Automated Action Recognition Using an Accelerometer-Embedded Wristband-Type Activity Tracker

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Abstract

Automated worker action recognition helps to understand the states of workers, enabling effective management of work performance in terms of productivity, safety, and health issues. A wristband equipped with an accelerometer (e.g., activity tracker) allows us to collect the data related to workers' hand activities without interfering with their ongoing work. Considering that many construction activities involve unique hand movements, the use of acceleration data from a wristband has great potential for action recognition of construction activities. In this context, the authors examine the feasibility of the wrist-worn accelerometer embedded activity tracker for automated action recognition. Specifically, masonry work was conducted to collect acceleration data in a laboratory. The classification accuracy of four classifiers, such as the k-nearest neighbor, multi-layer perceptron, decision tree, and multi-class support vector machine, was analyzed with different window sizes to investigate classification performance, and it was found that the multi-class support vector machine with a 4-second window size showed the best accuracy (88.1%) to classify 4 different sub-tasks of masonry work. The present study makes one noteworthy

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contributions to the current body of knowledge. First, the study allows for automatic action recognition not interfering with workers' ongoing work only with a wrist worn sensor, which can be widely deployed to construction sites. Second, a variability of movement between subject and experience group were examined; so that consideration of abundant and relevant data acquisition is suggested. Finally, the use of a single sensor greatly reduces a burden to carry multiple sensors as well as computational cost and memory.

Keywords: Construction management, Worker, Automation, Accelerometer, Action recognition, Machine learning, Data analysis, Wearable device.

INTRODUCTION

Construction, which is among the most labor-intensive industries, involves heavy manual lifting, and repetitive, physically demanding tasks (Arndt et al., 2005; Seo et al., 2016). As a result, construction workers are suffering from low productivity, and also are frequently exposed to safety and health risks (Cheng et al., 2013; Gatti et al., 2014). A comprehensive field data collection on the workers' activities is not only essential for evaluating and improving productivity, but also for identifying any potential issues in safety and health. However, the current practice, which heavily relies on manual approaches (e.g., work sampling) to collect data on workers' activities, suffers from several limitations including time-consuming and expensive procedures, and error-prone due to the subjective judgement from observer (Golparvar-Fard et al., 2013; Taneja et al., 2010).

Recently, the use of sensors has gained attention for its potential to replace human observers with automated monitoring technologies. The advancement of sensing technologies, such as computer vision, global positioning system (GPS), radio-frequency identification (RFID), and inertial measurement units (IMUs), enable us to monitor workers with automatically collected data on their activities (Akhavian & Behzadan, 2016). Among these sensors, a body-worn accelerometer that measures inertial body motions in three axes (i.e., X, Y and Z axes) has demonstrated great potential for automated activity monitoring, as it provides information-rich data on workers' activities, and data processing is also computationally inexpensive (Joshua & Varghese, 2010). As each activity creates unique acceleration signal patterns, machine learning algorithms are commonly used to differentiate diverse activities by learning the signal patterns. In addition, this approach enables continuous data collection, regardless of site conditions, by attaching a small, light-weight sensor on the human body (Joshua & Varghese, 2010). With these benefits, action recognition using accelerometers has been studied in the context of automatic worker monitoring (Chernbumroong et al., 2011; Joshua & Varghese, 2010; Lim et al., 2015; Tsai 2014).

Previous studies have recommended the attachment of an accelerometer on a worker's waist or back, as it can reflect movements of the center of gravity of the body and can minimize discomfort due to the attachment of a sensor on the body (Bouten et al. 1997; Joshua & Varghese, 2010; Jebelli et al. 2014, 2015, 2016, 2018; Kim et al. 2018). However, it would be challenging to differentiate upper-limb dominant activities such as hand brushing as the accelerometer attached on waist or back is difficult to capture acceleration signals generated by hand movements (Ravi et al. 2005). In particular, construction tasks involve a large portion of hand and upper-limb dominant activities such as manual tool and material handling, and all construction tasks somehow require unique arm movement. Therefore, accelerometer placed on wrist can directly capture hand and upper-arm movement acceleration signals resulting in better-reflecting construction activities including many upper-limb movements. Recently, with the availability and affordability of a lightweight commodity wristband-type activity tracker equipped with an accelerometer, acceleration signals from hand movements can be easily collected. Considering all, acceleration signals directly collected from upper limbs possess immense potential to be used to recognize many construction activities with low cost and high accuracy.

In this regard, the authors investigated the feasibility of automatic activity recognition by analyzing acceleration signals collected from a wristband-type activity tracker. Considering that construction activities mostly includes hand and upper-body movement (CPWR 2013), the underlying hypothesis of this research is able to be posited as follow: acceleration signals generated from wrist are possible to differentiate diverse construction activities by forming unique patterns that can represent both upper-limb dominant and whole-body movement. To test the feasibility, the authors collected acceleration data while conducting masonry work with ten masons by using a wristband-type activity tracker, and applied machine learning algorithms for recognizing sub-tasks for masonry work. With special consideration for disparities in worker performance, the effect of the human variability of workers' motions on the classification performance was also investigated. Based on the testing results, the feasibility of the proposed approach and its potential application areas are discussed.

LITERATURE REVIEW

Automated worker activity monitoring by using sensing techniques

In recent years, automated construction-worker activity recognition, using both vision-based and sensor-based technologies, has drawn attention because it provides continuous data collection and understanding of current activities. Computer vision technologies, which identify and categorize actions by using pictures and videos from a single or multiple cameras, have been widely investigated for analyzing the productivity of construction workers and monitoring their safety and health (Brilakis et al., 2011; Escorcia et al., 2012; Han et al., 2013; Weerasinghe & Ruwanpura, 2009). Peddi et al. (2009) proposed a human pose analyzing algorithm, using a video camera for construction-productivity estimation. Han and Lee (2013) suggested a motion-capture approach with 2-D images obtained from multiple cameras for behavior-based safety management. Computer vision-based approaches have also been applied to identify any potential ergonomic risks by detecting awkward postures on recorded images (Seo et al., 2015). Previous vision-based activity recognition studies have shown its advantages, such as providing a rich set of information with less intrusively collected data even though this approach can be adversely affected by lighting conditions and occlusions, and needs tedious post-processing (Seo et al., 2015).

Location sensor-based approaches have also been widely explored to automatically collect worker-activity-related data. One of the widely-explored applications in construction is a real-time location tracking technology, such as GPS, RFID, and ultra-wideband (UWB) (Cheng et al., 2012). Location-related data collected using such sensors has been used to monitor workers' job status (Jaselskis & El-Misalami 2003; Montaser & Moselhi 2014) or to manage construction-worker safety (Carbonari et al. 2011). Furthermore, Cheng et al. (2012 and 2013) proposed a system for analyzing construction-worker productivity and ergonomics, based on real-time location data combined with physiological status monitoring technologies. However, detailed activity monitoring is not available with this approach, as the location information is not enough to distinguish between different activities conducted in the same position (Seo et al., 2015).

