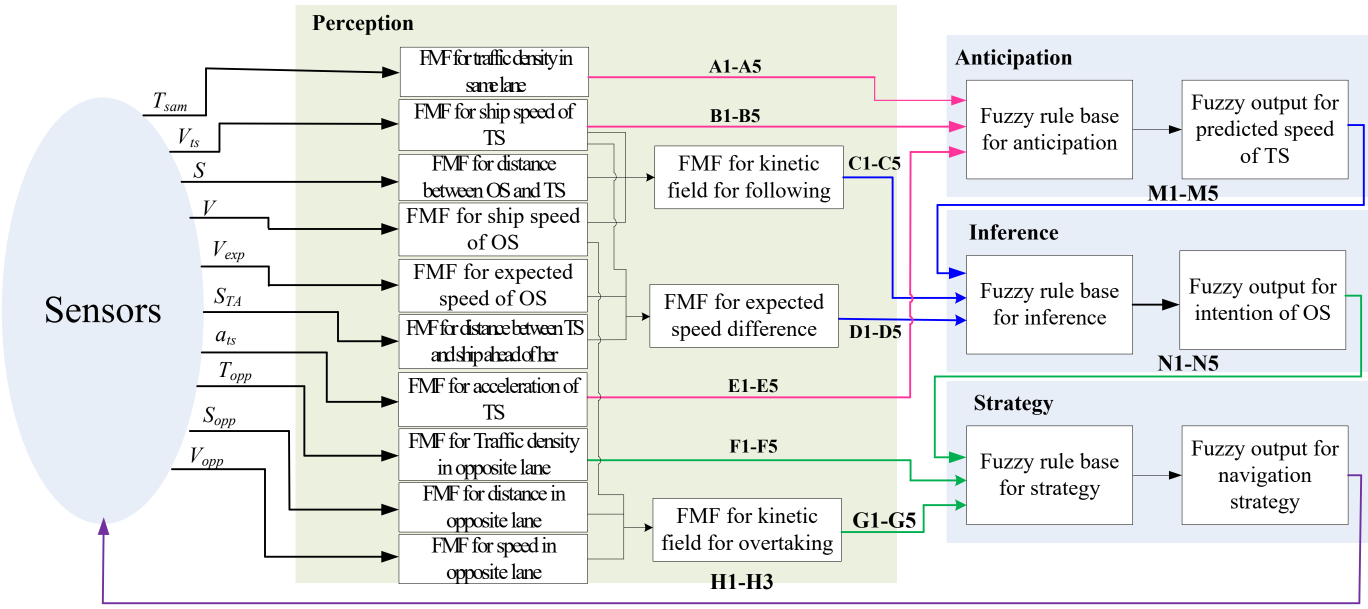


Figure 6 Decision-making model for navigation strategy selection

Before developing the decision-making model, the notations should be defined for the input variables. The meaning of the notations, data range and reasons of choosing these variables in the decision-making model are shown in Table 1. Another factor should be mentioned is the expected speed of the OS. This is because if the OS intendeds to overtake the TS owing to the high traffic density in opposite lane and can't use the opposite lane to overtake, therefore, OS has to reduce the ship speed. However, if the current traffic density is low, the OS can overtake the TS in the opposite lane, therefore, the expected speed of OS is introduced to consider this scenario.

Table 1 Notations used for navigation strategy selection

Notation	Meaning	Range	Reason of variable selection
T_{sam}	Traffic density in the same lane	0 *to* $d_{\max}$	Traffic density in the same lane will influence the intention of the TS
V_{ts} (kn)	Speed of TS	0 to $V_{\max}$	The overtaking strategy is only considered when the speed of TS is higher than speed of OS
S (m)	Distance between OS and TS	−2000 to 2000	Too close distance will cause a collision and actions should be taken in this situation
V (kn)	Ship speed of OS	0 to $V_{\max}$	Ship speed is significant for situation awareness
$V_{\exp}$ (kn)	Expected speed of the OS	0 to $V_{\max}$	The ship speed was reduced in some special conditions and the expected speed can well represent the ship intention
S_{TA} (m)	Distance between TS and the ship ahead of her	−2000 to 2000	Too close distance will cause a collision and the TS may take actions in this situation
T_{opp}	Traffic density in opposite lane	0 *to* $d_{\max}$	Traffic density in the opposite lane will influence overtaking strategy
a_{ts} (m/s^2)	Acceleration of TS	0 to $a_{\max}$	The ship may accelerate or decelerate due to the navigational environment
S_{opp} (m)	Distance with the ship in opposite lane	−5000 to 5000	This can be used for estimating whether an overtaking is feasible

V_{opp} (kn)	Ship speed in opposite lane	0 to $V_{\max}$	This can be used for estimating whether an overtaking is feasible

The data range for the different variables are also defined in Table 1. The traffic density in both opposite and same lane should be lower than the maximum capacity of this lane, which is denoted as $d_{\max}$. The ship speed, including both the OS and TS, should be lower than the maximum speed that the ship can provide, and it is denoted as $V_{\max}$. The distance between the OS and TS, and the distance between TS and the ship ahead of her may be very large, however, if the distance is very long, this is not considered as an encounter situation because the ship need not to overtake or follow, 2000 meters is defined in this inland waterway, and "+" means the OS is following the TS, while "-" means the TS is following OS. However, the distance between the ship in opposite lane is larger as the two ships are with the different speed direction, and 5000 meters is defined. The acceleration of ships is also defined as the maximum acceleration, which is denoted by $a_{\max}$.

3.2 Fuzzification of the input and output variables

The fuzzification of the input and output variables is the first step in fuzzy logic modelling. When fuzzifying the factors, three to seven linguistic variables are widely used. This is owing to the following reasons. (1) If there are less than three linguistic variables, it is hard to distinguish the output after fuzzy inference (Wu et al., 2016; Imprialou et al., 2014), for example, if only "Very heavy", "Stable" and "Very light" are used for describing the traffic density, the decision-maker may be confused because there will be some conditions that between "Stable" and "Very heavy". (2) If there are more than seven linguistic variables are used, too many fuzzy reasoning rules should be established. In this paper, five linguistic variables are used for the majority of the output variables, and they are shown in Table 2.

Table 2 Linguistic variables for output variables

Variables	Linguistic terms and meaning
Traffic density in the same lane	Very heavy (A1), Heavy (A2), Stable (A3), Light (A4), Very light (A5)
Ship speed of TS	Very high (B1), High (B2), Moderate (B3), Low (B4), Very low (B5)
Kinetic field for following	Very high (C1), High (C2), Moderate (C3), Low (C4), Very low(C5)
Expected speed difference	Much higher (D1), Higher (D2), Equal (D3), Lower (D4), Much lower (D5)

Acceleration of TS	Quick deceleration (E1), Deceleration (E1), Maintaining (E3), Acceleration (E4), Quick acceleration (E5)
Traffic density in the opposite lane	Very heavy (F1), Heavy (F2), Stable (F3), Light (F4), Very light (F5)
Kinetic field for overtaking	Very high (G1), High (G2), Moderate (G3), Low (G4), Very low(G5)
Predicted speed of TS	Very high (M1), High (M2), Moderate (M3), Low (M4), Very low (M5)
Intention of OS	Quick deceleration (N1), Deceleration (N1), Maintaining (N3), Acceleration (N4), Quick acceleration (N5)
Navigation strategy	Free navigation (H1), Following (H2), Overtaking(H3)

The fuzzification of the input variables are much complicated. As the traffic density in different waterways will be different, the linguistic variables are used, and the decision-maker can define this according to the capacity of the channel.

