

Received November 12, 2020, accepted December 16, 2020, date of publication January 5, 2021, date of current version January 13, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3049238

Collision Risk Inference System for Maritime Autonomous Surface Ships Using COLREGs Rules Compliant Collision Avoidance

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This work was supported in part by the Basic Science Research Program through the National Research Foundation of Korea (NRF) by the Ministry of Education under Grant 2020R111A1A01060533, and in part by the National Research Foundation of Korea (NRF) Grant funded by the Korean Government (MSIT) under Grant NRF-2019RG1A1098184.

ABSTRACT Maritime autonomous surface ships (MASS) need to be sufficiently safe to gain commercial acceptance. Collision avoidance strategies in such MASS should comply with the International Regulations for Preventing Collision at the Sea (COLREGs). According to the COLREGs, collision risk assessment, which determines the optimal positioning and timing via all available means appropriate to the prevailing circumstances and conditions, is crucial for preventing collisions. However, existing collision risk assessment methods do not consider all vital factors for the COLREGs rules compliant collision avoidance. We propose a collision risk inference system for MASS that complies with COLREGs vital rules for collision avoidance as follows: 1) actions to avoid collision are defined according to the degree of danger, and a suitable response distance is determined; 2) a collision risk index according to the enlarged ship domain based on the designated response distance by each level is set; 3) all vital factors of the COLREGs rules compliant collision avoidance are extracted as the data when the ship domain enlarged by each level is overlapped; 4) the collision risk inference system is developed by learning extracted data via the adaptive neuro fuzzy inference system. In contrast to existing research, the proposed system considers all vital variables in the COLREGs rules compliant collision avoidance guidelines, thereby improving the timings and positionings of the potential collision warning. Consequently, it could secure more time for decision making to take necessary collision prevention action.

INDEX TERMS Adaptive neuro fuzzy inference system, collision avoidance, collision risk inference system, COLREGs, maritime autonomous surface ships, near-collision accident, ship domain.

I. INTRODUCTION

Maritime autonomous surface ships (MASS) have continued to expand their scope from military purposes to commercial use. These developments have been made possible because of wireless communication technology advancements, enabling the transmission and reception of data over thousands of nautical miles. The international maritime organization (IMO) defines a MASS as “a ship which, to a varying degree, can operate independently of human interaction,” and divides MASS autonomy levels [1] into four degrees as follows:

The associate editor coordinating the review of this manuscript and approving it for publication was P. Venkata Krishna¹.

- 1) **Degree one:** Ship with automated processes and decision support.
- 2) **Degree two:** Remotely controlled ship with seafarers on board.
- 3) **Degree three:** Remotely controlled ship without seafarers on board.
- 4) **Degree four:** Fully autonomous ship.

In Korea, there are plans to develop 1,700 TEU container ships with degree three MASS autonomy for ocean navigation and degree two MASS autonomy for coastal navigation from 2020 to 2025. Various MASS are being developed in different locations, such as the European Union, Norway, Japan, and China, and preventing collision accidents between vessels is essential to successfully accomplish their purpose

at sea. According to a statistical investigation presented by the Korean Maritime Safety Tribunal (KMST) [2], over the past five years approximately 95% of all collision accidents in Korea were due to operation negligence such as failure to comply with general principles of navigation and International Regulations for Preventing Collision at the Sea (COLREGs) [3].

COLREGs rules consist of five parts, A–E, covering different areas. Part B is the most relevant as it consists of sailing rules. Within part B, rules 5, 7, 8, and 13–17 are the most important for satisfactory performance of MASS in collision avoidance situations. Because the COLREGs rules can produce various interpretations, “A Guide to the Collision Avoidance Rules” [4] has been compiled to comprehensively interpret key rules through various precedents and expert discussions to ensure proper action for collision avoidance between vessels. Therefore, in this study, the process of collision avoidance between vessels was based on the said guide, as shown in Fig. 1.

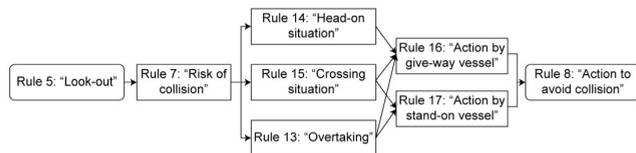


FIGURE 1. Process of collision avoidance between vessels.

Action to avoid collision starts from the collision risk assessment. First, every vessel shall, at all times, maintain a proper look-out using all available means to assess the collision risk. Radar plotting is a suitable method to obtain an early warning or a collision risk from observation of detected objects, and such risk is deemed to exist if the compass bearing of an approaching vessel does not appreciably change. Second, the encounter situation (i.e., head-on, crossing, or overtaking) is determined if a collision risk exists. Third, the give-way and stand-on vessels are determined according to the encounter situation. Fourth, actions to avoid collision are taken.

The ship domain was initially utilized to assess the collision risk between vessels. The concept of ship domain was introduced by Fujii and Tanaka [5]. Subsequently, ship domains of various shapes and sizes [6]–[16] were developed considering the COLREGs rules compliant collision avoidance, speeds of the Own-Ship (OS) and Target-Ship (TS), and margin of the relative distance between the OS and TS. The ship domain can be largely divided into three types: elliptical, circular, and polygonal, as shown in Fig. 2. Subsequently, the collision risk index (CRI), which integrates both spatial and temporal factors in real time into a single number via the Automatic Radar Plotting Aid and Automatic Identification System (AIS), was developed. CRI is very flexible and is not limited by geometrical shapes, such as the ship domain [17]. Methods that adopt the CRI [18]–[28] employ algebraic expression and fuzzy logic, as shown in Fig. 2.

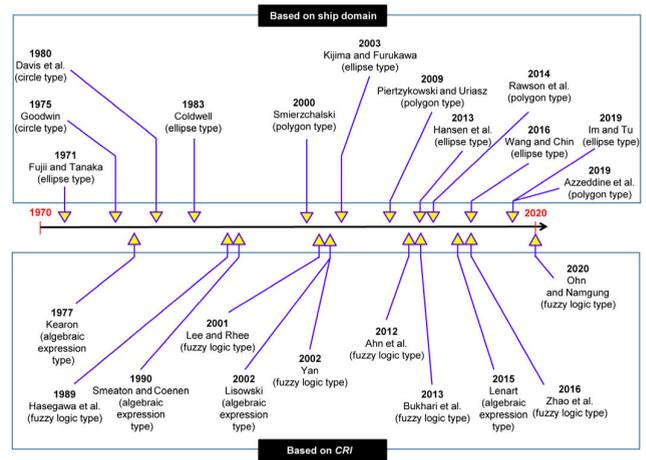


FIGURE 2. Development timeline of collision risk assessment.

The characteristics of the collision risk assessment methods using the ship domain and CRI are compared and analyzed in Table A1. The collision risk assessment methods proposed by Hasegawa *et al.* [19], Lee and Rhee [21], Ahn *et al.* [24], and Ohn and Namgung [28] not only comply with the COLREGs rules, but simultaneously assess the collision risk when multi-vessels are approaching. However, their proposed methods do not consider the variance of the compass bearing degree (VCD) according to “Rule 7(b)(i).” According to [4], the VCD is not only important for detection of the collision risk faster than other factors, but also for indication of the initial effectiveness of the avoiding action. Although the collision risk assessment method proposed by Bukhari *et al.* [25] reflects the VCD as the input variable, it was developed from the vessel traffic system (VTS) operator’s viewpoint, without considering the COLREGs rules compliant collision avoidance strategies.

This paper proposes a collision risk inference system using IF-THEN fuzzy rules based on the COLREGs rules compliant collision avoidance for MASS to avoid collision at optimal positioning and timing. The study applies system development approaches, to MASS developed in Korea, based on ship near-collision accident data without any intervention from the navigator. This study has two parts: First, vital ship domain factors based on the COLREGs rules compliant collision avoidance from the near-collision accident between vessels were extracted as data. Second, the extracted data were learned via the adaptive neuro fuzzy inference system (ANFIS) [29] to generate IF-THEN fuzzy rules for the given input–output dataset.

The remainder of this paper is organized as follows: the necessary background theory is presented in Section II. The collision risk inference system for MASS based on the COLREGs rules compliant collision avoidance, ship domain, near-collision accident, and ANFIS, developed with the use of MATLAB, are outlined in Section III. In Section IV, the results of computational simulations using MATLAB and discussions are presented. Finally, conclusions are drawn in Section V.

