Detecting Hook Attachments of a Safety Harness Using Inertial Measurement Unit Sensors

Hoonyong Lee[a], Namgyun Kim[a], and Changbum Ryan Ahn[b]*

[a]Department of Architecture, College of Architecture, Texas A&M University, Texas, USA
[b]* Department of Architecture and Architectural Engineering, Seoul National University, Seoul, South Korea
E-mail: onarcher@tamu.edu, ng1022.kim@tamu.edu, cbahn@snu.ac.kr

Abstract

Construction workers are required to wear a safety harness while working at height, and safety managers need to ensure that a safety hook is attached to proper anchorage points to prevent falls from height. However, it is difficult for the managers to monitor all the worker's hook attachments continuously and remotely in dynamic workplace environments. This study developed an approach to detect an individual worker's hook attachments by assessing the relative movements between the hook and the worker's body. An Inertial Measurement Unit sensor was attached to the hook and the body strap to monitor the relative movements. The collected IMU data was transformed into image data by Markov Transition Field. The detection algorithm was developed based on the convolution neural networks that classify the worker's postures, activities, and hook attachments simultaneously, and the developed detection system provided classification accuracies of 86.40%, 86.97%, and 96.58, respectively. The results validated that the relative movement between the hook and the worker's body is a key feature for hook attachment detection.

Keywords –

construction safety; safety harness; hook attachment detection; wearable computing

1 Introduction

Falls from height (FFH) have been identified as a significant source of fatal accidents at construction sites [1]. In order to protect workers from FFH, some prevention measures have been proposed [2]. For example, the use of a safety harness is required while working at height. However, workers could often be reluctant to use a safety harness because of non-compliance and restrictions to movement [3]. Although construction worker education and training are effective ways to address the reluctance, these are not always effective entirely [4,5]. Real-time monitoring and warning of the improper use of a safety harness would contribute to change workers' safety behaviors. One of the safety manager's tasks is to frequently monitor workers and site conditions to get real-time data through direct observation and interaction with workers [6]. Although a safety manager should identify workers who do not properly use a safety harness in a hazardous zone (e.g., a roof and top floor), it would be a challenge to monitor all the workers who are working at height from the ground level, continuously and remotely.

In recent years, advances in sensing technology and machine learning algorithms have enabled safety managers to monitor the activity and physical status of workers in real-time [7]. Previous studies have applied these technical improvements to develop detection systems for the use of a safety harness. A previous study [8] developed an approach that uses an image classification algorithm to detect whether a worker wears a safety harness. In this study images of workers taken with a monocular camera were used, but the quality of image data is affected by environmental factors (e.g., weather and light) that would degrade the detection performance. In another previous study [9], based on the distance between the hook and the lifeline, it was detected whether the worker attached the safety hook to the lifeline. This approach used Bluetooth Low Energy beacons to measure the distance based on the worker's location. If the distance is less than the threshold, the safety hook is considered to be attached to the lifeline. However, a close distance between the hook and the lifeline does not always guarantee the connection.

In this context, this study aims to develop a novel detection approach for the proper use of a safety harness. The sensing sources of the developed approach were safety hook and worker's bodily movements, measured by wearable Inertial Measurement Unit (IMU) sensors. In this current study, a distinct body movement pattern according to postures and activities and a distinct hook movement pattern according to attachments were assessed. The developed system simultaneously detects the worker's posture, activity, and hook attachment. Therefore, the main contribution of this study is to detect the proper use of a safety harness while undertaking various construction tasks at the workplace.

2 Background

2.1 Wearable Sensors in Construction Worker Safety

Various sensor technologies have been used to improve the safety of workers on construction sites. For example, Real-Time Locating Systems (RTLS) have been implemented by Radio-Frequency Identification (RFID) and Bluetooth Low Energy (BLE) technologies [10]. These systems consist of a transmitter and several receivers. The transmitter is attached to a worker while transmitting radio signals with an identification number, and the receivers are attached to a moving object, PPE, or located in hazardous areas. RTLS measures the current location of the worker based on the distance between the transmitter and the receiver. One parameter for calculating the distance is the Received Signal Strength Indicator (RSSI), which measures the attenuated power at the receiver. For construction safety management, RTLS has been used to warn workers when entering hazardous zones (e.g., a roof and top floor) or approaching dangerous moving objects (e.g., heavy machines) [11]. RTLS can warn workers of danger even in blind spots because radio signals can penetrate or reflect from some obstacles to reach the receivers in non-line of sight environments [12]. Additionally, the transmitter can be attached to PPE, such as a safety helmet or harness to monitor whether individual workers wear PPE in the workplace [9]. However, since RFID and BLE beacons have a limited coverage area and signal propagation can be affected by environmental factors, the accuracy can decrease as the distance between beacons increases.

