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Classification of Construction Worker's Activities Towards Collective Sensing for Safety Hazards

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Abstract: Although hazard identification is one of the most important steps of safety management process, numerous hazards remain unidentified in the construction workplace due to the dynamic environment of the construction site and the lack of available resource for visual inspection. To this end, our previous study proposed the collective sensing approach for safety hazard identification and showed the feasibility of identifying hazards by capturing collective abnormalities in workers' walking patterns. However, workers generally performed different activities during the construction task in the workplace. Thereby, an additional process that can identify the worker's walking activity is necessary to utilize the proposed hazard identification approach in real world settings. In this context, this study investigated the feasibility of identifying walking activities during construction task using Wearable Inertial Measurement Units (WIMU) attached to the worker's ankle. This study simulated the indoor masonry work for data collection and investigated the classification performance with three different machine learning algorithms (i.e., Decision Tree, Neural Network, and Support Vector Machine). The analysis results showed the feasibility of identifying worker's activities including walking activity using an ankle-attached WIMU. Moreover, the finding of this study will help to enhance the performance of activity recognition and hazard identification in construction.

Key words: Construction Safety, Machine Learning, Activity Classification, Inertial Measurement Unit

1. INTRODUCTION

The hazard identification is an important first step of safety management process and the visual inspection is the primary method of hazard identification in construction. However, the visual inspection has the limited performance in hazard identification because of the dynamic work environment of construction site [1] and limited resource for manual inspection [2]. Thereby, numerous hazards still remain as unidentified and present a risk of accidents in the construction site [3]. Our previous study [4] developed the hazard identification technique which analyzes worker's gait patterns for hazard identification. The developed technique utilized collective sensing technique to combine the multiple workers' gait abnormalities and the proposed approach showed a strong correlation ($r>0.7$) with the existence of hazard. Thereby, the previous study presented an opportunity of identifying hazard in the construction environment.

However, hazard identification through the developed technique in our previous study [4] is available when workers are performing the walking activity. Specifically, the completion of gait cycle is essential for measuring the abnormality of the worker's gait patterns. Considering that construction workers would have not only walking activity but also many different types of activities during construction tasks, activity classification is required to filter out movements from other activities to accurately measure the gait abnormality for the hazard identification. Thereby, high accuracy in classifying walking activity provides the high chance of identifying hazard by capturing workers' abnormal gait patterns. In this context, this study investigated the feasibility of identifying the walking activity during construction tasks using wearable inertial measurement units (WIMU). Since attaching a WIMU to the worker's ankle is necessary for hazard identification approach, this study performed the activity classification using data from the ankle-attached WIMU.

In fact, achieving the high level of accuracy in activity classification through the ankle-attached WIMU is challenging because body movements during construction tasks do not closely related to the worker's lower body movements. To increase the activity classification performance, this study added worker's locational data in activity classification. The locational data were collected from ultra-wideband (UWB) localization system, which achieved less than 0.5m in tracking accuracy in the construction environment [5]. This study investigated the effectiveness of adding additional features from locational data in activity classification. Then, the performance of activity classification using existing machine learning algorithms was tested. The result of this study revealed an opportunity of classifying worker's activities using an ankle attached WIMU and the UWB system. Also, the result of this study will help to develop an automated hazard identification system which enhances the safety of the construction site.

The remaining sections of this paper are same as following. The research background will introduce previous literatures on hazard identification and activity classification in construction. The methodology section will explain about data collection in the laboratory and data processing steps for activity classification. Activity classification, discussion and conclusion sections will discuss about achieved results and its contributions toward the hazard identification.

2. RESEARCH BACKGROUND

2.1. Hazard Identification

With the importance of hazard identification in safety management, several research has been conducted to increase the identification performance [6]. Given the fact that visual inspection is a typical approach of hazard identification, many of these studies focused on to increase the knowledge of the construction worker about hazardous conditions by safety training or other methods. Albert et al. [3] developed the maturity model to increase the performance of hazard identification and showed the increase of performance during the construction project. Sacks et al [7] introduced an approach using virtual reality and showed the effectiveness of safety training in the virtual environment for hazard identification. However, although previous studies showed the effectiveness of safety training for hazard identification, several limitations are remained due to the dynamic work environment and qualitative aspect of visual inspection. Also, visual interference during material handling may increase the difficulty of hazard identification in the construction workplace.

