Inference Model of Collision Risk Index based on Artificial Neural Network using Ship Near-Collision Data

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Abstract. The judgement of Collision Risk Index (CRI) is important for safe navigation. The autonomous ship need to analyze and decide taking an action for collision avoidance. Recently, it has been possible of navigator to obtain navigation information in real time. By using such collected navigation information, many researchers have proposed inference models which are based on the fuzzy theory in order that they can make decision for safety of navigation. The conventional inference model, however, have several limitations: (i) establish a membership function with Distance of the Closest Point of Approach (DCPA) and Time to the Closest Point of Approach (TCPA) without any considerations for other ship dynamic parameters; and (ii) rely on values of simulation result using virtual navigation information. In order to overcome these limitations, we introduces the inference model with Artificial Neural Network (ANN) by learning input vector, i.e., own ship’s speed, target ship’s speed, own ship’s course, target ship’s course, bearing between own ship and target ship, distance between own ship and target ship, and target vector. Taking an actual near-collision situation into account, the proposed model can express various CRI, keeping the desirable TCPA and distance to take a proper action for collision avoidance. The proposed method conducts better decision-making than conventional ones.

1. Introduction

According to statistic investigation of Korean Maritime Safety Tribunal (KMST) [1], approximately 80% of collision accidents at sea have reported in results of human errors. Many collision avoidance algorithms have been studied on purpose of supporting the safe navigation.

The collision avoidance algorithm can be mainly divided into three categories: (i) detects target ship or obstacles and assesses a collision risk; (ii) establish navigation plan on the basis of the calculated collision risk and environmental factors; and (iii) executes a control command to perform the planned navigation. In process of control command, a navigator should take an action for collision avoidance. The Collision Risk Index (CRI) can be used as an important factor to take a right action among ships. The CRI has been calculated by conventional fuzzy inference methods [2-5]. Hasegawa
K. et al. (1989)[2] connected the DCPA (Distance of the Closest Point of Approach) and TCPA (Time to the Closest Point of Approach) to the collision risk via interviews of navigators. But Lee and Rhee (2001)[3] pointed out that his method only relied on the empirical factors of navigators, accordingly, the Fuzzy Inference System (FIS) may be changed according to the each navigators’ interviews. Hence, Ahn et al. (2012)[4] suggested the FIS considering ship’s characteristic in virtual navigation situation on simulator without interviews of navigators, and designed the inference model using Multilayer Perceptron (MLP) neural network taking into consideration of many factors associated with navigation environments. Nonetheless, it still had a significant limitation not reflecting information in real collision situations among ships. For this reason, even though Namgung et al. (2019)[5] improved the FIS by using near-collision data which were extracted from Automatic Identification System (AIS) data. However, it also focused on the improved membership function and rule not determined by values based on simulation result [2-6].

In order to overcome the limits of the existing inference system [4,5], we proposed the inference model by reflecting near-collisions in real ship encountering situations. The proposed inference model is incorporated with Artificial Neural Network (ANN).

The section 2 describes about the decision of near-collision, and then the FIS using the concept of near-collisions. In section 3, we suggest the inference model obtained by learning near-collision data with ANN. The simulation result represents the superiority of the proposed system, compared to the existing FIS, as discussed in section 4. This paper is concluded in section 5.

2. Related work

2.1. Decision of the Near-Collision

The number of real collision accidents between ships was not enough in many sea areas so that it was very difficult to verify a model for assessing the probability of the collision risk based on previous marine accidents [11]. Therefore, near-collision, which was a situation in which there was the danger of collision between ships approaching each other, but with no collision eventually occurring, either due to deceleration, or evasion by the change of course, was used. In order to decide the near-collision between ships, various works have been carried out on the basis of the ship domain. Wu, X. et al. (2016)[12] made use of the near-collision data extracted from the ship domain for analyzing of a safe navigation criterion. Van Westrene, F. and J. Ellerbroek (2017)[13] collected near-collision data by examining violation of circular or elliptical ship’s domains as well as relative speeds between ships. Szlapczynski, R. (2018)[14] constructed a ship domain for detection of the near-collision by utilizing input vectors such as ship’ domain concept, relative speed between ships as well as their course difference. Namgung et al. (2019)[5] decided the near-collisions as criteria when ship domains were overlapped, and ship’s trajectory data were used for reconstruct the FIS based on near-collision (i.e., FIS-NC). Thus, in this study, near-collision was determined by applying the ship domain [15] to encounter ship, and ship’s trajectory data for designing of inference model were extracted until ship domain were overlapped.

