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Navigator Lookout Activity Classification Using Wearable Accelerometers

Ik-Hyun Youn and Jong-Hoon Youn*, *Member, KIICE*

Department of Computer Science, College of IS&T, University of Nebraska at Omaha, Omaha, NE 68182, USA

Abstract

Maintaining a proper lookout activity routine is integral to preventing ship collision accidents caused by human errors. Various subjective measures such as interviewing, self-report diaries, and questionnaires have been widely used to monitor the lookout activity patterns of navigators. An objective measurement of a lookout activity pattern classification system is required to improve lookout performance evaluation in a real navigation setting. The purpose of this study was to develop an objective navigator lookout activity classification system using wearable accelerometers. In the training session, 90.4% accuracy was achieved in classifying five fundamental lookout activities. The developed model was then applied to predict real-lookout activity in the second session during an actual ship voyage. 86.9% agreement was attained between the directly observed activity and predicted activity. Based on these promising results, the proposed unobstructed wearable system is expected to objectively evaluate navigator lookout patterns to provide a better understanding of lookout performance.

Index Terms: Lookout activity classification, Machine learning, Maritime information, Wearable sensor

I. INTRODUCTION

Rapid advances in information and communication technologies (ICTs) have recently been made in marine navigation. Integrated navigation systems (INSs) and unmanned vessels (UVs) represent emerging technical advances in the maritime industry [1, 2]. However, it is not surprising that ship collisions are still occasionally occurring despite the development of navigation technologies. The recent collisions of two US Navy destroyers with commercial merchant marine vessels off the coasts of Japan and Malaysia demonstrate that even well-equipped vessels with advanced navigation technologies does not guarantee the elimination of such tragic collisions [3].

Notwithstanding technical advances, the importance of maintaining proper lookout by sight and hearing cannot be overemphasized. Poor lookout has been a predominant reason for marine vessel collisions [4]. Many previous studies have reported that the majority of collision accidents were due to poor lookout of navigators, and only a small portion of accidents was caused by technical deficits of navigational equipment [5, 6]. Research methods to monitor navigators’ lookout patterns have been manually and subjectively conducted. For example, the evaluation of navigator lookout performance was carried out in various marine traffic conditions by Murai et al. [7] in 2006, but the limitation of the study was the use of direct observation of navigators' lookout activities by human observers. The situation awareness of bridge officers related to lookout activity patterns was studied by Harma et al. [8] by using self-reported diaries and questionnaires. Furthermore, although the routine lookout activities of navigators have

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***Corresponding Author** Jong-Hoon Youn (E-mail: jyoun@unomaha.edu, Tel: +1-402-554-2187)
Department of Computer Science, College of IS&T, University of Nebraska at Omaha, Omaha, NE 68182, USA.

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been significantly changed, there are few studies that have monitored patterns of navigators' lookout activities without human intervention.

Therefore, the purpose of this study was to develop and validate an automated navigator's lookout activity classification system using wearable sensors for navigator lookout pattern analysis. Wearable sensors are beneficial in developing this classification system, because a wearable sensor-based system is capable of capturing continuous acceleration and deceleration produced by lookout activities of navigators in an unobstructed manner. The following sections describe data collection and data analysis methods used in this study.

II. METHODS

A. Data Collection

Twenty-seven senior college students (n=27) participated in the study. All participants were senior cadets at the Mokpo National Maritime University in South Korea. The descriptive characteristics of the participants are summerized in Table 1.

All participants were familiar with the ship's lookout routines and navigation instruments. All participants completed the controlled experiment protocol in the first session. Table 2 presents the fundamental lookout activities defined in the study. Since the lookout activity routine mainly consisted of dedicated and inactive physical activities such as standing still to observe around the ship and tuning the radar to adjust the scanning distance while standing, the participants wore two Shimmer3 [9] devices on the wrist of their dominant hands and their chests using an elastic strap. The wrist-worn sensor was intended to capture the acceleration of wrist movements, and the chest-worn sensor was attached to monitor whether subjects walked or stood.

