Construction Activity Recognition and Ergonomic Risk Assessment Using a Wearable Insole Pressure System

Maxwell Fordjour Antwi-Afari[1], Heng Li[2], Waleed Umer[3], Yantao Yu[4*], Xuejiao Xing[5]

[1]Postdoctoral Research Fellow, Department of Building and Real Estate, Faculty of Construction and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZN1002, E-mail: maxwell.antwiafari@connect.polyu.hk

[2]Chair Professor, Department of Building and Real Estate, Faculty of Construction and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZS734, E-mail: heng.li@polyu.edu.hk

[3]Postdoctoral Research Fellow, Department of Building and Real Estate, Faculty of Construction and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZN1002, E-mail: waleed.umer@connect.polyu.hk

[4]Ph.D. Candidate, Department of Building and Real Estate, Faculty of Construction and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZN1002, E-mail: yt.yu@connect.polyu.hk

[5]Ph.D. Candidate, Department of Building and Real Estate, Faculty of Construction and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZN1002, E-mail: xue.xu.xing@polyu.edu.hk

***Corresponding author:**
Miss Yantao Yu
E-mail: yt.yu@connect.polyu.hk

Abstract

Overexertion-related construction activities are identified as a leading cause of work-related musculoskeletal disorders (WMSDs) among construction workers. However, few studies have focused on automated recognition of overexertion-related construction workers' activities as well as assessing ergonomic risk levels which may help to minimize WMSDs. Therefore, this study examined the feasibility of using acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system for automated recognition of overexertion-related construction workers' activities and for assessing ergonomic risk levels. The proposed approach was tested by simulating overexertion-related construction activities in a laboratory setting. The classification accuracy of five types of supervised machine learning classifiers was evaluated with different window sizes to investigate classification performance and further estimate physical intensity, activity duration and frequency information. Cross-validation results showed that the Random Forest classifier with a 2.56s window size achieved the best classification accuracy of 98.3% and a sensitivity of more than 95.8% for each category of activities using the best features of combined data set. Furthermore, the estimation of corresponding ergonomic risk levels was within the same level of risk. The findings may help to develop a non-invasive wearable insole pressure system for continuous monitoring and automated activity recognition—which could assist researchers and safety managers in identifying and assessing overexertion-related construction activities for minimizing the development of WMSDs' risks among construction workers.

Keywords: Activity recognition; Construction workers; Overexertion risk; Supervised machine learning classifiers; Wearable insole pressure system; Work-related musculoskeletal disorders.

Introduction

The construction industry is regarded as one of the most hazardous occupations and labor-intensive industries (Wang et al. 2015a). Although significant efforts have been demonstrated to reduce occupational injuries and fatalities in the construction industry (Valero et al. 2016; Antwi-Afari and Li 2018g; Kong et al. 2018), statistics show that it is still regarded as one of the most dangerous occupations (Center to Protect Workers' Right (CPWR) 2018). These health and safety issues in the construction industry are mostly attributed to ergonomic risk factors such as awkward working postures, repetitive lifting, and excessive force or overexertions (Wang et al. 2015a; Umer et al. 2017b; Antwi-Afari et al. 2017a). Ergonomic risk factors associated with workplace activities may lead to construction workers developing work-related musculoskeletal disorders (WMSDs).

Compared to different industry sectors, construction workers are faced with the highest risk of developing WMSDs (OSHA 2017). Examples of WMSDs include low back pain, shoulder pain, tendonitis, and carpal tunnel syndrome (Umer et al. 2017a; Antwi-Afari et al. 2018a). According to the Bureau of Labor Statistics (BLS) in the United States, WMSDs accounted for a median of 12 days of work absenteeism in 2015 (BLS 2016). In Germany, WMSDs constitute a major cause of occupational disabilities among construction workers (Arndt et al. 2005). The high prevalence rate of WMSDs among construction workers not only causes work absenteeism, schedule delays and increased the cost of insurance premium but also lead to loss of productivity and early retirement (Umer et al. 2017a). Given above, there is a critical need to assess ergonomic risks which may lead to WMSDs among construction workers.

To minimize WMSDs among construction workers, there is a crucial need to identify potential risk factors associated with workers' activities. Overexertion has been identified as the leading risk factor for developing WMSDs among construction workers (BLS 2016). Notably, existing methods or approaches for identifying potential risk factors of developing WMSDs include self-reports (e.g., questionnaires), observational-based methods (e.g., strain index), vision-based methods (e.g., Kinect^{TM}), and direct measurement methods (e.g., inertial measurement units (IMUs)). Despite their advantages, these approaches are characterized as time-consuming, relatively imprecise, require expert's subjective judgment, intrusive and a direct line of sight is required to register workers' movement (David 2005). Consequently, it is difficult to identify and evaluate the potential ergonomic risks using the existing approaches. Despite the high prevalence rate of WMSDs among construction workers and the possible approaches to mitigate WMSDs, less attention has been given to the use of a wearable sensing system—which can serve as a non-invasive tool for recognizing workers' activities and mitigating the risk of developing WMSDs.

To address these issues, the authors proposed a non-invasive wearable insole pressure system for recognizing overexertion-related workers' activities and to assess ergonomic risk levels. To this end, it was hypothesized that each overexertion-related workers' activity creates unique patterns of acceleration and foot plantar pressure distribution data, which can enable the detection and classification of different categories of activities. Overall, the proposed approach could provide a relatively accurate and objective assessment of ergonomic risk level—which could help other researchers and safety managers to understand the level of exposure of workers' risk and provide effective interventions to mitigate WMSDs' risks in construction.