As an alternative approach of hazard identification, our previous studies [4,8,9] proposed the gait/body movements based hazard identification approaches which quantified the change of gait/body movement patterns when workers meet hazardous conditions during the walking activity. These studies were motivated by the fact that human body responds to the changes of physical environment [10]. Thereby, hazard identification can be achieved by capturing such changes of the human body movement. However, magnitude and frequency of these changes are different depending on the subject and the environment. Thereby, our previous studies implemented the collective sensing approach which accumulated changes of multiple workers' movements depending on its occurring locations. With collective processing, our previous studies found a strong correlation between the abnormality of gait/movement patterns and the existence of hazard in ironwork environment. However, it still has remaining issues for an implementation to the construction workplace. As explained earlier, proposed hazard identification approach requires walking movements which are the completed gait cycles to measure the abnormality of gait patterns for hazard identification. Thereby, classifying the walking activity is essential step since construction tasks consist of different activities and postures. In this manner, this study tested the feasibility of activity classification using an WIMU sensor.

2.2. Activity Classification

In construction, activity classification has been studied to analyze the construction workforce (e.g., worker, equipment) for productivity measurement, training and safety management [11]. Most of the activity classification studies utilized the data from inertial measurement units or accelerometer with machine learning algorithms.

Joshua and Varghese [12] showed the feasibility of classifying masonry tasks using body attached accelerometer placed at the waist level. This study is the first study which classified the worker's activities in the construction domain. However, this study remained on classifying brick installation tasks in stationary position without consideration of other required activities, such as material transporting, during construction task.

Cheng et al. [13] proposed an approach combining UWB and physiological status monitoring systems (PSM) for productivity measurement. This study introduced the productivity measurement framework which consists of activity zone identification, activity reasoning and productivity measurement. This study utilized the concept of task zone which was identified based on pre-defined area and the user's locational data collected from UWB. Then, data from PSM sensor were used to classify worker's activities by analysing worker's physiological responses (e.g., posture). However, the previous study focused on the analysis of productivity rather than investigating and increasing the classification accuracy. Cheng et al. [14] also utilized the similar concept of model (i.e., combining the UWB and PSM) for classifying safe bending and unsafety bending postures for ergonomic analysis of the worker. However, the accuracy of identifying walking activity and task activity was also not fully investigated in the previous study.

Recently, Akhavian and Behzadan [11] introduced smartphone-based activity classification approach. This study attached a smartphone to the worker's upper-arm area for data collection and classified different types of construction tasks while testing different machine learning algorithms (i.e., decision tree, artificial neural network, k-nearest neighbor, logistic regression and support vector machine). However, this study also has few limitations. This study remained on the use of worker's movement data from smartphone rather than using or testing other types of available data, such as locational data, in activity classification. Also, the location of the smartphone may distract worker's movements during material handling task in the construction site.

Considering that additional sensor installation for activity classification would not be an appropriate way for our hazard identification approach, further study on the feasibility of activity classification using ankle attached WIMU sensor is necessary. In this manner, this study tested the feasibility of identifying activities during construction tasks using ankle attached IMU sensor. Also, this study investigated the usefulness of adding worker's locational data in activity classification with different machine learning algorithms.

3. METHODOLOGY

3.1. Data collection

The laboratory experiment was conducted for data collection while simulating the masonry work which consists of material pickup, material moving and brick installation at the task area. During an experiment, subject first pick up cement bricks from the material stockpile and moved these bricks to designed task areas. During moving activity, experiment subject can carry only two bricks from the material stockpile to the task area for each installation. At the task area, experiment subject asked to install bricks at the ground while bending their knee during installation. Experiment environment is shown in Fig 1.

In this study, total four volunteer subjects participated in data collection. These experiment subjects repeated the installation process total 27 times to install bricks to three different task areas. For data collection, a WIMU (OPAL, APDM Inc) and a UWB tag (UBISENSE Inc) were attached to the subject's ankle and a safety helmet respectively to collect the subject's leg movements and locational data (See Fig 2).

The WIMU system wirelessly collected 3 axes of acceleration, angular velocity and magnetic field data with 128-Hz sampling frequency. The UWB system recorded X, Y, and Z coordinates of the subject's location with 9-Hz sampling frequency. The WIMU and UWB systems shared their timing source (i.e., laptop) and both data were synchronized later based on the collected time stamp. Additionally, whole experiment processes were video-recorded and these video data were used as a reference for data labeling..