2.2. FIS based on Near-Collision

The CRI based on the fuzzy theory can be inferred by using DCPA and TCPA. DCPA is the minimum distance between own-ship and a target ship when they are approaching each other. TCPA is the time when DCPA is expected to arrive at a point where it occurs at the ship’s present location.

Figure 1 shows the surface of the Fuzzy Inference System based on Near-Collision (FIS-NC)[5]. The fuzzy membership function of TCPA/(L/V) and DCPA/L, where L is a length of ship and V is a ship’s speed as presented in Figure 1. The CRI can be expressed from 0.0 to 1.0. Variables used in the FIS-NC are Collision (C), Dangerous (D), Threat (T) and Attention (A) as shown in Table 1. When the CRI exceed more than 0.33, the FIS-NC proposes that a give-way ship must take an action for collision avoidance. In case of a stand-on ship in the FIS-NC, a point of time for collision avoidance is
when the CRI is more than 0.66, whereas, a point of time for taking an action for collision avoidance of a give-way ship and a stand-on ship was above the CRI 0.6, CRI 0.8, respectively [3,4].

![Figure 1. Surface of the FIS-NC [5].](image)

Table 1 shows a part where the CRI was determined in order that an input and an output can express the inference rule as a two-dimensional matrix. In other words, it is determined by a condition part of the \( i-th \) inference rule out of all the inference rules. The CRI at conclusion as numeral in the fuzzy inference table as shown in equation (1).

\[
Collision \ Risk \ Index \ (CRI) = \frac{\sum_{i=1}^{n} CRI_i \cdot a_i}{\sum_{i=1}^{n} a_i} 
\]  

Where,
\( n = \) number of reasoning rules,
\( CRI_i = \) singleton value of conclusion part of \( i-th \) rule,
\( a_i = \) contribution factor of conditional part of \( i-th \) rule.

| Division | DCPA/L |
|----------|--------|
| Collision | 0.994 | 0.773 | 0.477 | 0.021 |
| Dangerous | 0.777 | 0.662 | 0.401 | 0.017 |
| Threat | 0.395 | 0.423 | 0.335 | 0.015 |
| Attention | 0.062 | 0.246 | 0.152 | 0.011 |

3. Inference model of collision risk via ANN

3.1. Procedure for inference model of collision risk index via ANN

Inference model design of the CRI based on ANN has been composed of two steps. In the first step, the CRI was obtained through the FIS-NC [10] by using DCPA and TCPA converted from ship near-collision data. In the second step, original information (i.e., speed, course, distance and bearing) before converting DCPA and TCPA were used as input vectors, and the CRI occurred at this time were used as target values. Inference model of the CRI by learning through above step was generated. Procedure for design of inference model of the CRI based on ANN is illustrated as Figure 2.
3.2. Ship’s trajectory data based on Near-Collision

By applying the ship domain (8L×3.2L)\(^{15}\) to both ships (i.e., own ship, target ship), ship trajectory was extracted when they overlapped. This was to compare and analyze the information generated from the beginning of the collision risk to the near-collision. Ship near-collision trajectory by encounter situation is shown in Figure 3. Red circles show near-collision situations when ship domains were overlapped. In order to collect trajectory data of ship near-collision, we observed encounter ships navigating at Mokpo sea area during 24 hours. 83 ships out of total 137 ships had encounter situation. At this time, a total of near-collision accidents occurred was 46. Until near-collisions occurred, the total number of extracted trajectory data was 1164.

(a) Crossing situation                          (b) Head-on situation                        (c) Overtaking situation

Figure 3. Ship near-collision trajectory according to encounter situations.
3.3. Learning Result

ANN is an information processing method derived from the learning data [16]. It is composed of an input layer, one or more hidden layer(s) and an output layer. The difference between network output and the target could lead to determination of an error function. The error is adjusted by back propagation and both the biases and weights are fixed using specific optimization methods which minimizes the error. The whole process called training step, goes over of several epochs to reach the most accuracy in outputs. The validation step, which comes after the training step, is used indirectly while the ANN is trained to monitor the over-fitting of the neural network. It stops the training of the ANN when the error of the validation step begins to increase. The final step of the ANN modelling is called test step which evaluates the accuracy of the machine learning algorithm.