The Gaussian membership function is introduced for the fuzzification of the factors involving speed and distance. This is because if the speed is close to a certain speed, the degree of membership should be increased quickly. Therefore, the Gaussian membership function is introduced. This equation is descried by using equation $f(x, \delta, c)=\mathrm{e}^{-\frac{(x-c)^{\wedge}2}{2\delta^2}}$, where c and δ are the parameters for this membership function. The parameters of the factors are defined according to the degree of membership. Take the distance between OS and TS as an example, the five times of the L_{sum} is assumed to be very long because in the ship domain, 4 times of the L_{sum} (eight times of one ship) is assumed to be safety, similarly, 4 times of the L_{sum} is assumed to be moderate because the ship may take actions to avoid collision even the TS is not under control (Wu et al., 2018b). Similarly, other parameters can also be obtained. Note that the summation length of two ship (OS and TS) is used as a unit of distance between OS and TS because the ship domain is often denoted as several times of the ship length, therefore, the fuzzification of this variable can achieve a non-dimensional description of the safe distance.

Table 3 Fuzzification of the input variables

Variables	Type	Term 1	Term 2	Term 3	Term 4	Term 5
T_{sam}	Linguistic	Very heavy	Heavy	Stable	Light	Very light
V_{ts} (kn)	Gaussian	Very low (0.78, -0.58, 0.78, 0.58)	Low (1.27, 3)	Moderate (1.27, 6)	High (1.27, 9)	Very high (0.78,11.42, 0.78,12.58)
S (L_{sum})	Gaussian	Very close (0.32, -0.24 0.32,0.24)	Close (0.53, 1.25)	Moderate (0.53, 2.5)	Far (0.53, 3.75)	Very far (0.32, 5, 0.32,5)
V (kn)	Gaussian	Very low	Low	Moderate	High	Very high

		(0.78, -0.58, 0.78, 0.58)	(1.27, 3)	(1.27, 6)	(1.27, 9)	(0.78,11.42, 0.78,12.58)
$V_{\exp}$ (kn)	Gaussian	Very low (0.78, -0.58, 0.78, 0.58)	Low (1.27, 3)	Moderate (1.27, 6)	High (1.27, 9)	Very high (0.78,11.42, 0.78,12.58)
S_{TA} (L_{sum})	Gaussian	Very close (0.32, -50, 0.32,0.24)	Close (0.53, 1.25)	Moderate (0.53, 2.5)	Far (0.53, 3.75)	Very far (0.32, 5, 0.32,50)
T_{opp}	Linguistic	Very heavy (F1)	Heavy (F2)	Stable (F3)	Light (F4)	Very light (F5)
a_{ts}	Linguistic	Quick deceleration (E1)	Deceleration (E2)	Maintaining (E3)	Acceleration (E4)	Quick acceleration (E5)
S_{opp} (m)	Gaussian	(0.64, -0.5, 0.64,0.5)	(1.06, 2.5)	(1.06, 5)	(1.06, 8)	(0.64, 10, 0.64,10)
V_{opp} (kn)	Gaussian	(0.52, -0.40 0.52,0.40)	(0.85,2)	(0.85,4)	(0.85,6)	(0.52,8,0.52,8)

3.3 Sub-model for current situation perception

The sub-model for perception of current situation is developed to facilitate the modelling process and to have a human-like understanding of the current situation. Specifically, as some input data (e.g. speed or distance) should be considered from a relative perspective, it would be much easier to achieve a human-like decision making process by introducing the perception sub-model. However, for the other data that can be directly used for decision-making, they are directly fuzzified for anticipation or inference. The developed sub-model for current situation perception is shown in Figure 7. Note that in this figure, the output of the perception results can be used for inference or strategy, and it doesn't mean it includes all the input variables for inference or strategy fuzzy logic box.

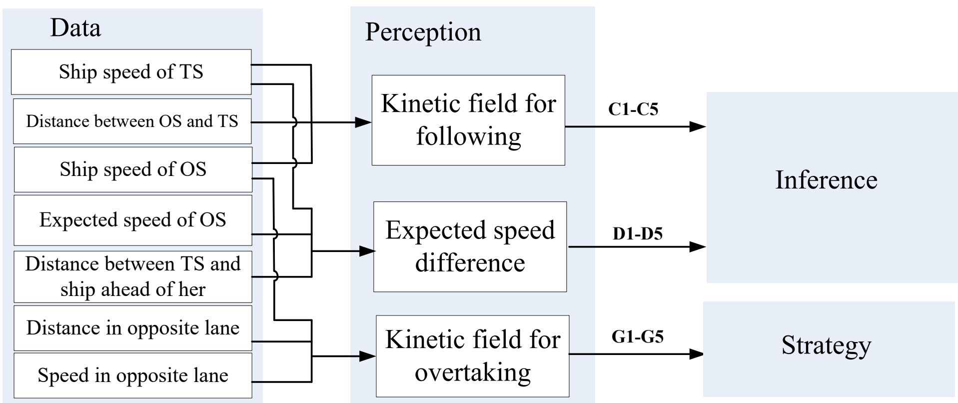


Figure 7 Fuzzy logic box for sub-model of perception

It can be seen from this figure, the kinetic filed, which has been used for road transportation (Wang et al., 2015; Wang et al., 2016), also uses a similar equation to describe the safe distance. The kinetic filed used in this paper can also be defined and shown in Figure 8. Note that in this figure the distance is measured by the summation length of the encounter two ships (L_{sum}), which has been explained when fuzzification of the input variables. It can be seen that when the distance between two ships increase to a relatively close distance, the collision risk increases sharply. This is reasonable because when the distance is shorter than the threshold of the safe distance, the ship will not have time to take response action to avoid collision and the collision risk will sharply increase.

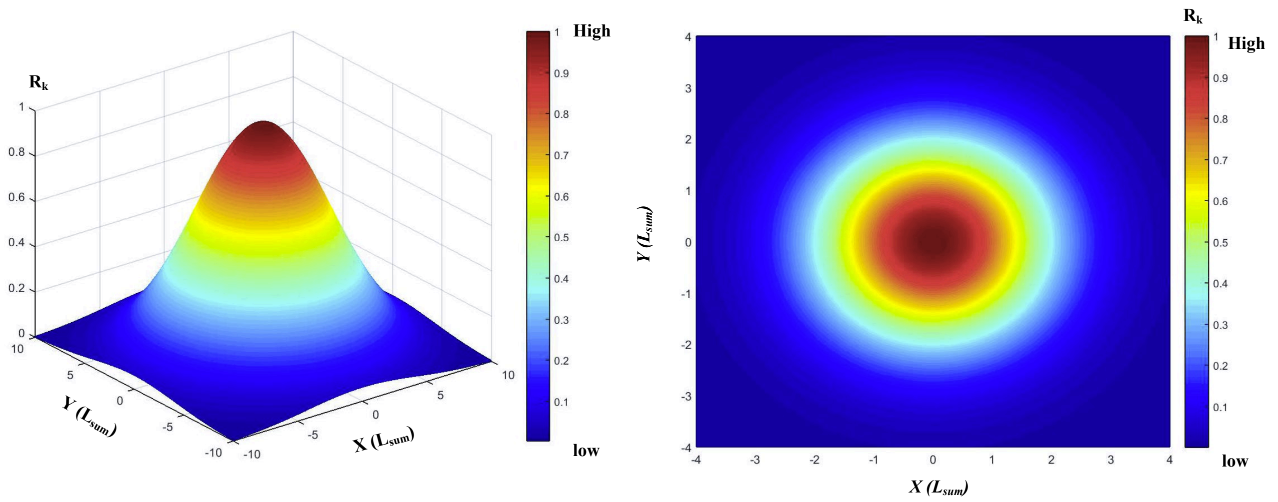
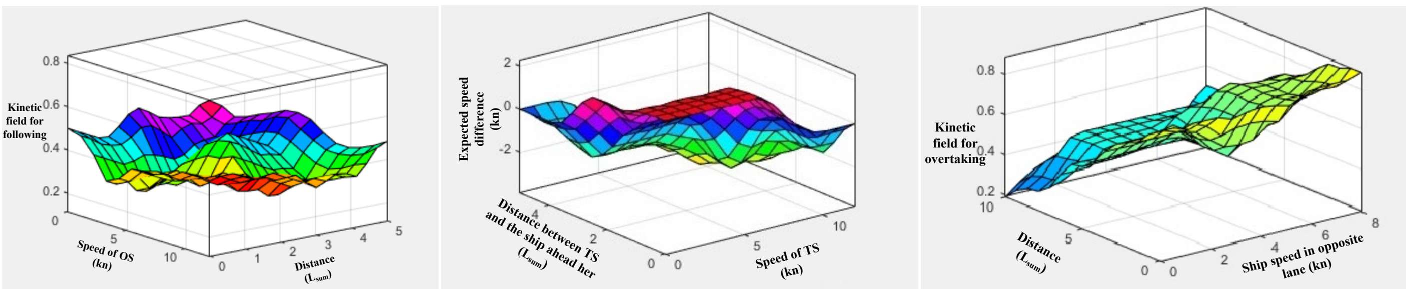