Research Background

Ergonomic Risk Assessment Methods for Identifying Potential Risk Factors of WMSDs

There are four ergonomic risk assessment methods for identifying potential risk factors for developing WMSDs. These methods are 1) self-reported methods; 2) observational-based methods; 3) vision-based methods; and 4) direct measurement methods.

In the self-reported methods, data is collected on both physical and psychosocial factors through interviews or questionnaires (Li and Yu, 2011; Reme et al. 2012). These methods have the advantages of being straightforward to use, applicable to a wide range of working situations and require low initial cost (David 2005). However, a major problem with these methods is the inter-rater difference in workers' perception of exposure levels (Wang et al. 2015a). Many observational-based methods have been developed to evaluate workers' exposure factors on the job site (McAtamney and Corlett, 1993; Buchholz et al. 1996). Despite being inexpensive and practical for a wide range of work situations, these methods are time-consuming, disruptive in nature, and are subjected to intra- and inter-observer variability (David 2005). Vision-based methods use either depth sensors or stereo camera systems to capture human motion data to extract a three-dimensional (3D) skeleton models (Han et al. 2013; Han and Lee 2013). These methods provide accurate, non-invasive and automated human motion data for analyzing unsafe actions in construction (Han et al. 2013). However, they are limited because they: (1) are occasionally ineffective with moving backgrounds; and (2) require a direct line of sight to register the movements in a construction environment (Han and Lee 2013). Direct measurement methods use wearable sensor-based systems which are attached to workers' bodies to collect human motion-related output data (Akhavian and Behzadan 2016; Valero et al. 2016; Antwi-Afari et al. 2017b; Nath et al. 2017). Previous studies have reported that direct measurement methods provide accurate and reliable data for identifying WMSDs risk factors as compared to other methods (David 2005; Umer et al. 2017b). However, these methods: (1) require sensors to be attached to the workers' skin which may cause discomfort; (2) cannot acquire the ground reaction force data; and (3) require additional attachments such as straps, belts to prevent detachment of sensors from the body when performing tasks.

To overcome these limitations, the current study proposed a wearable insole pressure system for identifying a potential risk factor of developing WMSDs among construction workers. In the realm of construction, recent studies have demonstrated the feasibility of using the proposed approach for automated detection and classification of workers' loss of balance events (Antwi-Afari et al. 2018e) and awkward working postures (Antwi-Afari et al. 2018f). While these previous studies mainly focused on awkward working postures and loss of balance events, no research study has been conducted by using a wearable insole pressure system for recognizing overexertion-related construction workers' activities and assessing ergonomic risk levels.

Wearable Sensing Technologies for Automated Activity Recognition in Construction—the Feasibility of Using a Wearable Insole Pressure System

Wearable IMU-based systems are the commonest wearable sensing technologies used for activity recognition and fall risk assessment in construction (Kim et al. 2016; Valero et al. 2016; Yang et al. 2016; Yang et al. 2017; Jahanbanifar and Akhavian 2018; Antwi-Afari et al. 2019). For example, Valero et al. (2016) developed a system to detect unsafe postures of construction workers (e.g., stooping and squatting with back bending). To expand the applications of wearable IMU-based systems, smartphones are now embedded with sensors to collect human motion-related data in the construction field for activity recognition (Akhavian and Behzadan 2016; Nath et al. 2018; Ryu et al. 2018). Akhavian and Behzadan (2016) used a smartphone with embedded accelerometer and gyroscope sensors to capture body movement data to classify different categories of construction activities. Nath et al. (2018) collected time-stamped motion data from body-mounted smartphones with embedded accelerometer and gyroscope sensors to recognize workers' activities. They also estimated activity duration and frequency information through a classification framework to evaluate the ergonomic risk levels of the activities caused by overexertion. Ryu et al. (2018) examined the feasibility of the wrist-worn accelerometer-embedded activity tracker for automated action recognition of four different subtasks of masonry works. Albeit wearable IMU-based systems have demonstrated reliable and accurate classification of various construction activities, wearing these sensors at different body parts make workers' feel uncomfortable, and they also have high hardware costs—limiting their applications on construction sites (Zhang et al. 2018). In addition, they can only monitor body motions based on velocity, acceleration, and orientation output data without considering ground reaction force data.

To address the above limitations, a wearable insole pressure system offers the following advantages as compared to wearable IMUs-based systems. First, it can measure the vertical force component of the ground reaction force data to estimate the physical intensity and subsequently assess corresponding ergonomic risk levels. Second, it can be easily inserted or detached from workers' safety boots, which minimizes restrain in body movement and discomfort (Antwi-Afari and Li 2018g). Third, multiple footsteps of workers can be continuously monitored on construction sites. Ultimately, it offers higher portability, ease of use, and great potentials in complex and dynamic applications without being invasive. Wearable insole pressure system has been demonstrated as a useful and reliable tool in several areas of applications such as gait, posture and activity recognition (Sazonov et al. 2011; Tang and Sazonov 2014), sport biomechanics (Queen et al. 2007), and improving balance in the elderly (Mickle et al. 2011). In particular, these previous studies used a wearable insole pressure system to recognize activities of daily living such as sitting, standing, walking, running, stair ascent or descent and cycling (Sazonov et al. 2011; Tang and Sazonov 2014). In the realm of construction, workers' activities are more physically demanding and dynamic. The feasibility of using a wearable insole pressure system for recognizing overexertion-related construction workers' activities has not been explored. In addition, no study has been conducted by using the proposed approach for estimating the physical intensity, activity duration and frequency information for assessing corresponding ergonomic risk levels.

