Article

Analysis of Lookout Activity in a Simulated Environment to Investigate Maritime Accidents Caused by Human Error

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Abstract: Maritime accidents remain a significant concern for the shipping industry, despite recent technological developments. In the Republic of Korea, the leading cause of maritime accidents is navigator error, particularly in collisions and groundings; this cause has led to 79% of maritime accidents, according to a recent assessment. The reduction of navigator error is crucial for accident prevention; however, the lack of objective measures to monitor navigator error remains a challenge. The purpose of this study was to develop an objective classification of navigation behaviors in a simulated environment. The statistical model of classification of lookout activity was developed by collecting participants' lookout behavior using a Kinect sensor within a given scenario. This classification model was validated in non-scenario experiments. The results showed that seven standard lookout activities during a lookout routine were accurately classified in both the model development and validation phases. The proposed model classification of lookout activity using an optical sensor is expected to provide a better understanding of how navigators behave to help prevent maritime accidents in practice.

Keywords: maritime accidents; lookout behavior classification; optical sensor; machine learning model; simulation environment

1. Introduction

As global trade has grown in recent decades, the shipping industry has grown dramatically in response. Safety requirements have become increasingly important [1]. To ensure the safety of maritime transportation, scientific measures should be taken to respond to and prevent the various types of maritime accidents instead of putting ambiguous anticipations of possible human errors into place [2–4]. Navigator error was involved in 79% of accidents in the Republic of Korea over the past five years, based on a recent assessment [5]. Moreover, inappropriate behaviors accounted for 49% of all maritime accidents [6]. Although the majority of maritime accidents were directly related to navigator error, evidence of the navigator error has not yet been explored objectively [7]. Most existing assessments of navigators' lookout behaviors have depended on indirect data-collection methods such as diaries, surveys, and questionnaires [8–10]. Harma et al. used self-reported diaries and questionnaires to investigate the situational awareness of navigators related to lookout activity patterns [11]. The use of such indirect approaches remains a subjective limitation for the accurate monitoring of the lookout behavior of navigators during navigation. This limitation could be addressed using more objective data-collection measures for navigator behavior, such as eye trackers and optical sensors. Lutzhoft

and Dukic conducted eye tracker-based research to investigate the association between the allocation of navigational equipment and navigation safety in the simulated environment [12]. Moreover, the eye tracker was also utilized to evaluate the navigational workload and concentration in the given navigational environment [13,14]. However, there is still a lack of investigation into navigators' physical behavior to measure lookout activity patterns. The purpose of this study was to establish a classification model for lookout behaviors using the Kinect sensor in a simulated navigation environment.

The proposed sensor-based lookout activity classification model was employed with 27 senior cadets at a maritime university in the Republic of Korea. In the standard navigation scenario, participants performed seven standard lookout activities in navigation simulation. The infra-red images collected by the Kinect system were then utilized to develop a machine-learning activity classification model, which was validated in a non-scenario navigation experiment that used direct observation as ground truth. The two main contributions of this study are a scientific research framework for the investigation of the navigator error and objective evidence of how navigators physically performed navigational lookout.

2. Materials and Methods

The research framework of this study is presented in Figure 1. In the model development phase (the left part of Figure 1), Kinect image data were obtained during scenario-based navigation experiment; then, feature extraction and selection were performed to obtain statistically significant feature subsets of human movement. In the model-validation phase (the right part of Figure 1), additional non-scenario navigation experiments were performed with direct observation to record true activity. A directly observed lookout activity record was used to validate the activity classification model that was developed in the previous step.

Figure 1. Research framework for the development of lookout-activity classification models.

2.1. Data Collection

2.1.1. Experiment Configuration

Data were collected in the full-mission-ship-handling simulator at Mokpo National Maritime University. The Microsoft Kinect sensor is a promising human-movement registration system (Xbox On, Microsoft); it uses a wide-angle time-of-flight camera to read the environment. The Kinect system was launched in combination with a software development kit for use with 3D human-posture recognition. The Kinect sensor has been validated with the use of an impressively large training dataset of compared-depth data for accurate recognition of movement [15,16]. Kinect has an increased field of view that can detect movement up to 4 meters away. In skeletal tracking, a human body is represented in the system by a number of joints corresponding to body parts, including the head, trunk, and limbs. As illustrated in Figure 2, each joint is represented by its 3D coordinates [17–20]. The sampling frequency of kinematic images was 30 Hz. Figure 3 exhibits the experimental setting of the Kinect sensor in the full-mission ship-handling simulator room. The Kinect sensor was located in the left corner of the simulation room to record the full body kinematics of each navigator during experiments. The sensor for Windows Software Development Kit 2.0 was provided by Microsoft, and the list and locations of 25 body points are indicated in Table 1 and Figure 4. Lookout behavior features using body-joint kinematic data were computed with custom software developed using MATLAB 9.0 (Mathworks, Natick, MA, USA).