The sampling frequency of the wearable sensors was set at 100 Hz in this study. Once participants wore the two sensors, the wrist and body movement characteristics of the fundamental lookout activities were examined in the first session. The second session was to validate the developed classification models in the first session by comparing the predicted lookout activity outcomes with the actual activity record detected by the observer. The real lookout activity of the third officer of the training ship was directly observed by trained observers for the cross-validation. Two trained observers recorded the third officers' lookout activities at one-minute intervals. Both sessions were conducted during an international voyage between the Port of Mokpo, South Korea and Manila, Philippines.

Table 1. Descriptive characteristics of participants (n=27)

Characteristic	Value
Sex (female:male)	6:21
Age (yr)	22.3±1.8
BMI (kg/m^2)	23.4±2.6
Height (cm)	174.1±8.3
Weight (kg)	68.2±14.2

Values are presented as number or mean±SD.

B. Data Analysis

To develop accurate lookout activity classification models, the distinctive raw acceleration data from both wrist and upper body movements were grouped into a one-second epoch, and wrist and body movement characteristics were analyzed from each of the data segments. Nine movement features were extracted from each data window. Table 3 lists the computed wrist and body movement features.

The standard deviation (SD) of directional accelerations and vector magnitudes were computed to estimate the different magnitudes of body segment motion, and the roll and pitch angles were calculated to estimate the orientation of the wrist and upper body relative to the horizontal plane. To classify each lookout activity, lookout time, and radar watch time, three estimation models were developed: (1) five types of lookout activity classification model, (2) lookout or not classification model, and (3) radar watch or not classification model. These three categories were previously used for lookout performance evaluation in the

Table 2. Fundamental lookout activities for data collection in the first session

Lookout activity	Body activity	Wrist activity	Activity description
Lookout	Standing	Natural pose	Bare-eye lookout while standing
	Walking	Natural pose	Bare-eye lookout while walking
	Standing	Binocular holding	Binocular lookout while standing
Radar watch	Standing	Radar controlling	Radar watch by controlling Radar
Hand writing	Standing	Writing	Writing navigational condition on a logbook

Table 3. Extracted feature descriptive information

Feature	Acronym	Method
Wrist motion	W-VM	SD of vector magnitude of wrist
	W-X	SD of X-axis acceleration of wrist
	W-Y	SD of Y-axis acceleration of wrist
	W-Z	SD of Z-axis acceleration of wrist
Wrist orientation	W-Roll	Wrist roll angle of wrist
	W-Pitch	Wrist pitch angle of wrist
Body motion	B-VM	SD of vector magnitude of body
Body orientation	B-Roll	Wrist roll angle of body
	B-Pitch	Wrist pitch angle of body

literature [7, 10]. For the development of the classification models, the following three machine learning algorithms were considered as classifiers: neural networks, decision tree, and nearest neighbors. These algorithms have been applied to classify physical activities using acceleration data [11]. After examining the machine learning algorithms, the K-nearest neighbors algorithm (KNN) was selected as a classifier since KNN can represent a wide variety of associations between movement features and lookout activities. The lookout activity features were computed by custom software developed in the MATLAB 9.0 (Math works, Natick, MA, USA) environment.

III. RESULTS

A. Controlled Experiment

The raw acceleration patterns of the fundamental lookout activities selected in this study are illustrated in Fig. 1. Each lookout activity showed different characteristics of body and wrist acceleration patterns. For example, since the only locomotion activity (i.e., walking for bare-eye lookout) generated an apparently different acceleration pattern from the rest of the lookout activities, the detection of the walking lookout from other activities was done accurately. For the walking classification, the detection of body acceleration patterns was crucial because the variation of the body acceleration generated by walking was much higher than that of other lookout activities. We noticed that the wrist acceleration did not effectively capture the differences between the walking lookout and other lookout activities listed in Table 2.

However, the wrist acceleration patterns were useful to classify other dedicated lookout activities. Since the fundamental lookout activity routine mainly consists of static activities (i.e., standing for bare-eye lookout, standing for binocular lookout, standing for radar control, and standing for recoding), further classification of the static activities is crucial. For example, although the wrist movement of the binocular lookout was static and similar to other static lookout activities, the wrist pitch angle was an important factor to capture the distinctive characteristics of