II. THEORETICAL BACKGROUND

A. COLREGs RULES COMPLIANT COLLISION AVOIDANCE

At sea, vessel maneuvers must be logical for the surrounding vessels. Because odd actions could lead to the surrounding vessels being uncertain about the navigational initiations, all maneuvers between vessels must be clear and precise. Collisions could result from any of the following four situations: head-on, overtaking, crossing from the port, and crossing from starboard [3]. COLREGs rules are based on human judgment of situations. Therefore, there are few specific regulations in place to decide which COLREGs situation applies at a certain time. The rules contain one boundary condition (Rule 13(b)), which mentions that a vessel is in an overtaking situation if it comes up with another vessel from a direction more than 22.5° from the beam of the second vessel, as illustrated in Fig. 3.

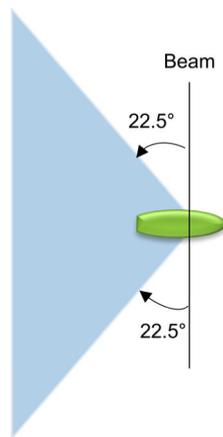


FIGURE 3. COLREGs rules defining an overtaking situation.

The remaining boundaries are decided according to [4], as shown in Fig. 4. The relative bearing angle β between the MASS and TS is calculated as

$$\beta = \tan^{-1} 2(y_{MASS} - y_{TS}, x_{MASS} - x_{TS}) - \phi_{TS} \quad (1)$$

where the position of MASS is given as (x_{MASS}, y_{MASS}) ; and position and course of TS are given as (x_{TS}, y_{TS}) , and ϕ_{TS} , respectively.

Based on the COLREGs rules, the actions in different situations are as follows:

- **Head-on:** Both vessels should take action to avoid collision by altering the course to the starboard.
- **Overtaking:** The vessel being overtaken should maintain a steady course and speed. COLREGs Rule 13 allows the overtaking vessel to pass the other vessel from both sides.
- **Crossing:** When crossing from either port or starboard, the vessel having the other vessel on its starboard side is the give-way vessel and should alter course such that it passes behind the other vessel. The other vessel (i.e., stand-on vessel) should maintain a steady course and speed. However, the stand-on vessel shall take action

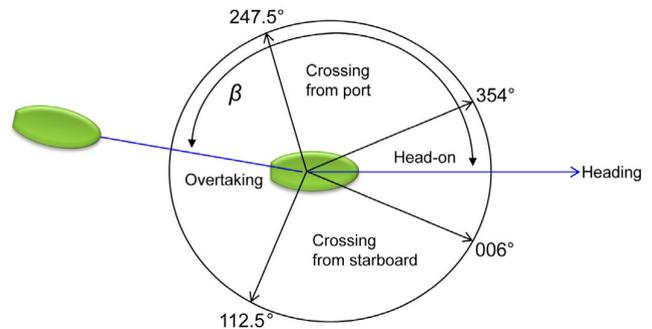


FIGURE 4. Boundaries for the different COLREGs situations.

to avoid collision if the give-way vessel does not take appropriate action or cannot avoid the collision despite the action.

B. CLOSEST POINT OF APPROACH

The closest point of approach (CPA) is the point where the OS is closest to TS at any time and can be used to measure CRI [18]–[28]. CPA has two components: D_{CPA} , which is the distance to CPA, and T_{CPA} , which is the time to CPA. As shown in Fig. 5, D_{CPA} and T_{CPA} can be obtained by geometric calculation of the vessel collision avoidance conditions.

Given the coordinate, course, and velocity of MASS and TS as (x_{MASS}, y_{MASS}) , ϕ_{MASS} , and V_{MASS} , and (x_{TS}, y_{TS}) , ϕ_{TS} , and V_{TS} , respectively, the relative moving variables are calculated as

$$D_r = \sqrt{(x_{TS} - x_{MASS})^2 + (y_{TS} - y_{MASS})^2} \quad (2)$$

$$V_r = V_{MASS} \times \sqrt{1 + \left(\frac{V_{TS}}{V_{MASS}}\right)^2 - 2 \times \frac{V_{TS}}{V_{MASS}} \times \cos(\phi_{MASS} - \phi_{TS})} \quad (3)$$

$$\phi_r = \cos^{-1} \left(\frac{V_{MASS} - V_{TS} \times \cos(\phi_{MASS} - \phi_{TS})}{V_r} \right) \quad (4)$$

$$D_{CPA} = D_r \times \sin(\phi_r - \alpha_t - \pi) \quad (5)$$

$$T_{CPA} = D_r \times \cos(\phi_r - \alpha_t - \pi) / V_r \quad (6)$$

where D_r is the relative distance between the MASS and TS, V_r is the relative velocity, ϕ_r is the relative course, α_t is the azimuth of TS, and α_r is the relative bearing. VCD is then calculated as

$$VCD_i = |\alpha_{r_i} - \alpha_{r_{i-1}}| \quad (7)$$

where i denotes the current time.

C. NEAR-COLLISION ACCIDENT

A near-collision accident means that no collision has occurred between the two vessels that pass each other in a close state. This study considers the decision of the near-collision accident, as obtained from the collision risk assessment criteria [30]–[32] when ship domains of MASS and TS are

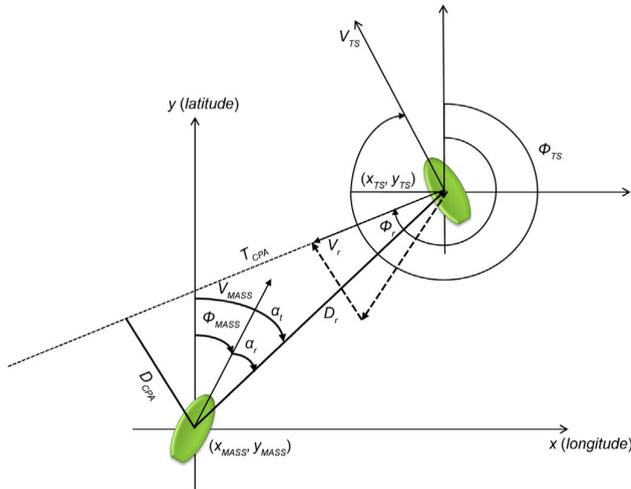


FIGURE 5. Closest point of approach.

overlapping [17], as shown in Fig. 6. However, it is necessary to select the size and shape of the ship domain most suitable for MASS operation. According to [12], based on the AIS maritime traffic data, which can be widely applied to assess the collision risk between vessels due to an automated history tracking record, from Danish waters, the ship domains most suitable for vessel operation were identified as a long radius (a) of $4L$ and short radius (b) of $1.6L$ (L is the vessel length) proposed in [5], as shown in Fig. 6.

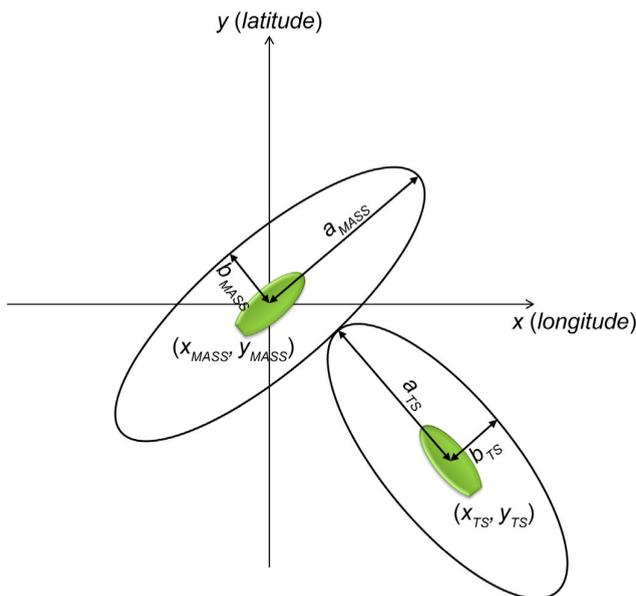


FIGURE 6. Ship domain with elliptical dimension.

