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Determining the Proper Times and Sufficient Actions for the Collision Avoidance of Navigator-Centered Ships in the Open Sea Using Artificial Neural Networks

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Abstract: Ship collisions are a major maritime accident; various systems have been proposed to prevent them. Through investigating and analyzing the causes of maritime accidents, it has been established that ship collisions can either caused by delaying actions or not taking the sufficient actions to avoid them. Recognizing the limitations in providing quantitative numerical values for avoiding ship collisions, this study aimed to use Bayesian regularized artificial neural networks (BRANNs) to suggest the proper time and sufficient actions required for ship collision avoidance consistent with the Convention on the International Regulations for Preventing Collisions at Sea. We prepared the data by calculating the proper times and sufficient actions based on precedent research and used them to train, validate, and assess the BRANNs. Subsequently, an artificial neural network controller was designed and proposed. The data of the proposed neural network controller were verified via simulation, validating the controller. This study is limited in cases such as overtaking a ship in front. However, it is expected that this controller can be improved by establishing the criteria for an appropriate overtaking distance after further examining the closest point of approach (CPA) and time to the CPA (TCPA) for overtaking a ship in front and using the method presented herein.

Keywords: ship collision avoidance; proper time; sufficient action; simulation validation

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1. Introduction

Maritime accidents continue to occur, and ship collisions are recognized as a major event based on maritime accident statistics in major countries, such as the EU, Canada, and Japan [1–3]. To provide a solution to such collisions, autonomous ships are being developed based on advances in artificial intelligence (AI) systems and technologies [4]. As the development of autonomous ships is still in its early stages, ship collisions are a major threat to the navigation safety at sea [5]. Additionally, ship collisions cause a considerable level of environmental pollution, loss of lives, and economic losses [6]. It is known that the primary cause of ship collisions is human error [7–9], and autonomous ships may provide a solution to this problem. The International Maritime Organization (IMO) is making various efforts for the safety and security of life at sea, the protection of the marine environment, and global trade [10], as it believes that at least 80% of such accidents depend on the expertise and capabilities of seafarers.

A crucial challenge for autonomous ships is the development of a system that ensures safety by including an autopilot system [4]. In this context, an autopilot system is one that performs autonomous navigation using algorithms based on AI and deep learning. Autonomous navigation can provide a solution to the issues of maritime collisions [4,11]. To prevent maritime collisions, research is currently being conducted in areas under the categories of ship motion prediction, own ship (OS) trajectory prediction, collision situation detection, and collision avoidance (CA) algorithm development [12]. Recent studies have investigated CA methods using AI techniques [13–15]. Xu et al. [13] proposed a method for avoiding the collisions of autonomous ships using an optimal algorithm for unidentified obstacles via deep reinforcement learning. Studies are also being conducted on multi-ship CA via deep learning and training [14,15].

Many studies related to ship collisions have been conducted as the data provided by the Convention on the International Regulations for Preventing Collisions at Sea (COLREG), which form the base of ship CA at sea, are not quantitative [16]. STCW Convention A-II/1 requires seafarers on duty to have a sufficient level of knowledge, understanding, and proficiency of COLREG for preventing close encounters or collisions with other ships, and to understand ships' maneuvering characteristics, including the turning circle and the stopping distance. In addition, seafarers on duty are also required to determine the appropriate and sufficient maneuvers to avoid a maritime collision (decisions to amend the course and/or speed should be timely and in accordance with the accepted navigation practices). However, COLREG's Rule 6 "Safety speed" and Rule 8 "Action to avoid collision" do not clearly state when and how to avoid a maritime collision [17]. Therefore, the proper time and sufficient actions required to avoid a collision is usually determined by a seafarer with a lot of experience on duty and understanding with regard to maneuvering a ship [18]. For inexperienced seafarers, a human error can occur in the decision-making process regarding the proper time and sufficient actions required for CA. This means that even though seafarers can have a good understanding of the COLREG, mistakes in this process can lead to collisions as a consequence. Therefore, the objective of this research was to recognize the limitations in providing quantitative numbers for ship CA and suggest the proper times and sufficient actions required for CA that are consistent with the rules of the COLREG.

This study proposed a timely and proper action for CA based on the information from navigation equipment, such as from RADAR and automatic identification systems (AIS), which can provide information on OSs and target ships (TSs). The information obtained using the navigation equipment provided the input to the proposed model, and the corresponding outputs revealed the values for the proper time and sufficient actions required for CA based on the empirical knowledge of seafarers, which was collected herein based on literature reviews, theoretical considerations, case laws, and navigator surveys. As neural networks can solve a non-linear problem and deal with a large amount of data, they are employed to develop models that are both trained and validated to provide the quantitative representations of the abstract concepts of the proper time and sufficient actions for generalized CA [19]. Artificial neural networks (ANNs) can help solve the problem of CA via training and verification by processing a lot of data for non-linear problems. Moreover, a representative reason for choosing Bayesian regularized ANNs (BRANNs) over many ANNs is due to their advantage of preventing overfitting when solving problems in areas where data are sparse. By providing quantitative indicators of the proper time and sufficient actions for CA, this work will help prevent ship collisions and contribute in improving the maritime safety and protecting the marine environment. It can also be used in assessing the proper time and sufficient actions for the CA of autonomous ships.

The organization of this paper is as follows: Section 2 presents the research methodology and describes the theoretical considerations for avoiding collision situations and seafarers' empirical knowledge obtained using questionnaires. Section 3 describes a method for realizing a general model that employs a neural network to compute values for the inputs. We also analyzed the results of the proposed time and sufficient action for a general model which was implemented using neural networks. In Section 4, the results of simulation analysis performed to validate the model are presented, and a discussion was provided to clarify the contributions and differences of this work in comparison to precedent research. Finally, in Section 5, we present our conclusions.

2. Methodology

The research methodology employed herein is based on a review of the available literature regarding the determination of the proper time and sufficient actions for CA consistent with the COLREG. The signals obtained from the navigation equipment were classified based on the positions relative to the OS for generating input values via calculations, and a neural network was employed to obtain the proper time and sufficient actions for CA. Moreover, a model was developed by training the neural network using data. The results obtained from the developed model were verified via simulation.

2.1. Review of Vessel Collisions

The IMO issued the 1972 COLREG to prevent collisions and ensure the safe navigation of ships, with a focus on the decision-making processes of the seafarers [13,17]. In this context, human errors that cause the largest proportion of collisions include negligence in watch keeping, the continuous monitoring of TSs, and the inadequate cooperation of give-way vessels [20,21]. To further investigate the causes of collisions, the marine accident investigation reports of each country are usually analyzed. Table 1 summarizes the major merchant vessel collisions off the coasts of South Korea and Japan over the past decade. As shown in Table 1, analyzing situations according to the occurrence of a collision can confirm the path and the speed of OSs and TSs, respectively, as well as the time of the first recognition and the time and the extent of the first CA. Owing to the nature of marine casualty reports, accessing all the information was not available; therefore, although several collisions occurred, only a limited number of them have been reported. Nevertheless, vessels first recognize another vessel when the distance between them is sufficiently less, which corresponds to an average of 16 min before collision. However, it can be seen that the first action to avoid a TS is taken as when a collision is almost imminent, with an average time of 4.1 min before collision (i.e., the action is not taken early), and that the action taken to avoid a collision is not sufficient (meaning substantial action is not taken), which is different from the action required as per the COLREG Rules 8 and 16, respectively.

Table 1. Analysis of the situation of collision occurrence.

Related Work	Ship's Code	Course (°)	Speed (Knots)	Ship Length (m)	Time of the First Recognition (before Collision)	Time of the First Collision Avoidance Action (before Collision)	Type of the Avoidance Action
Investigation report of a collision accident (KMST, 150915)	A	050	17.0	159.5	10 min	2 min	Port steer from 050° to 040°
	B	270	10.7	66.7	1 min	1 min	Hard a starboard
Investigation report of a collision accident (KMST, 150204)	A	213	6.0	87.8	24 min	4 min	Hard a port
	B	021	11.5	225.0	34 min	8 min	Starboard steer from 021° to 050°
Investigation report of a collision accident (JTSB, MA2019-6)	A	012	12.2	397.7	13 min	2 min	Stop engine and hard a port
	B	285	5.7	147.8	8 min	7 min	Increasing speed
Investigation report of a collision accident (JTSB, MA2021-3)	A	040.6	18.0	338.2	27 min	7 min	Port steer from 040.6° to 019.7°
	B	290	13.8	141.0	12 min	2 min	Starboard 10°

Abbreviations: KMST, Korea Maritime Safety Tribunal; and JTSB, Japan Transport Safety Board.

