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MODELING NAVIGATOR ERRORS IN COLLISIONS USING HIDDEN MARKOV MODELS

Deuk-Jin Park¹, Jeong-Bin Yim², and Chun-Ki Lee²

Key words: ship collision; navigator's errors; slips, lapses and mistakes; Hidden Markov Model.

ABSTRACT

Understanding navigator errors can be used as a basis for preventing collisions. Here, Hidden Markov Models (HMMs) are applied to navigator errors of fishing and merchant ships in collisions. Information on navigator errors provided in accident investigation reports issued by the Korean Maritime Safety Tribunal is surveyed. The surveyed information is converted into data using the framework of slips, lapses, and mistakes proposed in this study. The results of framework data states are inferred using the unsupervised learning of HMMs, with sequences of navigator errors contained in the error data. The expected errors learned using the navigator error models for fishing and merchant ships are compared and analyzed. Results show that the proposed models can be used to define the types of navigator errors and provide an understanding of these errors in a ship collision event. Several interesting results are also discussed, including some ideas on how to alter navigator errors.

I. INTRODUCTION

Understanding navigator errors when they are involved in a ship collision is crucial for preventing collisions caused by human errors (Allianz, 2017; Montewka et al., 2011), which continue to be a major issue in shipping accidents (Chauvin et al., 2013; Park et al., 2020). In this regard, Allianz (2018) addressed the following two points: (i) using and analyzing better marine-accident data can appreciably improve safety and (ii) an understanding of navigator errors and how they can cause accidents is the missing link in the shipping industry today.

Navigator errors causing ship collisions occur during bridgework (Lin et al., 2014). Bridgework includes all

operations, such as the planning of navigational equipment, which can be performed when maneuvering a ship (Park et al., 2020). To classify these errors, Reason and Norman developed a general classification of human errors, which were divided into two categories (Reason, 1990). The error models of navigators who operate in complex, high-risk domains (e.g., ship operation systems) are crucial because of high losses resulting from navigator failures (Boussemart et al., 2009). Many techniques have been used to model various means of preventing human errors (Davis, 1981; Inoue, 2000; Lin, 2006; Chin and Debnath, 2009; Yim et al., 2018; Youn et al., 2019). While partially observable models such as Hidden Markov Models (HMMs) have been shown to be a good fit, in general, for modeling unobservable states (Sathyanarayana et al., 2008; Jiang et al., 2011; Phan et al., 2015), this study particularly focuses on applying HMMs to ship-collision situations.

HMMs are primarily used to model and predict sequences of symbols. In various ship-collision situations, HMMs can be used to recognize and predict a navigator error for some levels of intermittent interactions with various systems (e.g., navigational equipment or ship-control systems). However, the modeling of real-world processes using HMMs is difficult because such models are parametric. Here, the challenge is that the HMM inference algorithm requires a priori information on the likelihoods of (i) specific observations and (ii) state changes. Nevertheless, these parameters can be obtained from training data in the model learning process. However, such investigation data cannot be directly applied to HMM learning. To define observable error levels in ship-collision situations, this study proposes a framework of human error classification slips, lapses, and mistakes based on the slip-lapse-mistake-violation model of Reason (1990). Reason's model (1990) involves three types of errors associated with human performance, namely, Skill-Based Slips (SBSs), Rule-Based Mistakes (RBMs), and Knowledge-Based Mistakes (KBMs). Using the proposed framework, recruited participants survey the navigator errors and manually categorize them into three levels. Then, the categorized results are converted into discrete error data suitable for HMM learning using discretization rules based on the framework.

Herein, two types of navigator error models are implemented, one for fishing ships and another for merchant ships. Further, the differences among these navigator errors are

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compared. Additionally, the results pertaining to navigator error transitions and the most likely decision-making pathways are presented, and some interesting findings are discussed.

The remainder of this paper is structured as follows. In Section II, the data and methodology, including the theory of HMMs, navigator error data, and HMM learning strategies, are described. In Section III, results pertaining to model interpretation and error pathways are presented and certain specific findings are discussed. In Section IV, the findings of this study are summarized.

II. METHODOLOGY

1. Data Curation

Data from collision accident investigation reports are collected and abstracted into collision events to determine the performance of the navigator. Thereafter, the navigator error framework is used to investigate and categorize the errors into three levels. Then, the categorized results are transformed into discrete error observation data suitable for HMM learning.

