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Field Test of Automated Activity Classification Using Acceleration Signals from a Wristband

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Abstract: Worker's awkward postures and unreasonable physical load can be corrected by monitoring construction activities, thereby increasing the safety and productivity of construction workers and projects. However, manual identification is time-consuming and contains high human variance. In this regard, an automated activity recognition system based on inertial measurement unit can help in rapidly and precisely collecting motion data. With the acceleration data, the machine learning algorithm will be used to train classifiers for automatically categorizing activities. However, input acceleration data are extracted either from designed experiments or simple construction work in previous studies. Thus, collected data series are discontinuous and activity categories are insufficient for real construction circumstances. This study aims to collect acceleration data during long-term continuous work in a construction project and validate the feasibility of activity recognition algorithm with the continuous motion data. The data collection covers two different workers performing formwork at the same site. An accelerator, as well as portable camera, is attached to the worker during the entire working session for simultaneously recording motion data and working activity. The supervised machine learning-based models are trained to classify activity in hierarchical levels, which reaches a 96.9% testing accuracy of recognizing rest and work and 85.6% testing accuracy of identifying stationary, traveling, and rebar installation actions.

Key words: activity recognition, continuous filed data, acceleration, automation, safety

1. INTRODUCTION

Activity analysis is a technique for monitoring, recognizing, and assessing the activities of workers during ongoing projects(Thomas & Mathews, 1986). This technique has a great potential for improving construction productivity, as it efficiently measures the time spent on specific activities and identifies any issues that hinder labor productivity (Gouett, Haas, Goodrum, & Caldas, 2011). Activity analysis has been used to identify potential safety risks by combining with hazard assessment techniques, such as job hazard analysis (Rozenfeld, Sacks, Rosenfeld, & Baum, 2010). However, as this approach relies on manual observation, significant time and effort are required for data collection and analysis.

Recent advancements in automation technologies in construction have provided considerable opportunity for measuring and tracking workers' activities by using sensor data and analytics techniques, such as machine learning. In comparison with conventional observation methods, automated data collection and analysis for activities is not only time-saving and objective but also applicable to the collection of massive data from multiple workers. Among these sensors, wearable devices equipped with accelerometer are gaining attention, as they allow motion data collection (i.e., accelerations) without interfering with ongoing work. Recently, remarkable achievements on acceleration-based action recognition have been obtained using different wearable devices, such as single IMU sensor (Joshua & Varghese, 2014), smartphone (Akhavian & Behzadan, 2016), and wristband (Ryu, Seo, Jebelli, & Lee, 2018). These studies have applied machine learning approaches to classify diverse predefined construction activities automatically on the basis of acceleration signals, which have reported high performance on classifying actions. Although these previous research efforts have tested the usage potential of IMU data (i.e., acceleration signals) for activity analysis, the applicability of these approaches in practice has not been fully tested, as they rely on the data collected from controlled experiments by repeating specific types of activities (Yan, Li, Li, & Zhang, 2017). The data collected during actual construction tasks are noisy and unstructured due to the dynamic nature of construction work. The movements of workers vary depending on site conditions even for same tasks, leading to potential errors in acceleration-based action recognition. Moreover, activity types are difficult to predefine in practice, as construction activities are unstandardized. Considering these remaining challenges, further investigation of these approaches in practice is required to improve the practical applicability of automated activity analysis using acceleration-based action recognition approaches.

In this regard, the study attempts to validate acceleration-based action recognition protocol for field construction tasks with continuous data. In particular, a wristband (i.e., Apple Watch) was selected to collect acceleration data, as many construction activities are hand-dominant; thus, acceleration signals from a wristband efficiently represent dynamic activities involving complicated arm movements (Ryu et al., 2018). We collected acceleration data from two rebar workers by attaching an Apple Watch to their dominant hands during concrete formwork of a housing project in Hong Kong. Then, the collected data were used to test the performance of action recognition based on machine learning approaches. Potential issues when applying these approaches in practice were discussed on the basis of the results.