However, the ship domain proposed by [5] reflects only the vessel length as the variable. It thus created a ship domain of a static shape regardless of the velocity change [17]. The ship domain proposed by [16] considered the vessel's length and velocity changes for maneuvering the vessel based on the IMO standard. a , and b were set at $1L$, and $0.2L$ at 0 kt,

and $4L$ and $2.25L$ at 10 kt, respectively. It was identified that the ship domain proposed in [16] at 10 kt is similar to that proposed in [5]. This study thus defines the ship domain according to the MASS's length and velocity change per 0.1 kt by utilizing [5], and [16] via the proportional expression, calculated as

$$a_{MASS} = \begin{cases} 8L - \left(\frac{(V_{10kt} - V_{MASS}) \times 0.06}{0.1kt} \right) & \text{if } V_{MASS} \leq V_{10kt} \\ \frac{2}{2} & \\ 8L + \left(\frac{(V_{MASS} - V_{10kt}) \times 0.06}{0.1kt} \right) & \text{if } V_{MASS} \gg V_{10kt} \end{cases} \quad (8)$$

$$b_{MASS} = \begin{cases} 3.2L - \left(\frac{(V_{10kt} - V_{MASS}) \times 0.028}{0.1kt} \right) & \\ \frac{2}{2} & \text{if } V_{MASS} \leq V_{10kt} \\ 3.2L + \left(\frac{(V_{MASS} - V_{10kt}) \times 0.028}{0.1kt} \right) & \\ \frac{2}{2} & \text{if } V_{MASS} \gg V_{10kt} \end{cases} \quad (9)$$

where V_{10kt} is 10 kt; Similarly, a_{TS} and b_{TS} can be calculated as in (8) and (9) by replacing V_{MASS} with V_{TS} .

III. COLLISION RISK INFERENCE SYSTEM USING IF-THEN FUZZY RULES

A. PROCESS OF SYSTEM DEVELOPMENT

Development of a collision risk inference system using IF-THEN fuzzy rules based on the COLREGs rules compliant collision avoidance, as shown in Fig. 7, can be divided as follows: conceptualization, data collection, and system development. In the conceptualization stage, the definition of the COLREGs rules compliant collision avoidance, determination of the suitable response distance, and setting of CRI via enlargement of the ship domain are conducted for each level. In the data collection stage, all vital factors of the COLREGs rules compliant collision avoidance are extracted from the near-collision accidents via the AIS maritime traffic data. Finally, in the system development stage, the system is developed by learning the input-output dataset divided from the near-collision accident data via the ANFIS.

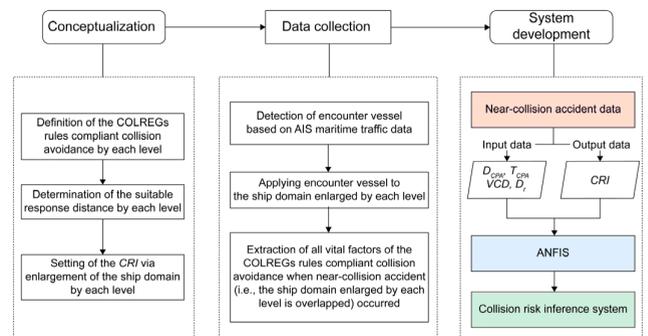


FIGURE 7. Development process of collision risk inference system.

B. CONCEPTUALIZATION

1) DEFINITION BY LEVEL

Based on the action of the give-way and stand-on vessels according to [3], [4], the COLREGs rules compliant collision avoidance by each level is defined as shown in Table 1.

TABLE 1. COLREGs rules compliant collision avoidance by each level.

Level	Definition
Collision	● Both vessels have a collision
Danger	● Both vessels are required to take such action that will best aid avoidance of a collision
Threat	● Stand-on vessel is permitted to take action to avoid a collision
Attention	● Give-way vessel is required to take early and substantial action to achieve a safe passing distance
	● Stand-on vessel must keep her course and speed

2) DETERMINATION OF A SUITABLE DISTANCE

In [4], a close quarters situation, which begins the collision risk between vessels, is defined as approximately 3 nm according to the COLREGs rule 22 [3]. At this time, the give-way vessel is required to take early action to avoid collision, and the stand-on vessel must maintain its course and speed. However, if it becomes apparent that the give-way vessel is not taking appropriate action within approximately 2 nm, the stand-on vessel is permitted to take action to avoid collision by its maneuver alone. In a case where the collision cannot be avoided by the give-way vessel alone until approximately 1 nm, the stand-on vessel is required to take such action as will best aid collision avoidance.

Table 2 summarizes the collision accident status according to the first recognition distance compiled by the KMST in 2019 [2].

TABLE 2. Status by collision accident according to first recognition distance in 2019.

Less than 1 nm	1–2 nm	2–5 nm	More than 5 nm	Undetected vessel	Total
10 (7.8%)	53 (41%)	6 (4.7%)	1 (0.8%)	59 (45.7%)	129

The suitable response distance by level, as designated by [4] and Table 2, is listed in Table 3. In the attention level, a distance of 3 NM is applied as the time the collision risk begins between the vessels. In the threat level, where the distance between the two vessels reduces to 2 NM, the stand-on vessel is allowed to take action to avoid collision by observing the action of the give-way vessel. In the danger level, where the distance between the vessels drops to within 1 NM, the give-way vessel applies action that will best aid collision avoidance between the vessels. In the collision level, the response distance is not defined because collision is inevitable.

3) SETTING OF CRI VIA SHIP DOMAIN

The ship domain was enlarged by the designated response distance of each level from the collision to attention levels, and CRI was set according to the enlarged ship domain in each level. The standard ship domains, i.e., the ship domain in the collision level, was determined using (8) and (9). The length of the MASS to be developed in Korea was set as 172 m [33] based on the length of 1,700 TEU container ships currently in operation at sea, and that of the TS was set as the length of the ship operating at actual sea. Thus, the enlarged ship domain for each level considering the length of the MASS and TS is calculated as

$$\alpha = \frac{1,852m}{(172m + L_{TS})} \tag{10}$$

$$\beta = \frac{3,704m}{(172m + L_{TS})} \tag{11}$$

$$\gamma = \frac{5,556m}{(172m + L_{TS})} \tag{12}$$

where L_{TS} is the length of TS; and α, β, γ are the weights for creating the ship domain in the danger, threat, and attention levels, respectively.

Accordingly, the enlarged ship domain corresponding to the designated response distance of each level was set, as shown in Table 3. The greater the length of the TS and velocity of both vessels, the greater the ship domain can enlarge beyond the collision and danger levels to the threat level. This study thus considered the collision step when the above occurred.

Next, the CRI was set as the point in time for taking action to avoid collision according to the designated level’s response distance. The CRI ranges from 0.00 to 1.00, as shown in Table 3. In the attention and threat levels, CRI was set as 0.01 and 0.33 to avoid collision by the give-way and stand-on vessels, respectively. CRI in the danger level was set as 0.66 to avoid collision by both vessels via the best cooperation. The collision level has a CRI of 1.00 due to the occurrence of a collision.

C. DATA COLLECTION

Close navigation involving several small and medium-sized cargo ships, coastal ferries, and fishing boats often occurs in the Mokpo sea area. Hence, this area was used to collect all vital factors in the COLREGs rules compliant collision avoidance. The blue lines in Fig. 8 show the ship trajectory obtained via the AIS maritime traffic data in this area.

Over the course of 10 days—from 00:00 of July 1, 2019 to 24:00 on July 10, 2019—a total of 1,591 ships were identified. Among them, 976 cases of encounter situations occurred, of which 493 cases occurred as a result of identifying near-collisions by establishing ship domains in the collision level, which defined ship-to-ship conflicts. Thus, a total of 1,972 cases were extracted as the input–output dataset (the input data consisted of D_{CPA}, T_{CPA}, VCD , and D_r , whereas CRI formed the output data) when overlapping

TABLE 3. Range of relative distance, ship domain, and CRI by level.