Figure 8 Kinetic filed for the safe distance between two ships

The fuzzy rule base for the three fuzzy logic boxes should also be established. When establishing the reasoning rules for kinetic field of following, two principles are used. 1) If the distance between TS and OS is very close, the kinetic field is very high. This is because the close distance cannot allow the captain to take response actions for collision avoidance. 2) If the ship speed of OS is lower than the speed of TS, the kinetic field is often set not to be very high. This is because the OS will not collide with the TS since the ship speed of OS is lower than the speed of TS. However, if the distance between these two ships is very close, the kinetic field will also set to be very high. By using these two principles, the reasoning rules for kinetic field is established and shown in Figure 9 (a).

There are also two principles to establish the fuzzy reasoning rules for the expected speed difference. 1) If the distance between TS and the ship ahead of her is far or very far and the ship speed of TS is very low or low, the TS is assumed to increase the ship speed. However, if the distance between TS and the ship ahead of her is close or very close and the ship speed of TS is very high or high, the TS is assumed to decrease the ship speed. 2) The expected speed difference is estimated by comparing the expected ship speed of OS and the expected ship speed of TS after using principle 1. The expected ship speed of OS is introduced rather than the real ship speed is used here because the expected ship speed can reflect the intention of the OS. For example, the real ship speed of OS is very low when the OS cannot overtake and the speed TS is very low, therefore, the OS have to reduce the speed. However, the OS intend to overtake and will overtake the TS when the traffic density in the opposite lane is light. Hence, the expected speed of OS is used in this sub-model. Another thing should be noted is that the output of this sub-model is used to predict the intention of OS, and it doesn't mean the OS will take such action. Moreover, the overtaking action can be taken or not will be assessed in the strategy sub-model from a comprehensive consideration.



(a) Kinetic field for following (b) Expected speed difference (c) Kinetic field for overtaking

Figure 9 Fuzzy reasoning rules for sub-model of perception

Note that the reasoning rules of kinetic filed for following and overtaking are the different, which are shown in Figure 9 (a) and Figure 9 (c), respectively. There are two differences when defining such reasoning rules. First, the fuzzification of the input variables (i.e. speed and distance) is different, which are shown in Table 3. This treatment will make the following and overtaking different, and the distance for overtaking is much longer than that of the distance for following. This is because the relative speed for following and overtaking are quite different, which makes the requirement on the safe distance also quite different. Second, as the two ships in the overtaking scenario are in the different lanes with different navigation directions, this means when considering the ship speed in overtaking, the summation of the two ships should be considered to estimate whether these two ships will be collided, while in the following scenario, the speed difference between OS and TS is used.

3.4 Sub-model for future situation anticipation

The sub-model for anticipation of the future situation is developed to predict the potential variance of ship speed for TS. This is because if the traffic flow is heavy in the same lane, the TS have to decelerate, and if the traffic flow is low, the TS may accelerate. Therefore, three variables, which are traffic density in the same lane, ship speed of TS, and acceleration of TS, are treated as the input variables and the predicted speed of TS is treated as the output variable. The developed sub-model for future situation anticipation is shown in Figure 9.

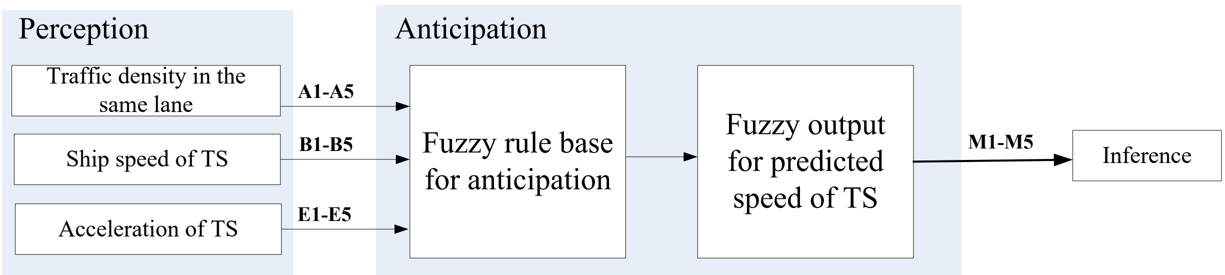


Figure 9 Fuzzy logic box for sub-model of anticipation

Moreover, the fuzzy rule base should be developed in this anticipation process. Some selected rules for this fuzzy logic box are shown in Table 4. It can be seen that even the ship intends to acceleration with a low speed, he predicted speed is also very low when the traffic flow is very heavy. This is because the heavy traffic cannot allow a high speed. However, if the traffic flow is light, which allows the ship to accelerate, the ship speed will be increased accordingly.

Table 4 Fuzzy rule base for predicted speed of TS

Rules	V_{ts} (kn)	V_{ts} (kn)	a_{ts} (m/s^2)	Predicted speed of TS
1	A1	B5	N1	B5
2	A1	B5	N2	B5
3	A1	B5	N3	B5
4	A1	B5	N4	B5
…	…	…	…	…
16	A1	B2	N1	B4
17	A1	B2	N2	B3
…	…	…	…	…
42	A2	B2	N2	B3
43	A2	B2	N3	B2
…	…	…	…	…
58	A3	B4	N3	B4
…	…	…	…	…
90	A4	B3	N5	B1
…	…	…	…	…
124	A5	B1	N4	B1
125	A5	B1	N5	B1

3.5 Sub-model for intention inference of OS

The sub-model for intention of OS is to judge whether the OS can follow the ship ahead of her or not. This is determined by the linguistic variables of the intention of OS. There are three input variables for this sub-model, which are kinetic field for following, expected speed difference, and the precited speed of TS. Note that two variables, which are the traffic density in the same lane and the distance between TS and ship ahead of her, seem to be similar. In fact, they are quite different, by introducing the traffic density in the same lane, the captain can determine whether to follow or overtake from a macro perspective while the distance between TS and ship ahead of her is used to determine increase or reduce the ship speed from a micro perspective. For example, even if the ship ahead of her is slow and OS intend to overtake her, the OS have to give up overtaking when the traffic density is heavy. This is because the OS cannot overtake several ships at one time, which will take a lot of time for overtaking and occupy the opposite lane for a long time. In this situation, the OS has to follow the TS by reducing the ship speed. The developed sub-model for inference is shown in Figure 10.