2.2. Proper Time for Collision Avoidance

The COLREG Rule 8 stipulates that "any action taken to avoid collision shall be taken in accordance with the rules and shall, if the circumstances of the case admit, be positive, made in ample time and with due regard for the observance of good seamanship" [17]. This means that the appropriate evasive maneuvers to avoid a collision must be performed at a proper time (i.e., within a sufficient amount of time to avoid a collision). The COLREG was written in general terms to be applicable to as many situations as possible [22], and it requires decisions to be made based on the experience of seafarers with the rules and the culture at sea [23]. Notably, it has the limitation of not being able to provide quantitative guidance to seafarers [16]. The way to resolve a conflict is to answer the question of what actions were taken to prevent the collision [24]. To answer the question, collision risk can be assessed through many ways [12].

First, the concept of a ship domain proposed by Fujii and Tanaka [25] was employed in studies related to collision risk assessment to evaluate the collision risk. This concept was later carried forward in various forms by Goodwin [26], Davis [27], and Coldwell [28]. With the development of electronic navigation equipment, the use of this equipment, such as RADAR and AISs on ships became essential, and collision risk assessment using time to the closest point of approach (TCPA) began to be studied [29]. This concept was extended, and risk indices, such as the relative distance [30] and the velocity ratio [31] for collision cases were introduced. In recent years, ship maneuverability and the encounter angles between ships have been actively researched [32–36]. Many studies were conducted on action lines to identify the risk of a collision and to determine the proper timing of actions to avoid the collision [12,37]. The action line is represented by a line that shows the last chance for the OS to avoid a collision through a CA action [38]. Determining the action line depends on simulations rather than the judgment of an expert, and it has been referred by various terms in the literature, such as the last line of defense, or the critical distance [39]. As shown by several studies on CA, action lines, vessel encounter angles, risk assessments, etc., do not address the question of proper timing. The reason for this is that the timing of ship CA is obtained by actual navigators according to the general customs of seafarers, such as the myths of 3 miles as the minimum visibility distance for sidelights and 6 miles as the minimum visibility distance for mast lights. Furthermore, the numbers for the proper time for CA suggested by empirical numbers or judicial precedents vary with the situation depending on the size and the speed of the ship. Therefore, determining the proper time for CA is based on the relative distance to another ship and the TCPA if the distance of the closest point of approach (DCPA) is close to zero. The reason for utilizing the TCPA is that it is insensitive to the speed and direction of the TSs and OSs, which can yield some distance to the TS if the TCPA is the same [40,41]. The relationship between the Oss and the TSs, the two ships at a risk of collision, is depicted in Figure 1. Based on this, the distance and the direction of these two ships in a CA situation can be derived as follows.

First, the ship proceeds from the point of CA between the OS and the TS at a veering angle α; the ship movement does not occur in a linear manner until reaching the veering point OS_{v} after time Δt. Therefore, the ship's veering has a turning radius of its reach, where the reach is generally approximately as one-to-two times of the ship length. L_{OS} is the length of the OS, R_{OS} is the turning force coefficient of the OS, and Δt is the time it takes to proceed from the start of the CA action. The CA action is the ship's movement based on Δt and α for the OS to avoid the TS.

The distance of collision avoidance position, D_{pca}, is obtained through Equation (1). In other words, D_{pca} is defined as the margin distance required for collision avoidance (here, the intended TCPA is multiplied by the ship's speed) and the turning delay. The intended TCPA, Δt, was set as 15 min, as applied multiple times in a number of past studies and cases [42–44]. In this study, as described above, reach is 1 to 2 times the length of the ship, meaning R_{OS}, the median value of the reach point range, was set to 1.5. In addition, by dividing the ship's speed by D_{pca}, T_{pca}, which is defined as the time from the collision point to the point of collision avoidance, can be obtained, as shown in Equation (2).

$$D_{\mathrm{pca}} = R_{\mathrm{OS}} L_{\mathrm{OS}} + V_{\mathrm{OS}} \Delta t, \tag{1}$$

$$T_{\mathrm{pca}} = \frac{R_{\mathrm{OS}} L_{\mathrm{OS}} + V_{\mathrm{OS}} \Delta t}{V_{\mathrm{OS}}}. \tag{2}$$

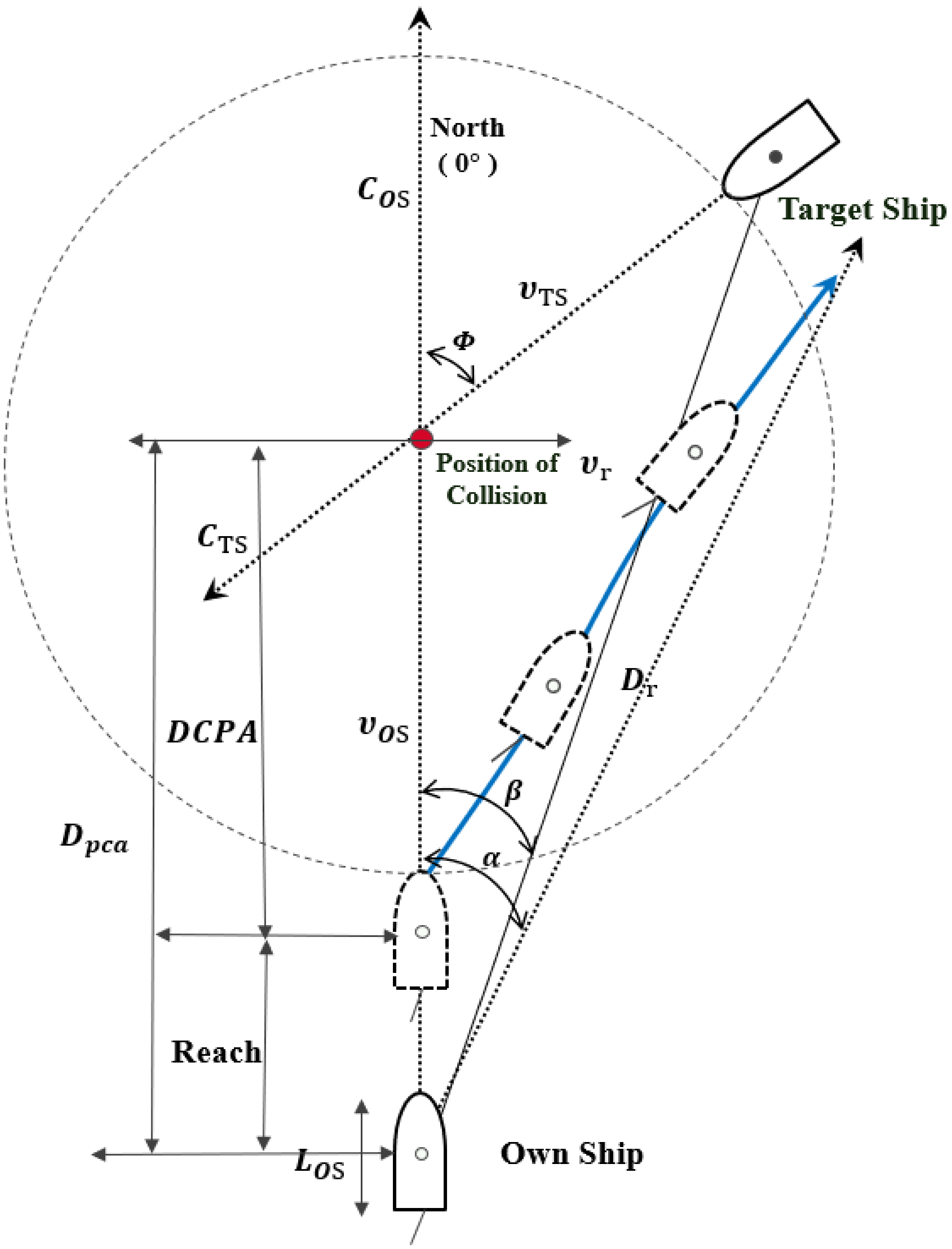

Figure 1. Coordinate system of a collision situation between the own ship (OS) and the target ship (TS). (red is position of collision and blue line is own ship's avoiding action line).