Division	Collision	Danger	Threat	Attention	
D_r	-	Collision $< nm \leq 1.00$	$1.00 < nm \leq 2.00$	$2.00 < nm \leq 3.00$	
Ship domain	MASS	$2a_{MASS} \times 2b_{MASS}$	$2\alpha \times \left(\frac{\alpha}{a_{MASS}} \times 2b_{MASS} \right)$	$2\beta \times \left(\frac{\beta}{a_{MASS}} \times 2b_{MASS} \right)$	$2\gamma \times \left(\frac{\gamma}{a_{MASS}} \times 2b_{MASS} \right)$
	TS	$2a_{TS} \times 2b_{TS}$	$2\alpha \times \left(\frac{\alpha}{a_{TS}} \times 2b_{TS} \right)$	$2\beta \times \left(\frac{\beta}{a_{TS}} \times 2b_{TS} \right)$	$2\gamma \times \left(\frac{\gamma}{a_{TS}} \times 2b_{TS} \right)$
CRI	1.00	$0.66 \leq CRI < 1.00$	$0.33 \leq CRI < 0.66$	$0.01 \leq CRI < 0.33$	

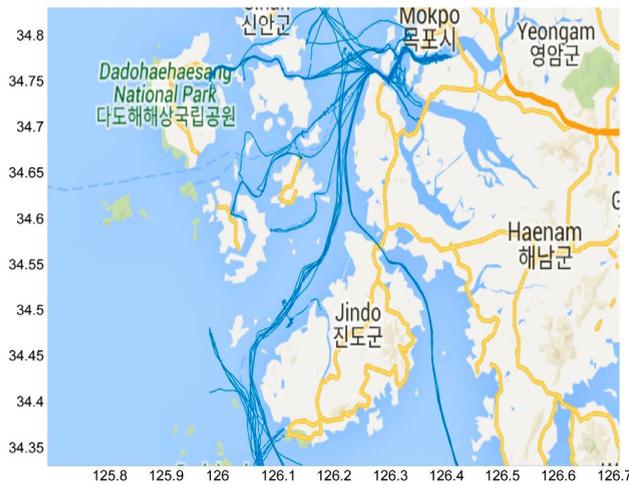


FIGURE 8. Ship trajectory extracted from the AIS maritime traffic data at the Mokpo sea area.

according to the enlarged ship domain based on the collision level, as shown in Fig. 9.

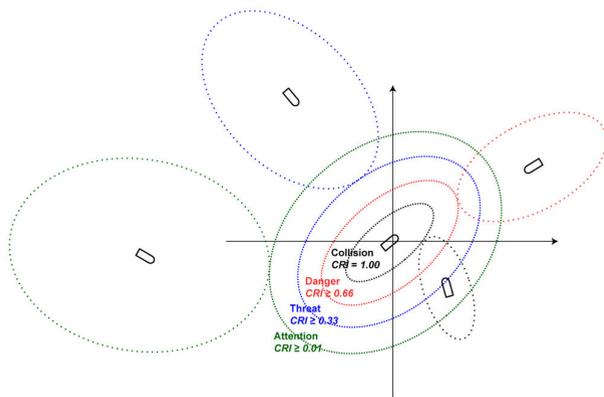


FIGURE 9. Overlapping situations of the ship domain by levels.

Because the VCD did not change significantly during near-collision accidents, VCD with changes in NM, as presented in Table 4, is applied according to [4].

In [4], the give-way vessel shall pass the stand-on vessel with the least 1 NM of a safe passing distance. For example,

TABLE 4. VCD with changes in NM.

D_{CPA}	1 NM	2 NM	3 NM
0.25 NM	7.3° (From 2NM to 1NM)	2.4° (From 3NM to 2NM)	
0.50 NM	15.5° (From 2NM to 1NM)	4.9° (From 3NM to 2NM)	
0.75 NM	26.6° (From 2NM to 1NM)	7.5° (From 3NM to 2NM)	
1.00 NM	60.0° (From 2NM to 1NM)	10.5° (From 3NM to 2NM)	

for D_{CPA} of 1.00 NM, VCD from 3 NM to 1 NM is 70.5° according to Table 4. Thus, given an initial D_{CPA} of 0.00 NM between the MASS and TS with 3 NM, the level to obtain D_{CPA} of 1.00 NM was defined as the attention level. The collision level was defined to obtain D_{CPA} of 0.25 NM as the least safe passing distance between the MASS and TS to avoid a collision accident. The danger and threat levels were defined to obtain D_{CPA} of 0.50 and 0.75, respectively, to secure the safe passing distance. VCD of the attention, threat, danger, and collision levels were set as 70.5°, 34.1°, 20.4°, and 9.7°, respectively.

D. SYSTEM DEVELOPMENT

The development process of the collision risk inference system by learning the collected data via the ANFIS was as follows:

First, fuzzy rules were determined from the given input-output dataset:

$$\begin{aligned}
 & \text{Rule}_i : \\
 & \text{if } x_1 \text{ is } \mu(D_{CPA}) \\
 & \text{and } x_2 \text{ is } \mu(T_{CPA}) \\
 & \text{and } x_3 \text{ is } \mu(VCD) \\
 & \text{and } x_4 \text{ is } \mu(D_r) \\
 & \text{then } R_c \text{ is } f_i(x_1, x_2, x_3, x_4) \tag{13}
 \end{aligned}$$

where x_1, x_2, x_3, x_4 are the input variables of $D_{CPA}, T_{CPA}, VCD, D_r$; and $\mu(D_{CPA}), \mu(T_{CPA}), \mu(VCD), \mu(D_r)$ are the fuzzy sets of the input variables (i.e., antecedent variable), and R_c

or *CRI* is either a constant or a linear function of the input variable (i.e., consequent variable). $f_i(x_1, x_2, x_3, x_4)$ is a first-order polynomial proposed by the Sugeno fuzzy model [34], and is calculated as

$$f_i = k_{i,0} + k_{i,1} \times x_1 + k_{i,2} \times x_2 + k_{i,3} \times x_3 + k_{i,4} \times x_4 \quad (14)$$

Thus, 256 fuzzy rules with combinations of each membership function using the linguistic variables Collision (C), Danger (D), Threat (T), and Attention (A) were formed, as summarized in Table 5.

TABLE 5. Components of the fuzzy inference rules for the collision risk inference system.

$Rule_i$	D_{CPA}	T_{CPA}	VCD	D_r
$Rule_1$	Collision	Danger	Threat	Attention
$Rule_2$	Collision	Collision	Collision	Collision
$Rule_3$	Danger	Danger	Danger	Danger
$Rule_4$	Threat	Threat	Threat	Threat
$Rule_5$	Attention	Attention	Attention	Attention
\vdots	\vdots	\vdots	\vdots	\vdots
$Rule_{252}$	Collision	Threat	Danger	Collision
$Rule_{253}$	Collision	Threat	Danger	Danger
$Rule_{254}$	Danger	Danger	Threat	Threat
$Rule_{255}$	Threat	Attention	Attention	Attention
$Rule_{256}$	Danger	Collision	Attention	Danger

Second, learning by the ANFIS was done using a hybrid learning algorithm, which combines the least-squares estimators for the forward pass and error backpropagation based on the gradient descent for the backward pass [29]. Fig. 10 shows the ANFIS structure, consisting of a six-layer feedforward neural network for the collision risk inference system that corresponds to the first-order polynomial.

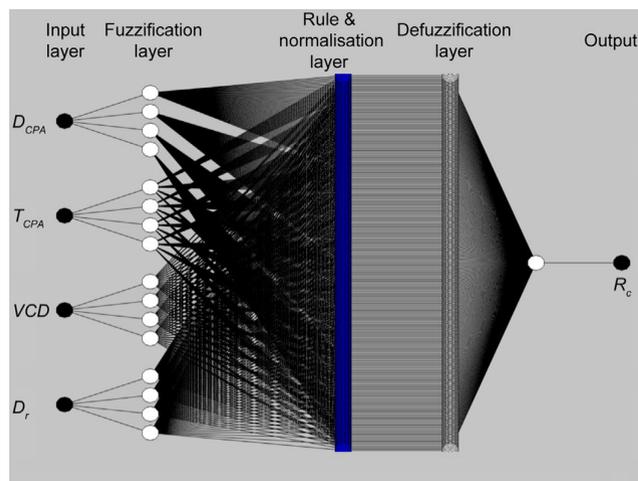


FIGURE 10. ANFIS structure for the collision risk inference system.

The computation of each layer is as follows:

- **Layer 1:** As the input layer, neurons pass the external crisp signals to Layer 2. That is,

$$R_c^{i(1)} = x_i^{(1)} \quad (15)$$

where $x_i^{(1)}$ is the input and $R_c^{i(1)}$ is the output of the input neuron i in Layer 1.

- **Layer 2:** As the fuzzification layer, neurons conduct fuzzification using a bell activation function. That is,

$$R_c^{i(2)} = \frac{1}{1 + \left(\frac{x_i^{(2)} - a_i}{c_i}\right)^{2b_i}} \quad (16)$$

where $x_i^{(2)}$ is the input and $R_c^{i(2)}$ is the output of the input neuron i in Layer 2; a_i , b_i , and c_i are the variables that control the center, width, and scope of the bell activation function of neuron i , respectively.

- **Layer 3:** In the rule layer, each neuron corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. In ANFIS, the conjunction of the rule antecedent is evaluated by the operator product. Thus, the output of neuron i in Layer 3 is obtained as

$$R_c^{i(3)} = \prod_{j=1}^k x_{ji}^{(3)} \quad (17)$$

where $x_i^{(3)}$ is the input and $R_c^{i(3)}$ is the output of the input neuron i in Layer 3.