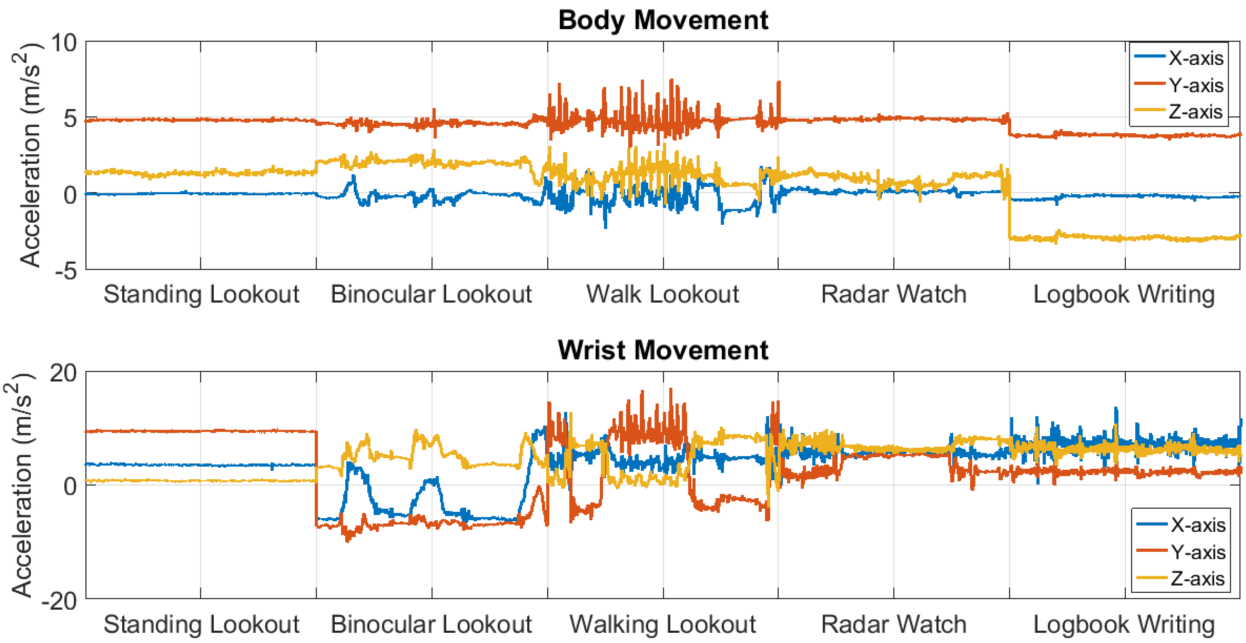

Fig. 1. Acceleration patterns of five fundamental lookout activities including bare-eye lookout, binocular lookout, walking lookout, radar watch, and hand writing.

the binocular lookout. The pitch angle efficiently captured unique characteristics of binocular holding wrist orientation during the lookout activity.

Similarly, the radar watch and writing activities showed a similar pattern of wrist movements, but the wrist orientations between the radar watch and writing activities were clearly distinctive. This is because the pitch angle of radar handling was below the horizontal plane, whereas the pitch angles for writing were typically parallel to the horizontal plane. Table 4 summarizes the classification accuracy of the lookout activities by the first classification models, and Table 5 summarizes the confusion matrices of the binary classification models for lookout and walk. The accuracy of the real-lookout experiment was measured. Where *TP* is a true positive measure, *TN* is a true-negative measure, and *N* is the number of measures, accuracy was defined by Eq. (1):

$$Accuracy = \frac{(TP + TN)}{N}. \tag{1}$$

An accuracy rate of 90.4% was achieved in classifying the fundamental lookout activities. The achieved accuracies in classifying the lookout from other activities and walking from others were 91.6% and 96.6%, respectively.

The main challenge while classifying the fundamental lookout activity routine was the bare-eye lookout activity with natural wrist poses. This activity was the most common lookout physical activity, but it was difficult to accurately classify due to a wide range of variations of wrist poses. Various standing lookout behaviors including crossing arms, were observed during the control experiment, and the resting on the windowsill, and putting hands in the pockets natural wrist pose made more classification errors during the development stage of the classification model.

B. Real-Lookout Experiment

The classification models were cross-validated by two trained observers who recorded activities during the real-lookout experiment session. The third officer of the training ship wore two accelerometers on the wrist of his dominant hand and on his chest and conducted his ordinary lookout activity during a real voyage between the Port of Mokpo, South Korea, and Manila in the Philippines. Two hour-long real-lookout activities were recorded at one minute intervals by two trained observers. One observer directly recorded one of the five activity categories in each epoch, and the other observer wrote down whether the navigator walked or not, and performed any lookout activities or not.