The use of body-worn sensors integrating accelerometer, gyroscope, and magnetometer, in so-called IMUs for construction activity monitoring has gained great attention, especially, for ergonomic assessment. In particular, with a capability of collecting acceleration, velocity, and orientation, the body-worn sensors enable to measure workers’ posture and motions in various construction activities. Valero et al. (2016) developed a system to detect basic unsafe postures of construction workers (i.e., stooping and squatting with back bending) using wearable IMU suit. In their following study (Valero et al., 2017), inadequate working postures of bricklaying work were assessed using the IMU-based system with standardized rules defined by International Organization for Standardization (ISO). Finally, Umer et al. (2016) assessed biomechanical characteristics in truck during simulated rebar tying work by using the combination of IMUs and surface electromyography electrodes. The addressed research efforts showed great potential to use motion data for unsafe activity monitoring; however, most of the approach requires workers to wear or attach multiple sensors, which results in more computational cost in data processing.

Compared with these approaches, the use of an accelerometer for activity monitoring can have several advantages. An accelerometer provides real values for acceleration data containing reliable body motion information that can be used to recognize different construction activities (Lim et al., 2015; Ryu et al., 2016). In addition, advanced sensing technologies enable small-sized and low-cost microelectromechanical (MEMS) accelerometers to be equipped with various wearable devices, such as activity trackers and smartphones. Thus, today's wearable devices with an accelerometer allow for detailed data collection on construction workers' activities from individual workers, regardless of the construction site conditions.

Previous studies on accelerometer-based action recognition

Accelerometer-based action recognition, which aims to identify physical actions from a set of acceleration signals, can be achieved by utilizing machine-learning techniques. The overall process is as follows: first of all, raw acceleration data is collected and then labeled to pre-determined actions. The labeled data is segmented into a specific window size to extract a set of features representing the unique patterns of acceleration signals. According to Figo et al. (2010), three different signal-processing techniques for feature extraction are available, based on the domain involved: the time domain, frequency domain, or discrete representation domain. Then, classification algorithms learn different actions from labeled training datasets to identify the actions from new acceleration signals (i.e., testing datasets) (Preece et al., 2009). For example, support vector machine (SVM), multilayer perceptron, and decision tree classifications have often been used in accelerometer-based action recognition (Chernbumroong et al., 2011; Joshua & Varghese, 2010; Yang & Hsu, 2010).

In the last decade, accelerometer-based action recognition has been applied for occupational tasks in various industries, such as for identifying assembly tasks in manufacturing industries (Koskimaki et al., 2009; Lukowicz et al., 2003) and for classifying activities by automotive workers (Zappi et al., 2007), like sawing, drilling, and hammering. In construction, this approach has also been applied in several applications, such as the activity analysis of construction workers (Joshua & Varghese, 2010; 2014) and equipment (Ahn et al., 2013; Akhavian & Behzadan, 2014), and fall risk detection (Lim et al., 2015; Tsai, 2014; Yang et al., 2015). In particular, Joshua and Varghese (2010) attached wired accelerometers to a mason's waist to investigate accelerometer-based action recognition for productivity analysis. In the study, they classified three actions (i.e., fetching and spreading mortar, fetching and laying bricks, and filling joints), and obtained the best performance of 79.83% with two accelerometers attached on the right and left side of waist.

Previous research efforts have revealed that sensor placement on the body can significantly affect action recognition performance because acceleration signal patterns from the same activities may vary depending on the position of sensors (Bao et al., 2004). Generally, the waist has been considered to be a promising location for accelerometer-based action recognition because it is close to the center of the whole-body mass (Yang & Hsu, 2010), and thus the sensor signal from the waist better represents the major body motions. However, waist-oriented acceleration signals could have a limitation to reflect hand and arm movement, so it is hard to differentiate activities including these movements (Ravi et al., 2005). On the other hand, accelerometer, particularly using a single module, placed on the dominant wrist better-discriminates activities which involve hand and upper-limb movement (Bao & Intille, 2004). Many previous studies reported the acceptable performance to classify physical activities using a wrist-worn accelerometer in different domains (e.g., healthcare, sport, and manufacturing industry). Chernbumroong et al. (2011) used a single wrist-worn sensor to classify daily activities, such as walking, running, standing, sitting, and lying, and achieved 94.13% as the best accuracy. Shoaib et al. (2016) classified more complex daily activities (e.g., cycling, ascent and descent stairs, eating, typing, and drinking coffee) using mobile phone placed at right wrist and pocket. Yang et al. (2008), also, used a single accelerometer on the dominant wrist to classify domestic activities including standing, sitting, walking, running, vacuuming, scrubbing, brushing teeth, and working at computer, with overall recognition accuracy of 95%. Furthermore, in the industry domain, Koskimaki et al. (2009) classified basic tasks in an assembly line, which are hammering, screwing, spanner use, power drilling, and showed 88.2 of overall classification accuracy.

As such, using a single accelerometer placed on wrist also has a significant potential to for automated recognizing construction activities. However, the feasibility of wrist-oriented acceleration signals to classify complex construction activities, involving whole body movement and unique hand movement patterns in terms of direction, speed, and range, has not been fully investigated. In the presented study, unique patterns from acceleration data collected from lightweight commodity wristband-type activity tracker are analyzed to recognize construction actions containing both whole-body and upper-limb dominant movements.

RESEARCH METHODOLOGY

The objective of this research is to test the feasibility of the use of a wrist-worn accelerometer as a means for construction workers' action recognition. In particular, masonry work was selected as a case-study. Masonry tasks involve typically both whole-body movement and upper-limb dominant moments, such as repetitive back-bending and material/tool handling, so that the case study allows the authors to see how the proposed approach can handle both movements. Figure 1 shows the overall research methodology that consists of: 1) data collection; 2) data preprocessing including data labeling and segmentation; 3) feature extraction; 4) classification; and 5) validation.