- **Layer 4:** As the normalization layer, each neuron receives inputs from all neurons in the rule layer and is calculated by the normalized firing strength of a given rule. Thus, the output of neuron i in the normalization layer is obtained as

$$R_c^{i(4)} = \frac{x_{ji}^{(4)}}{\sum_{j=1}^n x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^n \mu_j} = \bar{\mu}_i \quad (18)$$

where $x_{ji}^{(4)}$ is the input from j located in the rule layer to neuron i in the normalization layer, and n is the total number of the rule neurons.

- **Layer 5:** At the defuzzification layer, each neuron is connected to the respective Layer 4 neurons and receives the initial inputs x_1, x_2, x_3 , and x_4 . The defuzzification neuron is calculated with the weighted consequent value of a given rule as

$$R_c^{i(5)} = x_i^{(5)} \times f_i = \bar{\mu}_i \times f_i \quad (19)$$

where $x_i^{(5)}$ is the input and $R_c^{i(5)}$ is the output of the defuzzification neuron i in the defuzzification layer.

- **Layer 6:** As a single summation neuron, the neuron calculates the sum of outputs of all defuzzification neurons

and produces the overall ANFIS output R_c .

$$R_c = \sum_{i=1}^n x_i^{(5)} \times f_i = \sum_{i=1}^n \bar{\mu}_i \times f_i \quad (20)$$

In the forward pass, input variables x_1, x_2, x_3 , and x_4 are presented to the ANFIS, the neuron outputs are calculated on a layer-by-layer basis, and output R_c is identified by the least-squares estimator. Because the output of the ANFIS follows a linear function according to the Sugeno-style fuzzy inference, a total of 256 linear equations were created in terms of the consequent variables as

$$\left\{ \begin{array}{l} R_c(1) = \bar{\mu}_1(1)[k_{1,0} + k_{1,1}x_1(1) + k_{1,2}x_2(1) \\ \quad + k_{1,3}x_3(1) + k_{1,4}x_4(1)] \\ \quad + \cdots + \bar{\mu}_{256}(1)[k_{256,0} + k_{256,1}x_1(1) + k_{256,2}x_2(1) \\ \quad + k_{256,3}x_3(1) + k_{256,4}x_4(1)] \\ \vdots \\ R_c(1, 972) = \bar{\mu}_1(1, 972)[k_{1,0} + k_{1,1}x_1(1, 972) \\ \quad + k_{1,2}x_2(1, 972) + k_{1,3}x_3(1, 972) \\ \quad + k_{1,4}x_4(1, 972)] \\ \quad + \cdots + \bar{\mu}_{256}(1, 972)[k_{256,0} + k_{256,1}x_1(1, 972) \\ \quad + k_{256,2}x_2(1, 972) + k_{256,3}x_3(1, 972) \\ \quad + k_{256,4}x_4(1, 972)] \end{array} \right. \quad (21)$$

(21) can be expressed in matrix form as

$$R_c(P) = Ak \quad (22)$$

where $R_c(P)$ is a $P \times 1$ desired output vector, A is a $P \times n(1+m)$ matrix, and k is an $n(1+m)$ vector of unknown consequent variables. Here, P is the number of input-output datasets, m is the number of input variables, and n is the number of neurons in Layer 3. Because P, m , and n are 1,972, 4, and 256, respectively, A is a $1,972 \times 1,280$ matrix and k is a 256×5 matrix. $R_c(P), A$, and k are obtained as (23)–(25), shown at the bottom of the page.

The least-squares estimator of k^* (i.e., k) should be found to minimize the squared error $\|R_c(P) - Ak\|^2$. k^* is obtained

using the pseudoinverse as

$$k^* = (A^T A)^{-1} A^T R_c(P) \quad (26)$$

where A^T is the transpose of A , and $(A^T A)^{-1} A^T$ is the pseudoinverse of A .

After assigning the rule consequent variables, the actual output vector R_c is calculated. Then, the error vector e is obtained as

$$e = R_c(P) - R_c \quad (27)$$

In the backward pass, the error signals are propagated back, and antecedent variables are updated according to the chain rule.

Consider the first neuron in Layer 2 to be denoted as A_1 . The correction applied to variable a in the bell activation function can be expressed as

$$\Delta a = -\alpha_l \frac{\partial E}{\partial a} = -\alpha_l \frac{\partial E}{\partial e} \times \frac{\partial e}{\partial y} \times \frac{\partial y}{\partial(\bar{\mu}_i f_i)} \times \frac{\partial(\bar{\mu}_i f_i)}{\partial \bar{\mu}_i} \times \frac{\partial \bar{\mu}_i}{\partial \mu_i} \times \frac{\partial \mu_i}{\partial \mu_{A1}} \times \frac{\partial \mu_{A1}}{\partial a} \quad (28)$$

where α_l is the learning rate, and E is the instantaneous value of the squared error for the ANFIS output neuron. E is expressed as

$$E = \frac{1}{2} e^2 = \frac{1}{2} (R_c(P) - R_c)^2 \quad (29)$$

Thus,

$$\Delta a = -\alpha_l (R_c(P) - R_c) (-1) f_i \times \frac{\bar{\mu}_i(1 - \bar{\mu}_i)}{\mu_i} \times \frac{\mu_i}{\mu_{A1}} \times \frac{\mu_{A1}}{\mu_a} \quad (30)$$

where

$$\begin{aligned} \frac{\partial \mu_{A1}}{\partial a} &= -\frac{1}{\left[1 + \left(\frac{x_1 - a}{c}\right)^{2b}\right]^2} \times \frac{1}{c^{2b}} \times 2b \times (x_1 - a)^{2b-1} \\ &\quad \times (-1) \\ &= \mu_{A1}^2 \times \frac{2b}{c} \times \left(\frac{x_1 - a}{c}\right)^{2b-1} \end{aligned} \quad (31)$$

Similarly, corrections applied to variables b and c can be obtained.

$$R_c(P) = \begin{bmatrix} R_c(1) \\ R_c(2) \\ R_c(3) \\ \vdots \\ R_c(1, 972) \end{bmatrix} \quad (23)$$

$$A = \begin{bmatrix} \bar{\mu}_1(1) & \cdots & \bar{\mu}_1(1)x_4(1) & \cdots & \bar{\mu}_{256}(1) & \cdots & \bar{\mu}_{256}(1)x_4(1) \\ \bar{\mu}_1(2) & \cdots & \bar{\mu}_1(2)x_4(2) & \cdots & \bar{\mu}_{256}(2) & \cdots & \bar{\mu}_{256}(2)x_4(2) \\ \vdots & & \vdots & & \vdots & & \vdots \\ \bar{\mu}_1(1, 972) & & \bar{\mu}_1(1, 972)x_4(1, 972) & & \bar{\mu}_{256}(1, 972) & & \bar{\mu}_{256}(1, 972)x_4(1, 972) \end{bmatrix} \quad (24)$$

$$k = [k_{1,0} k_{1,1} k_{1,2} k_{1,3} k_{1,4} \cdots k_{256,0} k_{256,1} k_{256,2} k_{256,3} k_{256,4}]^T \quad (25)$$

Of the 1,972 input–output datasets, 60% were selected for training, 20% for validation, and 20% for testing. The best validation performance was confirmed at epoch 9, as shown in Fig. 11.

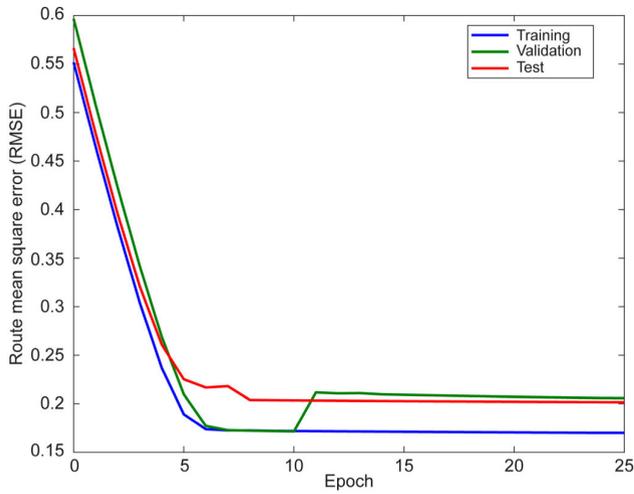


FIGURE 11. Validation and test performance for the collision risk inference system via the ANFIS.