Research Objective and Contributions

The objective of this research was to automatically recognize overexertion-related construction workers' activities and assess the corresponding ergonomic risk levels by using acceleration and foot plantar pressure distribution data measured by a wearable insole pressure system. The main contributions of this research were to: (1) propose a non-invasive wearable insole pressure system for continuous monitoring and automated recognition of overexertion-related construction workers' activities based on acceleration and foot plantar pressure distribution data; and (2) estimate the physical intensity, activity duration, and frequency information for assessing the ergonomic risk levels of overexertion-related construction workers' activities.

Research Methods

Fig. 1 shows the framework for overexertion-related ergonomic risk assessment. The first step involves recruiting participants to participate in the proposed approach. Next, acceleration and foot plantar pressure distribution data were collected in a laboratory setting using a wearable insole pressure system. The two streams of sensor data were collected to examine which extracted features contribute more to the classification performance. Following data collection, the sliding window technique was adopted to divide sensor streams into smaller window size segments. This data segmentation technique has been widely used due to its simplicity and classification performance in handling both acceleration and foot plantar pressure distribution data (Akhavian and Behzadan 2016; Antwi-Afari et al. 2018b; Nath et al. 2018; Ryu et al. 2018). In this study, four window size segments were evaluated to select the optimum window size segment. Three groups of features (i.e., time-domain, frequency-domain, and spatiotemporal) were extracted as input variables for supervised machine learning classifiers to test the classifier models. Also, the hybrid feature selection method was adopted in this research to identify the most distinctive or best features. Reference data in activity recognition provides the ground truth to evaluate the classification performance. Afterwards, a classifier model is built and the performance of the model was assessed in terms of the sensitivity and accuracy metrics. This study examined five types of supervised machine learning classifiers to select the best classifier with the highest classification performance. Based on the trained models and classification performance, the various categories of activities are detected and classified. Overall, the goal to find the optimum window size segment, select the best features, and use different types of classifiers was to identify and built a classifier model that provides the highest classification performance for activity recognition. Finally, the physical intensity, activity duration and frequency information are estimated from the activity recognition and then used to determine the ergonomic risk levels associated with each category of activities performed by the participants. In the following sections, the detailed procedure of each method is discussed.

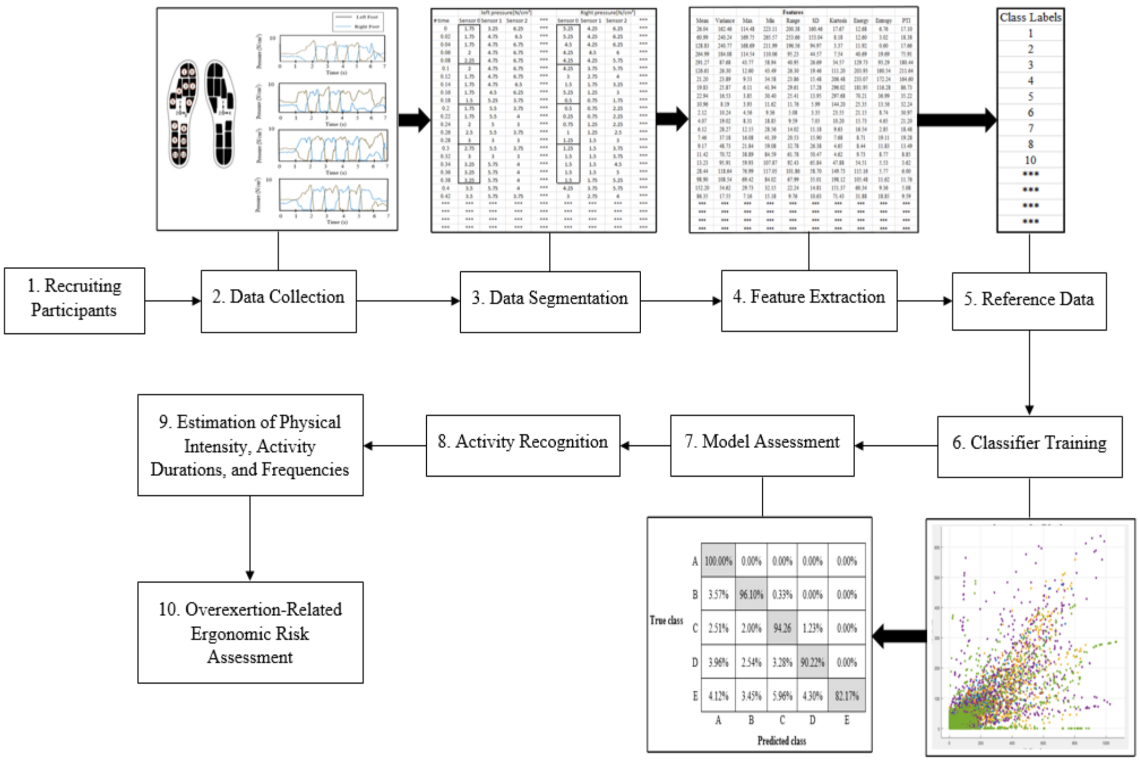

Fig. 1. Framework for overexertion-related ergonomic risk assessment

Participants

Two healthy male participants volunteered to participate in this study. Each participant was a student who had basic construction engineering knowledge and experience in working at construction sites. The participants mean age, weight, and height were 27 ± 4.24 years, 66 ± 5.66 kg, and 1.65 ± 0.21 m, respectively. Both participants had no history of mechanical pain/injury of upper extremities, back, or lower extremities.