Physical response measurement systems have been also implemented to improve worker safety management. IMU sensors have frequently been used to assess workers' physical changes while undertaking construction tasks. A typical IMU sensor consists of an accelerometer and a gyroscope. The IMU sensor is attached to the worker's body part and measures the movement of the body part in three-axis acceleration and angular velocity. Most construction tasks require physical demands without sufficient rest, which can lead to work-related musculoskeletal disorders (WMSDs) [13]. Therefore, measuring a worker's physical response to repetitive and prolonged construction tasks would help prevent overexertion injuries. Measured bodily movements were used to detect awkward postures [14,15], excessive load carrying that produced distinct patterns of bodily movements [16]. Gait kinematics were also measured by IMU sensors to assess exposure to slip, trip, and fall (STF) hazards that generated abnormal gait patterns [17]. Because IMU-based monitoring systems directly record the worker's bodily movement, their performances are less affected by environmental factors (e.g., light or weather). However, the bodily movements could be different for each worker and may vary depending on the worker's physical status, which may cause performance variations depending on training data.

2.2 Monitoring Use of Safety Harness in Construction

A previous study [8] developed an approach to detect whether workers are wearing their safety harnesses using an image classification algorithm. The developed approach has two phases: (1) worker presence detection and (2) safety harness identification. Although this approach provided 99% and 80% precision performance on phases 1 and 2, respectively, this approach did not detect hook attachments. Even if a worker wears a harness, the worker may not properly use the safety harness. For example, the safety hook would be attached to the worker's body or placed on the ground. Therefore, it is necessary to monitor not only wearing a safety harness but also properly using the safety harness.

Another previous study [9] developed a system detecting the proper use of a safety harness using BLE technologies. This system detected whether the safety hook is attached to the lifeline hook according to the distance between the lifeline hook and the worker who needs to attach the safety hook. Once the worker attaches the safety hook to the lifeline hook, the worker's location would be identical to the lifeline hook. A BLE receiver was attached to the worker's safety hook and a BLE beacon was attached to the lifeline hook. The distance between these BLE devices was calculated based on RSSI. Another BLE beacon was located in the hazardous zone where the worker must attach the safety hook to the lifeline. The third BLE beacon was placed at an interval of 2m, where the working began at height. Due to the limited coverage area of the BLE beacons, a distance between 1 and 2 m was required between beacons. Although this system was validated in a field experiment, this approach had some practical limitations. Multiple BLE beacons are required to cover the space, and those beacons need to be relocated when the working environment changes. Also, the distance-based detection approach would produce false detection if the worker is working near the lifeline without attaching the safety hook to the lifeline.

In this context, this study developed a new detection system for the proper use of a safety harness. This study measured the hook and the bodily movements using IMU sensors attached to the hook and body strap and found that the hook movement is affected by both the worker's bodily movement and hook attachment points (e.g., attaching to a rigid structure and the worker's body or placing on the ground). Therefore, the hook attachment can be detected by assessing the relative movements between the worker's body and the safety hook.

3 Methodology

3.1 Data Collection

Five subjects participated in the experiment to collect IMU data of the safety hook and bodily movements while performing different activities: (1) walking, (2) moving bricks, and (3) using a drill machine. While performing the activities, the safety hook was attached at several points: (1) attached to scaffolding, (2) attached to the body strap (chest), and (3) placed on the ground. Also, moving bricks and using a drill machine were performed by two postures: (1) standing and (2) kneeling. Therefore, 18 cases of relative movements between the hook and the body were collected from each subject (2 postures, 3 activities, and 3 attachment points). Figure 1 shows an example of moving bricks while standing with a scaffolding attachment. The subjects performed each activity repeatedly for 3 minutes. They did not change their locations while moving bricks and using a drill machine, but randomly changed locations when walking. While the hook was always attached to the chest for a body strap attachment, the subjects attached the safety hook to various parts of the scaffolding.