As shown in Figure 1, in the case where the ship's course is C_{OS} and the other ship's course is C_{TS}, the relative bearing $\varnothing\Phi$ between the ships at the collision point can be calculated by Equation (3), which is as follows,

$$\varnothing\Phi = \begin{cases} if\ |C_{TS} - C_{OS}| < \pi,\ \pi - |C_{TS} - C_{OS}| \\ if\ |C_{TS} - C_{OS}|\ \geq\ \pi,\ |C_{TS} - C_{OS}| - \pi \end{cases}. \quad (3)$$

Here, the distance D_r and the azimuth β between these two ships can be found using Equations (4) and (5), respectively, given that the time until the CA action is T_{pca}.

$$D_r = \sqrt{(V_{TS}T_{pca}\cos\varnothing + V_{OS}T_{pca})^2 + (V_{TS}T_{pca}\sin\varnothing)^2}, \quad (4)$$

$$\beta = \begin{cases} if\ (V_{TS}T_{pca}\cos\varnothing + V_{OS}T_{pca}) < 0,\ \pi - \tan^{-1}\frac{V_{TS}T_{pca}\sin\varnothing}{|(V_{TS}T_{pca}\cos\varnothing + V_{OS}T_{pca})|} \\ if\ (V_{TS}T_{pca}\cos\varnothing + V_{OS}T_{pca}) \geq 0,\ \tan^{-1}\frac{V_{TS}T_{pca}\sin\varnothing}{|(V_{TS}T_{pca}\cos\varnothing + V_{OS}T_{pca})|} \end{cases}. \quad (5)$$

2.3. Sufficient Action for Collision Avodiance

As previously discussed, the COLREG requires evasive maneuvers to be actively taken to avoid collisions, and these maneuvers should be performed in an appropriate time under good seamanship [17]. This rule recommends that the extent of the initial response should be based on the subjective judgment along with the experience of the ship operator based on the ship's operating environment at the time. However, as not all navigators have proper experience in making excellent judgments on evasive maneuvers, providing sufficient evasive maneuvers and initial deflection angles can thereby contribute to the prevention of these ship collisions. To solve this problem, many studies have been conducted on CA methods; these methods involve the departing of ships (manned or unmanned) from their planned trajectory to avoid potential undesired physical contacts with other ships [12]. Yim and Park [45] obtained the minimum distance for CA via regression analysis. Ahn et al. [46] proposed a collision prevention method using fuzzy logic which used the ship's length, speed, DCPA, and TCPA for CA. Recently, algorithms incorporating AI technologies have been employed to demonstrate how to avoid collisions [47,48]. These studies arbitrarily selected and used ship-to-ship transverse distances for passage under different navigation environments. In this study, the open sea was selected as the navigation environment, and the criteria obtained from actual navigators were reviewed to develop objective criteria for determining the proper time of the initial evasive maneuver and the sufficient evasive maneuver. We examined the subjective criteria for the initial evasive maneuver judgment of the navigators who had already learned the COLREG Rule 8 "Action to avoid collision". Lee et al. [49] conducted a survey of 192 mariners, including captains, and the resulting minimum safe separation distances are detailed in Table 2.

Table 2. Survey result for the minimum safe distance.

Rank / Distance	Third Officer	Second Officer	Chief Officer	Captain
0.5 mile	2 (6.9%)	13 (21.6%)	32 (35.6%)	5 (38.5%)
1.0 mile	24 (82.8%)	46 (76.7%)	52 (57.8%)	7 (53.8%)
2.0 miles	2 (6.9%)	1 (1.7%)	5 (5.5%)	1 (7.7%)
3.0 miles	1 (3.4%)	0 (0.0%)	1 (1.1%)	0 (0.0%)

Source: Lee et al. [49].

As shown in Table 2, seafarers perceived the minimum safe separation distance as 1.0 mile, and this trend was characterized by a higher percentage of respondents at lower ranks. The higher the rank, the closer the response to 0.5 mile. Herein, the threshold for the initial evasive maneuver was calculated as 1.0 mile. As shown in Figure 2, this criteria can be observed in the CA maneuver between two ships at a collision risk [50]. With regard to the relationship between the OSs and the TSs, we defined the slope of a tangent to a circle with the radius D as m_1 and m_2. The calculation of the slope m along the two ships' course is given by Equation (6).

$$m = \frac{V_{TS} \times \cos\varnothing - V_{OS}}{V_{TS} \times \sin\varnothing}. \quad (6)$$

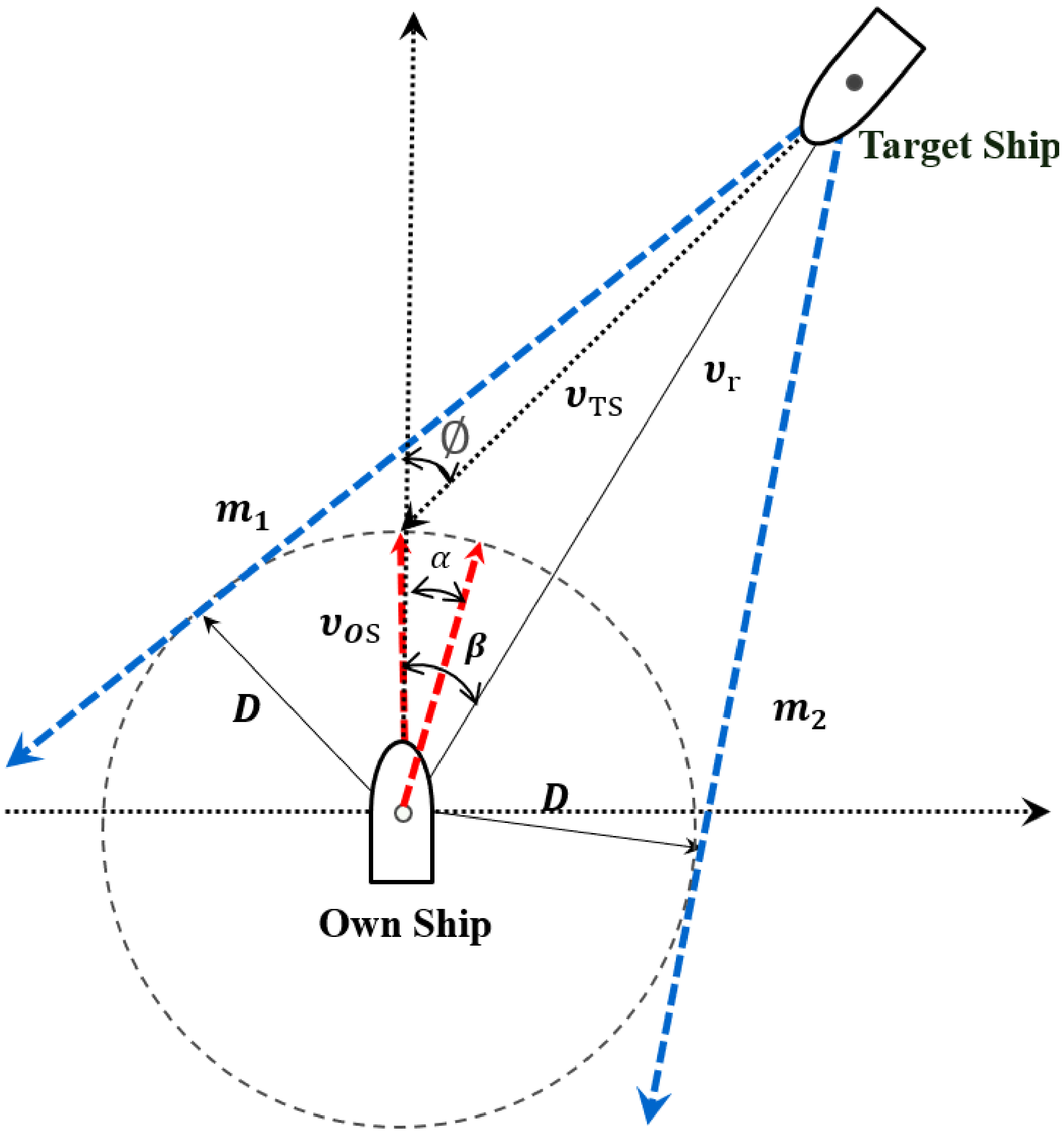

Figure 2. Coordinate system for a collision avoidance action between the OS and the TS.