As a result of learning the input–output dataset via the ANFIS, the developed collision risk inference system was determined by triangular membership functions, as shown in Fig. 12. The numerical range of the membership functions D_{CPA} , T_{CPA} , VCD , and D_r are $[0, 3.9]$, $[0, 34.3]$, $[9.7, 70.5]$, and $[0, 3]$, respectively.

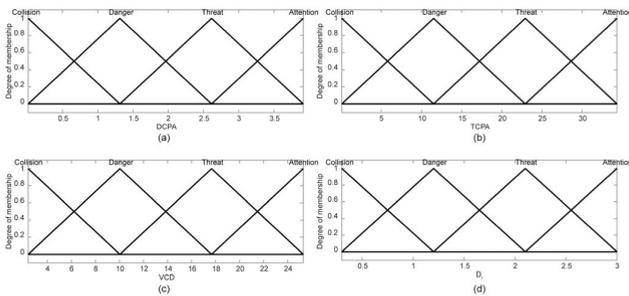


FIGURE 12. Fuzzy membership function of the collision risk inference system. (a) D_{CPA} , (b) T_{CPA} , (c) VCD , and (d) D_r .

D_{CPA} membership functions via linguistic variables Collision (C), Danger (D), Threat (T), and Attention (A) were determined as

$$\mu_C(D_{CPA}) = \begin{cases} 1, & \text{for } D_{CPA} \leq 0 \\ \frac{1.3 - D_{CPA}}{1.3}, & \text{for } 0 < D_{CPA} \leq 1.3; \\ \frac{D_{CPA} - 0}{2.6 - 1.3}, & \text{for } 1.3 < D_{CPA} \leq 2.6; \\ 0, & \text{for } D_{CPA} > 2.6 \end{cases}$$

$$\mu_D(D_{CPA}) = \begin{cases} \frac{D_{CPA} - 0}{1.3}, & \text{for } 0 < D_{CPA} \leq 1.3 \\ \frac{2.6 - D_{CPA}}{1.3}, & \text{for } 1.3 < D_{CPA} \leq 2.6; \\ 0, & \text{for } D_{CPA} > 2.6 \end{cases}$$

$$\mu_T(D_{CPA}) = \begin{cases} \frac{D_{CPA} - 1.3}{3.9 - 1.3}, & \text{for } 1.3 < D_{CPA} \leq 2.6 \\ \frac{1.3}{3.9 - D_{CPA}}, & \text{for } 2.6 < D_{CPA} \leq 3.9; \\ 0, & \text{for } D_{CPA} > 3.9 \end{cases}$$

$$\mu_A(D_{CPA}) = \begin{cases} \frac{D_{CPA} - 2.6}{1.3}, & \text{for } 2.6 < D_{CPA} \leq 3.9 \\ 0, & \text{for } 3.9 \leq D_{CPA} \end{cases} \quad (32)$$

T_{CPA} membership functions via linguistic variables Collision (C), Danger (D), Threat (T), and Attention (A) were determined as

$$\mu_C(T_{CPA}) = \begin{cases} 1, & \text{for } T_{CPA} \leq 0 \\ \frac{11.5 - T_{CPA}}{11.5}, & \text{for } 0 < T_{CPA} \leq 11.5; \\ 0, & \text{for } T_{CPA} > 11.5 \end{cases}$$

$$\mu_D(T_{CPA}) = \begin{cases} \frac{T_{CPA} - 0}{11.5}, & \text{for } 0 < T_{CPA} \leq 11.5 \\ \frac{22.9 - T_{CPA}}{11.4}, & \text{for } 11.5 < T_{CPA} \leq 22.9; \\ 0, & \text{for } T_{CPA} > 22.9 \end{cases}$$

$$\mu_T(T_{CPA}) = \begin{cases} \frac{T_{CPA} - 11.5}{34.3 - 11.5}, & \text{for } 11.5 < T_{CPA} \leq 22.9 \\ \frac{11.4}{34.3 - T_{CPA}}, & \text{for } 22.9 < T_{CPA} \leq 34.3; \\ 0, & \text{for } T_{CPA} > 34.3 \end{cases}$$

$$\mu_A(T_{CPA}) = \begin{cases} \frac{T_{CPA} - 22.9}{11.4}, & \text{for } 22.9 < T_{CPA} \leq 34.3 \\ 0, & \text{for } 34.3 \leq T_{CPA} \end{cases} \quad (33)$$

VCD membership functions via linguistic variables Collision (C), Danger (D), Threat (T), and Attention (A) were determined as

$$\mu_C(VCD) = \begin{cases} 1, & \text{for } VCD \leq 9.7 \\ \frac{30 - VCD}{20.3}, & \text{for } 9.7 < VCD \leq 30; \\ 0, & \text{for } VCD > 30 \end{cases}$$

$$\mu_D(VCD) = \begin{cases} \frac{VCD - 9.7}{50.2 - 9.7}, & \text{for } 9.7 < VCD \leq 30 \\ \frac{20.3}{50.2 - VCD}, & \text{for } 30 < VCD \leq 50.2; \\ 0, & \text{for } VCD > 50.2 \end{cases}$$

$$\mu_T(VCD) = \begin{cases} \frac{VCD - 30}{70.5 - 30}, & \text{for } 30 < VCD \leq 50.2 \\ \frac{20.2}{70.5 - VCD}, & \text{for } 50.2 < VCD \leq 70.5; \\ 0, & \text{for } VCD > 70.5 \end{cases}$$

$$\mu_A(VCD) = \begin{cases} \frac{VCD - 50.2}{20.3}, & \text{for } 50.2 < VCD \leq 70.5 \\ 0, & \text{for } 70.5 \leq VCD \end{cases} \quad (34)$$

D_r membership functions via linguistic variables Collision (C), Danger (D), Threat (T), and Attention (A) were determined as

$$\mu_C(D_r) = \begin{cases} 1, & \text{for } D_r \leq 0 \\ \frac{1.2 - D_r}{1.2}, & \text{for } 0 < D_r \leq 1.2; \\ 0, & \text{for } D_r > 1.2 \end{cases}$$

$$\mu_D(D_r) = \begin{cases} \frac{D_r - 0}{1.2}, & \text{for } 0 < D_r \leq 1.2 \\ \frac{2.1 - D_r}{0.9}, & \text{for } 1.2 < D_r \leq 2.1; \\ 0, & \text{for } D_r > 2.1 \end{cases}$$

$$\mu_{T(D_r)} = \begin{cases} \frac{D_r - 1.2}{0.9}, & \text{for } 1.2 < D_r \leq 2.1 \\ \frac{3.0 - D_r}{0.9}, & \text{for } 2.1 < D_r \leq 3.0; \end{cases}$$

$$\mu_{A(D_r)} = \begin{cases} \frac{D_r - 2.1}{0.9}, & \text{for } 2.1 < D_r \leq 3.0 \\ 0, & \text{for } 3.0 \leq D_r \end{cases} \quad (35)$$

Crisp output using the determined membership functions of the developed collision risk inference system can thus be obtained by the aggregation operation of a total of 256 rules. The weighted average function (WA, \hat{f}) [34] is thus given as (36), shown at the bottom of the next page.

IV. RESULTS AND DISCUSSION

A. NUMERICAL SIMULATION RESULTS

For the performance validation the developed fuzzy inference system based on near-collision (FIS-NC) was compared with the existing research in [21] and [27] by applying the near-collision accidents between vessels at actual navigation area, as shown in Fig. 13, and the results analyzed. At this time, the abovementioned existing research was utilized for the collision risk assessment of the MASS. The developed collision risk inference systems in [21] and [27] are denoted as the fuzzy inference system (FIS), and fuzzy comprehension evaluation (FCE), respectively.

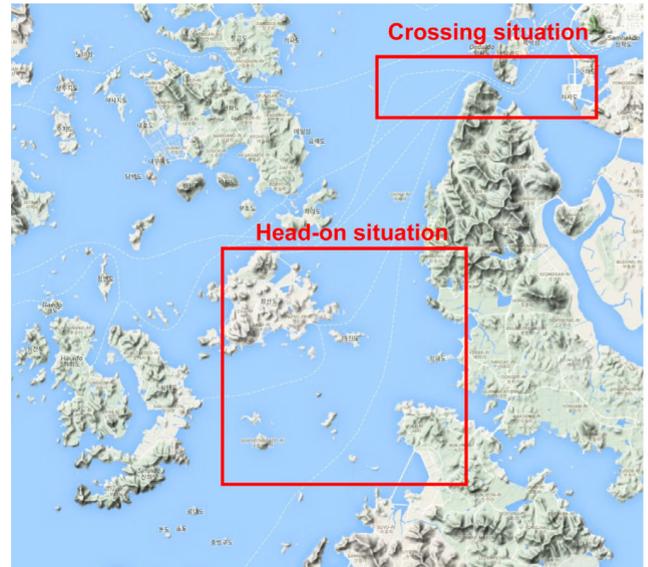


FIGURE 14. Near-collision accident occurrence area.