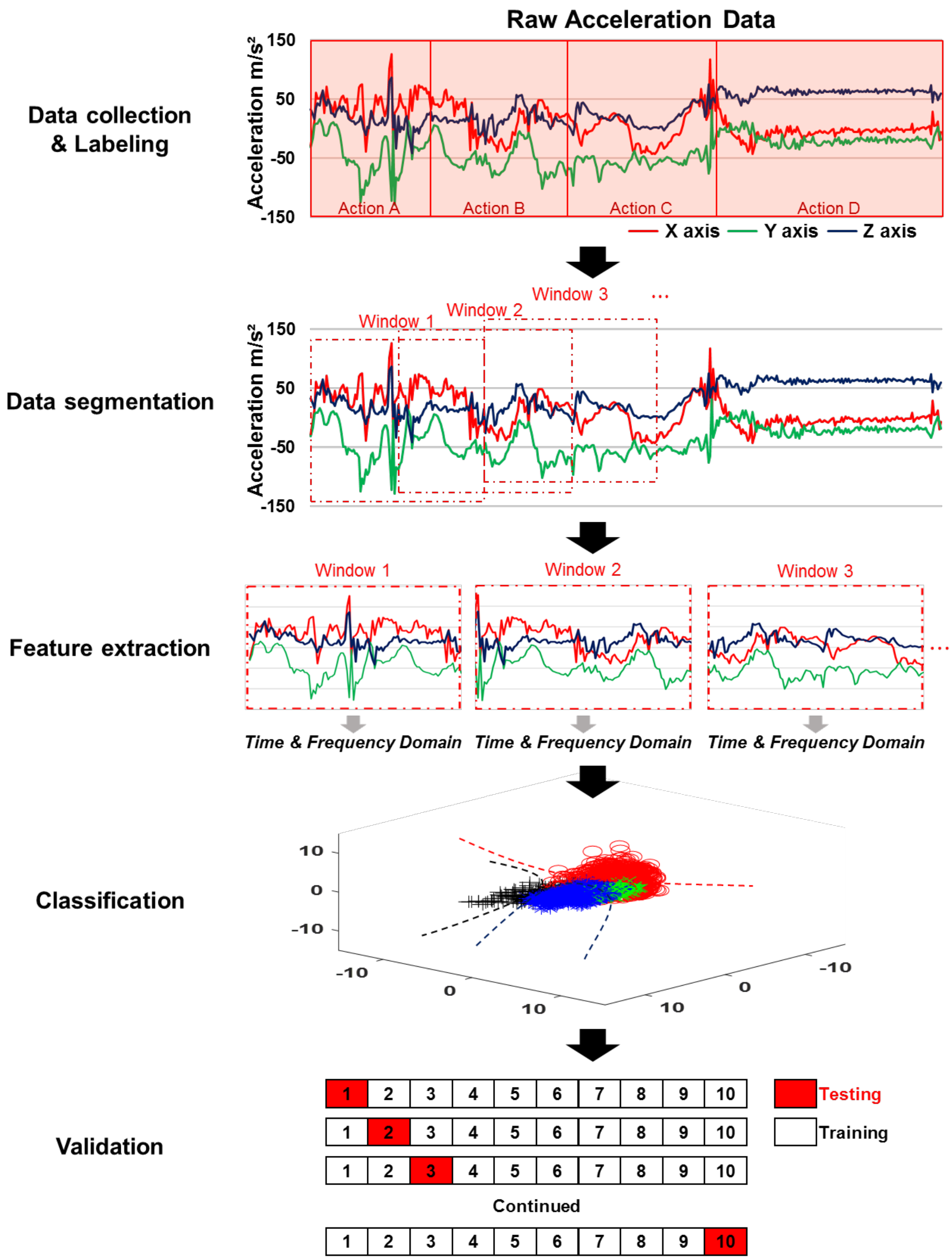

Figure 1. Research methodology

Data collection and acceleration data labeling

Using a wrist-worn accelerometer embedded activity tracker, workers' acceleration signal were collected. The sensor was firmly attached on the wearer's dominant wrist to collect well-reflected acceleration data of movement. Recent commodity wristband-type activity tracker enables to provide sensor data wirelessly via Bluetooth connection so that the data can be collected without interrupted the ongoing work during experiment.

The obtained acceleration signals were then labeled based on predetermined actions. According to Everett and Slocum (1994), a construction project can be divided into seven levels (i.e., project, division, activity, basic task, elemental motion, orthopedics, and cell). Among those levels, the basic tasks are the fundamental actions of construction field work, which represents a series of steps that comprise of an activity.

Feature extraction

The labeled data was divided into specific time segments (i.e., window sizes). Then, features representing each of the segments were extracted to be used for action classification. After an initial analysis and comparing the performance of different windowing approaches (e.g., activity-defined windows, event-defined-window, and sliding window), the authors selected sliding window approach, which is the most widely employed segmentation technique in activity classification due to the simplicity and less effort of preprocessing (Banos et al., 2014). Determining optimal window size is critical to use sliding window approach. According to the Preece et al. (2009), previous studies have used a range of window sizes from 0.25 to 6.7 seconds, depending on types of actions to be recognized Within a wide range of window size, the optimal window size can be determined by whether segment length is long enough and the sampling frequency is high enough to reflect unique signal patterns of each action. Banos et al. (2014) reported that the window size for optimal recognition ranged between 0.5 and 6.5 seconds, and, especially, for the activities involving the movement of all body part achieved the best performance with raging of between 0.5 and 4 seconds window size. Also, the overlap size was selected as 50% of the window size, which has demonstrated success in a previous study (Bao & Intille, 2004).

Afterward, features that characterize segmented data were extracted with respect to both time- and frequency- domain. Time- and frequency- domain features represent various useful context characterizing information in the selected segment (Preece et al., 2009). Time-domain features, which are statistical measures, are directly computed from the segmented data with four different window sizes respectively. Frequency-domain features are computed by using the fast Fourier Transform (FFT) to represent the frequency components (Preece et al., 2009). Since the input length of the FFT function is required to be a power of two, the next smallest exponents of each segment were selected for the frequency-domain features. For example, the 32 data points were used for extracting frequency domain features in a 1-second window size instead of 22 data points. Then, 10 different features (8 for time domain features and 2 for frequent domain features), which have been widely used in accelerometer-based activity recognition studies and have emerged as typical principle components, were selected (Beak et al., 2004; Figo et al., 2010; Joshua & Varghese, 2010; Koskimaki et al., 2009; Ravi et al., 2005). The selected features were extracted for acceleration signals in x-, y-, and z-axes, respectively, so the total number of potential features considered was 30. The time domain features include: 1) mean, an average value of acceleration data over the window; 2) standard deviation of acceleration values in each window; 3) maximum; 4) minimum; 5) range (difference between maximum and minimum values); 6) skewness (a degree of asymmetry in the distribution of acceleration data); 7) kurtosis (a sharpness of the peak in acceleration data); and 8) correlation, a variation in acceleration across each paired axis (x and y, y and z, x and z axis) (Beak at al., 2004). The features in the frequency domain are 9) energy and 10) entropy that have been used to capture periodicity of the data (Figo et al., 2010). Energy and entropy features have also been used to identify the states of movement and differentiate actions that have a similar energy level, respectively (Figo et al., 2010).

According to Hall (1999), theoretically, the use of more features can produce a better distinction, but empirical studies have shown the less relevant features can add noises, and degrade classification performance. In this study, the ReliefF algorithm was used as a feature selection method from the potential set of 30, because it is not only one of the most used algorithms for feature selection but also robust to noise and redundancy (Menai et al., 2013). The algorithm iteratively determines *k* nearest features of the same and different classes from randomly sampled instances in training dataset; also, it measures and updates the importance weight by averaging their contribution (Hall 1999). According to Robnik-Šikonja and Kononenko (2003), the parameter *k*, relating to the distance of estimations, can be determined heuristically and safely set to 10 for most purposes. The importance weight of each feature indicates how well it distinguishes the classes so that a larger feature weight represents a more important feature, and the algorithm imposes a rank on each feature based on the weight (Hall 1999).

Learning and recognizing different actions through machine learning

Machine learning techniques were applied to learn acceleration signal patterns of different sub-tasks by using extracted features from training data, and then classifying types of sub-tasks from testing data. The authors selected four machine learning classifiers that have been widely used for action recognition, and compared their performance. Those are: 1) *k*-nearest neighbors (*k*-NN) (Koskimaki et al., 2009); 2) Multilayer Perceptron (Joshua & Varghese, 2010); 3) Decision Tree (J48) (Chernbumroong et al., 2011; Joshua & Varghese, 2010); and Multi-Class Support Vector Machine (Multiclass-SVM) (Qian et al. 2010).

k-NN is a non-parametric method for a classification based on the *k*-closest training dataset, vectors in a feature space (Ke et al., 2013). The algorithm predicts the label of the unlabeled data by picking the *k*-closest data points in n-dimensional feature space and determining the most frequent label among the k nearest training samples (Sutton, 2012). It is simple, robust, and efficient with relatively short computational time (Ke et al., 2013). Multilayer perceptron is a neural network classification model that maps a set of input data onto a set of appropriate outputs, where each connection of input and output has weight measuring the degree of correlation of connections (Pal & Mitra, 1992). The neural networks have advantages of not only providing a better performance with complex movements, but also having potentially high tolerance for noisy data (Joshua & Varghese, 2010). Decision Tree (J48) is a tree-based classifier that predicts responses by following the decisions from an internal node (i.e., input features) down to leaf node (i.e., a response of the labeled class). C4.5 is one of the widely-used decision tree classifiers, and J 48 is the implementation of the C4.5 decision tree algorithm. SVM is a binary discriminative classifier that defines the optimal separating hyperplane which categorizes two different classes (Suykens and Vandewalle 1999). Multiclass SVM is a more general form of SVM, applicable to many real world problems, where there are more than two labels. Multiclass SVM trains a classifier and defines optimum separating hyperplanes for each possible pair of classes (Hsu and Lin 2002).