Here, if the point coordinates of the TS are (x_o, y_o), then the equation of a straight line through the point with a slope m is given by Equation (7).

$$mx - mx_{t0} - y + y_{t0} = 0. \tag{7}$$

The perpendicular distance D from the origin in a Cartesian coordinate system X–Y to the straight line given above can be calculated using Equations (8) and (9) below,

$$\mathrm{D} = \frac{-mx_{t0} + y_{t0}}{\sqrt{m^2+1}}, \tag{8}$$

$$m = \frac{-2x_{t0}y_{t0} \pm \sqrt{(2x_{t0}y_{t0})^2 - 4(D^2 - x_{t0}{}^2)(D^2 - y_{t0}{}^2)}}{2(D^2 - x_{t0}{}^2)}. \tag{9}$$

Here, given the point coordinates of the TS and the value of the distance D, we can find the slope m. An m with a value of >0 indicates that the TS is approaching from the starboard side of the OS, while an m with a value of <0 indicates that the TS is approaching from the port side of the OS. Additionally, two slope values—m_1 and m_2—were obtained, and if $|m_1| < |m_2|$, this indicates that m_1 corresponds to the TS passing the port side of the OS, and m_2 corresponds to the TS passing the starboard side of the OS, respectively.

The slope m (including m_1 and m_2) can be represented as follows, using the relative orientation $\varnothing$ at the point of collision, and the initial deflection angle α using Equations (10) and (11).

$$m = \frac{V_{\rm TS}\cos\varnothing - V_{\rm OS}\cos\alpha}{V_{\rm TS}\sin\varnothing - V_{\rm OS}\sin\alpha}, \tag{10}$$

$$V_{\rm TS}(\cos\varnothing - m\sin\varnothing) = V_{\rm OS}(\cos\alpha - m\sin\alpha). \tag{11}$$

If we substitute the relative orientation of the collision point $\varnothing$, we can obtain the initial deflection angle α using Equation (12); that is, if we use $V_{\rm TS}(\cos\varnothing - m\sin\varnothing) = k$, we get the following:

$$\begin{cases} if\ m > 0,\ \alpha = \pm\cos^{-1}\left(\frac{k}{V_{\rm OS}\sqrt{m^2+1}}\right) - \tan^{-1}(m) \\ if\ m < 0,\ \alpha = \pm\sin^{-1}\left(\frac{k}{V_{\rm OS}\sqrt{m^2+1}}\right) + \tan^{-1}\left(\frac{1}{m}\right) \end{cases}, \tag{12}$$

where $-180° < \alpha < 180°$.

Herein, D was calculated to be 1.0 mile, which is consistent with the results of a previous study [49].

2.4. Use of Artificial Neural Networks (ANNs)

Several studies have been conducted on detecting and avoiding collision risks. Previously, studies using the fuzzy theory were primarily conducted. Hasegawa [51] attempted to model the degree of collision risk using a fuzzy inference system with the TCPA and DCPA values.

In recent years, many studies on the CA maneuver and the course prediction of ships have been conducted using ANNs [46,52,53]. This is because ANNs have an extremely high ability to learn complex relationships from imprecise data. Moreover, they can be employed to extract the patterns and detect the trends that are too complex for humans or other computer technologies to recognize. They are thought to be a versatile and powerful way to analyze samples, generalize and predict data, remember the features of the data, and match or connect new data [54]. Thus, a well-trained neural network can be considered as an "expert".

Neural networks begin with a simple model of the neural organization of the human brain. ANNs are a computational organization that learns from past experiences to make abstract values concrete, thereby providing a way to extract features from uncorrelated data or to generalize results from the inputs that cannot be estimated [55].

Recently, deep learning-based neural networks have been found to exhibit superior performances compared to other machine learning algorithms [56]. Deep neural networks with vast hidden layer structures have solved many problems in neural networks that were previously either unsolved or poorly solved [57]. However, deep learning requires relatively longer computation times than other machine learning models, owing to its deep hidden layer structure. With regard to this, Bayesian inference and regularization were introduced to reduce the computation time while maintaining the predictive power on a deep learning level. The prediction results of the Bayesian neural networks are not significantly different from those of the deep neural networks, but the probability distribution of the Bayesian statistics is used to reduce the computation time [58]. The structure of BRANN's model is shown in Figure 3. In particular, the models of BRANNs are robust enough to not require the validation procedures needed for regular regression methods. In the supervised learning step, we typically change the weights to reduce the mean squared error. The main problem with these techniques is the possibility of overfitting and overtraining, leading to noise fitting and a loss of generalization of the network. To reduce the likelihood of overfitting, a mathematical technique, known as Bayesian regularization, was developed to convert the non-linear system into a well-defined problem [59,60]. In general, the training step aims to reduce the sum of the squared errors between the model output and the target value. Bayesian regularization is expressed by the following equation:

$$F = \beta E_d + \alpha E_w, \tag{13}$$

where F is the objective function, E_d is the sum of the squared errors, E_w is the sum of the square of the network weights, and α and β are the objective function parameters [60]. Bayesian network weights are considered as random variables; therefore, the density function can be written according to Bay's rules [61]:

$$P(w|D, \alpha,\ \beta, M) = \frac{P(D|w,\ \beta,\ M)P(w|\alpha,\ M)}{P(D|\alpha,\ \beta,\ M)}, \tag{14}$$

where w is the vector of network weights, D is the data vector, and M represents the neural network model in use.

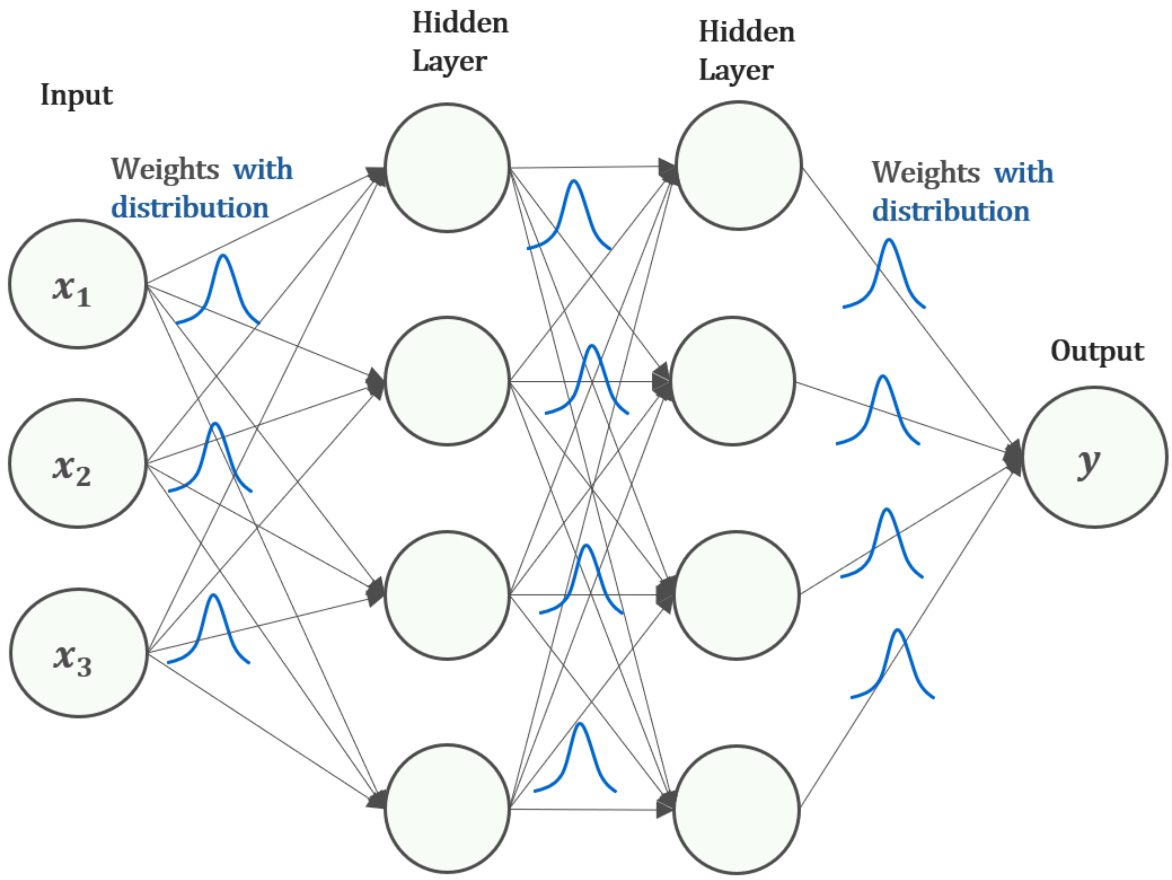

Figure 3. Structure of a Bayesian regularized artificial neural network (BRANN).