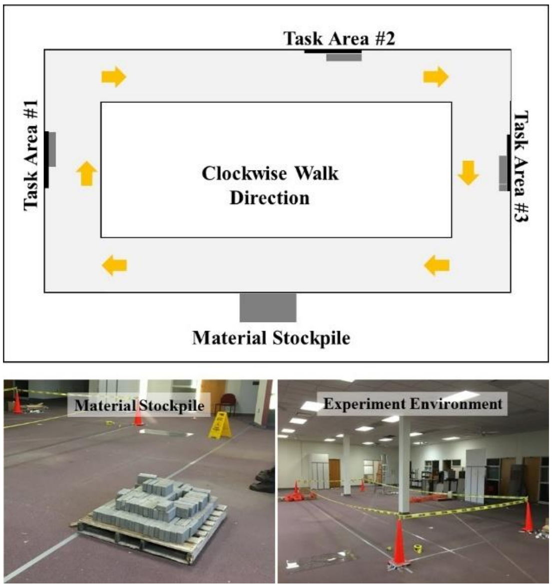

Fig. 1. Data collection: experiment layout, material stockpile and experiment environment

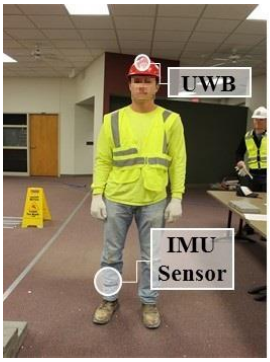

Fig. 2. Location of WIMU and UWB tag

For data labeling, this study divided all performed activities into three different classes which are material pick up, material moving, and brick installation. (See Fig 3) For example, this study labeled material moving when subjects are having entire gait cycles during walking activity. Side steps and other posture changes before and after material pick up or material installation are labeled as material installation activity or material pick up activity. Thereby, material installation activity is labeled when subjects performed installation tasks or changed their posture or having side step for installation.

Fig. 3. Three different types of activities during masonry task during experiment

3.2. Data processing and feature extraction

After data collection, this study performed data processing steps which include low-path filtering and feature extraction for activity classification. This study applied the low-pass band filter with a cut-off frequency of 4 Hz to remove sensor noise of WIMU data since most of the human movement energy is located under 3Hz frequency [15]. Then, this study used a moving window sampling approach to extract features from WIMU data. This study sampled 64 IMU data as a single window which represent worker's movement data during 0.5-second. Also, this study overlapped 50% of data window to increase the classification performance similar with the previous study [11]. With moving window sampling technique, this study extracted both time and frequency domain features from WIMU data and only time domain features from UWB data (See Table1). The wavelet analysis related features are not included in this study due to its low performance in activity classification [16].

Table 1. Extracted time and frequency domain features from WIMU and UWB data

WIMU		UWB
Time Domain	**Frequency Domain**	**Time Domain**
Mean, Standard Deviation, Max, Min, Correlation, Signal Vector Magnitude	Spectral Entropy, Spectral Centroid	Mean, Standard Deviation, Max, Min, Correlation, Moving Distance

With 3 different axes of accelerations and 3 different axes of angular velocities from WIMU, total 44 features are extracted. In feature extraction using UWB data, X, Y, and Z coordinates are used to extract feature through a moving window sampling technique with a 0.5-second window (4 UWB data samples). Additionally, distance between the first sample and the last sample of UWB data within a sampling window is also used as an additional feature which represents a maximum moving distance for each axis. However, the signal vector magnitude was not used since it does not mean anything with locational data. Thus, total 62 features (i.e., 44 features from WIMU and 18 features from UWB data) are extracted for activity classification.

Through the feature extraction process, total 15,853 data samples (900 samples of material pick up, 12,938 samples of material moving, and 2014 samples of material installation) from 4 subjects were combined into a dataset and this dataset was used for activity classification. Before performing the activity classification, data from our experiment is visualized in Fig 4. As designed, the material pick up and material installation activities are located near the material stockpile and three different work areas while material moving activity is widely distributed on the experiment site.