2. LITERATURE REVIEW

2.1. Monitoring human activity via sensors

Activity analysis can evaluate and improve the safety (Chhokar & Wallin, 1984) and productivity (Haas, Borcherding, Allmon, & Goodrum, 1999) in construction. Previous practices mainly rely on safety supervisors to assess the behavior of workers manually; thus, the procedure is time-consuming (Hendrickson, Hendrickson, & Au, 1989) and subjective (Mattila, Hyttinen, & Rantanen, 1994). With the improvement of sensor technologies, video- and sensor-based approaches have been demonstrated feasible for monitoring construction workers. Vision-based approaches require the cooperation of the surveillance system and computer vision-based algorithms, which generate the models from videotapes for identifying posture and action types. Consequently, experts can assess worker health (Han & Lee, 2013) and estimate productivity (Peddi, 2008) in an automatic and effective protocol. Risk assessment can also be accomplished through vision-based ergonomic analysis (Seo, Han, Lee, & Kim, 2015). Vision-based methodologies have not only gained abundant achievements in motion monitoring and analysis but also been proven to have a great potential in the construction domain. However, the application of vision-based approaches is limited by the construction environment. For instance, weak light condition and obstruction profoundly disturb the video quality, thereby declining the model performance (Seo et al., 2015). To address this limitation, researchers have developed various sensor-based methods, such as location sensor-based and body-worn sensor approaches, for assessing construction workers' activities (Ryu et al., 2018). The location sensor includes, but is not limited to, a global positioning system, radiofrequency identification, ultra-wide band, and wireless local area network, which allow the tracking of workers' activities in the construction site (Aryan, 2011; Montaser & Moselhi, 2014; van Diggelen, 2002; Woo et al., 2011). However, the location information is insufficient for action recognition and posture assessment. On this basis, the body-worn sensor, particularly IMUs, has drawn attention and demonstrated its feasibility in acceleration data collection and action classification (Akhavian & Behzadan, 2016).

2.2. Accelerometer-based action recognition research

As a portable sensor for tracking triaxial acceleration signals, the accelerometer is widely embedded in wearable devices, which is a broadly used sensor in activities recognition due to the low cost, low energy-consuming and low interference (Lara & Labrador, 2012). Human action recognition divides the annotated signal streams into patterns and then extracts acceleration data into feature variables, which are set as the inputs of action classifiers (Chernbumroong, Atkins, & Yu, 2011). The high performances were reported on recognizing daily activities such as walking, jogging, sitting, and standing (Kwapisz, Weiss, & Moore, 2011; Ravi, Dandekar, Mysore, & Littman, 2005). Meanwhile, the successful application in construction comprises fall detection (Lim, Park, Lee, & Lee, 2015; Yang, Jebelli, Ahn, & Vuran, 2015) and activity classification (Joshua & Varghese, 2010).

The position for mounting the sensor is varied and significantly affects the analysis (Bao & Intille, 2004). Attaching the accelerometer to the waist is a reasonable option because waist motion can represent the trend of body movement. Joshua and Varghese (2014) used a waist-worn acetometer to develop an acceleration-based classification protocol. The high performance of the scheme demonstrated that waist-mounted acceleration is suitable for action recognition. However, construction-related action comprises several micromovements that are difficult to capture by waist acceleration, such as wrist and upper-limb movements. On this basis, researchers suggested attaching a wearable device equipped with accelerometer on dominant waist to track acceleration information. The feasibility has been proven in multiple publications (Chernbumroong et al., 2011; Koskimaki, Huikari, Siirtola, Laurinen, & Roning, 2009; Lara & Labrador, 2012; Ryu et al., 2018). Meanwhile, IMU embedded wristband-type device (e.g. smartwatch) is an idea device for collect hand movement in consistent position with little discomfort (Weiss, Timko, Gallagher, Yoneda, & Schreiber, 2016). Joshua and Varghese (2014) introduced IMU-based activity classification into the field and developed action identification models with the motion data collected from the waist and lower arms from carpentry and ironwork. As the prediction accuracies reached 90.07% and 77.74% for ironwork and carpentry, respectively, the study validated that wear-based activity analysis can be applied for field-collected acceleration data. However, several gaps existed in applying acceleration-based action identification in the construction site: 1) Previous studies removed the junction among the segments in the training material. While, the data collected from the site are supposed to be continuous and noisy. 2) Comparing with the action types conducted in instructed environment, the activity categories are more complex and diverse.

3. METHODOLOGY

This research aims to test a wearable accelerometer-based approach for automatically recognizing construction workers' activity category on the basis of the continuous data collected from the field. This research focuses on rebar work, one of the most standard construction activities on the site, which consists of complex body activities and numerous micromovements in the wrist joint. To analyze the complicated acceleration signals captured from the IMU-embedded wearable sensors, multiple significant operations, such as optimizing the features, segment size, and training algorithms, are considered to achieve high performance. The training and validation procedure comprises the following steps: 1) collecting and labeling data, 2) segmenting data and extracting feature variables, 3) training classifiers, and 4) validating the model.