Forsee and Hagan [61] proposed an approximation of the Gauss–Newton algorithm using the Levenburg–Marquardt training algorithm, with the assumption that the noise in data is Gaussian. This technique reduces the likelihood of hitting a local minima, increasing the generalizability of the network. Although this technique has the advantage of knowing the probabilistic nature of the network weights associated with a given dataset and a model framework, the size of the neural network increases with the additional hidden layer of neurons, dramatically increasing the likelihood of overfitting and requiring a validation set to determine the stopping point. In Bayesian regularized networks, overly complex models are penalized by effectively treating the unnecessary linkage weights as zero. The network is computed and trained with non-trivial weights, known as the effective number of parameters. This converges to a constant as the network grows [59]. This allows for a more compact network that reduces the likelihood of overfitting, while also increasing the data available for training by eliminating the need for a validation step.

Herein, the Levenburg–Marquardt training algorithm was employed to determine the proper time and sufficient actions for a ship to avoid a collision using a BRANN, which improves on the Levenburg–Marquardt training algorithm, reduces the likelihood of overfitting, and reduces the need for a validation phase.

3. Determining the Proper Time and Action of Evasive Maneuver Using ANNs

Herein, an ANN was designed by applying the above-mentioned methods to determine the proper time and sufficient actions for avoiding ship collisions. The designed neural network was validated by calculating the mean squared errors (MSEs). Moreover, the controller designed using the ANN was verified by changing the OS speed, OS length, and TS course (the relative position of the OS and the TS).

3.1. Design of an ANN

An ANN was designed to determine the proper time and sufficient maneuver for avoiding ship collisions. In this study, from the information obtained by employing the commonly used navigation equipment, such as RADAR and AISs, five parameters were considered as inputs with regard to CA: OS course (C_{OS}); OS speed (V_{OS}); TS course (C_{TS}); TS speed (V_{TS}); and OS length (L_{OS}). Based on these input values, the following two parameters were selected as the outputs: CA timing (D_{pca}) and the initial deflection angle (α). Considering this, the inputs and outputs of the controller designed using the neural network were configured, as shown in Figure 4.

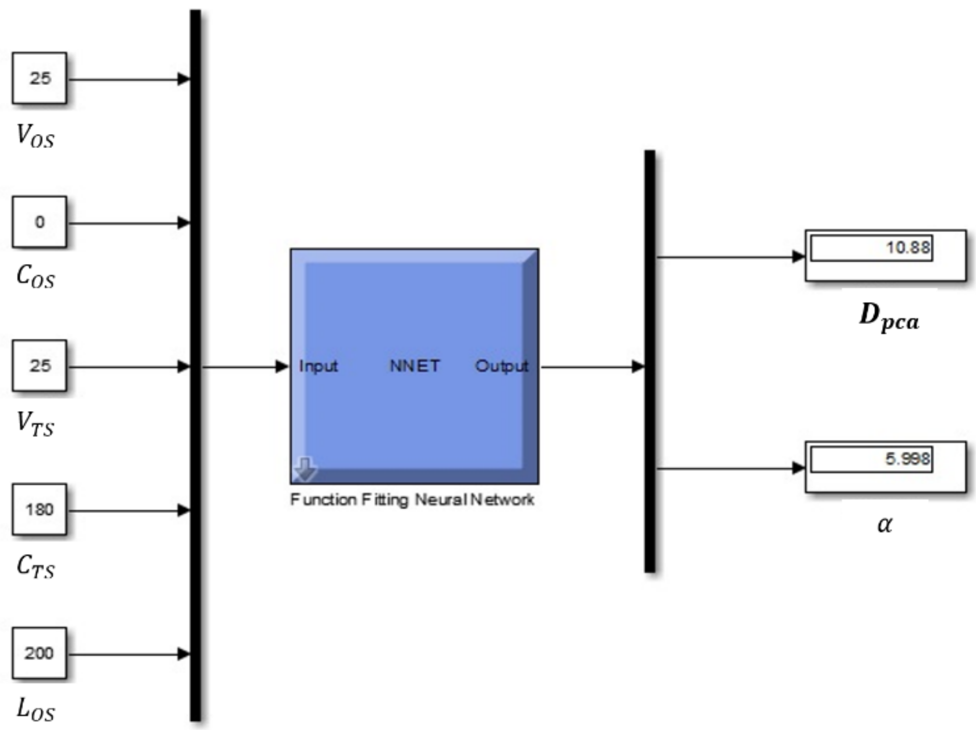

Figure 4. Construction of a controller using BRANNs.

To train the configured neural network, a training data model was built. The five inputs were obtained using the following rules, and the two outputs were calculated using the methodology described previously in Section 2:

- C_{OS} and C_{TS} were obtained at 30° intervals from 000° to 330°, respectively;
- V_{OS} and V_{TS} were obtained in five-knot intervals from 10 to 25 knots, respectively;

- L_{OS} was obtained in 50 m intervals from 100 to 200 m, respectively;
- The configuration is limited to cases where the ship is performing evasive maneuvers; therefore, only the following cases are considered: the ships encounter each other head-on, the ships overtake each other, and when the TS is on the starboard side of the OS in the case of crossing;
- When overtaking another ship in front, the difference in their speeds is not large enough to meet the TCPA of 15 min and the passage distance of 1 mile; therefore, this case was not included in this study.

Based on the above rules for generating inputs, 3816 case data were generated. Table 3 partially summarizes these inputs and the outputs that were calculated using these inputs.

Table 3. Evaluation of the model.

Case No.	Input					Output	
	V_{OS} (Knots)	C_{OS} (°)	V_{TS} (Knots)	C_{TS} (°)	L_{OS} (m)	D_{pca} (Mile)	α
1	10	0	15	300	200	3.5	−122.7
2	20	120	15	0	200	7.8	12.4
3	25	180	25	150	100	3.3	−30.0
4	15	300	25	210	150	7.5	25.4
5	15	270	20	90	150	9.0	14.8
				...			
3816	25	330	20	300	100	3.2	18.5

With regard to α (°), positive numbers indicate starboard-side deflection, while negative numbers indicate port-side deflection, respectively.

We used 70% (2672) of the generated data as the training data, 15% (572) as the validation data, and 15% (572) as the testing data, respectively. Moreover, BRANNs were designed as a neural network with ten hidden nodes in one hidden layer.

3.2. Analysis Results of the ANN

The number of epochs is an important part to solve the problem of the overfitting and underfitting of the dataset. To ensure the sufficient convergence of training, the batch size was set to 100 and the epochs to 1000 in this study [62], among which the weight with the lowest MSE value was designed with, and the MSE value of 9.0745, as shown in Figure 5.