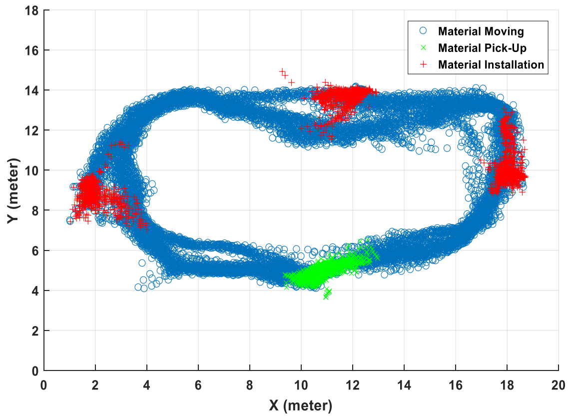

Fig. 4. Data visualization of performed activities and corresponding locations

3.3. Machine Learning Algorith

This study tested three different well-known machine learning algorithms (i.e., decision tree, support vector machine, and artificial network) to classify worker's activities (i.e., material pick up, material moving, and material installation).

The decision tree (DT) algorithm develops a decision tree model based on features and classes. The decision tree model consists of nodes, edges and leaves. The node relates with a feature that can effectively divide data based on its class. With a specific value of feature, data in the node are separated into child nodes and this process is repeated until data in the child node have only one class. These remained data then are classified based on the label of training data. The C4.5 algorithm [17] builds a decision tree based on information gain which is the measurement unit of the performance on splitting data. The J48, java version of C4.5, was used in this study to build a decision tree classification model.

The artificial neural network (ANN) algorithm consists of multiple layers and nodes which connected each other to mimic the structure of the human brain. The input layer, hidden layer and output layer have multiple nodes and every node in each layer are linked with all nodes in neighbor layers. The number of features is same as number of nodes in the input layer and the number of classes is same as the number of nodes in the output layer. Each link between nodes has a weight that represents the function for activity classification. During a training of ANN model, weights in the links are updated to minimize an error in the output layer. In this study, backpropagation algorithm is used to update weights between nodes. After training, activity classification is performed based on developed ANN model from backpropagation algorithm.

The support vector machine (SVM) algorithm is one of the popular machine learning algorithms and it has been achieved the high performance in activity classification. The SVM algorithm is seeking the hyperplane that can best separate set of data into two classes. Specifically, the algorithm transforms set of data to the feature space using kernel function and identifies the decision boundary in this feature space. Then, classification is performed based on this decision boundary. In case of multi-class classification, multiple decision boundaries are set up during training and each decision boundary is used for classifying each class.

4. ACTIVITY CLASSIFICATION

The activity classification was performed based on extracted features with different machine learning algorithms. The WEKA [18], a data mining software, was used for activity classification. All other computation processes in this study were performed in the MATLAB (R2016b, MATHWORKS). To investigate the effectiveness of adding locational data in activity classification, this study divided extracted features into two different datasets which are data from WIMU, and both WIMU and UWB. This study performed a 3-fold cross-validation process to investigate the generalized classification performance. The 3-fold cross validation approach divided whole data samples to three different subsets while having an equal number of data samples and classes on each subset. Then, training and testing processes are repeated three times while changing training and testing subset samples.

The classification accuracy using features from movement data (WIMU) is listed in Table 2. Among different machine learning algorithms, an ANN model achieved the highest classification accuracy (87.2%) while it also had the highest precision and recall rates. In this setup, the difference between the worst model and the best model was only 2% in accuracy. This result indicated that all tested machine learning algorithms have a similar performance in activity classification.

Table 2. Activity classification results with movement data (WIMU)

ML Algorithms	Movement Data (WIMU)		
	Accuracy	Precision	Recall
DT	85.5%	0.85	0.86
SVM	87.1%	0.85	0.87
ANN	**87.2%**	0.85	0.88

Additionally, this study tested the performance of activity classification using combined dataset which combined data from WIMU and UWB. (See Table 3) Same as previous analysis, an ANN model achieved the highest classification accuracy (91.5%). Also, all of machine learning algorithms showed the increased performance compared to the results when only using movement data. The amount of the increased accuracy by adding locational information were 5.9%, 2.4%, and 4.3% on DT, SVM and ANN algorithms respectively. Especially, a decision tree model, which showed the lowest performance when only using movement data, showed 5.9% performance increasing with locational information. The analysis results revealed that adding location information in activity classification along with movement data is beneficial to increase the classification performance.