3.1. Collecting and labeling data

This project arranged a long-term data collection from multiple workers in two ongoing sites and constructed a large-scale database on continuous construction actions. During data collection, the participants were equipped with an Apple Watch in the dominant hand and a GoPro camera at the chest. With the self-developed WatchOS app, the Apple Watch can cumulatively read 3D inertial data, which are transferred to the laptop afterward. The GoPro camera was used to target the hands and record simultaneously for identifying the activity category. The Figure 1 shows the photos during filed data collection. Field data collection lasted 19 days in total, which finished in three collecting periods from November 2018 to March 2019. The project acquired around 498 h of videotapes and 2.83 billion acceleration sets from 18 different workers, including rebar, concrete, and form workers. Prior to the labeling of acceleration signals, data quality assessment was conducted to indicate the following failures of data collection: 1) Data capture failure. Participants took off equipment due to disturbance, and equipment stopped working due to misoperation or accidents. 2) Poor-quality videotapes. Videotapes could not provide the action information due to poor light conditions, and the chest-mounted camera could not record the wrist movement. 3) Data transmission or storage failure. To ensure the high quality of data, training and testing materials were constructed from two rebar workers' acceleration signals collected on March 4, 5, and 8, which are strictly continuous and independent.

Figure 1. Site photos for data collection

Table 1. Rebar activity taxonomy

Activity			Activity examples
Level 1	**Level 2**	**Level 3**	
Break	Stationary	Standing/Sitting	Standing or Sitting
Work	Traveling	Transportation	Horizontal, vertical, included movement, jumping, skipping, going upstairs/downstairs, climbing up/down a ladder
		Transferring materials and tools	Dynamical wrist movement while traveling, carrying materials and tools in horizontal, vertical, and inclined movement, carrying materials and tools while going upstairs or downstairs, climbing up or down a ladder
	Rebar installation	Rebar preparation	Cutting and bending
		Rebar placing	Placing, adjusting, and lifting
		Rebar tying	Fixing and tying
		Supplement work	Irregular wrist movement, lifting materials and tools, squatting, standing up, rotating trunk
		Uncertain operation	Action with unclear video recording

The acceleration and video streams include the unique timestamps when recording, through which the inertial response can be synchronized with the predesigned action category (Table 1) on the basis of the videotapes. Considering the dynamic nature of construction work, the labeling procedure is challenging since the activities are transmitted too frequently to identify each pattern and the transmission pattern. The error will be huge considering that thousands of junctions exist in the hours of data. Therefore, the junction between action patterns will be assigned the label of later patterns in the labeling procedure. As long as the activity is detected as changing, the assigned label will change correspondingly. The predefined taxonomy includes two divisions. The activity comprises exercises hierarchically from level 1 to level 3 with corresponding construction-related responses. Meanwhile, the activity examples refer to the basic movements that support identifying activities in ergonomic perspective. For instance, if the worker's action is regarded as cutting rebar through the videotapes, the activity information could be concluded as rebar installation and rebar preparation in level 2 and level 3 respectively.

3.2. Segmenting data and extracting feature variables

Considering the nature of human actions, continuous acceleration data should be divided into equal segments to represent the actions in a particular duration. This study used a sliding window approach to construct optimal action windows because the classification performance relies on the window size (Banos, Galvez, Damas, Pomares, & Rojas, 2014). Bonomi, Goris, Yin, and Westerterp (2009) demonstrated that a 6.4 s segment is the optimal window for classifying various motions, such as lying, sitting, standing, dynamic movement, walking, running, and cycling. The present study tested a diverse segment duration from 1 s to 6.5 s and selected the best performance model as the optimal classifier. Meanwhile, the data operating procedures included a 50% overlap when conducting the sliding window method, which was demonstrated as necessary in handling continuous motion signals (Bao & Intille, 2004; Ryu et al., 2018).

Labeled action patterns were extracted as feature variables on the basis of vital signal properties to distinguish activity patterns (Figo, Diniz, Ferreira, & Cardoso, 2010). Time- and frequency-domain features are the most widely used features for analyzing human actions (Preece et al., 2009). Time-domain features include, but are not limited to, mean value, maximum value, median, and variance, which reveal the statistical characteristics of the motion signals (Bao & Intille, 2004). Meanwhile, frequency-domain features, such as energy and entropy, measure the acceleration streams in the perspective of frequency by utilizing fast Fourier transform and are frequently utilized to evaluate action complexity in acceleration-based activity analysis (Preece et al., 2009). Ten broadly used significant features variables (Ryu et al., 2018) are employed, which covers eight time-domain features and two frequency-domain features (Table).