During the experiment, an IMU sensor was attached to the safety hook and the body strap (back), indicated by blue circles in Figure 1. The IMU sensors collected acceleration and angular velocity data along three axes at a 50 Hz sampling rate. Figure 2 shows the IMU data collected while moving bricks by kneeling—(a), (b), and (c) —and standing—(d), (e), and (f). For each hook attachment point, the hook IMU data show a distinct pattern, whereas the back-worn IMU data show a very similar pattern for the same posture. Moreover, different postures generate different patterns of hook IMU data even for an identical hook attachment point, (see Figure 2(b) and (d)). Therefore, the hook IMU data depended on both the attachment point and the bodily movement related to activity and posture.

This study assessed the unique relative movement between the hook and the subject's body to detect hook attachments in various postures and activities.

Figure 1. Moving bricks with a scaffolding attachment

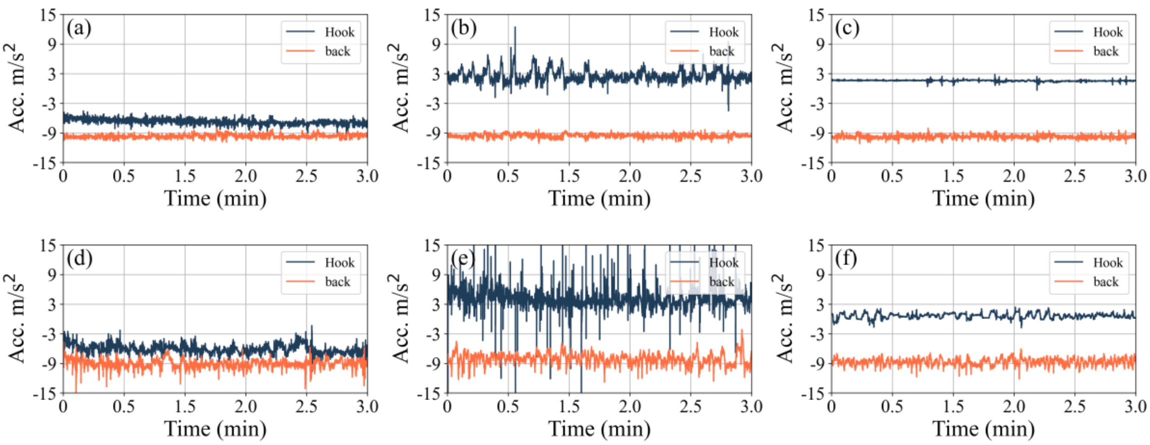

Figure 2. Collected IMU data while moving bricks: (a) keeling with a scaffolding attachment; (b) kneeling with a body attachment; (c) kneeling with the hook on the ground; (d) standing with a scaffolding attachment; (e) standing with a body attachment; (f) standing with the hook on the ground

3.2 Preprocessing

The collected IMU data were first filtered by a fifth-order low-pass filter with a 10 Hz cut-off frequency to remove high-frequency noise. The denoised IMU data were sampled by a 3-second moving window with a 2-

second overlap. A previous study has demonstrated that transforming time-series data into image data using Markov Transition Fields and extracting features by Convolutional Neural Networks (CNN) provides more stable and better classification results than raw data [18]. This study also transformed each IMU sample to an MTF that generated a 128×128×6 tensor for each IMU sample, where 128×128 represents the size of the image data, and 6 represents the number of channels composed of 3-axis acceleration and angular velocity data. Figure 3 shows examples of transformed image data for hook and back-worn IMU data. Both image data were simultaneously used to detect hook attachments.

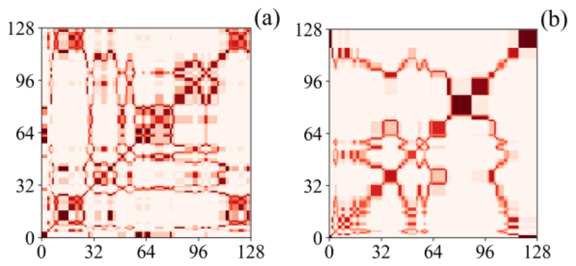

Figure 3. Transformed image data: (a) hook IMU data and (b) back-worn IMU data

3.3 Model Structure

CNNs were used to build a model to classify postures, activities, and hook attachment points from the transformed image data. Figure 4 shows the model structure consisting of three classifiers, C^1, C^2, and C^3, for the posture, activity, and hook attachment point, respectively. From the input data, four feature extractors, F^1, F^2, F^3, and F^4 extract features for each classifier. F^1 and F^2 extract features from the image data collected from the back and the hook, respectively. The extracted features by F^1 are used to classify the worker's postures by C^1 and the features are also inputted to the next feature extractor, F^3. The extracted features by F^3 are inputted to C^2 to classify the worker's activity. Each set of features extracted by F^1 and F^2 is concatenated and inputted to F^4. Also, each set of features extracted by F^2 and F^4 is concatenated and inputted to C^3. Therefore, the developed model detects the worker's posture, activity, and hook attachment at the same time.