The participants provided their informed consent forms in accordance with the procedure approved by the Human Subject Ethics Subcommittee of the Hong Kong Polytechnic University (reference number: HSEARS20170605001).

Data Collection

Data Acquisition Using a Wearable Insole Pressure System

The current study proposed an OpenGo system (Moticon GmbH, Munich, Germany), which is a wearable insole pressure system for measuring both triaxial acceleration and spatiotemporal foot plantar pressure distribution data (Antwi-Afari and Li 2018g). It consists of two sensor insoles (containing 13 capacitive sensors each) that measure the foot plantar pressure distribution. Each wearable insole sensor electronically incorporates 3D micro-electro-mechanical systems (MEMS) accelerometer (Bosh Sensortech BMA 150), which is located at the center with respect to gravity. In the current study, foot plantar pressure patterns and acceleration signals were sampled at 50 Hz.

Experimental Design and Procedure

The current study adopted a cross-sectional study design in a single visit. The experimental procedure was explained to the participants. In order to simulate overexertion-related construction workers' activities to mimic those conducted by a worker on construction sites (i.e., real-world conditions), the following criteria were set in the experimental protocol. First, each participant was asked to wear a pair of safety boots and a hard hat during the testing sessions. Second, each participant was shown representative videos of overexertion-related construction workers' activities—which are performed by workers in real-world conditions. These activities were basically related to manual material handling tasks involving excessive force exertions. They included upright holding, carrying, lifting, lowering, pushing and pulling.

In this research, each participant performed 20 cycles of each of the following overexertion-related construction workers' activities: (1) load a wooden box—measuring 30 × 30 × 25 cm with dumbbell weights and hold it in an upright standing position to receive further instruction from the experimenter (Fig. 2a); (2) walk while carrying the weighted box along a set path to a particular destination on the floor (Fig. 2b); (3)

lift the weighted box from the floor level onto a table at waist level for inspection (Fig. 2c); (4) lower the weighted box from the table at waist level onto a four-wheeled dolly (Fig. 2d); (5) walk while pushing the dolly on a set path to another destination (Fig. 2e); (6) wait while the experimenter offload the dumbbell weights from the wooden box (Fig. 2f); and (7) walk while pulling the dolly to a specific location in the laboratory (Fig. 2g). The entire experiment was recorded using a video camcorder and both acceleration and foot plantar pressure distribution data were synchronized. After data collection, the activities were manually annotated based on inspecting the recorded video and the collected data. Consequently, these activities were grouped into four different categories of activities, namely (1) category-1-activities: grip force; (2) category-2-activities: lift/lower/carry; (3) category-3-activities: push/pull; and (4) category-4-activities: any other non-risk activity. The categories of activities mostly require overexertion such as forces involved in grip force, forces involved in lifting, lowering, or carrying, and forces involved in pushing or pulling (Jaffar et al. 2011).

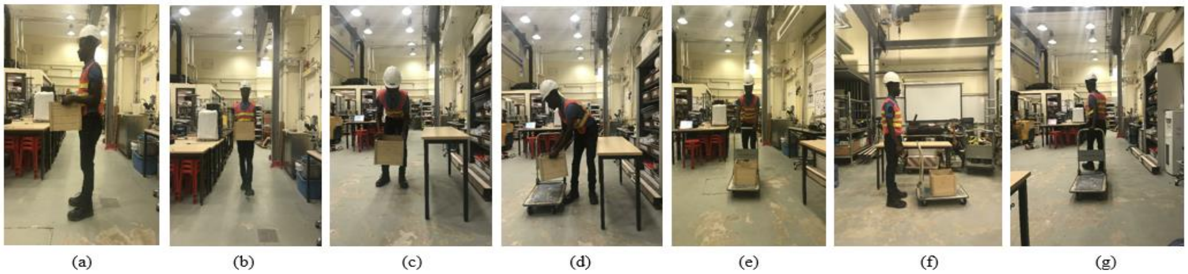

Fig. 2. Laboratory experimental setup (images by authors): (a) upright holding; (b) carrying; (c) lifting; (d) lowering; (e) pushing (f) upright standing (g) pulling

Data Segmentation

The sliding window technique was adopted to divide the raw sensor signals into smaller window size segments. This technique is well-suited for real-time applications since it does not require any pre-processing of raw sensor data (Preece et al. 2009). Also, overlapping adjacent windows reduces the error caused by transition state noise (Su et al. 2014). Similar to previous studies (Antwi-Afari et al. 2018b; Nath et al. 2018), a 50% overlap of the adjacent windows was adopted for this study. In order to find an optimum window size, four window size segments were examined in this research. These are 0.32s, 0.64s, 1.28s and 2.56s which corresponds to 16 (2^4), 32 (2^5), 64 (2^6), and 128 (2^7) data samples, respectively. They are selected because of the conversion of time-domain to frequency-domain using fast Fourier transform (FFT) in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA) requires the window size of a power of two (Akhavian and Behzadan 2016).