Waikato Environment for Knowledge Analysis (WEKA) workbench, which is "a collection of state-of-the-art machine learning algorithms and data preprocessing tools" (Witten & Frank, 2005), was used to perform the first three classification algorithms. A custom software written in MATLAB (version 8.1.0.604, The Math Works Inc., USA) is used for multiclass-SVM modeling and calculations. To evaluate the performance of the classifier, a 10-folds cross-validation, which is a model validation technique to assess the accuracy and validity of statistical models, was used. In the 10-folds cross-validation, the dataset is randomly split into 10 approximately equal size exclusive subsets. Then, each part is reserved as the test set, and the remaining parts are performed as training data set with a particular classifier (Kohavi, 1995).

According to Refaeilzadeh et al. (2009), 10-fold cross validation is reliable to estimate the performance of classifiers because it makes predictions with 90% of the dataset, which can be generalizable to the full dataset.

CASE STUDY ON MASONRY WORK

The proposed framework is applied to an indoor masonry work as a case study to test feasibility of the wrist-worn accelerometer embedded activity tracker for automated action recognition. Considering possible human variability in masonry work techniques, ten healthy masons with different years of work experiences were recruited to collect the acceleration data, and each was asked to perform identical masonry work that builds a concrete block wall with 45 blocks at the Ontario Masonry Training Centre (Waterloo, Canada). Each subject performed this work for 20 to 40 minutes, with the firmly-worn accelerometer embedded wristband on their dominant wrist. Figure 2 shows the workstation with a test setup.

Figure 2. Test setup and the subject's performance with detail of wearable device

The eZ430-Chronos sports watch from Texas Instruments was selected to collect raw acceleration data. The device contains a three-axis accelerometer with a range of ±2G and a sampling rate of 22 Hz, and it is based on the CC430F6137 microcontroller with 915 MHz wireless transceiver which allows wireless transfer the raw acceleration data to the PC through USB RF access points (Texas Instrument 2010). All subjects responded that the wearable device was comfortable and did not interfere with their ongoing actions after the completion of their work.

The collected acceleration data from masonry work was labeled as four sub-tasks at the basic task level, such as: 1) spreading mortar; 2) bring and laying blocks; 3) adjusting blocks; and 4) removing remaining mortar. Labeling of acceleration signals was done manually by observing video recordings, and the transitional signals, such as taking a rest and walking to grasp a tool, were removed.

Considering that the average cycle-time of four sub-tasks of each participant ranged between approximately 1 second and 4 seconds, window sizes of 1, 2, 3 and 4 seconds were tested respectively to determine the optimal window size for the best recognition performance. Figure 3 shows the average and standard deviation cycle-time of each action of Subject #1. While the "adjusting blocks" and "removing mortar" actions were completed in relatively shorter time, the other two actions took more time to finish. The "laying blocks" action had not only the longest performing time but also larger standard deviation, because it contained more complex process, such as picking up blocks, moving to the lead wall, and placing blocks.

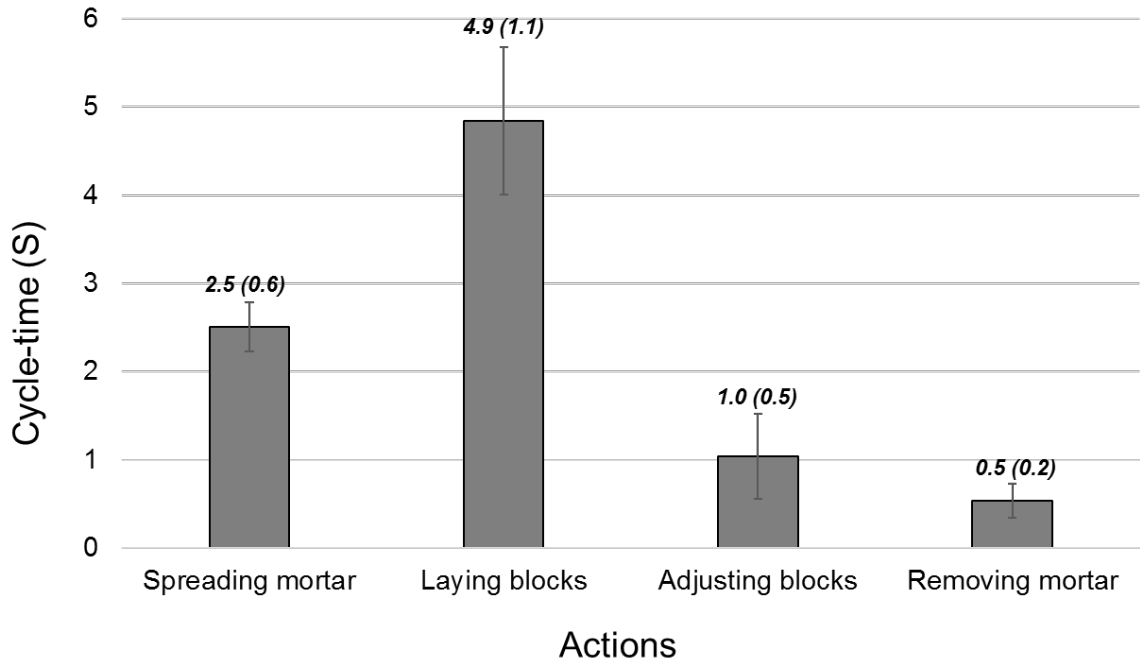

Figure 3. Average cycle-time of actions

Then, the segmented signals were processed following the process of research methodology addressed above including: 1) time- and frequency domain features extraction, 2) relevant feature selection, 3) classification and validation.

RESULTS

The present study evaluates the performance of the proposed approach for recognizing sub-tasks of masonry work in two ways. First, the data from all ten-masons was used for action recognition to determine the best combination of classifiers and window sizes. Second, given the best combination of a classifier and a window size, the classification accuracy was tested when using data from each subject for both training and testing data, and when grouping data according to subjects' working experiences. From this exercise, it was observed that the way to build the concrete block wall varied among masons in terms of movement speed or direction even though all participants performed the exact same work. Thus, the second test was to investigate whether the proposed approach is reliable for human variability.

Classification accuracy according to types of classifiers and window sizes

To determine the best combination of types of classifiers and window sizes, 10-folds cross validation was performed by using data from all subjects. The accuracy was then calculated by dividing the number of correctly classified actions by the total number of instances in the dataset.