Table 3. Activity classification results with combined data (WIMU + UWB)

ML Algorithms	Combined Data (WIMU + UWB)		
	Accuracy	**Precision**	**Recall**
DT	91.4%	0.91	0.91
SVM	89.5%	0.89	0.90
ANN	**91.5%**	0.91	0.92

The details of classification results from an ANN model with two different datasets are shown in Table 4 and 5. With movement data, the classification accuracy of material pick up was only 11.1%. However, the accuracy was significantly increased (70.6%) when adding locational data. This result indicated that movements during material pick up are similar with material moving and material installation. Thereby, locational information is important to differentiate such activities from our experiment data effectively. The similar increasing pattern was also observed on the classification of material installation. In material installation classification, 10.6% accuracy was increased by adding locational information. On the other hand, the classification performance of material moving task was slightly decreased (0.6%) when using combined dataset. However, overall classification results showed that adding locational data along with movement data was beneficial and it increased the classification performance from 2.4% to 5.9%.

Table 4. Confusion matrix of activity classification with movement data (WIMU)

ANN	Movement Data (WIMU)		
	Material Pick Up (Predicted)	**Material Pick Up (Predicted)**	**Material Pick Up (Predicted)**
Material Pick Up	11.1%	55.0%	33.9%
Material Moving	0.7%	96.2%	3.1%
Material Installation	3.6%	30.7%	65.7%

Table 5. Confusion matrix of activity classification with combined data (WIMU + UWB)

ANN	Movement Data (WIMU)		
	Material Pick Up (Predicted)	**Material Pick Up (Predicted)**	**Material Pick Up (Predicted)**
Material Pick Up	70.6%	29.2%	0.2%
Material Moving	1.5%	95.6%	2.9%
Material Installation	0.2%	24.7%	75.1%

5. DISCUSSION

In previous activity classification study [11], the accuracy of activity classification, which including material moving and material handling, was 78 to 88% with various machine learning algorithms. The previous study attached a smartphone on the upper-arm area for data collection which is one of the best locations to collect data for activity classification. Compared to the previous study, this study installed a WIMU to the subject's ankle which is not a recommended location for collecting data for activity classification. However, introduced approach that using locational information in activity classification achieved higher classification accuracy (89.5% to 91.5%).

An additional advantage of using locational information in activity classification is that classification results can be easily plotted using locational data (See Fig 5). Thereby, additional knowledge about classification errors and corresponding locations can be visually investigated. For example, the most of misclassified material installation data (Red in Fig 5) were collected during material moving activity near task area. This advantage is beneficial to develop the better activity classification system.

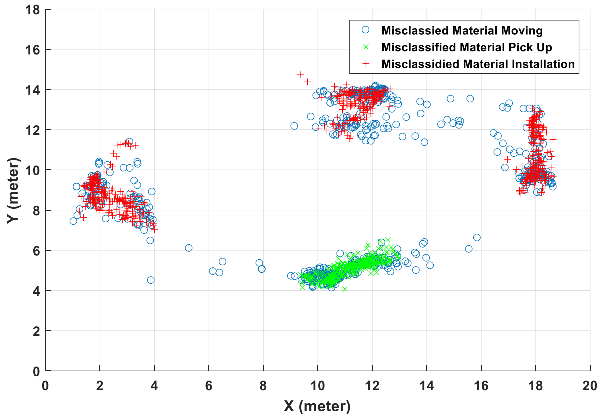

Fig. 5. Data Visualization of Classification Errors and Corresponding Locations

In order to collect location data in the construction site, installation of the location tracking system is essential. However, some of the existing applications, such as smartphone-based activity classification or our previous collective hazard identification approach [4] already have a sensor that can collect locational information (e.g., GPS sensor or location tracking system). Thereby, proposed activity classification process is already feasible in such applications. Therefore, proposed approach would be beneficial to have a better classification model and more understanding about the occurred error in activity classification.

6. CONCLUSION

This study investigated the performance of activity classification using data from ankle attached WIMU and UWB location tracking system. With collected data, this study utilized a moving window sampling technique to compute the time and frequency domain features from IMU and UWB data. The classification results showed an opportunity of identifying walking activity (i.e., material moving) as well as material pick and material installation activities during masonry work. For the hazard identification through gait analysis, further performance improvement or another filtering process would be necessary since most of the misclassifications from material pick up and material installation activities are related to the walking activity. However, this study revealed the effectiveness of adding locational data in activity classification. The proposed approach will help to build a better activity classification system and the high classification accuracy will help to decrease false alarm in hazard identification while effectively filtering out other activities. Thereby, the result of this study help to develop an automated hazard identification system in construction.

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