Table 6 presents the initial information of each vessel in head-on and crossing situations.

TABLE 6. Initial information in head-on and crossing situations.

Encounter situation	Vessel	Course	Velocity	Relative distance	Length
Head-on	MASS	217.4°	10.4 kt	9.85 nm	172 m
	Target-Ship	171.6°	7.5 kt	9.85 nm	192 m
Crossing	MASS	117.3°	7.3 kt	6.67 nm	172 m
	Target-Ship	049.5°	7.1 kt	6.67 nm	165 m

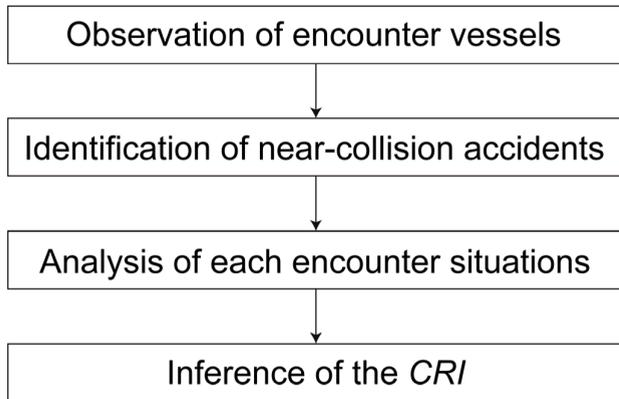


FIGURE 13. Process of performance validation.

First, the encounter vessels were observed from 00:00 on July 11, 2019, to 24:00 on July 11, 2019, using the AIS maritime traffic data of the Mokpo sea area. Second, the near-collision accidents were identified by applying the ship domain in the collision level to the encounter vessels. Third, any encounter situation was analyzed from a close quarter's situation to the near-collision accident. Finally, CRI was inferred for each encounter situation (i.e., head-on and crossing situations) by applying the corresponding input variables from the FIS-NC, FIS, and FCE to encounter vessels where the near-collision accident occurred.

Fig. 14 shows the area of the near-collision accident in the head-on and crossing situations between vessels. One of the two vessels is designated as the MASS to be developed in Korea, and the other was designated as TS.

1) HEAD-ON SITUATION

Fig. 15 shows the head-on situation between the MASS and TS. The inferred CRI when applying the FIS, FCE, and FIS-NC to MASS is presented in Table 7.

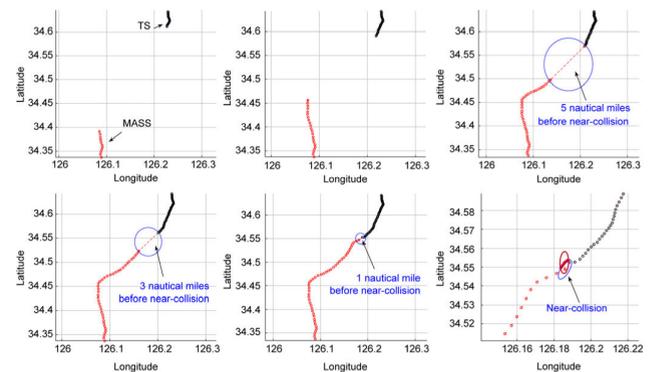


FIGURE 15. Head-on situation between MASS and TS.

In the initial encounter situation, the FIS, FCE, and FIS-NC inferred the CRI as 0.000, 0.478, and 0.000, respectively.

TABLE 7. Comparison results of inferred CRI in the head-on situation.

Time (s)	D_{CPA}	T_{CPA}	VCD	D_r	CRI		
					FIS	FCE	FIS-NC
0	0.21	35.62	-	9.85	0.000	0.478	0.000
90	0.28	33.12	1.2	9.38	0.000	0.464	0.000
180	1.73	31.92	0.0	8.90	0.000	0.513	0.000
270	2.17	32.65	2.2	8.47	0.000	0.468	0.000
360	0.83	33.11	6.5	8.10	0.000	0.467	0.000
450	0.54	33.61	7.8	7.70	0.000	0.463	0.000
540	0.68	30.85	0.3	7.29	0.000	0.470	0.000
630	0.38	28.31	0.5	6.92	0.000	0.464	0.000
720	0.39	24.59	0.3	6.46	0.000	0.495	0.000
810	0.03	22.36	0.4	6.02	0.177	0.492	0.000
900	0.25	20.91	2.8	5.57	0.156	0.509	0.000
990	0.51	19.16	0.2	5.15	0.150	0.483	0.000
1080	0.02	17.92	3.5	4.69	0.155	0.470	0.000
1170	0.16	16.55	1.7	4.28	0.250	0.469	0.008
1260	0.24	15.01	2.6	3.80	0.357	0.488	0.009
1350	0.27	13.54	4.6	3.39	0.461	0.465	0.011
1440	0.61	11.58	1.3	2.98	0.558	0.516	0.012
1530	0.76	9.53	1.4	2.56	0.686	0.483	0.170
1620	0.78	7.72	6.0	2.15	0.728	0.551	0.320
1710	0.74	6.02	3.2	1.76	0.818	0.483	0.470
1800	0.21	5.32	0.1	1.36	0.840	0.465	0.640
1890	0.18	3.34	0.0	0.91	0.940	0.464	0.840
1980	0.24	1.66	2.6	0.48	0.940	0.672	0.990
2070	0.21	0.24	0.4	0.22	0.940	0.938	1.000

When the near-collision accident occurred, CRI was inferred as 0.940, 0.938, and 1.000 by the FIS, FCE, and FIS-NC, respectively. In particular, FIS inferred the CRI as 0.940 at 0.91 NM to the near-collision accident. The measured point in time for collision avoidance of the give-way vessel using the FIS, FCE, and FIS-NC was more than the CRI of 0.6, 0.5, and 0.01, respectively, according to [21], [27], and Table 3. Therefore, from the point in time for collision avoidance of the give-way vessel to the near-collision accident, the remaining distance and time of the MASS using the FIS, FCE, and FIS-NC was 2.55 NM and 585 s, 8.68 NM and 1890 s, and 3.17 NM and 720 s, respectively.

2) CROSSING SITUATION

A crossing situation between the MASS and TS is shown in Fig. 16, and Table 8 presents the inferred CRI when applying the FIS-NC, FIS, and FCE to MASS.

The FIS, FCE, and FIS-NC inferred the CRI as 0.000, 0.512, and 0.000, respectively, at the initial encounter situation. At the near-collision accident, the CRI was inferred as 0.940, 0.989, and 1.000 by the FIS, FCE, and FIS-NC, respectively. Similar to the head-on situation, the FIS kept inferring the CRI as 0.940 from 0.61 NM to the near-collision accident. With MASS as the give-way vessel, from the point in time for collision avoidance of the give-way vessel to the near-collision accident, the remaining distance and time of the MASS using the FIS, FCE, and FIS-NC were 2.56 NM and 900 s, 6.56 NM and 2070 s, and 3.68 NM and 1260 s.

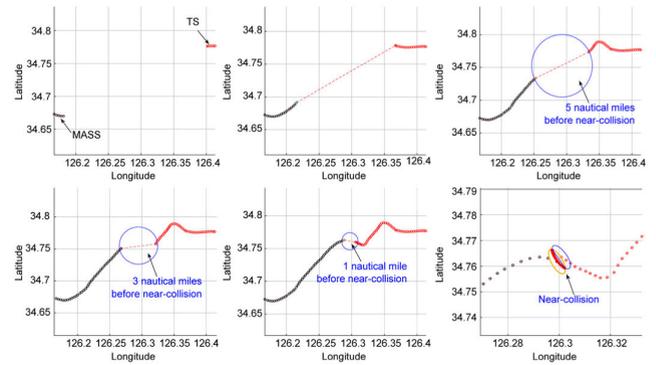


FIGURE 16. Crossing situation between MASS and TS.

TABLE 8. Comparison results of inferred CRI in the crossing situation.