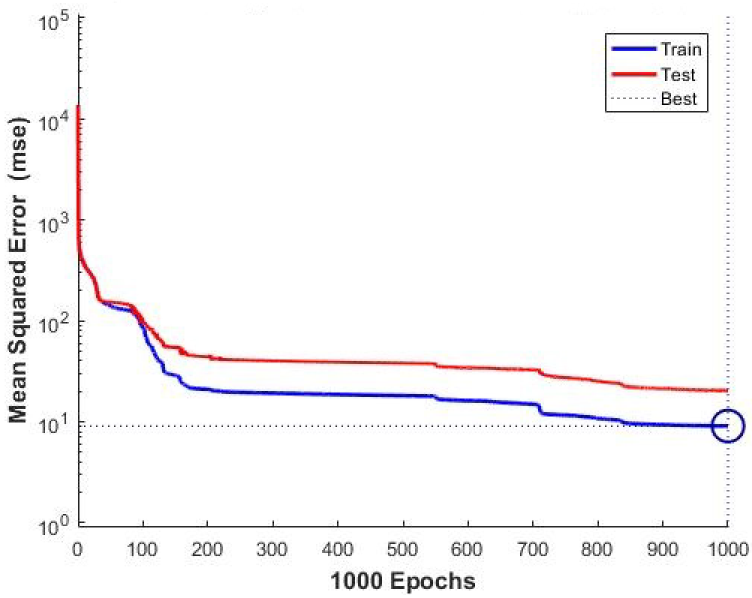

Figure 5. Graph of the best training performance for 1000 epochs.

To verify the controller results, they were compared with the calculation results using the following rules:

- C_{TS} was validated at 3° intervals from 180° to 330°, respectively, to determine changes in the encounter angle between the OS and the TS;
- V_{OS} was validated in 0.2 knot increments from 15 to 25 knots, respectively;
- L_{OS} was validated in 2 m intervals from 150 to 250 m, respectively.

3.2.1. Result of the Encounter Angle of the OS with the TS

Figures 6 and 7 show a comparison of the calculated values of the proper time and the sufficient maneuver for ship CA as the TS course changed from 180° to 330° in 3° intervals, respectively, with the corresponding values of the controller designed in this study. As shown in Figure 6, with regard to the proper time, the difference between the calculated and the corresponding controller values was the smallest at a TS course of 252°. Additionally, this difference increased when the OS was closer to the TS or closer to overtaking. Specifically, we found an error of approximately 2.34 miles at 330°, which was caused by the relatively short distance between the two ships, despite being based on a sufficient time. Moreover, in this case, a larger angle was required, and sometimes it was deemed to be necessary to turn to the other side. As shown in Figure 7, the sufficient maneuvers showed a close match until the TS course was between 180° and 310°, respectively, after which the error increased considerably as the ships approached the overtaking situation. This error was deemed to be likely due to the short relative distance between these two ships resulting in a large deflection angle, as discussed earlier.

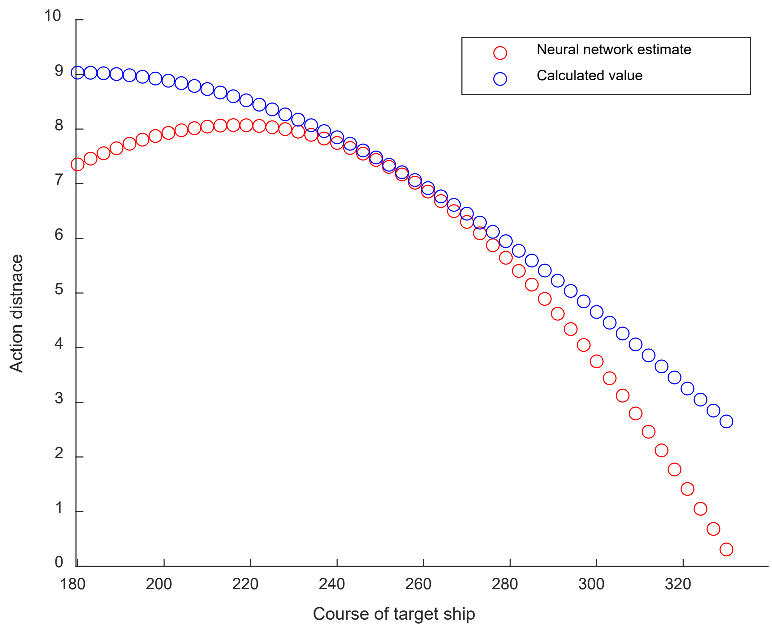

Figure 6. Action distance for collision avoidance versus the TS course.

As the TS course changed from 180° to 330° at 3° intervals, respectively, the controller began the CA at approximately 0.74 mile later than the calculated value but deflected approximately 2.72° more than the required deflection angle for a sufficient maneuver, which was thereby considered as a good overall design.

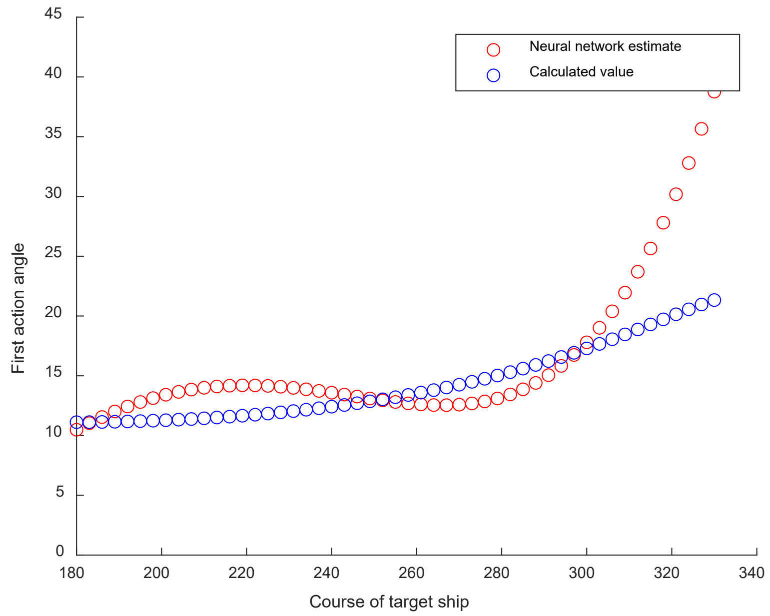

Figure 7. First action angle for collision avoidance versus the TS course.

3.2.2. Result of Changing the OS Speed

Figures 8 and 9 show a comparison of the calculated values of the proper time and the sufficient maneuver for ship CA with the corresponding values of the controller designed in this study as the OS speed varied from 15 to 25 knots in 0.2 knot increments, respectively. As shown in Figure 8, with regard to the proper time, the difference between the calculated value and the corresponding controller value was approximately 0.008 miles at an OS speed of 18.6 knots, which was found to be the smallest error. This error increases as the OS speed decreases or increases. Specifically, at 25 knots, we found an error of approximately 1.47 miles. We believe that this error was formed due to the fact that as the difference between the speeds of the two ships increases, their relative velocity increases and their maneuver becomes faster as a result. As shown in Figure 9, with regard to the sufficient maneuver, the difference between the calculated and the corresponding controller values was determined to be the smallest (approximately 0.038°) at an OS speed of 23.8 knots. Although these two values do not have a considerable error, the error increased slightly as the OS speed decreases. We believe that this error was due to the fact that as the difference between the speeds of these two ships increases, the proper time is accelerated as a result, requiring more initial maneuvers.

The controller was confirmed to be well designed overall, as the corresponding proper time for CA was only approximately 0.60 mile later compared to the calculated value for the OS speed varying from 15 to 25 knots in 0.2 knot increments, while the deflection angle required for the sufficient maneuver was approximately 0.75° more than the corresponding calculated value, respectively.

3.2.3. Result of Changing the OS Length

Figures 10 and 11 show the calculated values of the proper time and sufficient maneuver for ship CA as the OS length varied from 150 to 250 m in 2 m intervals, respectively; these values were compared with the corresponding values of the controller designed in this study. The error between the calculated and the corresponding controller values was found to be almost constant; the difference was not substantial. This was believed to be the result of a proportional increase in the proper time and the sufficient maneuver with the OS length.