Tables 1 and 2 summarize the model structures of the feature extractors. Since the input data of F^4 is the concatenated features of F^1 and F^2, the size of the input layer of F^4 is twice that of F^3. Table 3 shows the model structures of the classifiers. The output shape of the last dense layer means that each classifier classifies three different classes.

During the training, the model is trained to reduce the combined classification loss of C^1, C^2, and C^3, meaning that better classification accuracies on the posture and activity help to improve the classification of hook attachment points.

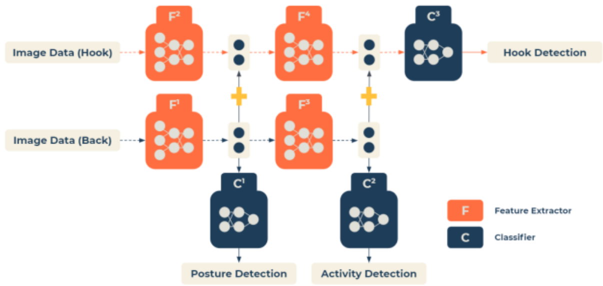

Figure 4. Model structure

Table 1. Model structures of F^1 and F^2

Layer	Output Shape
Input Layer	128×128×6
Convolution	128×128×32
Max Pooling	42×42×32
Batch Normalization	42×42×32
Convolution	42×42×64
Batch Normalization	42×42×64
Max Pooling	21×21×64
Dropout	21×21×64
Batch Normalization	21×21×64

Table 2. Model structures of F^3 and F^4

Layer	Output Shape	
	F^3	F^4
Input Layer	21×21×64	21×21×128
Convolution	21×21×128	
Batch Normalization	21×21×128	
Max Pooling	10×10×128	
Dropout	10×10×128	
Batch Normalization	10×10×128	
Convolution	10×10×256	
Batch Normalization	10×10×256	
Max Pooling	5×5×256	
Dropout	5×5×256	
Batch Normalization	5×5×256	

Table 3. Model structures of C^1, C^2, and C^3

Layer	Output Shape		
	C^1	C^2	C^3
Input Layer	21×21×64	5×5×256	5×5×512
Flatten	28224	6400	12800
Dense		256	
Dense		512	
Dropout		512	
Batch Normalization		512	
Dense		3	

4 Results

70% of the total data were randomly selected as the training data (9,345 samples), and the remaining 30% of the total data were used as the testing data (4,005 samples). The developed model was trained for 6,000 epochs in a 10-batch size. The classification results provided 86.40% of posture, 86.97% of activity, and 96.58% of hook attachment accuracies, respectively. While the back-worn IMU data were only used for the posture and activity classifications, the developed approach utilized both hook and back-worn IMU data to classify the hook attachment point. Therefore, the classification accuracy for the hook attachment was higher than that for the posture and activity classifications.

Figure 5 shows the training curves for each classification accuracy. In this study, the approach was designed to reduce overfitting by applying kernel regularization, dropout layers, and batch normalization layers. However, the developed model was slightly overfitted for the posture classification as compared to the activity and hook attachment classifications. One reason for this overfitting issue could be related to the number of features extracted by each feature extractor because too many features may fit the training dataset but fail to be generalized to the test dataset. For the posture classification, the number of features extracted by F^1 was 28,224 while F^3 extracted 6,400 features and F^4 extracted 12,800 features.

The developed approach provided a relatively lower performance on the posture and activity detections than the hook attachment. Figure 6 shows the confusion matrix for each classification result. In the posture classification, the developed model misclassified some cases of kneeling and standing because similar bodily movements could occur between kneeling and standing. For example, while using a drill, subjects often did not bend their backs when both kneeling and standing. Conversely, while moving bricks, the subjects gradually bent their backs as they were being exhausted when both kneeling and standing. In the activity classification, some cases of moving bricks and using a drill machine were misclassified. For each posture, the two different activities were performed by moving arms mainly, which could generate invariant back movements for activity. In this case, similar patterns of the IMU data could be collected from the back, thereby reducing the overall performance of the activity classification.