Table 2. List of feature variables

Feature type	**Feature variable** (including x, y, and z axes)
Frequency-domain features	Entropy
	Energy
Time-domain features	Mean value
	Skewness
	Maximum value
	Minimum value
	Range
	Standard deviation
	Kurtosis
	Correlation between two axes

3.3. Training classifiers and validation

This study used supervised machine learning methods to train the pre-labeled feature variables and generated classifiers for automatically identifying workers' action division. With the Classification Learner app in MATLAB (2019a, MathWorks), a platform implementing several classification training schemes, training and assessment were conducted productively. On the basis of the assessment, three classifiers generate the highest identification rate, namely, 1) ensemble bagged trees (Dietterich, 2000), 2) support vector machine (SVM) (Hsu & Lin, 2002), and 3) k-nearest neighbor (kNN) (Sutton, 2012).

The validation involves testing the model prediction performance with additional data. The two typical evaluating schemes are n-fold cross-validation and holdout validation. In n-fold cross-validation, the entire dataset is initially randomly split into equal-size subsets, one subset of which is the testing set and the rest of the (n-1) subsets are set as a training set. Each trail generates a classifier from training data. The prediction accuracy is the correct prediction rate by inputting the test data in the trained classifier. The n-fold cross-validation adopts an overall accuracy after being run over all the test datasets, which means *n* times in total (Kohavi, 1995). Holdout validation is another assessment protocol for large-scale data. The algorithms randomly extract a specific part (held-out percentage) of data as test dataset and trains the model with the rest of the data. The performance is evaluated by the test data, and the algorithm trains all data to obtain the final model. The overall accuracy is also calculated by the correct prediction rate, and all data train the generated classifier.

The overall prediction accuracy is an indicator for simultaneously measuring the model performance for all categories, which however cannot measure incorrect prediction cases among the categories. Therefore, the confusion matrix is introduced as the supplemental approach for quantifying the difficulty of distinguishing one category from another class of actions. The validation provides significant indications to adjust the window size, modify the category library, and promote the algorithms.

4. TESTING RESULTS

Part of continuous data period with high quality was selected as analysis objective in the study due to the low quality of raw data. The dataset consisted of the action data from two different rebar workers in three different working periods, lasting for 13.6 h and with 145,688 sets of data. Multiple data sessions were individually extracted as features, which would be combined as comprehensive dataset. For test demand, a period of around 1 h was randomly extracted as the test dataset. The training dataset contained the rest of the datasets. On the basis of different category levels, the testing procedure covered three classifiers. Classifier 1 was for recognizing activity level to classify ineffective and effective work; classifier 2 was for distinguishing stationary, traveling, and immobile working actions; and classifier 3 was for identifying basic task actions. The training procedure ran multiple training models with various window sizes. A 10% held-out validation measured the performance of each trained model. The training and testing results were presented in Table 3 to Table 5.

Table 3. Confusion matrix of Classifier 1 (best) with 0.5 s window size

Level 1 Activity

Classifier: Ensemble bagged trees

Work	Work	Break	Recall
Work	26177	177	99.3%
Break	419	9649	95.8%
Precision	98.4%	98.2%	

*Training accuracy: 98.4% Test accuracy: 96.9%

Table 4. Confusion matrix of Classifier 2 (best) with 0.5 s window size

Level 2 Activity

Classifier: Ensemble bagged trees

Work	Rebar installation	Traveling	Stationary	Recall
Rebar installation	7301	302	49	95.4%
Traveling	946	1925	16	66.7%
Stationary	120	18	3891	96.6%
Precision	87.3%	85.7%	98.4%	

*Training accuracy: 90.0% Test accuracy: 85.6%

Table 5. Confusion matrix of Classifier 3 (best) with 0.5 s window size

Level 3 Activity									
Classifier: Ensemble bagged trees									
Work	A	B	C	D	E	F	G	H	Recall
A = Uncertain operation	0	3	0	0	0	0	3	1	0.0%
B = Supplement work	1	1966	264	61	52	13	324	74	71.4%
C = Rebar tying	0	387	1416	52	55	0	108	48	68.5%
D = Rebar placing	0	165	72	946	14	2	28	6	76.7%
E = Rebar preparation	0	185	72	16	1125	2	115	21	73.2%
F = Transferring materials and tools	0	131	31	8	7	46	168	7	11.6%
G = Transportation	0	396	111	9	26	13	1911	20	76.9%
H = Standing/sitting	0	59	14	0	7	1	11	3995	97.7%
Precision	0.0%	59.7%	71.5%	86.6%	87.5%	59.7%	71.6%	95.8%	

*Training accuracy: 78.3% Test accuracy: 55.9%

5. DISCUSSIONS

The result shows that ensemble bagged tree has the best performance with an optimal window size of 0.5 s for each classifier. Previous research (Ryu et al., 2018) stated that a large window size generates high performance, which is contrast to the present case. One of the possible reasons is that the basic task level actions occur rapidly in the real construction site. For example, in rebar work, the worker typically bends rebar for 2 s and conducts supplement work, such as lifting, in the following second. Therefore, a small window size can help in efficiently distinguishing the categories under extensive situations.