1) Navigator Error Framework

When ships collide, navigators make various decisions involving complex cognitive states. Several factors influence the decision-making process of navigators, such as the ship type, navigator’s expertise, navigational environment, and collision-avoidance procedures. There is no technically elaborated simple approach for defining these decision-making processes and errors of the navigator (Sanderson and Harwood, 1988; Dankelman et al., 2004). Thus, there is a need for set of rules regarding how to define observable navigator errors in a ship-collision situation. Accordingly, a navigator error framework is proposed herein to provide these grammatical rules that define observable levels to describe navigator errors.

The navigator error framework is based on Reason’s error classification model (Reason, 1990) and Embrey’s skill-, rule- and knowledge-based method for classifying human errors (Embrey, 2005). Reason and Embrey classify and define the modes of human errors according to their skill-, rule-, and knowledge-based model as SBSs, RBMs, and KBMs. The navigator error framework proposed here consists of three categories, namely, given situations (Category 1), cognitive processes (Category 2), and human failures (Category 3) at the time of ship collision. These three categories are used to describe a single navigator error as a series of decision-making pathways.

Category 1 (situation) contains a level of familiarity with a given situation at the time of the collision and is divided into levels 1 (routine), 2 (familiar), and 3 (unfamiliar). Level 1 refers to errors controlled by patterns in the time–space domain (e.g., if a navigator sails the same route every day). Level 2 refers to errors controlled by rules corresponding to a combination of subroutines (e.g., if a navigator avoids a ship collision in a narrow channel). Level 3 refers to errors in a situation for which there is no experience or control rule from previous

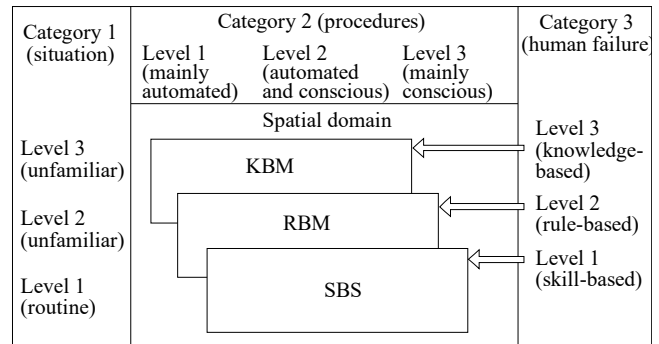


Fig. 1. Spatial domain of observable navigator error.

situations (e.g., the sudden emergence of a ship that was not observed as a result of bad weather).

Category 2 (procedures) contains a procedural level for a given mission at the time of collision. It is divided into level 1 (mainly automated), level 2 (both automated and conscious), and level 3 (mainly conscious). Level 1 refers to a smooth, unconscious, control-free procedure that exhibits very close coupling between the sensor input and response action (e.g., if a navigator monitors radar collision alarms). Level 2 is a mixed state of automation and conscious procedures and refers to a procedure controlled by stored rules (e.g., if a navigator monitors the radar collision alarm and then steers the ship according to navigation regulations). Level 3 refers to a procedure that requires planning using a conscious process and stored knowledge (e.g., if a navigator steers the ship after suddenly encountering a collision situation between multiple ships).

Lastly, Category 3 (human failures) identifies a level of navigator errors other than the intended ones. It is divided into levels 1 (skill based), 2 (rule based), and 3 (knowledge based). Level 1 refers to a mixture of slips and lapses, a slip being when a person’s action differs from what was intended and a lapse being an oversight (e.g., if a navigator changes the course of the ship for collision avoidance but forgets conducting this step). Level 2 refers to a case in which an action mismatches the intended action because of misapplication or improper planning of the rule, and the intended action is not performed (e.g., if a collision is caused by the incorrect application of a rule for collision avoidance). Level 3 refers to the failure in achieving the intended output because of insufficient knowledge (e.g., if a collision is caused by the application of a false collision-avoidance regulation owing to navigator’s lack of knowledge or insufficient knowledge).

Using this navigator error framework, the decision-making of a navigator is represented by a total of 27 (3 × 3 × 3) single pathways based on a combination of three categories with three different levels. Using these 27 single pathways, three types of observable errors are defined: SBSs, RBMs, and KBMs. SBSs, RBMs, and KBMs correspond to levels 1, 2, and 3, respectively, in Category 3 and any level of Categories 1 and 2. These definitions of SBSs, RBMs, and KBMs used

Table 1. Rules for discretizing error levels.