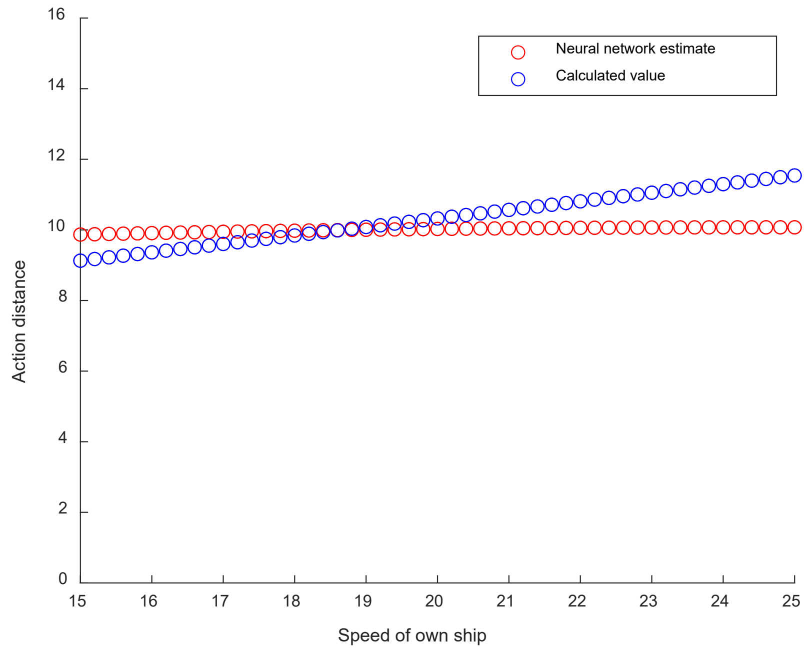

Figure 8. Action distance for collision avoidance versus the OS speed.

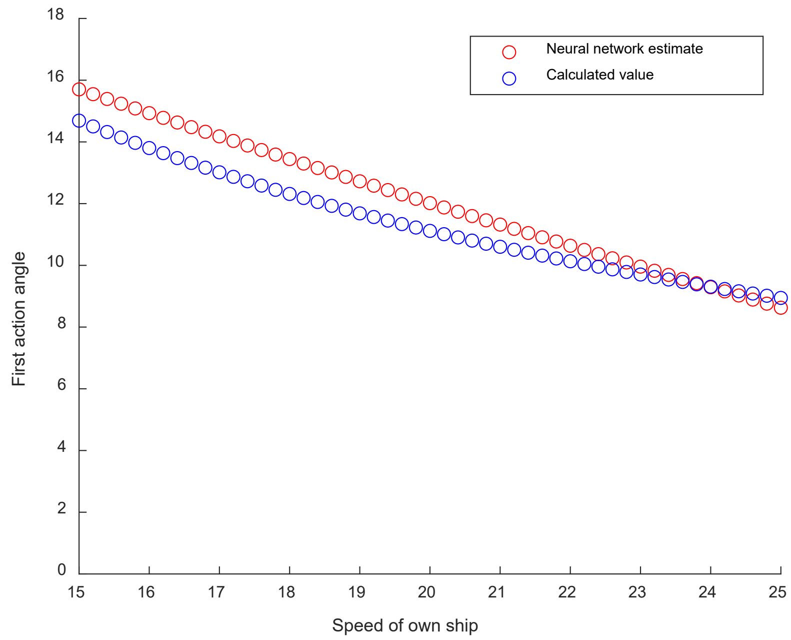

Figure 9. First action angle for collision avoidance versus the OS speed.

As the OS length varied in 2 m intervals from 150 to 250 m, the proper time for CA was found to approximately be 0.30 mile later compared to the calculated value, while the deflection angle required for the sufficient maneuver was found to be approximately 0.90° more, respectively, suggesting that the overall design is good.

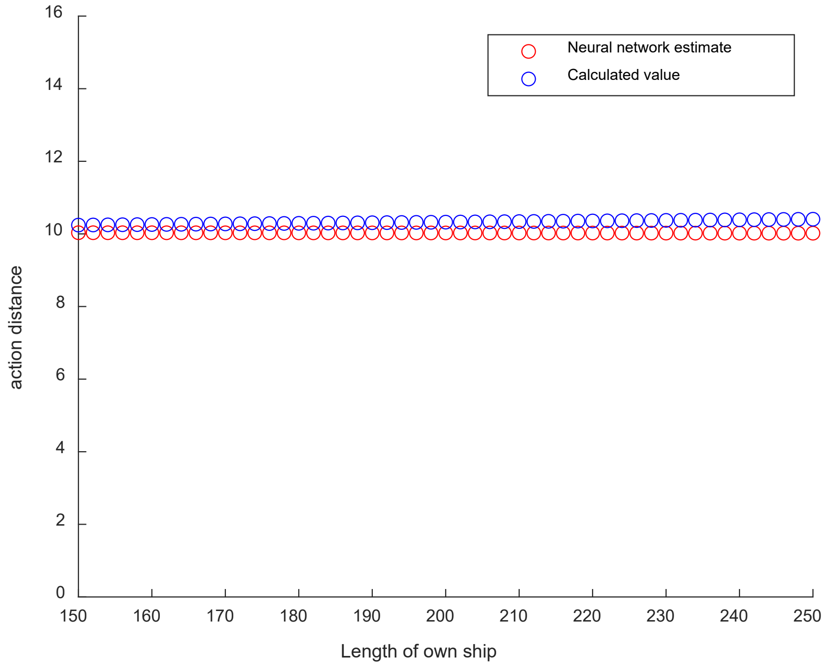

Figure 10. Action distance for collision avoidance versus the OS length.

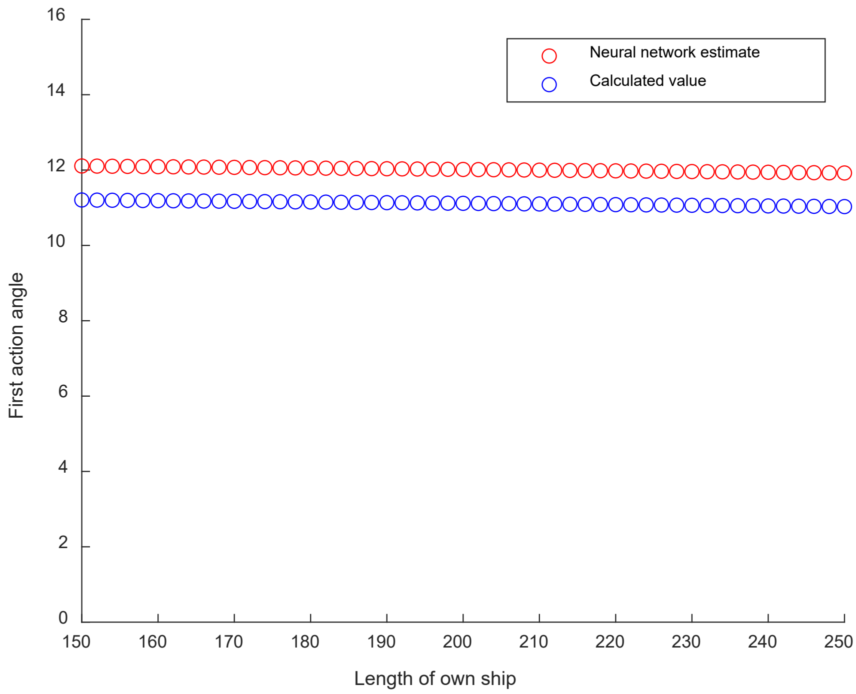

Figure 11. First action angle for collision avoidance versus the OS length.

4. Discussion

4.1. Research Validation

To verify the performance of the controller designed herein, the full-mission ship-handling simulator of the Korea Institute of Maritime and Fisheries Technology (KIMFT) was employed (Navi-Trainer Professional 5000 from Wärtsilä as a navigational simulator) (Figure 12). KIMFT's simulators meet the DNV class A code and are equipped with 360° visual projection and shipborne equipment. Thus, they are employed for research, as well as for the training of captains and pilots. Moreover, these simulators can store and analyze important data, such as the position, course, and speed of ships used in simulation exercises [63].

Figure 12. Full-mission ship-handling simulator of the Korea Institute of Maritime and Fisheries Technology.

The ship used to verify the performance of this controller was a container ship with a length of 203.6 m, a width of 25.4 m, and a maximum speed of 19.4 knots. Other details of this ship and simulation conditions are summarized in Table 4.

Table 4. Detailed information about the simulation ship and its conditions.