Table 3 indicates the high performance in recognizing break and work for rebar task. The training and testing accuracies are 98.4% and 96.9%, respectively. Thus, the trained classifier has a 96.9% possibility of correctly detecting break and work with the testing data. Meanwhile, the recall and precision ratio for the individual category is over 95%. Therefore, Classifier 1 can be an objective and efficient tool for measuring the resting time and working duration in the field.

Table 4 shows the validation results for Classifier 2, i.e., stationary, traveling, and rebar installation activities. The overall training and test accuracies reach 90.0% and 85.6%, respectively, thereby validating the feasibility of using the model in field situation to recognize whether the worker is standing and sitting for rest, traveling in the site, or installing the rebar. However, the confusion matrix in Table 4 indicates that 33.3% of traveling activity cannot be correctly predicted as traveling, which is unacceptable in field application. The main confusion is observed in the traveling and rebar installation categories, which means that several small movements exist when working at the certain spot. Either the algorithm does not detect micro-traveling or the actions are not appropriately annotated.

Table 5 shows the performance of Classifier 3 for rebar activities. The overall accuracy for Classifier 3 is 78.3% with a test accuracy of 55.9%, which are relative lower than the application threshold. Meanwhile, the confusion matrix indicates that the categories of rebar tying and transferring materials and tools have misprediction rates of 31.5% and 88.4%, respectively. The detection errors are mainly caused by supplement work. Hence, supplement work comprises numerous activities similar to other activities. Other reasons for the poor performance include the following: 1) The camera cannot capture the minimal rest or hand movement during rebar work; thus, distinguishing different categories is difficult in the data labeling stage. 2) The window size is too small to remove the noise from the junction that frequently occurs during work. 3) The uncertain movement category consists of numerous observations, which induce certain confusions when recognizing activities.

6. CONCLUSIONS

This study collects strictly continuous data from the construction site to validate the feasibility of action recognition algorithm and generate the classification model in the activity and action levels for rebar work. The activity indicates the construction nature of movement and the action related to motion features of elemental exercise. The activity includes three levels of category. Level 1 activity includes rest and work and determines the objective productivity by detecting whether the workers are working or resting. The results show that the testing accuracy of current classifiers reaches 96.9%. Thus, Classifier 1 can efficiently classify work and rest with external data from other rebar workers in filed situations and meets the demand for detect low productivity issue in the field. Level 2 activity has acceptable overall accuracy for classifying stationary, traveling, and rebar installation. The training and test accuracies in this level are 90.0% and 85.6%, respectively. Stationary action includes standing and sitting in the jobsite. Traveling covers activities with changing position in the site, such as walking and transferring materials. Rebar installation refers to activities at a constant position, such as bending and cutting rebars at a stable spot. Level 3 activity for rebar work has a 78.3% overall training accuracy and 55.9% test accuracy. The classifications of supplement work and rebar installation can evaluate the contribution on core construction work, which can help managers assign skilled and experienced workers to critical procedures, such as the rebar installation. Consequently, productivity will be improved.

Level 1 and level 2 activities have acceptable performance and can provide valuable information to meet the demands of managers and workers. Level 3 activity and action level classifier are unsuitable for field application due to poor performance. The misclassification between categories is high and is caused by the confusion between traveling and rebar installation activities, since minimal and short-duration movements exist during work.

The current result demonstrates the feasibility of applying the proposed action recognition protocol in filed construction. In this regard, the construction action would be classified instantly during the site work, which helps manager detect the low productivity activity efficiently, such as long time resting or traveling. As a result, the project procedure could be corrected in the perspective of productivity. Filed data collection is the most challenging part. The dataset employed in this study is still limited, 1) few workers' acceleration information are included, which is not able to eliminate the human variance; 2) this study only discuss the rebar work, which is not adequate for checking field project productivity. The future work will expand the dataset by adding data collected from additional workers to reduce the human variance. To remove the junction noise in continuous work, data processing methods will be adopted. For instance, post-processing is an ideal method for removing prediction class accidentally appearing in a series of continuous data. Meanwhile, additional machine learning-based algorithms, such as deep learning-based methods, will be validated. The present result indicates that a short window size contributes to a high overall result, whereas a large window size reduces the internal misclassification error among the categories. A trade-off will be discussed to balance overall and internal performances.

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