C 1	Number	C2	Number	C3	Number
L 1	1	L 1	1	L 1	1
L 2	2	L 2	2	L 2	2
L 3	3	L 3	3	L 3	3

C 1, category 1; C 2, category 2; C 3, category 3; L 1, level 1; L 2, level 2; L 3, level 3.

in this study are based on Category 3 in the navigator error framework, with the intention of focusing on navigator mistakes. The three observable error types can be described as a spatial domain as shown in Fig. 1, which contains the three categories with three different levels. In the spatial domain, the observable errors are represented by a probabilistic distribution of the 27 single pathways.

2) Experimental Data Collection and Abstraction

The experimental data were collected from a total of 2,934 collision investigation reports issued by the Korean Maritime Safety Tribunal (KMST) from 2006 to 2018.

There are three principal methods for surveying human errors in a maritime context: (i) using actual ships (Chin and Debnath, 2009; Yim et al., 2018), (ii) using ship simulators (Lee et al., 2016; Youn et al., 2019; Park et al., 2020), and (iii) using collision investigation reports (Grech et al., 2002; Celik and Cebi, 2009; Ung, 2018). In the first method, data are collected from the actual environment; however, this approach is very risky and expensive. The second method is safer than the first method but does not obtain data from the actual environment. Compared to the first and second methods, the third method requires time-consuming data processing and verification of data reliability and usability. However, despite these requirements, this study employed the third method to survey the error levels of navigators based on the following scientific evidence.

First, the collision investigation reports were verified by KMST (Yim, 2017). The reliability and usability of the investigation reports are supported by the following four key features. First, KMST is a government agency of the Ministry of Maritime Affairs and Fisheries of the Republic of Korea and confirms to the marine casualty investigation codes of the International Maritime Organization (IMO) (IMO, 1997, 2008). Its investigation results investigations are used as a legal basis for determining the causes of accidents. Second, the investigation reports were issued by a group of subject experts comprising experienced navigators, legal experts, and professional officials. Third, the investigation was based on verbal statements by navigators and comparisons of records of various electronic navigational equipment (e.g., voyage data recorders, electronic chart display and information systems, and automatic identification systems). Lastly, the reports detail the navigator errors chronologically in actual collision circumstances.

Table 2. Discretized combination rules for observable symbols (partial).

Symbol	1	2	...	9	...	18	...	27	
Levels	C 1	1	2	...	3	...	3	...	3
	C 2	1	1	...	3	...	3	...	3
	C 3	1	1	...	1	...	2	...	3

C 1, category 1; C 2, category 2; C 3, category 3.

Furthermore, these reports have been published since 1969, with an average of approximately 300 reports being generated each year. Anyone can download the reports free of charge from the KMST website (KMST, 2020).

Based on these aspects, the reports were deemed to be suitable for this study. The report contents are summarized and stored in an Excel file for surveying the error levels of navigators. The items and contents of abstraction are listed.

Item 1 (general): It includes the specifications of the fishing and merchant ships (e.g., type, length, and tonnage) and the qualifications of the navigators corresponding to each ship type (e.g., occupation, title, and level of certification).

Item 2 (situation): It includes the weather conditions at the time of the accident, traffic conditions of the route, and collision-encounter status of the ship. Based on Item 2, we can survey the level corresponding to Category 1 (situation) of the navigator error framework.

Item 3 (mission): It includes the navigators' duties (e.g., monitoring, collision avoidance, and steering). Based on Item 3, we can survey the level corresponding to Category 2 (procedures) of the navigator error framework.

Item 4 (causes of collision): It contains international regulations related to ship collisions (e.g., the Convention on the International Regulations for Preventing Collisions at Sea (IMO, 1972)) and the causes of human error (e.g., incorrect application of regulations, neglecting duties, and drowsiness). Based on Item 4, we can survey the level corresponding to Category 3 (mistakes) of the navigator error framework.

The summarized accident investigation was used to produce the error observation data described below.

3) Data Construction

For data construction, experts were recruited using the proposed framework to examine the level of grammatical errors. In total, eight participants were selected (six men and two women), each with a boarding career as an officer of 3–13 years (mean, 6.63 years; standard deviation, 3.04 years) and ages of 31–60 years (mean, 41.0 years; standard deviation, 19.98 years). Such a wide range of participants was selected to reduce personal biases to the maximal possible extent. The participants were asked to learn how to conduct a survey using the navigator error framework. The process of surveying the performance levels is presented.

First, each participant read one summarized accident investigation at a time and determined the error levels corresponding

Table 3. Portion of error observation data ($T = 2,858$).