In this paper, out of a total number of 1164 input vector (i.e., own ship’s speed, target ship’s speed, own ship’s course, target ship’s course, bearing between own ship and target ship, distance between own ship and target ship) and output vector (i.e., CRI) extracted from when being near-collision, 70% of the total data were selected for Training step, 15% for validation step, and 15% for test step. The sigmoid function was used to transfer the input vector to the number of hidden layers, and the linear activation function was used for an output layer. In addition, the number of hidden layers was chosen as 13, based on the formula presented in equation. (2) [17].

$$N_H \leq 2N_i + 1$$  

where $N_H$ is the maximum number of nodes in the hidden layer and $N_i$ is the number of inputs.

Figure 4 presents the Mean Squared Error (MSE) of the ANN model for training, validation and test steps. According to this figure, the least MSE in the validation step was happened at epoch 21 which had the best validation performance equal to 0.0045286. It was worth mentioning that model training keeps going as long as the error of the network on the validation vector was reducing. In addition, the analysis stop point was equal to 27, i.e. 6 error repetitions after the epoch with the best validation performance (i.e., epoch 21).

![Figure 4. Best validation performance in ANN.](image)

As presented in Figure 5, the following regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree
line, where the network outputs are equal to the targets. For this problem, the fit was reasonably good as average R values (correlation coefficient) of all datasets as 0.90.

![Graph showing regression plots for training, validation, test, and all subsets in ANN.]

**Figure 5.** Regression of training, validation, test and all subset in ANN.

### 4. Results and Discussion

#### 4.1. Results

In order to demonstrate the performance of the inference model by ANN (i.e. Multilayer based on near-collision, MLP-NC), the encounter ship extracted from the AIS in Mokpo sea area were used. Then, applying the proposed model to the encounter ship, we calculated the CRI until near-collision situation. At this time, the existing models [4, 5] were applied to the encounter ship in order to compare of the result values of the proposed model. In addition, a point of time for collision avoidance of the MLP-NC was complied with the FIS-NC due to construction based on the CRI obtained by the FIS-NC. Simulation was carried out based on Matrix Laboratory (MATLAB). Figure 6 presents the encounter situation between own-ship and a target ship, and red circle is a near-collision situation.
Figure 6. Near-collision situation.

Table 2 and Figure 7 present the results of the calculated CRI by applying models. As a result, the CRI calculated by all of models was continuously increased until a near-collision situation. At the initial encounter situation between ships, the inference model by the MLP-NC indicated the CRI 0.3. On the other hand, the MLP-SC [4], the FIS-NC [5] indicated the CRI 0.2, 0.0, respectively. In terms of a point of time for action of collision avoidance of a give-way ship, the MLP-SC, the FIS-NC and the MLP-NC indicated about 4.4 nm, about 6.3 nm and 6.6 nm. At this time, TCPA was about 8.2 minutes, about 11.8 minutes and about 12.3 minutes, respectively. In terms of a point of time for action of collision avoidance of a stand-on ship, the MLP-SC, the FIS-NC and the MLP-NC indicated about 1.5 nm, about 4.1 nm and 4.4 nm. At this time, TCPA was about 2.9 minutes, about 7.2 minutes and about 8.2 minutes, respectively.