Before determining the optimal classifier and window size, firstly, the ReliefF algorithm was used to see whether all selected features are robust for action recognition as described in the previous “Feature extraction” section. While this algorithm selects highly relevant features, it does not remove redundant features (Atallah et al., 2011). Thus, the threshold values were selected by comparing feature importance weights determined through the algorithm. The feature importance weight from each window size and average weight are shown in Figure 4. For all window sizes, the importance weights were lower than the averaged importance weights for the first 18 features. To only select highly relevant features for classification performance, therefore, upper 18 features were selected for the minimum threshold in this study. Also, considering more features can produce a better result, upper 21, 24, 27, and 30 features, which are corresponding 70%, 80%, 90%, and 100% of the features respectively, were also used as thresholds.

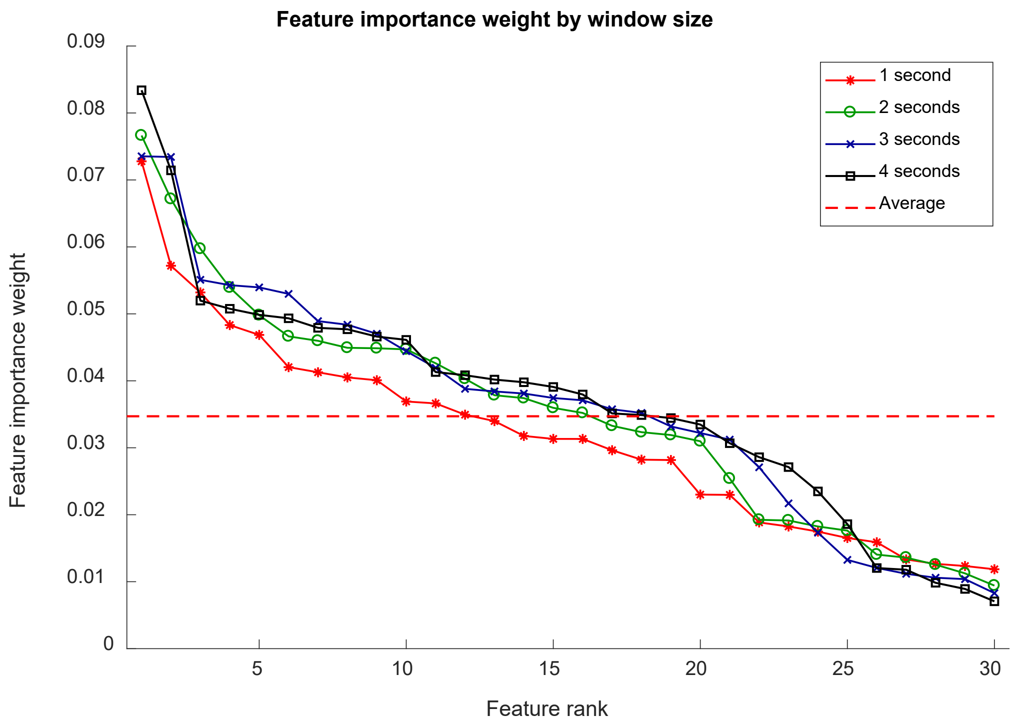

Figure 4. Feature importance weight

Then, Figure 5 shows the classification accuracy according to the number of selected features and the classifiers when using data from all four window sizes (each classification accuracy represents the average of the classification accuracy using all window sizes). The line graph at the top of the bar graph shows the highest accuracy. Given the average and highest accuracy, all four classifiers showed the best performance when using all 30 extracted features. Therefore, all the extracted features were used in the subsequent analysis.

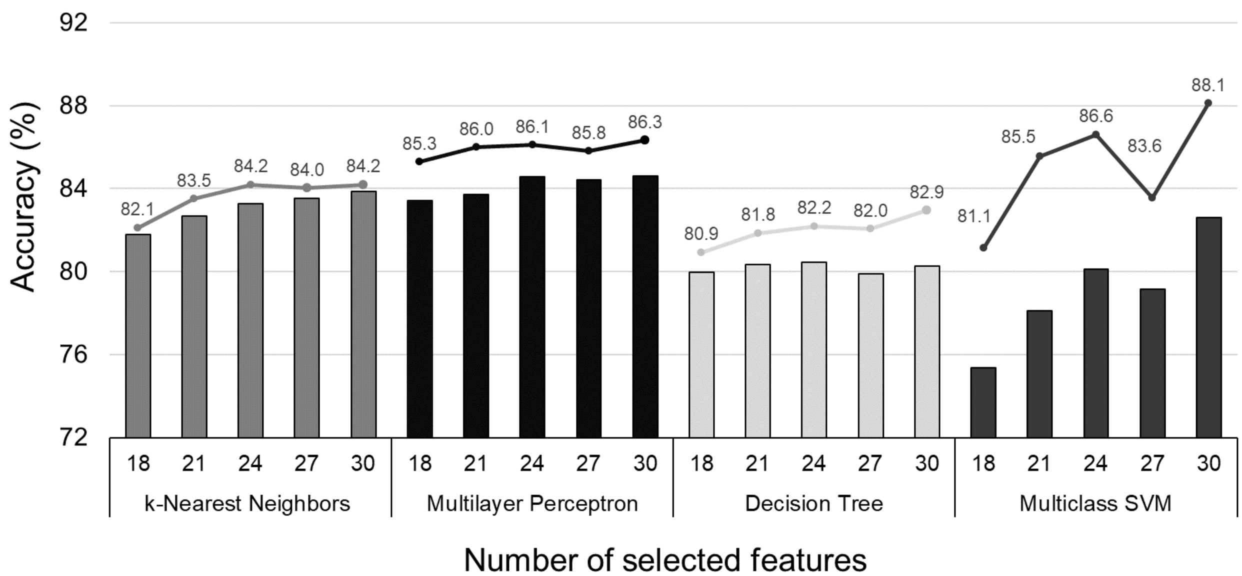

Figure 5. Average accuracy of classifications with selected features

Then, Figure 6 shows the overall accuracy for classifying four sub-tasks with all extracted features. It was found that classifiers with the larger window size tend to show higher accuracy. The accuracies of the multiclass SVM or multilayer perception classifier showed the highest among the four classifiers for each window size, except for the 1 second window size. The highest accuracy was 88.1% from the multilayer perceptron classifier with a 4 second window size and the lowest accuracy was 77.4 % from the decision tree with a 1 second window size.