Data Number	Ship Type	Error Level			Symbol
		C 1	C 2	C 3	
1	1	1	1	1	1
2	1	2	2	2	14
3	2	3	3	3	27
...
$t - 2$	2	1	2	2	13
$t - 1$	1	2	3	3	26
T	1	2	1	2	11

C 1, category 1; C 2, category 2; C 3, category 3.

to the three levels of each of the three categories of the navigator error framework. Next, a representative error level for each Category was determined by a group discussion among the participants. Lastly, three error levels corresponding to each of the three categories were surveyed for one accident. Table 1 shows the survey results presented as integers using the rules for discretizing error levels. This process was repeated until all the surveys were completed.

Thereafter, the surveyed data were converted into discrete error observation data using the observable symbols shown as integers in Table 2. These observable symbols represent the 27 single pathways comprising the combinations of the three levels of each of the three categories.

Table 3 shows a portion of the constructed error observation data. The first column presents the observation numbers of the surveys, the second presents the identification numbers of the fishing and merchant ships, the third and fifth present the survey results, and the sixth column shows the error observations represented by symbols. This process yielded a total of 2,858 sample data excluding the nonhuman error data from a total of 2,934 collision investigation reports.

2. HMMs

HMM consists of a stochastic Markov chain based on a set of hidden states whose values cannot be directly observed. Each hidden state generates an observable symbol according to a specific emission function. Although the sequence of hidden states cannot be directly observed, the probability of being in a specific state can be inferred from the sequence of observed symbols.

There are two types of learning: supervised and unsupervised. To guide the learning process, supervised learning requires labels using which prior information on the data are assigned; these labels typically consist of input data associated with the expected model output and are defined by subject experts. However, it would be difficult to label the training data in the present case because navigator error states are not observable in ship-collision situations. Consequently, unsupervised learning is used here to extract the optimal set of model parameters using only the information

contained in the training data.

In this approach, the initial values of the model parameters $\lambda=(A,B,\pi)$ are set, where λ is continuously updated and the expectation is computed to maximize $P(O|\lambda)$. Among all unsupervised learning algorithms, an iterative procedure known as the Baum–Welch algorithm is widely used (Baum and Petrie, 1966; Baum, 1972; Devijver, 1985). This algorithm uses the forward and backward variables $\alpha_t(i)$ and $\beta_{t+j}(i)$, respectively, to estimate the model parameters λ to determine the updated values of π_i , a_{ij} , and $b_j(k)$. For notation simplicity, we introduce

$$\xi_t(i, j) = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{P(o|\lambda)} \tag{1}$$

$$\gamma_t(i) = \sum_{j=1}^N \xi_t(i, j) \tag{2}$$

for a given model λ and observation sequence O , where $\xi_t(i, j)$ is the probability of being in states S_i and S_j at times t and $t + 1$, respectively, and $\gamma_t(i)$ is the probability of being in state S_i at time t .

Using (1) and (2), we can re-estimate the model parameter $\lambda=(A,B,\pi)$. A set of reasonable re-estimation formulas for π , A , and B are presented (Rabiner, 1989):

$$\bar{\pi}_i = \gamma_1(i) \tag{3}$$

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i, j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{4}$$

$$\bar{b}_j(k) = \frac{\sum_{t=1}^T \gamma_t(i)}{\sum_{t=1}^T \gamma_t(i)} \tag{5}$$

This updating procedure yields a new parameter $\bar{\lambda}=(\bar{A}, \bar{B}, \bar{\pi})$. The final optimal value of the parameter is obtained by repeatedly using $\bar{\lambda}$ instead of λ and repeating the update estimate calculation.

The process described above assumes that the number of hidden states is known in advance. However, this assumption is unrealistic in most practical situations, and the structure of the model must be determined using a process known as the model selection.

2. HMM Learning Strategy

The HMMs described above can be used to model navigator errors; however, there are three issues related to HMMs in their nominal form.

The first issue concerns the meaning and number of hidden states. A simple model with too few hidden states cannot model the complexity of human errors (Rabiner and Juang, 1986;

Table 4. Length of data sequences used for training and testing.

Model	Length of data sequence		
	Training	Testing	Sum
Fishing Ship	1,247	535	1,782
Merchant Ship	753	323	1,076
Sum	2,000	858	2,858

Rabiner, 1989). To resolve this issue, this study uses 2-norm, a scalar that provides some measure of the magnitude of the elements of the matrices with log-likelihoods for the training and test data (Bourbaki, 2013).