Table 2. Comparison of the CRI calculated by MLP-SC, FIS-NC, and MLP-NC

| Distance (nm) | TCPA (minute) | Collision Risk Index | A point of time for action of collision avoidance |
|--------------|---------------|----------------------|-----------------------------------------------|
|              |               | MLP-SC | FIS-NC | MLP-NC |                        |                                |
| 7.9          | 20.6          | 0.2 | 0.0  | 0.3   |                        | MLP-NC(give-way)               |
| 7.7          | 18.2          | 0.26 | 0.06 | 0.31  |                        | FIS-NC(give-way)               |
| 7.3          | 15.7          | 0.32 | 0.11 | 0.28  |                        |                                |
| 7.1          | 14.3          | 0.36 | 0.18 | 0.22  |                        |                                |
| 6.6          | 12.3          | 0.44 | 0.31 | 0.37  |                        |                                |
| 6.3          | 11.8          | 0.46 | 0.34 | 0.41  |                        |                                |
| 6.1          | 11.3          | 0.47 | 0.38 | 0.52  |                        |                                |
| 5.6          | 10.7          | 0.49 | 0.42 | 0.45  |                        |                                |
| 5.3          | 10.4          | 0.5  | 0.44 | 0.61  |                        |                                |
| 5.1          | 9.8           | 0.52 | 0.49 | 0.72  |                        |                                |
| 4.7          | 9.1           | 0.55 | 0.55 | 0.62  |                        |                                |
| 4.4          | 8.2           | 0.59 | 0.62 | 0.68  |                        | MLP-NC(stand-on), MLP-SC(give-way) |
| 4.1          | 7.2           | 0.64 | 0.73 | 0.62  |                        | FIS-NC(stand-on)               |
| 3.7          | 6.9           | 0.65 | 0.75 | 0.64  |                        |                                |
|     |     |     |     |     |
|-----|-----|-----|-----|-----|
| 3.4 | 6.1 | 0.68| 0.77| 0.68|
| 3.2 | 5.4 | 0.7 | 0.81| 0.71|
| 2.9 | 4.3 | 0.74| 0.82| 0.8 |
| 2.6 | 4.1 | 0.76| 0.83| 0.76|
| 2.3 | 3.9 | 0.76| 0.85| 0.77|
| 2.1 | 3.6 | 0.73| 0.87| 0.83|
| 1.8 | 3.4 | 0.76| 0.89| 0.89|
| 1.6 | 3.1 | 0.78| 0.9 | 0.93|
| 1.5 | 2.9 | 0.8 | 0.93| 0.96|
| 1.3 | 2.4 | 0.8 | 0.94| 0.99|
| 0.8 | 1.8 | 0.82| 0.97| 0.98|
| 0.6 | 1.2 | 0.84| 0.98| 1.0 |
| 0.3 | 0.6 | 0.87| 0.99| 0.97|
| 0.1 | 0.03| 0.93| 0.99| 1.0 |

**MLP-SC**: Multilayer Perceptron based on Ship’s Characteristic; **FIS-NC**: Fuzzy Inference System based on Near-Collision; **MLP-NC**: Multilayer Perceptron based on Near-Collision

4.2. Discussion

As presented in section 4.1, it could be seen that all of models were able to obtain the CRI according to the amount of change of the input vector. However, each models had a significant difference of a point of time for action of collision avoidance. According to [18-21], it observed that encounter ship must take an action for collision avoidance within at least 5 to 10 minutes of TCPA or within at least 2 to 3 nm of minimum distance. Therefore, by comparing of [18-21] with the results of the CRI obtained by the used models, a point of time for action of collision avoidance was discussed in this section.

When it comes to a point of time for action of collision avoidance of a give-way ship, all of models were suitable for collision avoidance between ships due to satisfying criteria. Whereas, in case of a stand-on ship, only the FIS-NC and the MLP-NC satisfied criteria by obtaining sufficient TCPA and distance. Because the MLP-SC indicated TCPA and safe distance below criteria, it would cause a collision accident between encounter ships.
For this reason, the MLP-NC can be suitable for collision avoidance between encounter ships as a result of the calculated CRI according to TCPA and distance. However, as shown in Figure 7, the amount of change of the CRI was calculated in unstable state until near-collision. That is, it is expected to be difficult to infer action of approaching ship due to nonlinear of the calculated CRI.

5. Conclusion

Even though various work on the basis of the fuzzy theory have been conducted, previous inference models were only composed of simulation result through virtual navigation information or member function of DCPA and TCPA. Therefore, in this study, we aimed to improve the MLP-SC and the FIS-NC by using original near-collision data not converted to DCPA and TCPA via ANN. Following procedure has been conducted: (i) obtained the CRI through the FIS-NC by utilizing ship near-collision data; (ii) designated the input vector as original information and the target vector as the CRI; and (iii) conducted learning input vector and target vector in order to design of inference model via ANN. As a result of demonstration applying to simulation, MLP-NC expressed the various the CRI for taking an action for collision avoidance based on original information not converted DCPA and TCPA. Accordingly, the MLP-NC not only overcame the issues pointed out, but also presented performance better than the MLP-SC. However, the amount of change of the CRI calculated in unstable state would make it difficult for efficient decision-making. Therefore, further research is needed to improve MLP-NC by securing the amount of encounter ship data until near-collision.

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