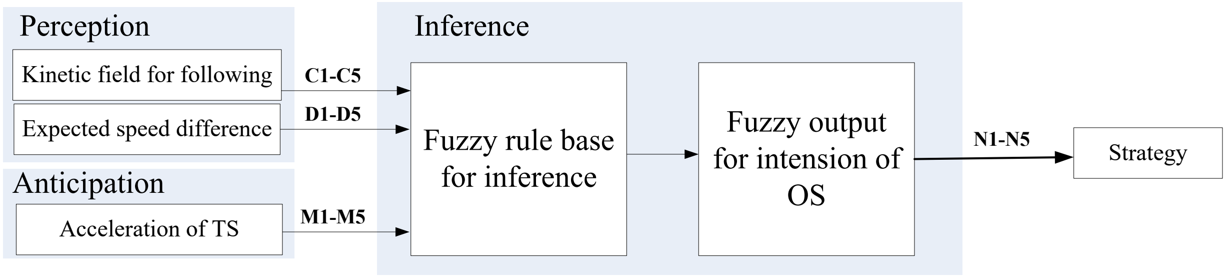


Figure 10 Fuzzy logic box for sub-model of inference

The fuzzy reasoning rules for sub-model of inference is established and shown in Figure 11. The principles of establishing such rules are as follows. 1) If the expected speed difference is much lower than the TS, the OS have to maintain or decrease the current speed, which means the ship will not take an overtaking action. This is because when considering the intension, the OS doesn't need to increase the speed, which means the OS intends to follow the TS. 2) If the expected speed difference is much higher than the TS, and the kinetic field is also high, the intention of OS is to accelerate or even quick accelerate. Moreover, since the kinetic field is also high, the OS has to take an overtaking action. Note that the overtaking action should be assessed comprehensively, and if the overtaking action cannot be taken, the ship has to decrease the speed and follow the TS.

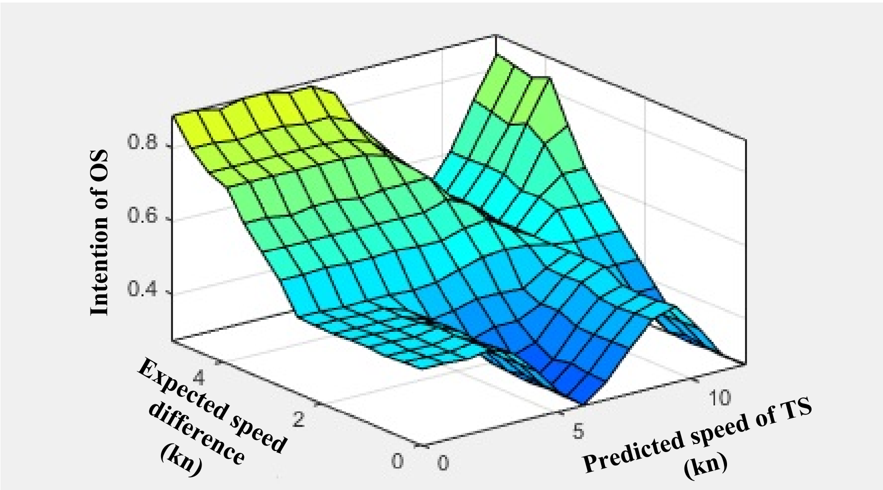


Figure 11 Fuzzy reasoning rules for sub-model of inference

3.6 Sub-model for navigation strategy selection

The sub-model for navigation strategy is to select the optimum strategy for navigation. There are three input variables for this sub-model, which are traffic density in opposite lane, kinetic field for overtaking and the intention of OS. The traffic density in the opposite lane is a factor to define whether the OS can overtake from a macro perspective, while the kinetic field for overtaking is from a micro perspective. Specifically, the kinetic field is to define the safe distance between OS and the nearest ship in the opposite lane by using the current speed. However, it doesn't mean that if the kinetic field for overtaking is low, the OS can overtake. This is because if the traffic density is heavy (e.g. another ship is close to the nearest ship in opposite lane), the OS has to reconsider the overtaking strategy. Moreover, the most important factor is that the OS should have the intention to overtake using the opposite lane. Therefore, these three factors are considered and treated as the input variables for such sub-model and this fuzzy logic box is shown in Figure 12.

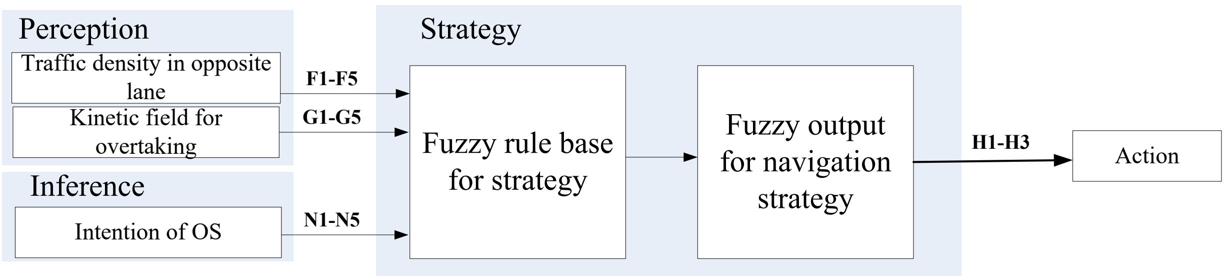


Figure 12 Fuzzy logic box for sub-model of strategy

The fuzzy reasoning rules for sub-model of strategy is established and shown in Figure 13. The principles for establishing the reasoning rules are as follows. 1) The OS can only take overtaking action when the kinetic field for overtaking is relatively low and the OS has the intention to overtake and the traffic density in the opposite lane is not relatively high. 2) The free navigation is selected only when the ship doesn't need to increase or decrease the current speed and intends to maintain the current speed. 3) The following strategy is selected when the ship has to decrease the ship speed. The developed fuzzy reasoning rules are shown in Figure 13.

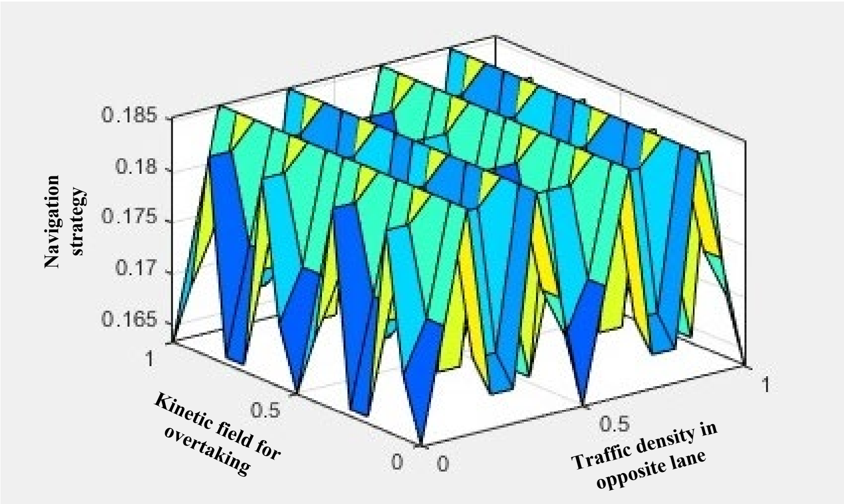


Figure 13 Fuzzy reasoning rules for sub-model of strategy

4 Application of the proposed model in the Yangtze River

4.1 Scaenerio description

The downstream of Yangtze River is a typical waterway and has introduced the traffic separation scheme (Wu et al., 2019) since 2005. In July 2016, the channels have been enlarged and dredged to ensure the two-way traffic flow for 50, 000DWT ships. Since then, the channel is 500m width for two-way traffic from Shanghai to Nanjin. Moreover, there is a special lane for the ships with draught lower than 7.0m. Note that it doesn't mean that the ships with draught lower than 7.0m cannot use the traditional lanes.