The second issue is the labeling of states, which allows easy interpretation of the underlying structure of HMM from unsupervised learning. Because of the variety of navigator errors in complex ship operations, no subject-matter expert was available to label the data manually (Boussemart et al., 2009). Therefore, in this study, the state labels were specified using an observed-symbol probability distribution with information regarding the navigator error levels.

Lastly, the third issue concerns parameter adjustment during HMM training. The HMM parameters provide indirect semantic information regarding the training data (Kam et al., 2004), and the resulting model must be interpreted in a manner that highlights the explanatory mechanisms. Herein, based on the HMM notation, the error of a navigator involved in a collision accident was inferred using the performances of the directly observable error.

HMM learning of navigator error models the time sequence of the error observation data. During this process, the HMM parameters are trained using the sequences of unlabeled error observation data. The initial HMM parameters are randomly selected, and the HMM outputs the data sequence. In this experiment, the sequence data were divided into two groups, one for training and another for testing. Out of the sequence data, 70% and 30% were used for training and testing, respectively. Table 4 shows the length of data sequences used for modeling the navigator errors of the fishing and merchant ships.

III. RESULTS AND DISCUSSION

1. Selecting a Model Size and Labeling the States

The model size was selected by evaluating the 2-norm of the log-likelihood matrix of the training and test sequence sets. The states were labeled by analyzing the distribution of the observed-symbol probabilities.

1) Selecting a Model Size

The model size was selected by evaluating the 2-norm of the log-likelihood matrix of the training and test sequence sets.

The results of the 2-norm calculations of both the models are presented in Figs. 2 and 3, wherein the 2-norm corresponding

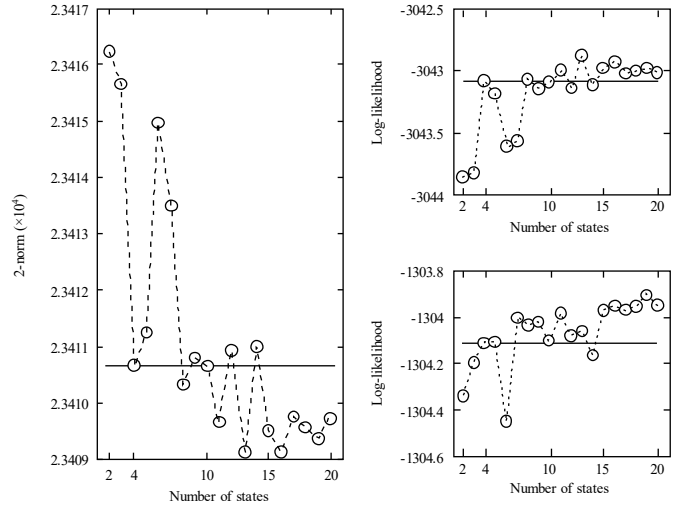


Fig. 2. 2-norm (left) and average log-likelihoods of training data (upper right) and test data (lower right) for the navigator error model of a fishing ship.

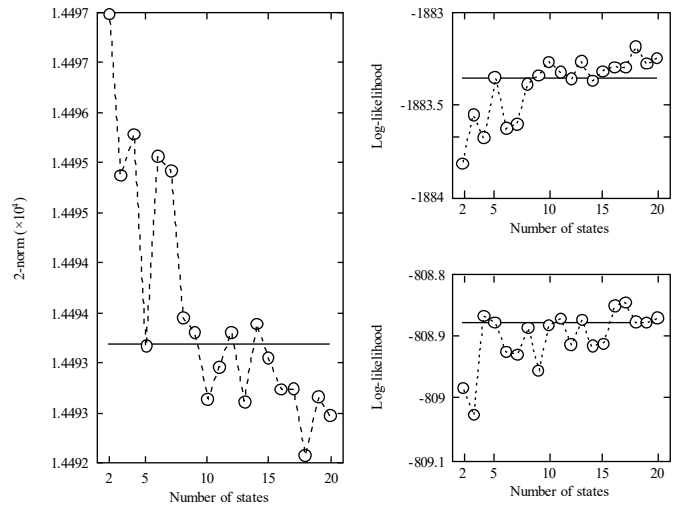


Fig. 3. 2-norm (left) and average log-likelihoods of training data (upper right) and test data (lower right) for the navigator error model of a merchant ship.

to the number of states increases from 2 to 20. In both the figures, the left-hand graph shows the 2-norm and the two graphs on the right illustrate the average log-likelihood of the training and test sequences applied to the 2-norm calculation. In this study, a logarithmic scale was used to avoid very small numerical probability values. In Figs. 2 and 3, the solid lines along the horizontal axis show the 2-norm and average log-likelihood values, which correspond to the number of states determined from the analysis below.