Feature Extraction

One of the most essential procedures in activity recognition and classification studies is feature extraction. This procedure involves extracting relevant informative features from raw sensor data of each window size to be used as input variables for model development and classification. The collected data by the wearable insole pressure system was a set of discrete points of acceleration and foot plantar pressure patterns. The three-axis acceleration and 13 plantar pressure distribution data of each foot depict the human motion acceleration and foot plantar pressure distribution when the participants conducted the overexertion-related activities. Consequently, the two forms of collected data could reflect unique patterns of different categories of activities, implying that a single data point could not be able to represent the activities. As a result, this research study extracted different groups of features from acceleration and foot plantar pressure patterns for classification performance. Three groups of common features mostly used by previous studies (Akhavian and Behzadan 2016; Antwi-Afari et al. 2018f; Nath et al. 2018; Ryu et al. 2018) for activity recognition were selected in this study and extracted from acceleration and foot plantar pressure data. They are (1) time-domain features, (2) frequency-domain features, and (3) spatiotemporal features. Table 1 presents a summary of the features. As shown in Table 1, twelve time-domain features were extracted from each window size. These features are also known as signal statistical features. They are relatively simple to calculate and, as such reduce computational time. Notably, the last three features (Table 1) were extracted from only acceleration data. Moreover, we extracted two frequency-domain features (Table 1) by converting signal streams in time-domain to frequency-domain by using the FFT function (Attal et al. 2015; Akhavian and Behzadan 2016). Furthermore, three spatiotemporal features (Table 1) were extracted from only foot plantar pressure distribution data. Considering data collection in 3 axes of acceleration data and 13 axes of foot plantar pressure distribution data of each foot and 17 independent features extracted (see Table 1), a total of 436 features were extracted.

Table 1. Summary of Features

Item	Time-domain	Item	Frequency-domain	Item	Spatiotemporal
1.	Mean	1.	Spectral energy	1.	Pressure-time integral
2.	Variance	2.	Entropy spectrum	2.	Anterior/Posterior centre of pressure (A/P COP)
3.	Maximum			3.	Medial/Lateral centre of pressure (M/L COP)
4.	Minimum				
5.	Range				
6.	Standard deviation				
7.	Root mean square				
8.	Kurtosis				
9.	Skewness				
10.	Standard deviation magnitude				
11.	Sum vector magnitude				
12.	Signal magnitude area				

Feature Selection

Fig. 3 presents a flowchart depicting the hybrid feature selection method. As presented in Fig. 3, a total of 436 features were initially extracted from acceleration and foot plantar pressure distribution data for the purpose of classification performance. Since numerous extracted features may lead to overfitting of data set, choosing an appropriate dimensionality reduction is a crucial feature selection step which helps to select an optimal set of features (i.e., best features), and also limit the complexity of the classifier model (Cates et al. 2018). This research adopted the hybrid feature selection method (Barkalla et al. 2017) as depicted in Fig. 3. This method comprises the successive application of both the filter and wrapper methods. To do this, the authors used two commonly filter methods, namely: (1) analyses of variance (ANOVA) and (2) Pearson correlation coefficient to evaluate the performance of each feature for discriminating between the categories of activities. Based on the average values, all the extracted features were ranked and the highest ranked features (i.e., 112 features) are selected for the wrapper method (Fig. 3). Next, the wrapper method was used to select the best features (i.e., 27 features) by using a Random Forest classifier to evaluate the performance accuracy of each feature (Fig. 3).

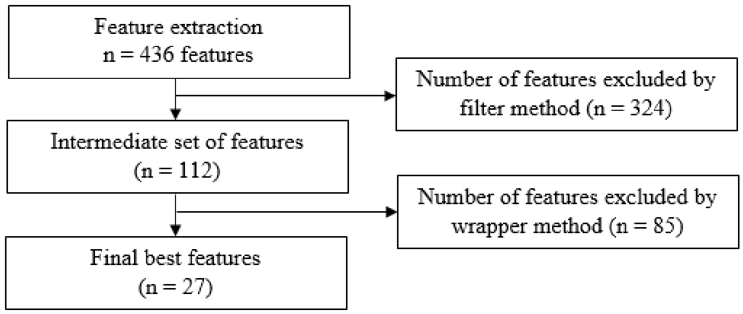

Fig. 3. A flowchart depicting the hybrid feature selection method

Reference Data

Following data preparation and feature extraction, a class label of each category of activity was assigned to each window size with the assistance of the video data. Table 2 shows the class labels and the number of collected data samples in each activity of category. This step in human activity recognition serves as the ground truth to evaluate the performance of the classifiers (Akhavian and Behzadan 2016; Antwi-Afari et al. 2018f).