In this waterway, there are two buoys (i.e. red and green) for the ships to identify the boundary of the channels. In practice, there are many ships overtaking others every day. When overtaking another ship, these ships have to use the other lane for overtaking. In order to apply the proposed model for navigation strategy selection, the actual data, which are derived from automatic identification system data, are collected. Note that the actual data is used for validation in this paper. This is reasonable because this paper intends to achieve the human-like decision-making, note that in the future, if the autonomous ships have been introduced, the criterion for the safe distance between ships may be different (e.g. shorter than human handling), and some criteria may be adjusted. However, in this paper, this factor is ignored and the human handing of the ships is used for validation.

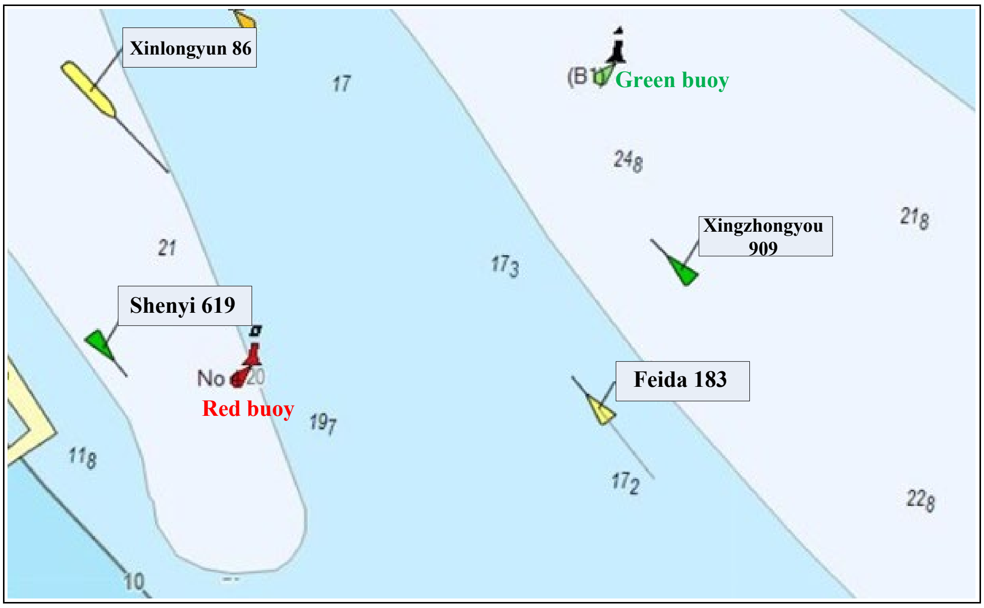
If the result of the proposed model is unanimous with the human handing, this is believed to be reasonable, and this will be further discussed in the discussion part.

Two typical scenarios in April 25, 2019 are selected for this application. The scenario of overtaking is that the inbound ship Feida 183 was overtaking the Xingzhouyou 909 ship. At that time, the outbound ship, Silongyun 86, was navigating in the opposite lane. The scenario of following is that the Xinghao 07 followed the Taishunji 999 ship, and the Hangjun 10 was navigating in the opposite lane. The detailed information for each scenario is descried as follows.

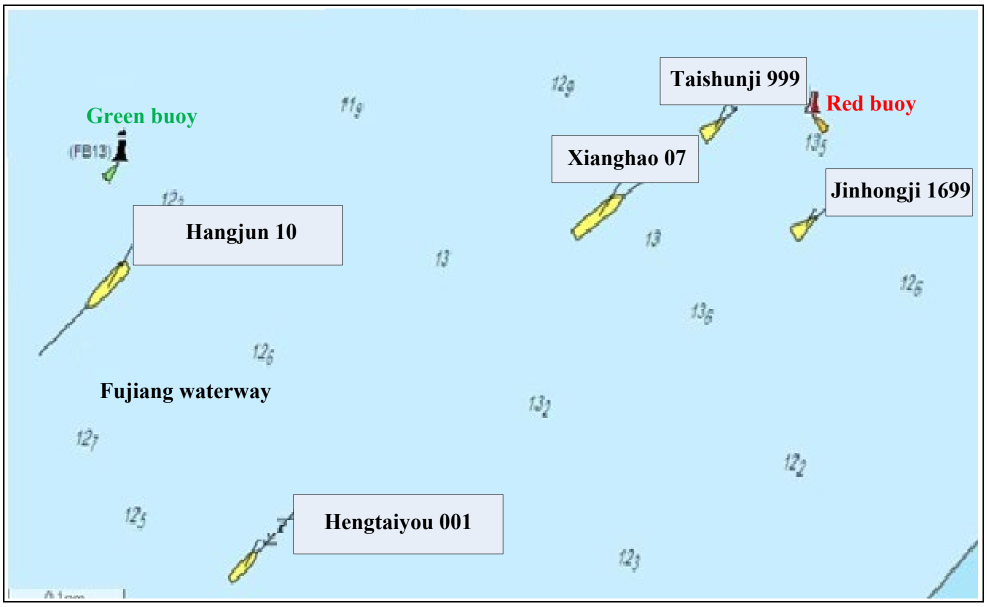
(1) Scenario of overtaking. This scenario is shown in Figure 13 (A). The ship length of Feida 183 is 96m, the ship speed is 6.4 kn when overtaking Xingzhongyou 909. As this ship did not intend to accelerate, the expected ship speed is also defined as 6.4 kn. The being overtaken ship was with ship speed of 5.3 kn, and the ship length is 59m. The distance between Feida 183 and Xingzhongyou 909 is around 255 m when Feida began to overtake, and this distance is around 1.8 (i.e. $255 \div 155 = 1.8$) times of L_{sum} (i.e. 96+59=155). Moreover, there was no ships ahead of her in a long distance. At that time, the traffic density in both the same and opposite lane are light. There was one ship (i.e. Xinlongyun 86) navigating in the opposite lane. The length of this ship is 184m and the ship speed was 12 kn. The distance between Feida 183 and Xinlongyun 86 was around 1.53nm before overtaking, which is around 9.8 (i.e. $1.53 \times 1812 \div 280 = 9.8$) times of L_{sum} (i.e. 96+184=280). The detailed information of this scenario is shown in Table 5. Note that Shenyi 619 is a ship using the special lane with ship length 49m.

(2) Scenario of following. This scenario is shown in Figure 13 (B). The ship length of Xianghao 07 is 93 m with the ship speed of 9.3 kn. As this ship did not intend to accelerate, the expected ship speed is also defined as 9.3 kn. The being followed ship (i.e. Taishunji 999) was with ship speed of 8.3 kn, and the ship length is 44 m. The nearest distance between Xianghao 07 and Taishunji 999 was around 150 m, after that, Xianghao 07 reduced the speed, which was approximately the same with Taishunji 999. It can be calculated that the nearest distance

between Xianghao 07 and Taishunji 999 was around 1.1 (i.e. $150 \div 137 = 1.1$) times of L_{sum} (i.e. 44+93=137). Moreover, there was no ships ahead of her in a long distance. At that time, the traffic density in both the same and opposite lane are light. There was one ship (i.e. Hangjun 10) navigating in the opposite lane. The length of this ship is 85 m, and the ship speed was 7.5 kn. The distance between Hangjun 10 and Xianghao 07 was around 360m when Xianghao 07 was very close (i.e. 150m) to Taishunji 999, which is around 2.0 (i.e. $360 \div 178 = 2.0$) times of L_{sum} (i.e. 93+85=178). The detailed information of this scenario is shown in Table 5. Note that Jinhongji 1699 is a ship using the special lane with ship length 58m.