In both the figures, the left-hand graphs show a drastic reduction in the 2-norm at a specific number of states, i.e., four and five in the navigator error models of the fishing and merchant ships, respectively. In particular, the 2-norm values below the solid line appear to be closer to the solid line

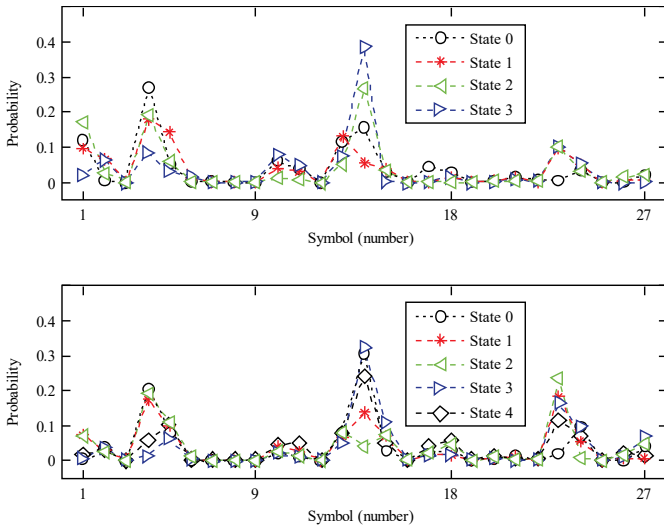


Fig. 4. Observation-symbol probability of the navigator error models: fishing-ship model (upper) and merchant-ship model (lower).

than are those above the solid line. Note that 2-norm indicates the similarity between the training and testing results—the smaller the 2-norm, the greater the similarity. Additionally, the model must be as small as possible for easy interpretation of the HMM structure.

Consequently, the model size was determined from the optimal fit, i.e., the models based on fishing and merchant ships contain four and five states, respectively.

2) Labeling of States

The sizes of the symbol probabilities of the navigator error models are shown in Fig. 4, in which the upper and lower graphs represent the fishing and merchant ships, respectively. The horizontal and vertical axes represent the number of 27 observable symbols and the symbol probability, respectively. These observable symbols can be distinguished by the three errors defined in the navigator error framework, i.e., SBS (symbol numbers 1–9), RBM (symbol numbers 10–18), and KBM (symbol numbers 19–27).

Fig. 4 shows that the symbols for the states have different probability distributions for the three errors. Consequently, each state can be specified using the distributions of the observed-symbol probabilities.

Tables 5 and 6 present the results of labeling the states for the navigator error models using the symbol probability distributions for the fishing and merchant ships, respectively.

Each label consists of a combination of the first letter of each error acronym and the weight of that error, the latter being the percentage of the cumulative probability of the symbols corresponding to that error. The ordering of the first letters corresponds to the weights arranged from the largest to smallest. For instance, the label “R47% + S45% + K8%” shown for state 0 in Table 4 has the following meaning: RBM has the largest weight, followed by SBS, and then KBM, with 47%, 45%, and 8% weights, respectively. This labeling method an

Table 5. Results of labeling the states for the navigator error model of the fishing ship.

State	Weight (%) errors				State label
	SBS	RBM	KBM	Sum	
State 0	45.21	46.56	8.23	100.0	R47% + S45% + K8%
State 1	49.47	31.43	19.10	100.0	S50% + R31% + K19%
State 2	44.40	37.29	18.31	100.0	S45% + R37% + K18%
State 3	21.32	60.84	17.84	100.0	R61% + S21% + K18%

SBS, skill-based slips; RBM, rule-based mistakes; KBM, knowledge-based mistakes.

Table 6. Results of labeling the states for the navigator error model of the merchant ship.

State	Weight (%) errors				State label
	SBS	RBM	KBM	Sum	
State 0	32.77	50.38	16.85	100.0	R50% + S33% + K17%
State 1	37.14	34.83	28.03	100.0	S37% + R35% + K28%
State 2	38.71	27.70	33.59	100.0	S39% + K33% + R28%
State 3	12.32	53.18	34.50	100.0	R53% + K35% + S12%
State 4	20.75	55.56	23.69	100.0	R55%+K24%+S21%

SBS, skill-based slips; RBM, rule-based mistakes; KBM, knowledge-based mistakes.

easy approach for model interpretation using the information on the weights and ranking of the errors included in each state.