Table 2. Class Label and Collected Data Samples in Each Category of Activity

Class label/activity category	Category of activity	Number of data samples
1	Grip force	98,896
2	Lift/Lower/Carry	487,274
3	Pull/Push	284,528
4	Any other non-risk activity	187,852

Classifier Training

In this research, supervised machine learning classifiers were adopted for training and classification. The goal was to generate a model by learning acceleration and foot plantar pressure distribution data by using the extracted features as input variables to match the class labels of the different categories of activities. The performance of the classifiers was assessed by evaluating the accuracy in predicting unseen class labels (i.e., output variables). These classifiers have achieved satisfactory results in the field of human activity recognition and fall risk events (Akhavian and Behzadan 2016; Antwi-Afari et al. 2018c; Ryu et al. 2018). In order to select the best classifier, five different types of supervised machine learning classifiers, namely 1)

Artificial Neural Network (ANN), 2) Decision Tree (DT), 3) Random Forest (RF), 4) K-Nearest Neighbor (KNN), and 5) Support Vector Machine (SVM) were examined. All data processing including the statistical computation of features and training, testing, and validation of the classifiers were performed using Toolbox in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA).

ANN has advantages of not only using a trained model to recognize previously unseen dataset but also having a potentially high tolerance for noisy data (Haykin 2009). As a result, this research used an ANN-based on a multilayer perceptron feed-forward neural network (Haykin 2009). DT is a schematic, tree-like classifier constructed to divide the training dataset into partitions according to a given set of splitting rules for each node, which is repeated iteratively until a leaf node is reached (Preece et al. 2009). The classification and regression tree (CART) algorithm was used to construct the best splitting rule for each node (Akhavian and Behzadan 2016; Zhang et al. 2018). RF classifier is a supervised ensemble classification method that makes use of multiple randomized decision trees to subdivide the feature space. Each decision tree in the RF is learned from a bootstrap aggregating sample (i.e., bagging) and a random subset of features (Breiman 1984). KNN is a non-parametric method for a classification based on the *k*-nearest training data set and vectors in the feature space (Ke et al. 2013). In this research, the distance of the neighbors over the feature space is calculated by using the Euclidean distance (Akhavian and Behzadan 2016). SVM is a non-probabilistic binary linear classifier (i.e., distinguish between two classes) in its standard soft margin, which attempts to find the best hyperplane that separates one class of dataset from the other class (Cortes and Vapnik 1995). In this study, the kernel function used for non-linear classification is the Gaussian radial basis function (RBF) (Akhavian and Behzadan 2016).

Model Assessment

Model assessment is the final step in human activity recognition in which the accuracy of the classifiers was assessed. The 10-fold cross-validation was used to assess the accuracy and validity of the classifier models (Barkalla et al. 2017). The accuracy and sensitivity indicators were used to evaluate the performance of the classifiers (Attal et al. 2015).

Activity Recognition

Once the model is trained, and its parameters are finalized, it can be used for recognizing activities for which it has been trained. While data is being collected to determine the activities according to a trained classifier, such data can be stored in a dataset repository and be added to the existing training data, so that the model is further trained with a richer training dataset.

Estimation of Physical Intensity, Activity Duration and Frequency

One of the great potentials of using a wearable insole pressure system is that it can provide the total ground reaction force data while performing a given activity. As such, it was assumed that the total ground reaction force is equal to the physical intensity (i.e., the amount of physical effort required to perform a given task) and self-weight of each participant. Consequently, the physical intensity was calculated by subtracting the participant’s self-weight from the total ground reaction force (Yu et al. 2018). Next, the activity duration was calculated from the corresponding windows. The duration of each instance was calculated by counting the number of windows in that category and multiplying the result by half of the window size (i.e., 50% overlap of adjacent windows) (Nath et al. 2018). The total duration of a category was evaluated by summing the durations of all instances of that category. Lastly, the frequency (i.e., how many times a category of activity was performed) was determined by counting all the instances of that category (Simoneau et al. 1996).

Overexertion-Related Ergonomic Risk Assessment

Table 3 presents the ergonomic risk levels (low, moderate, and high) that can be used to estimate the physical intensity, activity duration and frequency information of each category of activity (OSHA 2012). In order to estimate for the corresponding ergonomic risk levels, physical intensity, activity duration and frequency were expressed as weight of the object (kg), percentages of the work shift, and frequency per minute of the shift, respectively. In this study, a shift is the total duration of the experiment.

Table 3. Ergonomic Risk Levels of Categories of Activities

Activity category	Risk factor parameter	Low risk	Moderate risk	High risk
1	Grip effort	Hold object weighing 5 kg or low worker effort	Hold object weighing 5 kg or Medium worker effort	Hold object weighing 5 kg or high worker effort
	Duration/shift	Up to 25%	26 – 50%	51 – 100%
	Frequency	Gripping < 5 s at once	Gripping 5 – 30s at once	Gripping > 30 s at once
2	Weight of object	< 8 kg	8 – 23 kg	> 23 kg
	Duration/shift	Up to 25%	26 – 50%	51 – 100%
	Frequency per minute	< 1	1 – 5	> 5
3	Force required	< 9 kg	9 – 23 kg	> 23 kg
	Duration/shift	Up to 25%	26 – 50%	51 – 100%
	Frequency per minute	< 1/480	1/480 – 10	> 10
4	N/A	N/A	N/A	N/A

Results and Discussion

This is the first study to automatically recognize overexertion-related workers' activities and assess corresponding ergonomic risk levels using acceleration and foot plantar pressure distribution data measured by a wearable insole pressure system. The results of the present study evaluated the classification performance of the proposed approach in two main ways. First, the combined data set from both participants were used for activity recognition to determine the best classifier, optimal selected features and window sizes. Second, an individualized participant evaluation was conducted to evaluate the performance of the proposed approach.