(A) Scenario of overtaking



(B) Scenario of following

Figure 14 Scenarios of ship navigation in the Yangtze River

Table 5 Detailed information of the encountering scenarios in the Yangtze River

Notation	Scenario a	Scenario b
T_{sam}	Light	Light
V_{ts} (kn)	5.3	8.3
S (L_{sum})	1.8	1.1
V (kn)	6.4	9.3
$V_{\exp}$ (kn)	6.4	9.3
S_{TA} (L_{sum})	Long distance	Long distance
T_{opp}	Light	Light
a_{ts}	Maintaining	Maintaining
S_{opp} (m)	9.8	2.0
V_{opp} (kn)	12	7.5

4.2 Acquisition of the fuzzified values for ship navigation

After collecting the detailed data of the two scenarios, they should be fuzzified by introducing the criteria shown in Table 3. For the variables descried by linguistic terms, they can be easily defined by using the corresponding linguistic term. For example, as the traffic density in the same lane is light, the fuzzified values is defined as (*Light, 1.0*), similarly, the results for traffic density in the opposite lane and acceleration of TS can be also derived, which are shown in Table 6. The distance between TS and ship ahead of her is special because the distance is very long, and it can be directly defined by very far with a degree of 1.0 though this variable is quantitative factor.

For the quantitative factors, the fuzzification process is much complex. Take the ship speed of TS as an example, the fuzzification of this variable in Scenario A is as follows. First, as the value 5.3 is lower than 9 (high), 6 (moderate) and higher than 3 (low), this factor can be descried by using these three linguistic variables. Second, the degree belongs to these two linguistic variables should be calculated. The degree it belongs to moderate can be calculated by using equation $e^{-\frac{(5.3-6)^{\wedge 2}}{2*1.27^{\wedge 2}}}=0.86$, similarly, the degree it belongs to low can also be calculated by using equation $e^{-\frac{(5.3-3)^{\wedge 2}}{2*1.27^{\wedge 2}}}=0.19$, and the degree it belongs to high can be calculated by using equation $e^{-\frac{(5.3-9)^{\wedge 2}}{2*1.27^{\wedge 2}}}=0.01$. Third, by using the degrees, the speed of TS can be defined as *(Low, 0.19; Moderate, 0.86; High, 0.01).* By introducing this method, all the fuzzified values for the input variables in two scenarios can be calculated and the results are shown in Table 6.

Table 6 Fuzzified values for the input variables in two scenarios

Notation	Scenario a	Scenario b
T_{sam}	(*Light, 1.0*)	(*Light, 1.0*)
V_{ts} (kn)	*(Low, 0.19; Moderate, 0.86; High, 0.01)*	*(Moderate, 0.19; High, 0.86)*
S (L_{sum})	*(Moderate, 0.42; Close, 0.58)*	*(Moderate, 0.03; Close, 0.96)*
V (kn)	*(Low, 0.03; Moderate, 0.95; High, 0.12)*	*(Moderate, 0.03; High, 0.97; Very high, 0.02)*
$V_{\exp}$ (kn)	*(Low, 0.03; Moderate, 0.95; High, 0.12)*	*(Moderate, 0.03; High, 0.97; Very high, 0.02)*
S_{TA} (L_{sum})	(*Very far, 1.0*)	(*Very far, 1.0*)
T_{opp}	(*Light, 1.0*)	(*Light, 1.0*)
a_{ts}	*(Maintaining, 1.0)*	*(Maintaining, 1.0)*
S_{opp} (m)	*(Far, 0.24; Very far, 0.95)*	*(Very close, 0.24; Close, 0.89; Moderate, 0.06)*
V_{opp} (kn)	(*Very high, 1.0*)	*(High, 0.21; Very high, 0.63)*

4.3 Derivation of the output variables in different stages

The output values for the two scenarios in different stages can be derived by using the established fuzzy logic boxes. As shown in Table 7, both the fuzzy numbers and numerical values are derived. Specifically, the kinetic field for following in Scenario A has a large degree of moderate, while in Scenario B, this kinetic field for following is relatively high. The expected speed difference in Scenario A is higher, and is also with a large degree of higher in scenario B. the kinetic field for overtaking in Scenario A is between low and moderate, while in Scenario B is high with a relatively large degree. The predicted speed of TS is moderate in scenario A and is high in Scenario B. The intention of OS in both Scenario A and Scenario B is to accelerate.

Table 7 Output values in different stages

Output	Scenario A (fuzzy numbers)	Scenario A (numerical values)	Scenario B (fuzzy numbers)	Scenario B (numerical values)
Perception (kinetic field for following)	*(low, 0.25; moderate, 0.78)*	0.425	*(moderate, 0.25; high, 0.78)*	0.676
Perception (expected speed difference)	*(higher, 1.0)*	2.5	*(higher, 0.72; equal, 0.28)*	1.8
Perception (kinetic field for overtaking)	*(low, 0.51; moderate, 0.49)*	0.374	*(high, 0.39; very high, 0.61)*	0.895
Anticipation (predicted speed of TS)	*(low, 0.17; moderate, 0.89;*	5.38	*(moderate, 0.21; high, 0.84)*	8.26

	high, 0.02)			
Inference (intention of OS)	*(maintaining, 0.07; accelerate 0.93)*	0.732	*(maintaining, 0.16; accelerate 0.84)*	0.711

The kinetic field for following was moderate with a degree of 0.78 and low with a degree of 0.25 in Scenario A, this is reasonable because the ship speed of Feida 183 is higher than the Xingzhongyou 909, therefore, the Feida 183 was gradually closing to Xingzhongyou 909. Moreover, at that time the distance between Feida 183 and Xingzhongyou 909 was moderate with a degree of 0.42 and close with a degree of 0.58. Since the kinetic field for following is defined as Gaussian membership function, the kinetic field will be sharply increased when the distance is very close. Similarly, the kinetic field for following in Scenario B was high with a degree of 0.78 and moderate with a degree of 0.25, this is because Xianghao 07 and Taishunji 999 is close with a degree of 0.96.

The expected speed difference was higher with a degree of 1.0 in Scenario A. This is because Xingzhongyou 909 didn't intend to accelerate because this ship has used full ahead for navigation, however, Feida 183 navigated with a higher speed than Xingzhongyou 909 and though it also didn't intend to accelerate, therefore, Feida 183 intended to overtake and it was expected to have a higher speed than Xingzhongyou 909. Note that this value doesn't mean the Feida 183 will take this speed, this expected value is used to describe that Feida 183 intends to overtake Xingzhongyou 909 for the modelling reasons. Similarly, the expected speed difference was higher with a degree of 0.72 and equal with a degree of 0.28 in Scenario B. This is because the ship speed was relatively high (i.e. 9.3 kn), the expected speed difference was deduced to be a relatively lower than in Scenario A.

The kinetic field for overtaking in Scenario A was moderate with a degree of 0.49 and low with a degree of 0.51, this is because the distance between Feida 183 and Xinlongyun 86 is far with a degree of 0.24 and very far with a degree of 0.95. Moreover, the relatively speed (i.e. summation of the two ships) was not very high. Therefore, this scenario was appropriate for overtaking. However, the kinetic field for overtaking in Scenario B was high with a degree of 0.39 and very high with a degree of 0.6. This is because the distance between Hangjun 10 and Xianghao 07 was very close, which makes the conditions was not suitable for overtaking.

The predicted speed of TS in both Scenario A and Scenario B was approximately equal to the speed the ship is using. This is because both Xingzhongyou 909 and Taishunji 999 didn't intend to accelerate though the traffic flow was light and the ship ahead of them was in a long distance. Therefore, the predicted speed of TS didn't change.

The intention of OS in both Scenario A and Scenario B was to accelerate. This is because in both scenarios, the OS ship navigated with a higher speed than the speed of TS. Moreover, the traffic flow in the same lane was light, which means the OS can quickly go back to the original lane after overtaking by using the opposite lane. Note that the intention of OS doesn't mean that the OS will accelerate, but only an intension. In fact, as the distance between TS and OS was short, if the OS accelerate, the OS would collide with TS. In this part, the intention of OS was used to judge whether the ship should overtake, and this was implemented in the strategy sub-model.