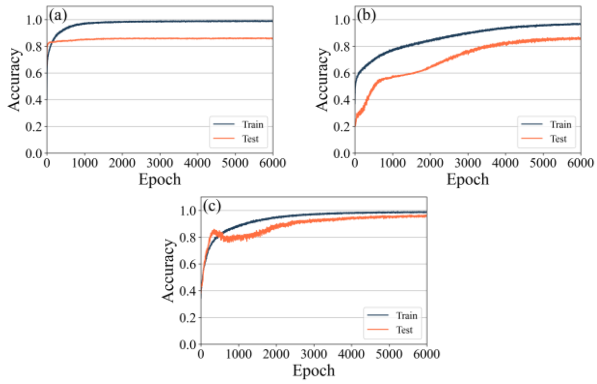

Figure 5. Training curves for (a) postures, (b) activities, and (c) hook attachments

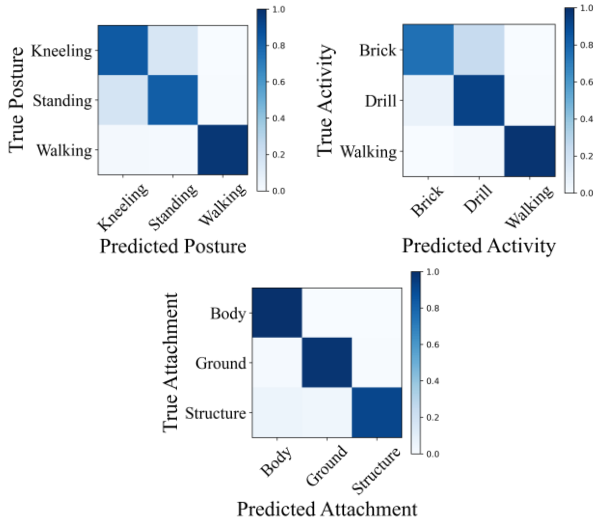

Figure 6. Confusion matrix of classification results

5 Discussion

5.1 Methodological Contribution

The previous study [9] detected the proper use of a safety harness based on the distance between the safety hook and the lifeline. Therefore, the previous approach would identify lifeline attachment whenever the worker is closed to the lifeline regardless of the hook attachment. However, the current study detected the proper use of a safety harness based on the relative movement between the hook and the worker's body. Since this approach directly detects the hook attachment, the developed approach could monitor the proper use of a safety harness wherever they are working.

Additionally, the previous approach would require further development to monitor multiple workers because the distance between the lifeline and the safety hook is the calculated distance of a pair of BLE beacons. Therefore, if multiple workers are working at height, more BLE beacons are required for each worker. The previous approach would need to detect each worker's pair of beacons and filter the signals receiving from other beacons. However, in this current study, hook attachments were detected based on the IMU data collected from an individual worker's safety harness. Therefore, the developed system is able to monitor the safety hook attachment individually, allowing to monitor multiple workers simultaneously without further methodological improvement.

5.2 Practical Application

The developed system detected hook attachments by utilizing attachable IMU sensors to the existing safety harness. This implementation would make it easy to deploy this detection system to construction sites without additional devices. In addition, a LED bulb can be attached to a safety harness and indicate the status of the hook attachment. This application would empower safety managers to monitor the proper use of the safety harness from a distance without any communication networks.

The developed system could monitor construction workers for a long period without causing intrusive associated with wearing additional sensors by attaching IMU sensors to the safety harness. The application of the developed system could allow safety managers to identify workers at risk of FFH as repeated improper use of the safety harness can be a precursor to FFH. This high-risk worker identification would serve as objective data for worker education and training that could effectively change the safety behavior of high-risk workers.

6 Conclusion

The developed approach provided an accuracy of 96.58% for hook attachment detection, and the approach provided a consistent performance on different activities and postures. The detection approach also provided classification accuracies of 86.40% and 86.97% for the postures and the activity, respectively. The hook movement is affected not only by the attachment point but also by the worker's posture and activity. These results validated that the relative movement between the hook and the worker's body is a key feature for hook attachment detection.

The developed system, in this study, was implemented by two IMU sensors that can be attachable to existing safety harnesses, allowing this system to be extended as the construction environment evolves in practice. By applying the developed detection system to construction sites, it would be possible to reduce FFH and to increase construction safety by reliably identifying high-risk workers to FFH.

However, the performance of this learning-based approach would be affected by the quality of the training data and have practical limitations as the training data needs to be collected from each worker. Therefore, a subject-independent approach needs to be developed for further study.

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