2. Navigator Error Transitions

The transitions among the hidden states of the navigator error models of the fishing and merchant ships are shown in Figs. 5 and 6, respectively. The annotated arrows between the states indicate the transition probability of moving from one state to another. The functions of the observation symbols are not expressed explicitly; however, the weighted errors associated with the observation symbols are indicated in the label of the hidden states.

For the navigator error model of the fishing ship in Fig. 5, the notable feature is that the transition probabilities from states 0 or 3 to states 1 or 2 are greater than those in the opposite directions. States 0 and 3 show the largest RBM weights, while states 1 and 2 exhibit the largest SBS weights. Consequently, the errors of the fishing-ship navigators can be expected to primarily transition from RBM to SBS.

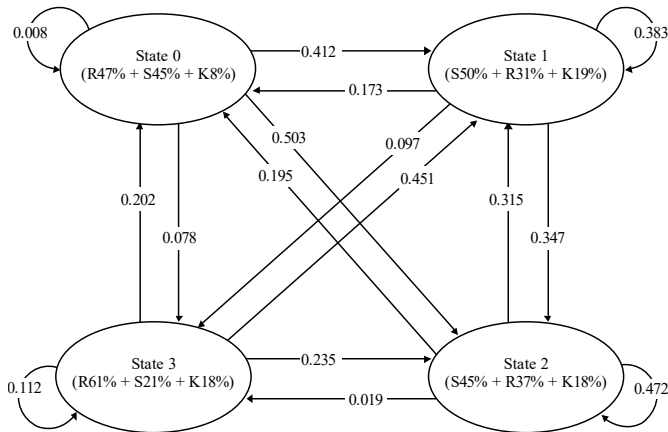


Fig. 5. Error model of the fishing-ship navigators obtained using unsupervised learning.

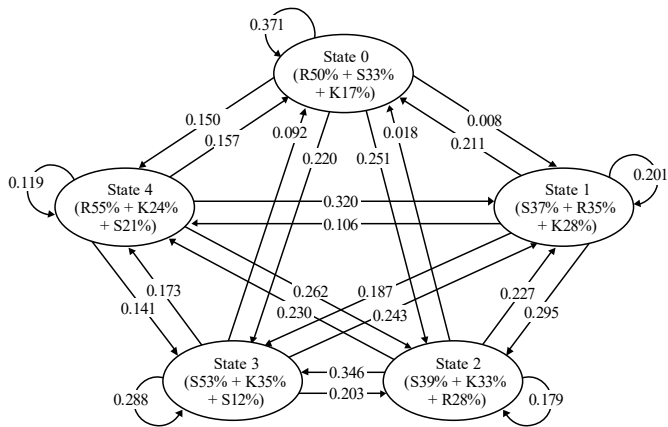


Fig. 6. Error model of the merchant-ship navigators obtained using unsupervised learning.

Additionally, the transition probabilities between states 1 and 2 are larger than those between states 0 and 3. Consequently, the transitions in the error domain distributed in the order of SBS–RBM–KBM are more likely to occur than those distributed in the order of RBM–SBS–KBM.

For the navigator error model of the merchant ship in Fig. 6, the transition probabilities between states 4 and 2 are similar at a significance level of 5% and those between states 3 and 1 are similar at a significance level of 5.6%. Furthermore, the average value (24.6% of the time) of the transition probabilities between states 4 and 2 and that of the transition probabilities between states 3 and 1 (21.5% of the time) are similar at a significance level of 5%. States 4 and 3 exhibit the largest RBM weights, while states 1 and 2 exhibit the largest SBS weights. Consequently, the errors of merchant-ship navigators can be expected to continuously transition from RBM to SBS and back.

Moreover, the transition probability from states 4 to 1 is larger than that from states 3 to 2, while the transition probability from states 1 to 4 is smaller than that from states 2 to 3.

Table 7. Some optimal log-likelihoods of observed symbols for navigator’s error models of fishing and merchant ships.

Ranking		1st	2nd	3rd	4th
Fishing Ship	Symbol	14	4	1	23
	log(P)	-1.67	-1.73	-2.05	-2.31
Merchant Ship	Symbol	14	4	23	5
	log(P)	-1.46	-2.01	-2.11	-2.46

log(P), logarithm of probability.

Moreover, the KBM weight in the labels is ranked third and second in states 1 and 2, respectively, while in states 4 and 3, it is ranked second with different values of the KBM weights. Consequently, the probability of transition in the merchant-ship navigator error depends on the KBM weight.

The following three interesting observations are obtained from the above results.

First, the error of the fishing-ship navigators is predicted to transition from RBM to SBS.