Classification Performance for Combined Data Set from both Participants

This section presents the results and discussion of the classification performance according to the types of classifiers, selected features and optimal window size using combined data set from both participants based on 10-fold cross-validation. Before determining the data optimization, the hybrid feature selection was used to select the best features for recognizing overexertion-related workers' activities. Table 4 shows the best features for each participant using the hybrid feature selection. As shown in Table 4, only 23 features were selected as the best features for classification performance using the combined data set. This is because these features are considered to be common optimal best features among the two participants.

Table 5 presents the classification accuracy for the combined data set using all extracted features and best features. Comparing the different classifiers, it is apparent from Table 5 that the RF classifier had the best classification accuracy among the five different types of classifiers. By using all extracted features, the RF classifier achieved the highest accuracy of 97.6% with a 2.56s window size, while the lowest accuracy was 36.9% from the ANN classifier with a 0.32s window size (Table 5). Similarly, the RF classifier had the best accuracy (98.3%) with a 2.56s window size followed by the SVM, KNN, DT and ANN classifiers using the best features (Table 5). It was found that all classifiers tend to increase classification accuracy with increasing window size. Compared with the findings of previous studies by using accelerometers for recognizing masonry activities, the classification performance of our results was higher, with the best result being 79.83% (Joshua and Varghese 2010), and 88.1% (Ryu et al. 2018). Although there are consistencies in adopting an overlap size of adjacent windows (i.e., 50%), the findings that were found based on the best window size and the best classifier were different from previous studies. In the study by Joshua and Varghese (2010), the classification accuracies of 79.83% (all extracted features) and 74% (best features) were obtained by using the multilayer perceptron neural network classifier with 256 samples (i.e., 4.23s window size) in an uninstructed environment. Alternatively, Ryu et al (2018) reported a classification accuracy of 88.1% using the multiclass SVM classifier with a 4s window size while classifying all the participants. In the present study, the classifiers had their highest classification accuracies with a 2.56s window size either by using all extracted features or best features (Table 5). Notably, the best accuracy achieved by the RF classifier demonstrates that both acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system show unique patterns for recognizing the categories of activities. Compared with other classifiers as reported by previous studies (Joshua and Varghese 2010; Ryu et al. 2018; Yang et al. 2019), the RF classifier 1) is less sensitive to the selection of features and window sizes, 2) can reduce the computational time during data preprocessing; and 3) can minimize over-fitting issues (Pavey et al. 2017). Consequently, the findings of this study indicate that the RF classifier could be reliably used to recognize and classify overexertion-related workers' activities, which is one of the main causes of WMSDs among workers.

In order to investigate the classification results in each category of activity, a confusion matrix of 10-fold cross-validation from the best classifier (i.e., RF) with a 2.56s window size is presented in Fig. 4. As illustrated in Fig. 4, the rows show the percentage of true classes, and the columns reveal the percentage of predicted classes of each category of activity. Also, the diagonal represents the percentage of true positives (i.e., sensitivity) (Fig. 4). As shown in Fig. 4, each category of activity had more than 95% in positive detection of the classes using the best features. This classification results obtained from the RF classifier substantiates the hypothesis that each category of activity creates unique patterns of acceleration and foot plantar pressure distribution data, which enabled the detection and classification of the different categories of activities. It was found that the most accurately classified and detected category of activity was category-2-activity (99.3%) (Fig. 4). Alternatively, the most misclassified categories of activities are category-1-activities and category-4-activities (2.7%) (Fig. 4). These errors might be attributed to (1) activity durations, (2) the number of data samples (3) similarities in conducting these two categories of activities. Compared to other categories of activities, category-1-activities and category-4-activities had shorter activity durations and smaller data samples (Table 2). Sensor streams in shorter window size segments and smaller data samples are not enough to differentiate categories of activities because they could contain similar acceleration and foot plantar pressure distribution patterns. In particular, the signal patterns in shorter window size segments are difficult to obtain unique patterns for each category of activity; as a result, they led to classification errors.

Table 4. Best Features for Participant I and Participant II

Rank	Participant I	Participant II
1	PP_2Mean	PP_2Mean
2	PP_4Mean	PP_4Mean
3	PP_7Mean	PP_7Mean
4	ACC_{28}Mean	ACC_{28}Mean
5	ACC_{32}Mean	ACC_{32}Mean
6*	*PP_{68}Max*	*PP_{70}Max*
7*	*PP_{88}Max*	*PP_{85}Max*
8*	*ACC_{93}Max*	*ACC_{91}Max*
9*	*ACC_{94}Max*	*ACC_{95}Max*
10	PP_{195}RMS	PP_{195}RMS
11	PP_{216}RMS	PP_{216}RMS
12	ACC_{220}RMS	ACC_{220}RMS
13	ACC_{222}RMS	ACC_{222}RMS
14	ACC_{224}RMS	ACC_{224}RMS
15	PP_{355}PTI	PP_{355}PTI
16	PP_{360}PTI	PP_{360}PTI
17	PP_{364}PTI	PP_{364}PTI
18	PP_{375}PTI	PP_{375}PTI
19	PP_{378}PTI	PP_{378}PTI
20	PP_{383}A/P COP	PP_{383}A/P COP
21	PP_{410}M/L COP	PP_{410}M/L COP
22	$ACC_{431}SDM_L$	$ACC_{431}SDM_L$
23	$ACC_{432}SDM_R$	$ACC_{432}SDM_R$
24	$ACC_{433}SVM_L$	$ACC_{433}SVM_L$
25	$ACC_{434}SVM_R$	$ACC_{434}SVM_R$
26	$ACC_{435}SMA_L$	$ACC_{435}SMA_L$
27	$ACC_{436}SMA_R$	$ACC_{436}SMA_R$