Time (s)	D_{CPA}	T_{CPA}	VCD	D_r	CRI		
					FIS	FCE	FIS-NC
0	2.39	28.16	-	6.67	0.000	0.512	0.000
90	2.21	28.09	1.0	6.36	0.000	0.465	0.000
180	1.97	27.75	0.3	6.00	0.000	0.461	0.000
270	2.05	26.74	0.5	5.68	0.000	0.481	0.000
360	1.56	25.72	0.1	5.37	0.000	0.465	0.000
450	1.47	23.61	0.0	5.05	0.000	0.487	0.000
540	1.62	21.69	0.3	4.72	0.167	0.471	0.000
630	1.77	19.90	0.2	4.41	0.169	0.462	0.000
720	2.06	17.26	0.7	4.09	0.207	0.461	0.009
810	1.73	16.39	0.4	3.79	0.260	0.470	0.011
900	1.82	14.73	0.2	3.49	0.266	0.475	0.012
990	1.82	12.48	0.3	3.20	0.382	0.479	0.013
1080	2.04	9.91	0.3	2.93	0.547	0.490	0.034
1170	1.81	8.82	0.0	2.67	0.613	0.486	0.134
1260	1.44	9.11	0.0	2.39	0.651	0.543	0.236
1350	0.64	14.13	0.6	2.12	0.427	0.466	0.331
1440	0.57	12.23	0.0	1.88	0.524	0.462	0.409
1530	0.36	10.66	1.5	1.65	0.625	0.466	0.520
1620	0.34	8.78	0.3	1.41	0.723	0.563	0.625
1710	0.27	7.37	0.7	1.15	0.801	0.468	0.738
1800	0.21	5.41	0.6	0.89	0.836	0.464	0.850
1890	0.01	3.69	1.6	0.61	0.940	0.623	0.968
1980	0.09	2.00	0.9	0.35	0.940	0.891	0.999
2070	0.13	0.09	0.6	0.11	0.940	0.999	1.000

With respect to the point in time for collision avoidance of the stand-on vessel, the FIS and FIS-NC are more than the CRI of 0.8 and 0.33, respectively according to [21] and Table 3. The FCE does not set the point in time for collision avoidance of the stand-on vessel. Therefore, from the point in time for collision avoidance of the stand-on vessel to the near-collision accident, the remaining distance and time of the MASS using the FIS and FIS-NC are 1.04 NM and 360 s, and 2.01 NM and 720 s, respectively. When it comes to the best aid to avoid a collision, FIS-NC provided the best results of 1.17 NM and 405 s until the collision accident.

In particular, because T_{CPA} increased at 1350 s, the CRI inferred from the FIS and FCE decreased. In contrast, the CRI inferred from the FIS-NC increased because the VCD was in the range of the collision level. Hence, we identified that the VCD of the FIS-NC was appropriately utilized.

$$\hat{f} = \sum_{i=1}^{256} \frac{\mu(k_{i,1}) \times k_{i,1} + \mu(k_{i,2}) \times k_{i,2} + \mu(k_{i,3}) \times k_{i,3} + \mu(k_{i,4}) \times k_{i,4}}{\mu(k_{i,1}) + \mu(k_{i,2}) + \mu(k_{i,3}) + \mu(k_{i,4})} \quad (36)$$

B. DISCUSSION

In simulation results, the CRI was inferred for each encounter situation by applying the FIS-NC, FIS, and FCE to MASS. However, because each system inferred a different CRI at the same distance and time according to the numerical changes of the input variables, the response distance and time for collision avoidance of the give-way and stand-on vessels were all different. Therefore, the inferred results are discussed according to [4] to ensure that the point of positioning and timing to act for collision avoidance at the CRI inferred from each system are adequate for the give-way, and stand-on vessels. Fig. 17 presents the CRI inferred from each system in head-on and crossing situations according to encounter time of Tables 7 and 8.

With MASS as the give-way vessel in head-on and crossing situations, the FCE and FIS-NC recommended taking action for collision avoidance before the close quarters' situation (i.e., approximately 3 NM). With MASS as the stand-on vessel in a crossing situation, the FIS and FIS-NC recommended collision avoidance action as soon as the TS did not take appropriate action. However, the recommendation of the FIS was 0.97 NM later than the recommendation of the FIS-NC. With respect to the best aid to avoid a collision in a crossing situation, the FIS-NC recommended counter-action at 0.28 NM ahead of the required distance of 1 NM. Thus, the early warning provides sufficient time and distance to take action for collision avoidance. Hence, MASS using the FIS-NC could take action for collision avoidance at an appropriate positioning point and time in any situation via the

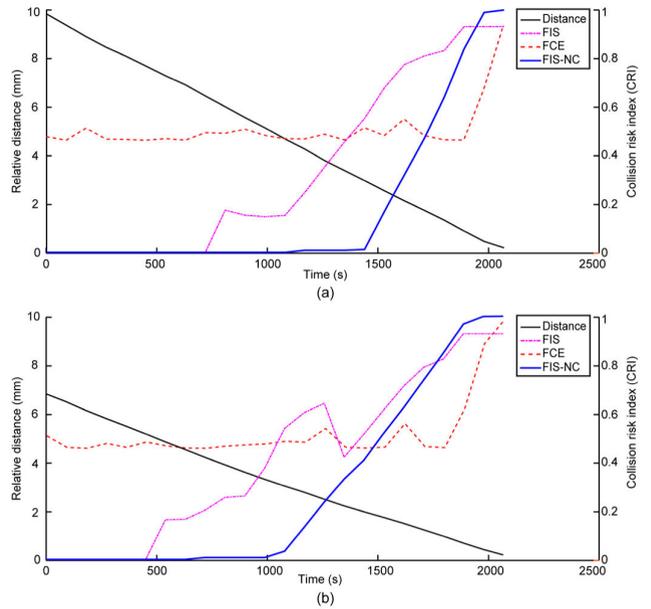


FIGURE 17. Comparison results of inferred CRI according to encounter time: (a) head-on situation and (b) crossing situation.

inferred CRI according to the numerical changes in the input variables.

V. CONCLUSION

Considering the COLREGs rules compliant collision avoidance, we proposed a collision risk inference system, FIS-NC, for MASS developed in Korea. In FIS-NC, all vital

TABLE A1. Comparison and analysis of collision risk assessment methods.

Type	Method	Rule 7 “Risk of collision”		Safety criterion		Collision risk assessment of approaching multi-vessels	Expert-based factor
		Radar plotting	Changing of compass bearing	Rule 16 “Action by give-way vessel”	Rule 17 “Action by stand-on vessel”		
Ship domain	Fujii and Tanaka [5]	-	-	-	-	-	-
	Goodwin [6]	-	-	-	-	-	-
	Davis et al. [7]	-	-	-	-	-	-
	Coldwell [8]	-	-	√	-	-	-
	Smierzchalski [9]	√	-	√	-	-	-
	Kijima and Furukawa [10]	-	-	√	-	-	-
	Piertzykowski and Uriasz [11]	-	-	√	-	-	-
	Hansen et al. [12]	-	-	-	-	-	-
	Rawson et al. [13]	-	-	-	-	-	-
	Wang and Chin [14]	-	-	-	-	-	-
	Im and Tu [15]	√	-	√	√	-	-
	Azzeddine et al. [16]	-	-	√	-	-	-
	Kearon [18]	√	-	√	-	√	√
	Hasegawa et al. [19]	√	-	√	√	√	√
	Smeaton and Coenen. [20]	√	-	√	-	√	√
CRI	Lee and Rhee. [21]	√	-	√	√	√	√
	Lisowski. [22]	√	-	√	-	√	√
	Yan [23]	√	-	√	-	√	√
	Ahn et al. [24]	√	-	√	√	√	-
	Bukhari et al. [25]	√	√	-	-	√	√
	Lenart. [26]	√	-	√	-	√	-
	Zhao et al. [27]	√	-	√	-	√	√
	Ohn and Namgung [28]	√	-	√	√	√	-

factors of the COLREGs rules compliant collision avoidance are extracted from the near-collision accident via the AIS maritime traffic data, and data are learned via the ANFIS. The results of comparison of FIS-NC with existing research indicate that FIS-NC can overcome the existing research drawbacks of not considering all vital variables in the COLREGs rules compliant collision avoidance guidelines in Table A1; further, the CRI at the optimal positioning and timing can be inferred so that the MASS takes early collision avoidance action in any situation. Accordingly, it could secure more time for decision makers to take suitable collision prevention action. This study is the first step toward collision avoidance for the MASS to be developed in Korea. Future studies will focus on the route generation algorithm for collision avoidance based on CRI via FIS-NC.

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