Fig. 2 shows the classification accuracy of three lookout activity classification models. The classification accuracy of all five lookout activities is below 80% whereas the accuracy of the second classification model of lookout including bare-eye, binocular, and walking lookout from the non-lookout activity including radar and writing was 89.9%. Although the accuracy of the walking classification model in the controlled experiment session performed well, the accuracy of the real-lookout activity was similar to the accuracy of the lookout activity classification model (92.2%).

Table 4. Confusion matrix of five fundamental lookout activity classification models using the KNN algorithm

True activity	Predicted activity				
	Stand	Walk	Binocular	Radar	Writing
Stand	83.2	10.8	1.8	2.9	1.3
Walk	2.9	94.7	0.4	1.7	0.3
Binocular	4.8	1.9	91.2	1.4	0.7
Radar	5.0	1.5	0.9	89.7	2.6
Writing	2.7	1.2	2.3	0.7	93.1

Table 5. Confusion matrices of lookout and walk classification models

True activity	Predicted activity			
	Lookout	No lookout	Walk	Stand
Lookout	91.6	8.4	-	-
No lookout	8.5	91.5	-	-
Walk	-	-	97.3	2.7
Stand	-	-	4.2	95.8

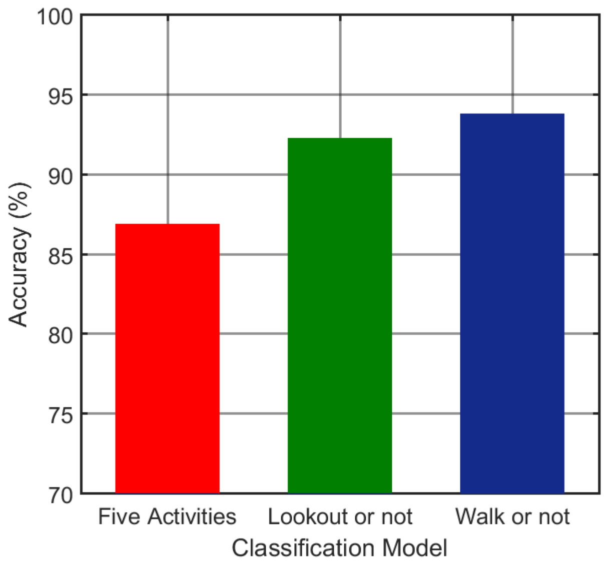

Fig. 2. Classification accuracy of three lookout activity classification models for real-lookout of third officer who is different from the training session.

IV. DISCUSSION AND CONCLUSIONS

In this paper, wearable-sensor based navigator lookout activity classification methods were proposed. In both controlled and real lookout experiments, the proposed systems yielded reasonable accuracies in classifying the fundamental lookout activities such as bare eye-lookout, navigation instrument handling, and hand recording.

The experimental results confirmed that the proposed approach is promising as a method for analyzing navigator lookout patterns. The proposed wearable method could improve our understanding of navigators' lookout patterns in relation to navigation safety. Future work will focus on the use of the proposed wearable approach to determine which lookout patterns are mainly performed in different maritime traffic constraints such as traffic densities and weather conditions.

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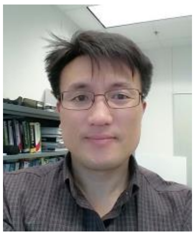
Ik-Hyun Youn
is currently a Ph.D. candidate in the College of Information Science and Technology at University of Nebraska at Omaha. He received a B.E., M.E., and M.S in 2004, 2011, and 2016 from Mokpo National Maritime University, Korea Maritime and Ocean University, and the University of Nebraska at Omaha, respectively. His current research interests are focused on wearable sensor-based human movement analysis from healthcare and safety management perspectives.



Jong-Hoon Youn
received the M.S. and Ph.D. degrees in Computer Science from Oregon State University in 1999 and 2002, respectively. He is currently a Professor of Computer Science at the University of Nebraska, Omaha (UNO). His current research interests are focused on wireless sensor networks, development of mobile applications, design and analysis of low-power communication protocols, and mobility monitoring using wireless sensors.