Figure 2. Experimental configuration with the Kinect infra-red (IR) camera system in the full mission-ship-handling simulation environment.

Figure 3. Experimental configuration with the Kinect IR camera system in the full mission-ship-handling simulation environment.

Table 1. List of lookout movement features.

Category	Location	Feature Number
Trunk	Base of spine	1
	Mid-spine	2
	Neck	3
	Head	4
	Left hip	13
	Right hip	17
	Shoulder-height spine	21
Upper limbs	Left shoulder	5
	Left elbow	6
	Left wrist	7
	Left hand	8
	Right shoulder	9
	Right elbow	10
	Right wrist	11
	Right hand	12
	Left hand tip	22
	Left thumb	23
	Right hand tip	24
	Right thumb	25
Lower limbs	Left knee	14
	Left ankle	15
	Left foot	16
	Right knee	18
	Right ankle	19
	Right foot	20

Figure 4. Anatomical locations of the 25 tracked joints.

2.1.2. Experiment Protocol

During the model development phase, 24 senior cadets (174.3 ± 8.4 cm, 67.3 ± 11.7 kg, 23.2 ± 1.8 years) at Mokpo National Maritime University participated in the study (Table 2). All participants completed a year-long onboard navigation training and performed scenario-based lookout activities, including the seven standard lookout activities in Table 3 and four sample lookout activities in Figure 5.

Table 2. Participant characteristics.

Characteristics	Mean (SD)
<i>N</i>	24
Female/male	4/20
Age (years)	22.1 (1.6)
Height (cm)	172.2 (6.9)
Weight (kg)	69.6 (11.7)

Table 3. Standard lookout activities scenario.

Lookout Type	Activity	Duration (Seconds)	Description
Lookout	Standing	50	Standing still for lookout
	Leaning	50	Reluctant posture for lookout
	Binocular	50	Active lookout
	Radar	50	Controlling nav. equipment
	Walking	50	Lookout while walking
Non-lookout	Writing	50	Recording navigation info
	Sitting	50	Resting and reluctant posture
Total duration		350	Including breaks ¹

¹ Each activity includes a 10-second break.

Figure 5. Examples of lookout activities: (a) standing lookout, (b) leaning lookout, (c) radar lookout, and (d) writing.

During the model-validation phase, the classification models developed in the previous phase were validated through a comparison of predicted outcomes of lookout activity with records of directly observed lookout activity. The non-scenario navigation experiments of the additional two participants were directly observed by trained observers and recorded with a video camera for cross-validation. Every five seconds, the direct observer recorded a representative lookout activity for the interval; the record of direct observation was also double-checked through a comparison of the video record to avoid observers' mistakes.

2.2. Data Analysis

2.2.1. Feature Extraction

The extraction of the features of the movement of the navigators is presented here. Although a non-feature extraction learning method, such as deep learning, might perform better for classifying lookout behavior, the features of the lookout movements were extracted and prioritized to allow a closer understanding of how a navigator physically performs navigational lookout. The features of lookout movement were organized using 25 kinematic parameters of joints obtained from the Kinect, and the raw kinematic data were included in five-second intervals. In this study, we focused on the joint kinematic features that could be used to recognize different lookout activities. The identification of features of lookout movements is important because the identified features should be closely considered to determine whether the quality of a lookout is positive. To determine the efficient movements, all 25 joint kinematic parameters were extracted as shown in Table 4.

Table 4. Navigator movement feature properties.

Feature	Description	Abbreviation Example
Joint motion magnitude	Vector magnitude of each joint obtained by using root mean squares of the x -, y -, and z -axis values	JMM-5 = JMM head
Joint motion variation	Standard deviations for each joint for the x -, y -, and z -axes	JMV-10 = JMI right elbow

2.2.2. Classification Model Development

To more easily interpret the classification model, linear machine-learning algorithms were used, including the decision-tree, support-vector machine, and K-nearest-neighbor (KNN) algorithms. After the three machine-learning algorithms were compared, the KNN was finally selected to create classification statistics because KNN provides better interpretability while yielding a similar degree of accuracy of lookout classification.

Moreover, to create a better understanding of efficient classifiers of lookout movements, the 25 movement features were categorized into three groups (trunk, upper limbs, and lower limbs). This provided information on the duplication and irrelevance of the selected kinematic features of the joints. The process allowed us to reduce the various information among the twenty-five kinematic features of joints. Additionally, no method of parameter tuning, such as principal component analysis, was used, although these could have increased the classificatory power. This is because the tuned kinematic features of joints provide less information on precisely which specific joint kinematic features are important.