4.4 Final selection of the navigation strategy

The final navigation strategy can be derived after defuzzification using the strategy sub-model, and the results are shown in Table 8. It can be seen that the navigation strategy for Scenario A was overtaking, and the strategy for Scenario B was maintaining. These results are unanimous with the real case; therefore, this proposed model is reasonable by using the actual data of human handling in the Yangtze River. Specifically, the reasons of why the different strategies are selected are explained as follows.

Table 8 Navigation strategy for two scenarios

Scenarios	Values
Scenario A (fuzzy numbers)	Overtaking

Scenario A (numerical values)	*0.825*
Scenario B (fuzzy numbers)	Maintaining
Scenario B (numerical values)	*0.565*

In scenario A, the final strategy was overtaking. This is because the distance between Feida 183 and Xinlongyun 86 was far and the overtaking would have little impact on the traffic flow in the opposite lane, which makes the kinetic field for overtaking was acceptable. Moreover, as the ship speed of Feida 183 was higher than Xingzhongyou 909, Feida 183 had to overtake Xingzhongyou 909 otherwise the speed reduction was needed. Therefore, the overtaking should be carried out and would have little impact on the traffic flow in the opposite lane, the overtaking strategy was selected and was the same with the real case.

The Scenario B was quite different from Scenario A. That is because the distance between Xianghao 07 and Hangjun 10 was close, this can be seen from the kinetic field of overtaking, which makes a high risk of overtaking. Therefore, Xianghao 07 has to reduce the ship and follow Taishunji 999. From the collected data, the ship navigated at the speed of 9.3 kn and reduced the ship speed to 8.3 kn. After Hangjun 10 has passed by, Xianghao 07 overtaken Taishunji 999 and increased the ship speed back to 9.3 kn. From this analysis, it can be clearly seen that the result of the selected navigation strategy is the same with reality, and this result can be assumed to be reasonable.

5 Discussions

When fuzzifying the input variables, the previous studies on the field and ship domain has been introduced. This fuzzifying process relies much on the working experience, another method, which uses the automatic identification system (AIS) data to identify the ship behaviours, is also an alternative method to be introduced for the fuzzifying. In practice, this method has been widely used for ship behaviours identification (Sang et al., 2015; Silveira et al., 2013; Tu et al., 2018) because it can achieve a data-driven method for modelling and doesn't need to rely on the expert experience. However, note that by introducing AIS for modelling, some issues should be carefully handled. For example, when considering the safe distance of two ships, the ship length should be considered because the different ships have different manoeuvrability, but this is hard to achieve this when solely using the AIS data. Another issue is that it will also take a lot of time to define the overtaking and following scenarios from a massive data. The most important reason that this paper doesn’t use AIS data to derive the parameters of fuzzy membership functions is that this paper intends to achieve a human-like decision-making for intelligent navigation strategy. When handling the ships, the captain doesn’t have enough time and data to make such decisions but only have to rely on the working experience.

Another thing should be mentioned is that this paper uses the actual data to validate the proposed model. This is treated as reasonable though some issues should be discussed. As the proposed model is developed to be applied to the autonomous ships in the future, use of the ship handling data from human beings seems to be unreasonable in some extent. The main problem of this is that some experts believe that the safe distance when the ships are handled by algorithms could be shorter than the distance when the ships are handled by human being. In fact, this issue is also discussing in the autonomous driving cars. However, some experts argue that if the car or ship handled by algorithms need to take emergency actions by human beings, the safe distance should be approximately the same. In this paper, this will not be further discussed since the objective of this model is to achieve a human-like decision-making, and the handling data collected from human beings is assumed to be reasonable and used for validation.

The last thing should be discussed is that this paper simplifies the overtaking process from two perspectives. First, there is only one ship intend to overtake the other ships. Second, the overtaking ship only has to overtake one ship and then return back to the original lane. However, if there are more than one ship are overtaking another ship, the following problem should be considered for the overtaking ships. Moreover, if the ship has to overtake more than one ships one time, the safe distance between the OS and the ship in the opposite lane should be much larger. These two problems should be further analysed in the future. In this paper, these two issues are not considered because these two phenomena are not common and in practice, these two phenomena are prohibited by the maritime authorities (e.g. in the Yangtze River) because these two phenomena does not observe good seamanship.

6 Conclusions

The main contribution of this paper is to develop an intelligent decision-making method for selection of navigation strategy. This proposed model is developed from the perspective of human-like decision-making. A four-stage decision-making process, which are perception, anticipation, inference and strategy, is developed by using fuzzy logic method. From the scenarios of following and overtaking, the developed method can be applied for navigation strategy selection and can be further implemented in the autonomous navigation system.

This paper focuses on the inland TSS waterways, which have the distinguishing characteristics that the ship has to change lane for overtaking and to change lane back after overtaking. In fact, this dynamic process is very common in inland TSS, and this proposed model can be directly applied to other similar TSS waterways because the models have taken the dynamic features (i.e. ship speed, ship length, traffic flow) of ships into consideration. However, some issues should also be carefully handled and be addressed in the future when implemented in the autonomous ships. Specifically, the model should consider the scenarios that there are more than one ships overtaking and more than one ships being overtaken.

Acknowledgements

The research presented in this paper was sponsored by a grant from National Science Foundation of China (Grant No. 51809206), National Key Technologies Research & Development Program (2017YFE0118000), Hubei

Natural Science Foundation (Grant No. 2017CFB202), the Fundamental Research Funds for the Central Universities (WUT:2019IVB062, WUT:2019IVB085) and the Hong Kong Scholar Program (No.2017XJ064).

References

Balal, E., Cheu, R. L., & Sarkodie-Gyan, T. (2016). A binary decision model for discretionary lane changing move based on fuzzy inference system. Transportation Research Part C: Emerging Technologies, 67, 47-61.

Chen, P., Huang, Y., Mou, J., & van Gelder, P. H. A. J. M. (2019). Probabilistic risk analysis for ship-ship collision: State-of-the-art. Safety Science, 117, 108-122.

Erol, S., Demir, M., Çetişli, B., & Eyüboğlu, E. (2018). Analysis of Ship Accidents in the Istanbul Strait Using Neuro-Fuzzy and Genetically Optimised Fuzzy Classifiers. The Journal of Navigation, 71(2), 419-436.

Fang, Z., Yu, H., Ke, R., Shaw, S. L., & Peng, G. (2018). Automatic identification system-based approach for assessing the near-miss collision risk dynamics of ships in ports. IEEE Transactions on Intelligent Transportation Systems, (99), 1-10.

Goerlandt, F., Montewka, J., Kuzmin, V., & Kujala, P. (2015). A risk-informed ship collision alert system: framework and application. Safety science, 77, 182-204.

Hao, H., Ma, W., & Xu, H. (2016). A fuzzy logic-based multi-agent car-following model. Transportation Research Part C: Emerging Technologies, 69, 477-496.

Hansen, M. G., Jensen, T. K., Lehn-Schiøler, T., Melchild, K., Rasmussen, F. M., & Ennemark, F. (2013). Empirical ship domain based on AIS data. The Journal of Navigation, 66(6), 931-940.

He, Y., Jin, Y., Huang, L., Xiong, Y., Chen, P., & Mou, J. (2017). Quantitative analysis of COLREG rules and seamanship for autonomous collision avoidance at open sea. Ocean Engineering, 140, 281-291.

Huang, Y., van Gelder, P. H. A. J. M., & Wen, Y. (2018). Velocity obstacle algorithms for collision prevention at sea. Ocean Engineering, 151, 308-321.