Second, the error of the merchant-ship navigators is predicted to continuously transition from RBM to SBS and back.

Finally, unlike the fishing-ship navigators, the KBM of the merchant-ship navigators affects the transition between RBM and SBS.

3. Decision-making Pathway of Navigator Error

The decision-making pathway of the navigator error was determined by analyzing the optimal likelihood of the observed symbols in a single path of states.

Table 7 shows some of the optimal log-likelihoods for the observed symbols of both models calculated using the Viterbi algorithm (Viterbi, 1967; Forney, 1973). These results show only the first to fourth highest values of the maximum log-likelihood among the 27 observation symbols.

In Table 7, for the two models, the combination of symbols 14, 4, and 1 or 23, which is common at the first to fourth positions, is analyzed as follows.

First, the log-likelihood of symbol 14 was ranked first in both the models. According to the rules of symbol combination in Table 2, symbol 14 is combined with error level 2 of Categories 1, 2, and 3. Using the level descriptions in the navigator error framework, these combinations can be described as follows: the first-ranked decision-making pathway of navigator error of both the fishing and merchant ships appears to be RBM in a familiar situation, primarily when performing the mixed state of automation and conscious procedures.

Second, the log-likelihood of symbol 4 was ranked second in both the models. According to the rules of symbol combination in Table 2, symbol 4 is combined with error level 1 of Category 1, level 2 of Category 2, and level 1 of Category 3. Using the level descriptions in the navigator error framework, these combinations can be described as follows: the second-ranked decision-making pathway of navigator error of both the

fishing and merchant ship appears to be SBS in a routine situation, primarily when performing the mixed state of automation and conscious procedures.

Finally, the log-likelihood of symbol 23 was ranked third or fourth in both the models. According to the rules of symbol combination in Table 2, symbol 23 is combined with error level 2 of Category 1, level 1 of Category 2, and level 3 of Category 3. Using the level descriptions in the navigator error framework, these combinations can be described as follows: the third- or fourth-ranked decision-making pathway of navigator error of both the fishing and merchant ships appears as to be KBM in a familiar situation, primarily when performing automated procedures.

In the above error path analysis, symbol 14 (corresponding to RBM) is ranked first, symbol 4 (corresponding to SBS) is ranked second, and symbol 23 (corresponding to KBM) is ranked third or fourth. These results are consistent with the interpretations of the error transitions in subsection 2 (navigation error transitions), thus indicating that SBS and RBM are prominent and KBM is not prominent. Consequently, the interpretations of the error transitions were partially validated.

4. Discussion

To prevent ship collisions, it is important to reduce the causes of navigator errors. In IMO (2016), various training courses have been proposed to manage human error. Nevertheless, the ongoing occurrence of collision accidents shows that additional measures are needed to reduce human errors (Allianz, 2018). Smart shipping and unmanned ships are being studied as alternatives to reduce human errors (Shaw and Tzu, 2019; Jung et al., 2018). However, it is also important to understand the characteristics of a navigator's error, which is the cause of marine accidents. From the results of the present study, three interesting observations were made. First, the fishing-ship navigators tended to primarily transition from RBM to SBS. Second, the merchant-ship navigators tended to transition from RBM to SBS and back, and KBM influences were also included. Lastly, RBM was ranked first in the decision-making pathway of navigator errors. These results can consider the working environment. A fishing-ship navigator is more concerned with sailing than following navigation rule when fishing. However, it is considered that the navigator of a merchant ship sails along a designated route or course line. Based on these results, a possible solution is changing how navigator errors occur, i.e., RBM in the case of fishing-ship navigators and both RBM and SBS in the case of merchant-ship navigators. However, to apply the above solution in the real world, additional research using more elaborate techniques is required because many factors influence how navigator errors occur.

IV. CONCLUSIONS

Herein, navigator errors of fishing and merchant ships in the event of a collision accident were modeled using HMMs. The

results of implementing the models are presented.

First, both models predicted navigators would exhibit RBM and SBS, primarily attributed to a ship collision.

Second, fishing-ship navigators tended to transition from RBM to SBS, while merchant-ship navigators continuously transitioned from RBM to SBS and back, wherein KBM influences were also included.

Finally, the most prominent decision-making pathway for navigators was RBM, primarily in a familiar situation, when performing the mixed state of automation and conscious procedure.

This study provided valuable insights into the modeling of navigator errors in the event of ship collisions based on the navigator error framework. Further, the resulting models are expected to provide ideas regarding how to change navigator errors to prevent collisions.

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