Ship Specifications				**Simulation Condition**			
Ship type	Container carrier	Depth	9.6 m	Wind force	5 knots	Visibility	10 miles
Length overall	203.6 m	Displacement	32,025 tons	Wind direction	000°	Target ship	Same as the own ship
Breadth	25.4 m	Ship's max speed	19.4 knots	Wave	0.4 m	Rate of turn	10°/min

To verify the controller via simulation, four scenarios were considered. Each scenario was simulated by calculating the proper time and the sufficient maneuver for CA using the controller in advance, as shown in Table 5.

Table 5. Detailed conditions of each simulation scenario.

Scenario	V_{OS} **(Knots)**	C_{OS} **(°)**	V_{TS} **(Knots)**	C_{TS} **(°)**	L_{OS} **(m)**	D_{pca} **(Miles)**	α
Case 1	19.4	000	19.4	180	203.6	10.0	12.3
Case 2				225		10.2	14.4
Case 3				270		7.9	14.0
Case 4				315		2.4	26.2

Simulations were conducted using a container ship for the four scenarios. For each scenario, a precalculated CA maneuver was performed using the controller at the proper time. In particular, the ship's course was changed while maintaining a turning rate of 10°/min, which is the turning rate that is typically used when the ship is maneuvered safely (except in special cases) [63]. After performing these simulations, the obtained data were used to measure the closest point of approach (CPA) between the two ships. The navigation of the ship according to these simulations is shown in Figure 13; the detailed results are presented in Table 5.

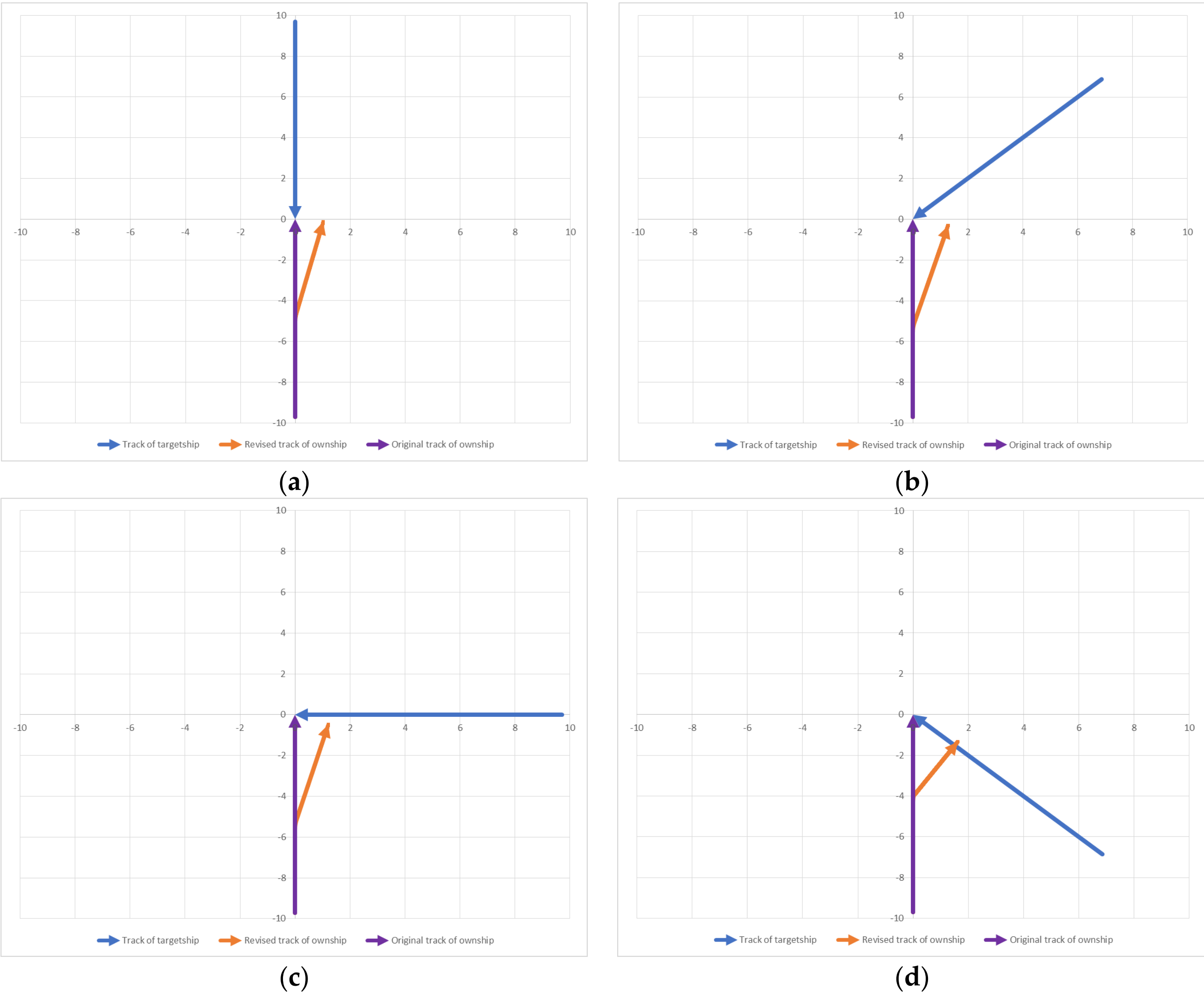

Figure 13. Simulated tracks of the ship: (**a**–**d**) Case 1–4, respectively.

As shown in Case 3, Table 6, right-angle crossing exhibited the smallest error between the intended passage distance and the simulation-validated CPA; the error between the two CPAs for each scenario was approximately −0.18–0.22 miles, indicating that the proper time and sufficient maneuver for CA recommended by the controller has been validated.

Table 6. Simulation results.

Scenario	Original CPA (Mile)	Passage Distance (*D*) (Mile)	Revised CPA by the Controller (Mile)	Error (Mile)
Case 1	0	1.0	1.03	+0.03
Case 2			1.22	+0.22
Case 3			0.92	−0.08
Case 4			0.82	−0.18

4.2. Research Contributions

The contributions of this research can be summarized as follows.

Herein, a controller was designed using a neural network to propose the proper time of the evasive maneuver and the sufficient maneuver for ship CA, which were proposed via regression analysis conducted by previous studies. The proposed proper time of the evasive maneuver and the sufficient maneuver were validated through simulations. It is anticipated that this controller will be able to provide guidance to inexperienced seafarers for avoiding ship collisions by utilizing these suggested evasive and sufficient maneuvers. The provision of such guidance will contribute considerably to the prevention of ship collisions at sea.

Moreover, the controller proposed in this study can further contribute to the development of an alarm system to avoid missing the proper time for an evasive maneuver and an autonomous ship collision–avoidance system, such as a ship's autopilot.

This study is somewhat limited in the case of overtaking a ship in front and other similar cases as the distance between the two ships was smaller than the distance to ensure safety, despite the sufficient time suggested in the previous study being applied. However, if further research is conducted to examine the CPA and the TCPA of overtaking, and if criteria for appropriate overtaking distances by surveying experienced seafarers is established, it may be possible to train the neural network controller in a way similar to that used in this work for further improving it.

5. Conclusions

Ship collisions at sea constitute a major maritime accident, causing the loss of lives and properties. After investigating and analyzing maritime accidents, it was found that ship collisions are caused by either missing the timing of a maneuver or not taking enough maneuvers. Therefore, the objectives of this research were to recognize the limitations in providing quantitative numbers for ship CA and to design a neural network controller that provides the proper time and sufficient maneuvers for CA in accordance with the COLREG rules. The data for training, validating, and assessing BRANNs were prepared by calculating the proper time of the evasive maneuver and the sufficient maneuver based on previous studies. Finally, an ANN controller was designed, and this designed controller was successfully verified via simulations.

The contributions and limitations of this study can be summarized as follows. The controller proposed in this study will be able to prevent ship collisions by suggesting the proper time for the evasive maneuver and sufficient actions for inexperienced seafarers. It has also been anticipated that this controller will contribute to CA warning systems, course-maintaining equipment, such as ship autopilots, and CA maneuvering systems for autonomous ships. This study is however limited for cases such as overtaking a ship in front. However, it is expected that the controller will be further improved by establishing criteria for the appropriate overtaking distance after further examining the CPA and TCPA for overtaking using the method presented in this study.

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