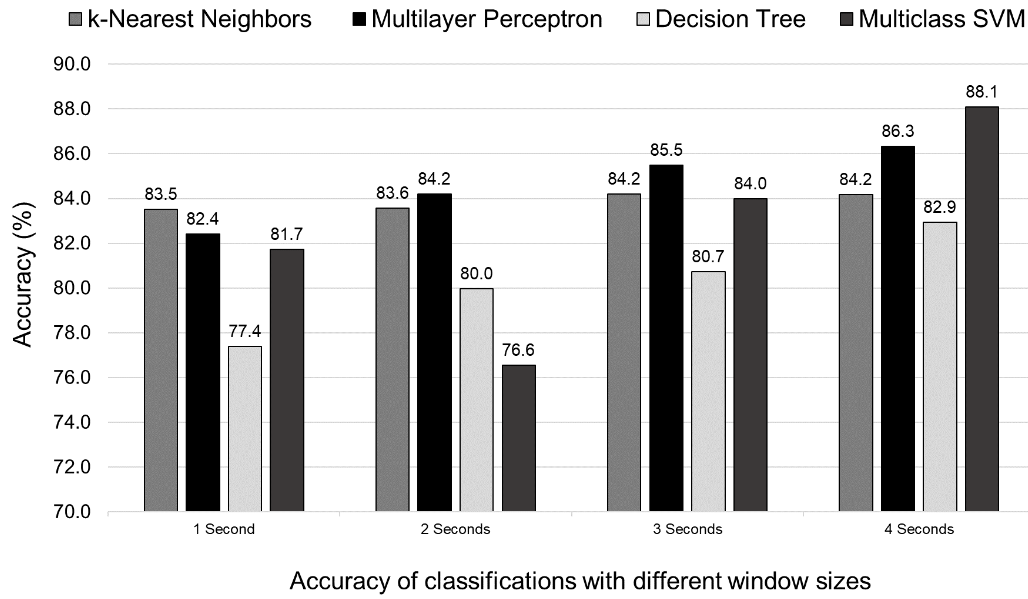

Figure 6. Accuracy of classifications with different window sizes using all features

To investigate the detailed classification result, the confusion matrices from the two most accurate results when using the multilayer perceptron and multi-class SVM with a 4-seconds window size are shown in Table 1. In the confusion matrix, each row represents actual classes while each column corresponds to predicted classes. Also, precision indicates that the ratio of the number of correct prediction to the total number of instances classified as positive. On the other hand, recall represents that the ratio of the number of correct predictions to the total number of positive instances. The “removing mortar” and “adjusting blocks” actions achieved relatively lower precision and recall, which means not only that most of the instances were classified as other classes, but also selected instances were less relevant. These errors were likely caused by the difference in action durations. For example, the “removing mortar” and “adjusting blocks” actions were completed in a relatively shorter time length than the other two actions. Furthermore, signal patterns in a shorten window size have a limitation to differentiate between actions because the similar acceleration patters can be generated within shorter segments.

Table 1. Confusion matrices of two tops classifiers (Multilayer perceptron and multiclass-SVM) using 4 seconds window and all features.

Multilayer perceptron	A	B	C	D	**Recall**
A=Spreading mortar	917	34	20	2	0.942
B=Laying blocks	49	648	24	7	0.890
C=Adjusting blocks	33	35	89	2	0.560
D=Removing mortar	22	20	15	5	0.081
Precision	0.898	0.879	0.601	0.313	Accuracy: 0.863
Multiclass SVM	A	B	C	D	**Recall**
A=Spreading mortar	903	70	0	0	0.928
B=Laying blocks	44	684	0	0	0.939
C=Adjusting blocks	50	26	83	0	0.522
D=Removing mortar	19	20	0	23	0.371
Precision	0.888	0.855	1	1	Accuracy: 0.881

Classification accuracy according to individual subject and work experience

To examine the variability of movement between subjects, the accuracy was compared, for all subjects, when the training and testing data only contain data for a specific subject._The classification accuracy of each subject was calculated by performing the cross validation for each subject, respectively. Again, multilayer perceptron and multiclass SVM classifiers with 4-seconds window size were used for this analysis because these two showed the best performance in calculating overall accuracy. As shown in Figure 7, training the classifiers only with the individual subjects' data lead to significantly lower prediction accuracy using Multiclass SVM algorithm compared to Multi-Layer Perceptron. This suggests that Multi-class SVM requires a larger dataset to optimize the classifier parameters. As a result, the authors suggest the use of Multilayer perceptron algorithm for the smaller datasets. It is noteworthy to mention that while applying Multilayer perceptron, classification accuracy varies according to subjects, and in general, is higher than the overall accuracy (86.3%) that was obtained when using data from all subjects, except Subject #4 and #5. This result indicates that there are both within-subject and between-subject variation on working techniques (e.g., direction and speed of movements when performing tasks) even though they performed exactly the same tasks. For example, Subject# 9 shows the best accuracy, implicitly indicating that he performed the tasks by using a more consistent working technique. On the other hand, Subject #5 had a large variation in working techniques, resulting in low accuracy. Therefore, it was revealed that a variability of movement between subject and experience group (e.g., working styles and skills). Furthermore, abundant and relevant training dataset (i.e., a similar level of experience or work-training) are required to be deployed to other construction trade.

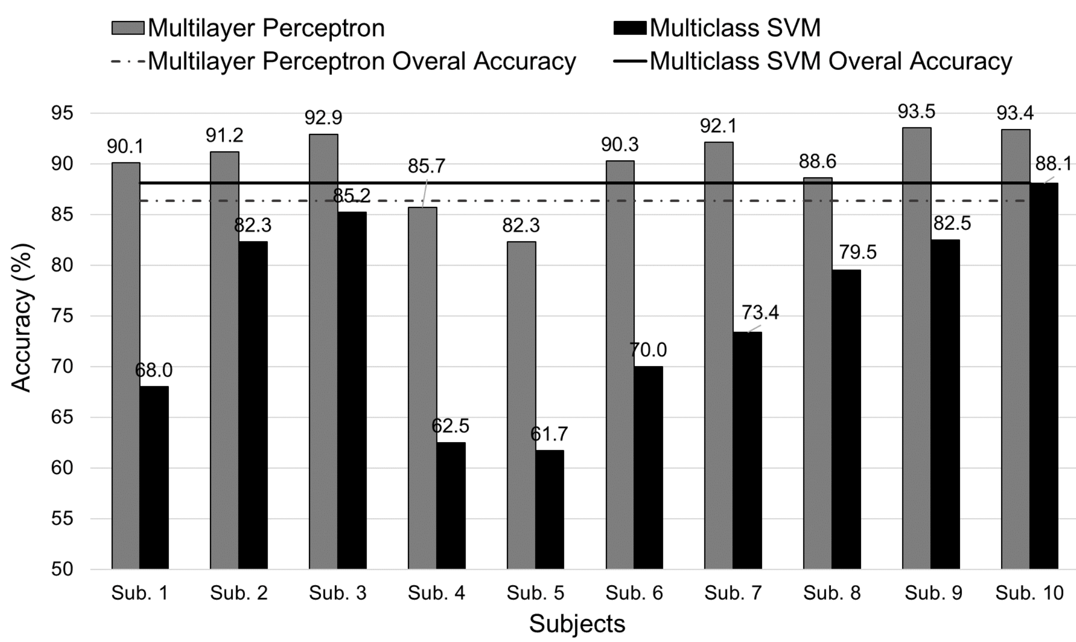

Figure 7. Average classification accuracy of different individual subjects' data sets

The ten subjects who participated in this study have various work experience from the novice who had no work experience to journeymen who had more than five years of work experience. To investigate the effect of difference on working techniques according to work experience, data from subjects were grouped into two: 1) an experienced group that included subjects with work experience more than 1 year and 2) a non-experienced group involving subjects who had no work experience. Among the ten subjects, the experienced group included eight subjects, and two subjects (i.e., Subject #4 and #9) were recruited for the non-experienced group. Despite, the small number of subjects in non-experienced group may be a constraint; however, enough the acceleration data were collected to train and test the different classifiers. According to the previous studies, the different levels in work experience can impact the way that the workers perform the same task (Alwasel et al., 2017a; Alwasel et al., 2017b). Classification accuracy was compared by splitting data according to groups for training and testing sets as shown in Figure 8. When using only data from the experienced group for both training and testing, the accuracy (89.2%) was higher than the accuracy (88.1%) from all data combined. It can be concluded that there is smaller variation among experienced workers in terms of working techniques, indicating that the work experience can affect regularized repetitive actions. It is not surprising that the accuracy (83.3%) when using data from the non-experienced group becomes lower because it is expected for non-experienced workers to perform the tasks with less consistent working techniques. Especially, it is found that there are significant differences on working techniques between the experienced and non-experienced group because the classifier learned by using data (i.e., training data) from the experienced group showed relatively low accuracy (71.0%) to classify data (i.e. testing data) from the non-experienced group and vice versa.