2.2.3. Validation

In feature selection, the subsets of the 25 joint kinematic features were carefully selected to avoid any overfitting of the proposed classification model. Preprocessing of the statistical data helped us to avoid overfitting the classification model, using non-overlapping features with multiple input features. Additionally, we applied 10-fold cross-validation [21] to improve the validity of the proposed model. In the cross-validation, 24 subjects were allocated to ten subfolders; one of these ten was used to test the model. The remaining subfolders were used to train the model. The procedure was intended to develop a robust model for lookout activity classification that could describe an unseen navigator's lookout behavior. Finally, the validated model for lookout activity classification was validated using directly observed record of lookout activity. The non-scenario navigation experiments of the three additional participants were directly observed by trained observers and recorded with a video camera for cross-validation. Every five seconds, the direct observer recorded a representative lookout activity

that took place in that interval; the record of direct observation was also double-checked with a comparison of a video recording to check for observation error.

3. Results

3.1. Lookout Classifications

In total, 94.9% classification accuracy was achieved for the seven standard lookout activities described with the 25 lookout movement features. Writing, walking, and sitting lookout activity classifications were promising, whereas standing and leaning resulted in relatively higher confusion. Moreover, standing and sitting were also confused because the Kinect sensor tracked the lower-limb joint features unreliably during sitting. This is because the trunk and upper limbs during the two activities are similar. Additionally, writing featured a distinctive pattern, particularly in the trunk and upper limbs, so the activity was correctly classified from other behaviors. The overall classification results using all 25 movement features are shown in Table 5.

Table 5. Confusion matrix for seven standard lookout classification model using the K-nearest-neighbor (KNN) algorithm.

True Activity	Predicted Activity (%)						
	Standing	Leaning	Binocular	Radar	Walking	Writing	Sitting
Standing	90	4	-	-	-	-	6
Leaning	4	95	-	-	-	-	1
Binocular	-	5	94	-	-	-	>1
Radar	-	-	1	93	3	-	3
Walking	-	-	-	2	97	>1	-
Writing	-	-	-	>1	-	99	-
Sitting	3	-	1	-	-	-	96

3.2. Categorical Lookout Classification Sensitivity

To determine the efficiency of the classification of lookout activities based on the movement feature categories, the 25 movement features were grouped into the following groups: trunk, upper limbs, and lower limbs. When the selected lookout movement features for each group were given to classify the same training data, the results of classification provided a rationale determining the efficiency for each group of movement features. As shown in Figure 6, there was an 87.1% accuracy in the classification of lookout activities using the trunk features, including base of the spine, mid-spine, neck, head, left hip, right hip, and shoulder-height spine; the determination of the 12 upper-limb features had a 77.1% accuracy. The six lower-limb features (i.e., left knee, left ankle, left foot, right knee, right ankle, and right foot) had the lowest classification accuracy, at 56.9%.

3.3. Non-Scenario Validation

In non-scenario-based lookout experiments, two additionally recruited participants acted as a free lookout, in the sense that they were not told what specific lookout activities they were intended to accomplish, apart from maintaining safe navigation. The patterns of lookout activity of the participant were directly observed and recorded every five seconds. This pattern allowed the seven standard lookout activities to be recognized in the non-scenario-based experiment. As a result, the results of the classification of lookout activities were promising. As shown in Figure 7, there was a 95.2% accuracy in the classification of lookout activities using the proposed lookout activity classification model, including 6 misclassified activities in validation experiment 1 and 4 misclassified activities in experiment 2.

Figure 6. Comparison of classification accuracies based using categorical lookout-activity classification accuracy.

Figure 7. Validation of results of lookout activity classification using direct observation: (a) validation experiment 1, (b) validation experiment 2.

4. Discussion

This study was undertaken to develop a classification model for standard lookout activities using data from the Kinect sensor in a simulated navigation environment. The approach was intended to address the limitations of the common indirect approaches to the issue of navigator assessment.

This study demonstrated the efficacy of a proposed novel method using an optical sensor system to address the limitations of other methods. Distinct from previous studies, which used aggregated patterns of lookout behaviors, this model precisely measured specific lookout activities performed for navigation practice. Moreover, the study compared the efficiency of different features of movement by categorizing the locations of the features of the body. The categories of lookout movements, trunk motions, and movements of the upper limbs should be used to monitor navigators' lookout patterns. Finally, validating the prediction model in non-scenario-based navigation indicated that it can be expected to be feasible for a real navigation environment. Nevertheless, the conditions of a real navigation environment should be considered in future research. For example, multiple navigators, such as a duty officer and a quartermaster acting as a navigation team, could perform navigation, meaning that a future study undertaken to track multiple objects at once should be implemented.

5. Conclusions

The results of the proposed classification of lookout activity showed that the optical sensor-based classification of navigator behavior can be used to accurately indicate the precise nature of such behavior during ship navigation. The proposed model can be expected to produce a better understanding of how a navigator behaves during ship navigation and to apply research into human error patterns that can prevent navigational accidents by showing harmful navigation routines or patterns of a navigator. Future work will examine the association between navigators' patterns and maritime accidents to prevent maritime accidents by precisely anticipating possible navigator error.

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