Huang, Y., Chen, L., & van Gelder, P. H. A. J. M. (2019). Generalized velocity obstacle algorithm for preventing ship collisions at sea. Ocean Engineering, 173, 142-156.

Imprialou, M. I. M., Quddus, M., & Pitfield, D. E. (2014). High accuracy crash mapping using fuzzy logic. Transportation research part C: emerging technologies, 42, 107-120.

Kim, K. I., Jeong, J. S., & Lee, B. G. (2017). Study on the analysis of near-miss ship collisions using logistic regression. Journal of Advanced Computational Intelligence and Intelligent Informatics, 21(3), 467-473.

Li, S., Liu, J., & Negenborn, R. R. (2019). Distributed coordination for collision avoidance of multiple ships considering ship maneuverability. Ocean Engineering, 181, 212-226.

Lyu, H., & Yin, Y. (2019). COLREGS-constrained real-time path planning for autonomous ships using modified artificial potential fields. The Journal of Navigation, 72(3), 588-608.

Mou, J. M., Van Der Tak, C., & Ligteringen, H. (2010). Study on collision avoidance in busy waterways by using AIS data. Ocean Engineering, 37(5-6), 483-490.

Ozturk, U., & Cicek, K. (2019). Individual collision risk assessment in ship navigation: A systematic literature review. Ocean Engineering, 180, 130-143.

Perera, L. P., Ferrari, V., Santos, F. P., Hinostroza, M. A., & Guedes Soares, C. (2015). Experimental evaluations on ship autonomous navigation and collision avoidance by intelligent guidance. IEEE Journal of Oceanic Engineering, 40(2), 374-387.

Polvara, R., Sharma, S., Wan, J., Manning, A., & Sutton, R. (2018). Obstacle avoidance approaches for autonomous navigation of unmanned surface vehicles. The Journal of Navigation, 71(1), 241-256.

Qu, X., Meng, Q., & Suyi, L. (2011). Ship collision risk assessment for the Singapore Strait. Accident Analysis & Prevention, 43(6), 2030-2036.

Ramos, M. A., Utne, I. B., & Mosleh, A. (2019). Collision avoidance on maritime autonomous surface ships: operators' tasks and human failure events. Safety Science, 116, 33-44.

Sang, L. Z., Wall, A., Mao, Z., Yan, X. P., & Wang, J. (2015). A novel method for restoring the trajectory of the inland waterway ship by using AIS data. Ocean Engineering, 110, 183-194.

Shen, H., Hashimoto, H., Matsuda, A., Taniguchi, Y., Terada, D., & Guo, C. (2019). Automatic collision avoidance of multiple ships based on deep Q-learning. Applied Ocean Research, 86, 268-288.

Silveira, P. A. M., Teixeira, A. P., & Soares, C. G. (2013). Use of AIS data to characterise marine traffic patterns and ship collision risk off the coast of Portugal. The Journal of Navigation, 66(6), 879-898.

Statheros, T., Howells, G., & Maier, K. M. (2008). Autonomous ship collision avoidance navigation concepts, technologies and techniques. The Journal of Navigation, 61(1), 129-142.

Szlapczynski, R., and Szlapczynska, J. (2017). Review of ship safety domains: Models and applications. Ocean Engineering, 145, 277-289.

Thieme, C. A., Utne, I. B., & Haugen, S. (2018). Assessing ship risk model applicability to Marine Autonomous Surface Ships. Ocean Engineering.

Tu, E., Zhang, G., Rachmawati, L., Rajabally, E., & Huang, G. B. (2018). Exploiting AIS data for intelligent maritime navigation: a comprehensive survey from data to methodology. IEEE Transactions on Intelligent Transportation Systems, 19(5), 1559-1582.

Wang, Y., Zhang, J., Chen, X., Chu, X., & Yan, X. (2013). A spatial–temporal forensic analysis for inland–water ship collisions using AIS data. Safety science, 57, 187-202.

Wang, N., Meng, X., Xu, Q., and Wang, Z. (2009). A unified analytical framework for ship domains. The Journal of Navigation, 62(4), 643-655.

Wang, J., Wu, J., Zheng, X., Ni, D., & Li, K. (2016). Driving safety field theory modeling and its application in pre-collision warning system. Transportation research part C: emerging technologies, 72, 306-324.

Wang, J., Wu, J., & Li, Y. (2015). The driving safety field based on driver–vehicle–road interactions. IEEE Transactions on Intelligent Transportation Systems, 16(4), 2203-2214.

Wróbel, K., Montewka, J., & Kujala, P. (2017). Towards the assessment of potential impact of unmanned vessels on maritime transportation safety. Reliability Engineering & System Safety, 165, 155-169.

Wróbel, K., Montewka, J., & Kujala, P. (2018a). Towards the development of a system-theoretic model for safety assessment of autonomous merchant vessels. Reliability Engineering & System Safety, 178, 209-224.

Wróbel, K., Montewka, J., & Kujala, P. (2018b). System-theoretic approach to safety of remotely-controlled merchant vessel. Ocean Engineering, 152, 334-345.

Wu, B., Yan, X., Wang, Y., & Guedes Soares, C. (2016). Selection of maritime safety control options for NUC ships using a hybrid group decision-making approach. Safety science, 88, 108-122.

Wu, B., Yan, X., Yip, T.L., Wang, Y. (2017). A flexible decision-support solution for intervention measures of grounded ships in the Yangtze River. Ocean Engineering, 141, 237-248.

Wu, B., Yip, T. L., Xie, L., & Wang, Y. (2018a). A fuzzy-MADM based approach for site selection of offshore wind farm in busy waterways in China. Ocean Engineering, 168, 121-132.
Wu, B., Zong, L., Yan, X., & Guedes Soares, C. (2018b). Incorporating evidential reasoning and TOPSIS into group decision-making under uncertainty for handling ship without command. Ocean Engineering, 164, 590-603.
Wu, X., Rahman, A., & Zaloom, V. A. (2018). Study of travel behavior of vessels in narrow waterways using AIS data–A case study in Sabine-Neches Waterways. Ocean Engineering, 147, 399-413.
Wu, B., Tian, H., Yan, X., & Guedes Soares, C. (2019). A probabilistic consequence estimation model for collision accidents in the downstream of Yangtze River using Bayesian Networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 1748006X19825706.
Xiao, F., Ligteringen, H., Van Gulijk, C., & Ale, B. (2015). Comparison study on AIS data of ship traffic behavior. Ocean Engineering, 95, 84-93.
Xue, J., Wu, C., Chen, Z., Van Gelder, P. H. A. J. M., & Yan, X. (2019). Modeling human-like decision-making for inbound smart ships based on fuzzy decision trees. Expert Systems with Applications, 115, 172-188.
Zaman, M. B., Kobayashi, E., Wakabayashi, N., Khanfir, S., Pitana, T., & Maimun, A. (2014). Fuzzy FMEA model for risk evaluation of ship collisions in the Malacca Strait: based on AIS data. Journal of Simulation, 8(1), 91-104.
Zhang, W., Kopca, C., Tang, J., Ma, D., & Wang, Y. (2017). A Systematic Approach for Collision Risk Analysis based on AIS Data. The Journal of Navigation, 70(5), 1117-1132.
Zhang, J., Zhang, D., Yan, X., Haugen, S., & Soares, C. G. (2015). A distributed anti-collision decision support formulation in multi-ship encounter situations under COLREGs. Ocean Engineering, 105, 336-348.
Zhang, W., Goerlandt, F., Kujala, P., & Wang, Y. (2016). An advanced method for detecting possible near miss ship collisions from AIS data. Ocean Engineering, 124, 141-156.
Zhang, L., Meng, Q., Xiao, Z., & Fu, X. (2018). A novel ship trajectory reconstruction approach using AIS data. Ocean Engineering, 159, 165-174.