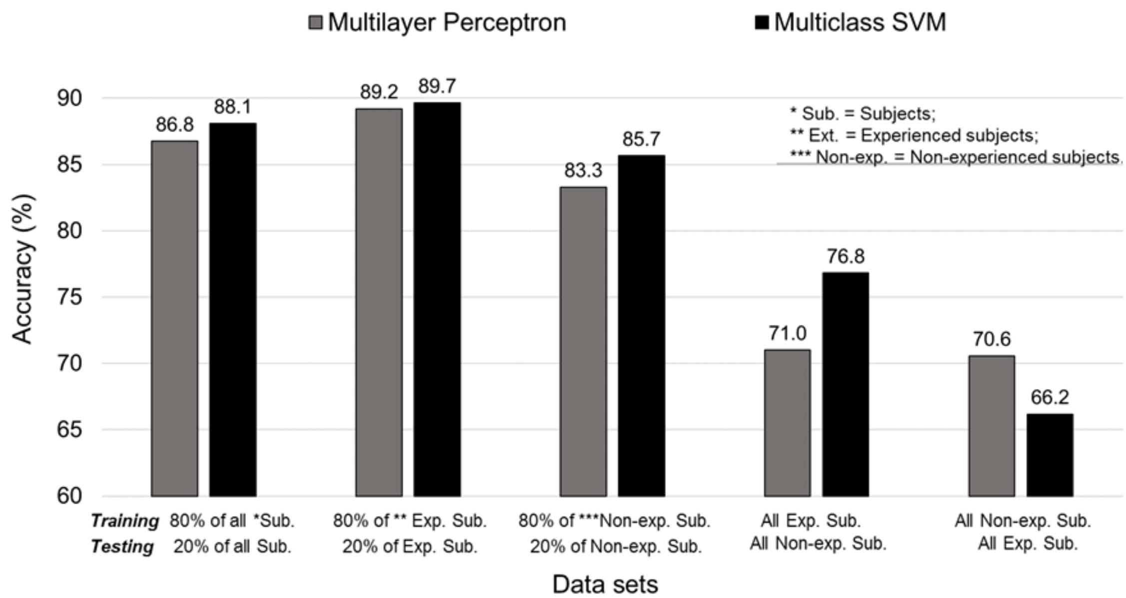

Figure 8. Classification Accuracy using different training and testing data sets

DISCUSSION

In the current study, indoors masonry work was conducted as a case study to test the feasibility of action recognition by using acceleration data from the dominant wrist. The best result from the case study was 88.10% classification accuracy, demonstrating that the acceleration signals generated by hand movements show unique patterns according to the types of tasks, enough to recognize construction activities. From the result, it can be concluded that the proposed approach has considerable potential as a means for automated and non-intrusive action recognition for masonry tasks which involve complex whole-body and upper-limb dominant movement. Furthermore, considering that a number of similar actions exist in construction tasks (i.e., material lifting and tool handling), the proposed approach is possible to be deployed to other construction trades.

However, the classification accuracy is significantly different depending on classification methods (e.g., types of classifier and window sizes) and subjects. Around and over 80%

classification accuracy is achieved by a different combination of classifier and window sizes, and the highest accuracy is 88.10% using multiclass-SVM classifier with a 4 seconds window size while classifying all the subjects. Furthermore, the accuracy of each individual classification is higher by applying a multilayer perceptron classifier. The classification accuracy of the experienced group was also better than the non-experienced group. The following subsections examine the details of the analysis and limitations of the current study.

Performance of classifications methods

In this study, the range of overall accuracy is from 82.9 % to 88.1 % depending on types of classifiers using 4 seconds window size and all extracted features. Among the classifiers, Multiclass SVM classifier shows slightly better performance. It may be because the classifier produces desirable accuracy by maximizing the distance between constructed hyperplane and nearest point, and then repeatedly optimizing classifier's parameters in training phase. (Weston and Watkins 1998; Franc and Hlavác 2002). Comparing the reported classification accuracy on recognizing masonry activities using accelerometers, the best result was 79.8 % (Joshua & Varghese, 2010), the performance of classifiers is competitive.

Feature selection algorithms are widely used in activity classification studies to improve classification performance and reduce computational effort by descarding irrelevant features (Hall 1999; Menai et al., 2013). In this study, the ReliefF algorithm was used for feature selection, which was also used in the previous accelerometer-based activity recognition study (Atallah et al., 2011; Gupta and Dallas 2014). As shown in Figure 3, which tested five different threshold values, similar accuracy values were found from the top 80% or more of features considered. However, all classifiers showed the highest accuracy when using all extracted features.

The accuracy with a 4-second window size was better than other smaller window sizes, but there was relatively large error classifying shorter-length action, “removing mortar.” As shown in Figure 3, each action has various cycle-time, such as the average cycle-time of “removing mortar” action is 0.5 second, but “laying blocks” action is 4.9 second. As such, the classification accuracy is varied depending on window sizes as shown in Figure 6. Table 2 shows a confusion matrix of multiclass SVM and multilayer perceptron classifiers with 1-second window size. It can be seen from the precision and recall in Table 2 that smaller window size is better to detect shorter cycle-time actions, such as "removing mortar" and "adjusting blocks," than using larger window sizes, which the accuracy is shown in table 1. At the same time, however, classifying longer cycle-time actions (i.e., "lifting blocks" and "spreading mortar") with shorter window size results in worse performance. Finally, the result in Table 2 indicates that smaller window size is difficult to reflect the longer cycle-time actions' information and generates noises, resulting in decreasing overall classification accuracy. Sun et al. (2010), also, indicated that shorter window size may be insufficient to have features and information to describe actions. Therefore, determining optimal window size, which well reflects characteristics of each action is critical. Specifically, for actions with various cycle times, selecting a window size that fully reflects actions with a relatively long cycle-time can minimize the missed information of actions so that a better classification performance can be produced. Also, generating different window segment length by actions can achieve better classification accuracy (Hyunh & Schiele 2005; Laguna et al., 2011). In particular, Laguna et al., (2011) proposed a dynamic sliding window model. In the model, different window lengths were established by events. In the study, test comparing average precision and recall between static and dynamic sliding window model, they showed higher precision and recall using the dynamic window size model (93.05% and 91.38%, respectively) than the static sliding window approach (80.55% and 80.08%, respectively) (Laguna et al., 2011). Thus, dynamically adjusting and shifting window segment size is worth exploring in feature research.

Table 2. Confusion matrix of the two best classifiers with 1 second window size

Multilayer Perceptron	A	B	C	D	**Recall**
A=Spreading mortar	3470	142	83	139	0.905
B=Laying blocks	276	2255	32	51	0.863
C=Adjusting blocks	140	43	471	18	0.701
D=Removing mortar	351	58	20	142	0.249
Precision	0.819	0.903	0.777	0.406	Accuracy: 0.824
Multiclass SVM	A	B	C	D	**Recall**
A=Spreading mortar	3578	240	1	15	0.933
B=Laying blocks	601	2010	0	3	0.768
C=Adjusting blocks	156	0	516	0	0.767
D=Removing mortar	377	14	1	179	0.3135
Precision	0.759	0.887	0.996	0.909	Accuracy: 0.817

Influence of human variances

With the investigation of individual and all subject dataset analysis, the multiclass SVM failed to reach a high classification accuracy while classifying actions for each individual. On the other hand, the multilayer perceptron classifier led to higher classification accuracy for each individual compared with training the model on all subject groups. This shows individual differences in worker performance while doing the same work. The differences can be attributed to the variation in working techniques, which can potentially affect classification performance. In particular, various movements, such as lifting blocks with one or both hands, create different patterns of the acceleration signal resulting in generating different features for the same action class. Furthermore, the difference in direction and speed of actions, such as performing with the right hand or left hand and moving faster or slower, can have a significant impact on classification accuracy with fixed window size approach, because variation in cycle-time can serve as noise. To address the issue of variability of the same actions being differently performed, Bulling et al., (2014) suggested: first, increasing the amount of training data to capture a large range of variability and second, developing person-independent features to increase robustness to the variability. Also, it is possible to collect and group the data based on similar working styles and skills for obtaining constant features and reducing noise.

Regarding the classification accuracy test on work experience, the classification result in the experienced group achieves higher accuracy than with the non-experienced group as shown in Figure 8. Furthermore, the classification result between two groups is considerably different. Such results are significant in at least two major aspects. First, a worker's cumulative work experience can be closely related to forming a regularized movement pattern for the same task, which consequently affects the action classification performance (Alwasel et al., 2017). On the other hand, non-experienced workers perform relatively less consistent movement patterns resulting in a lower classification accuracy. In addition, performing the action classification on a new subject should take into account the characteristics of the training dataset. In other words, it is important to use a training dataset that involves characteristics similar to a new dataset, because classification performance on the newly collected data can be influenced by the training dataset. For example, the classifier which was trained by the experienced group had a low accuracy to classify the non-experienced group, whereas the performance of classifying the same-working-experience group was relatively better. These findings, therefore, explain that a training dataset taking into account the characteristics of workers can lead to a different classification accuracy on the newly collected data. Furthermore, the authors recommend to train with the abundant and relevant dataset before deploying the proposed approach to other construction trades. A drawback of the classification accuracy test between the experienced and non-experienced group in this study is that the small number of subjects in the non-experienced group. Thus, it is recommended to collect more data on non-experienced subjects in future studies.

Challenges and opportunities

A single tri-axial accelerometer located on the dominant wrist demonstrated a promising result in classifying construction actions. Compared with previous classification results using accelerometers located at the waist, for which was 79.83% was the highest accuracy (Joshua & Varghese, 2010), the current study showed a higher classification accuracy, which presents the potential of using a wristband-type activity tracker for the classification of construction tasks involving upper body movements. However, it should be noted that there are several challenges to apply this approach in practice. First, the actions to be classified must be pre-determined and labeled. In this study, masonry work was conducted in a semi-controlled environment as the case study. Therefore, standardized and repeated actions were easily identified and applied to the proposed approach. However, a number of unstandardized actions may have existed in actual construction work, which would require more effort for pre-processing. Particularly, in this experiment, the other common actions, such as take a rest and walking were excluded, except for the pre-labeled four actions. Thus, it has a limitation to test how robust the labeled actions are to other common actions using the proposed approach. To address this problem, labeling other actions as "transaction actions" to test the robustness for other common actions. Furthermore, grouping actions based on purpose of use (e.g., productivity analysis) can be recommended to reduce effort determining the number of actions and enable a broader application area. Joshua and Varghese (2014) proposed work sampling analysis based categorizing (i.e., effective work, contributory work, and ineffective work). Thus, grouping construction actions on the basis of analysis types, such as the activity analysis category type or the safe and unsafe category type, can broaden the applicable area of accelerometer-based action recognition.

Action recognition using a wrist-worn accelerometer can be combined with other types of sensors, such as a physiological sensor, to expand to other applications for construction workers. Given that heart rate is an especially reliable indicator of physical demand (Hwang et al., 2016b), it is fortuitous that many activity trackers including accelerometers and heart-rate measuring sensors are widely available on the market. Hwang et al., (2016a and 2016b) studied physical demand measurement and feasibility of heart rate monitoring for construction workers using a heart rate measurement sensor included in a wristband-type activity tracker. In the studies, they showed the significant potential of heart rate monitoring and physical demand measurement using wearable activity trackers for construction workers. Thus, action recognition with a wrist-worn accelerometer can be enhanced by integrating with heart rate monitoring for in-depth understanding of physical conditions (e.g., heart rate variability and physical demands based on different tasks).

CONCLUSION

The current study tested the feasibility of using a wristband-type activity tracker embedding an accelerometer to automatically collect field data for classifying construction workers' activities. The case study was implemented to classify actions in masonry work that was conducted in a training facility by 10 masons. Also, current study is based the authors' earlier preliminary works (Ryu et al., 2016) and investigated the feasibility with considering various aspects in more details, in terms of classification performance and influence of human variances. The best classification accuracy of 88.1% was achieved using a multiclass SVM classifier with 4-s window size. Furthermore, the impact of human variation on the performance of classification was also investigated by comparing the accuracy between individual subjects as well as between an experienced and non-experienced group. Classification accuracy using the individuals' datasets was higher than the combined data set. Also, the performance of the classifier to classify testing dataset is affected by the characteristics of training dataset, such as degree of experience.

The findings from this study make important contributions to the current literature. First, it recognizes construction workers' action, especially, involving both whole-body and upper-limb movement using a single accelerometer on workers' dominant wrist. Particularly, by conducting masons' actions, which contain typical those movements, the feasibility of the approach was investigated. The reported results imply that each masonry construction activity is somehow hand-dominant and involves whole-body movement with unique hand movements, such that acceleration signals from a wrist are data-rich enough to classify construction activities. Second, by investigating classification accuracy according to individual subject and experience level, a variability of movement between subject and experience group were examined. As the finding in the result, the proposed approach has a potential to be deployed to other construction trades with consideration of abundant and relevant training dataset (i.e., a similar level of experience or work-training). Finally, the proposed approach uses only a wrist-worn single sensor, which will not only enable to continued data collection without interfering workers' ongoing work but also reduce burdens to carry multiple sensors. Also using one single sensor is expected to decrease the computational challenges of using multiple sensors (e.g., decreasing computational time, memory usage, and mitigating challenges in multisensory data synchronization in time and space). Thus, the proposed approach can be applied in a variety of ways for construction workers, such as detailed productivity tracking or automated unsafe action monitoring, regardless of construction site conditions or workers' activities. However, ethics of all potential applications must be taken into consideration because not only privacy laws differ by jurisdiction but also incorrect application may demotivate workers.

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