Note: Features marked in asterisk are distinct for each participant

Table 5. Classification Accuracy (%) for Combined Data of Participants Using All Extracted Features and Best Features

Window size	All extracted features					Best features				
	ANN	DT	KNN	RF	SVM	ANN	DT	KNN	RF	SVM
0.32s	36.9	69.3	81.5	91.1	90.2	40.5	72.5	82.1	93.7	91.3
0.64s	40.2	72.4	83.3	94.3	91.4	48.7	75.4	86.9	95.6	92.9
1.28s	50.1	75.3	86.7	95.6	92.1	55.2	77.5	88.3	96.1	94.2
2.56s	55.6	78.2	89.8	97.6	93.9	60.3	80.6	91.9	98.3	95.6

True class	1	95.8%	1.2%	0.3%	2.7%
	2	0.1%	99.3%	0.6%	0.0%
	3	0.0%	1.9%	98.0%	0.1%
	4	1.5%	0.7%	0.5%	97.3%
		1	2	3	4
		Predicted class			

Fig. 4. Confusion matrix of the RF classifier for combined data set using the best features with a 2.56s window size

Classification Performance for Individualized Data Set of Each Participant

In order to examine the variability of movement between participants the classification accuracies of the types of classifiers, optimal selected features and window sizes were compared when both the training and testing data sets were only attributed to a single participant. The best features of each participant are presented in Table 4. It was found that each participant had 27 best features using the hybrid feature selection.

Table 6 presents the classification accuracy for individualized data set of each participant based on all extracted features and best features. By using all extracted features, the classification accuracy based on the different types of classifiers for each participant was highest in the RF classifier as compared to the other classifiers (Table 6). Within each window size, the RF classifier had the highest accuracy in each participant by using all extracted features, followed by the SVM, KNN, DT, and ANN classifiers (Table 6). The highest accuracies of participant I and participant II based on the RF classifier with a 2.56s window size by using all extracted features were 98.7% and 98.3%, respectively (Table 6). Similar results were found when using the best features of each participant. Specifically, the RF classifier had the best accuracy by using the best features of each participant, followed by the SVM, KNN, DT, and ANN classifiers (Table 6). The aforementioned results were similar in each window size. A previous study had reported an average classification accuracy of 95.45% with a 6.4s window size for individualized data set based on the DT classifier (Zhang et al. 2018). Regardless of the optimal window size, these results indicate that with large samples of data sets, the RF classifier could be reliable for recognizing and classifying overexertion-related workers' activities when compared to the classifiers. On the other hand, the results, therefore, suggest that the ANN classifier requires a larger data set to optimize the classifier parameters. The highest accuracies of participant I and participant II based on the RF classifier with a 2.56s window size by using the best features were 99.3% and 99.1%, respectively (Table 6). These results suggest that a larger window size segment provides better classification performance when compared to a smaller window size segment, and these findings are consistent with reported findings of previous studies by using accelerometers for recognizing workers' activities (Joshua and Varghese 2010; Ryu et al. 2018; Zhang et al. 2018).

With regards to the different types of classifiers, best features, and optimal window size, the participant I had higher accuracies compared to participant II (Table 6). These results indicate that between-subject variations exist in recognizing overexertion-related workers' activities even though they performed similar tasks. It is therefore plausible to conclude that the participant I conducted activities with persistent working techniques similar to real-world situations as compared to participant II. Notably, the classification performances in different types of classifiers, optimal selected features and window sizes are higher for individualized data of each participant (Table 6) as compared to combined data set of participants (Table 5). Similar findings were reported in a previous study showing a decreased by 5.6% of classification accuracy for combined participants when compared to individual participants (Zhang et al. 2018). Taken together, there are two reasons to explain these findings. First, since there was a slight variation of data set between participants, the data set from one participant may be a noisy data to the other participant, thus resulting in lower accuracy when using combined data set from both participants. Second, using larger data samples may result in over-fitting of training data set with high computational time, thus, resulting in lower accuracy while using combined data set from both participants.

Again, confusion matrices of 10-fold cross-validation from the best classifier (i.e., RF) with a 2.56s window size of the participant I and participant II are presented in Fig. 5a and Fig. 5b, respectively. As shown in Fig. 5a and Fig. 5b, the sensitivity of each category of activity was more than 92% and 90%, respectively. This result further confirms that there are between-participant variations among the two participants although they performed the same categories of activities. In addition, the most misclassified category of activities had

4.2% in participant I (Fig. 5a) and 7.5% in participant II (Fig. 5b). These misclassified categories of activities were category-1-activity and category-4-activity in both participants.

Table 6. Classification Accuracy (%) for Individualized Data of Participants Based on All Extracted Features and Best Features

Window size		All extracted features					Best features				
		ANN	DT	KNN	RF	SVM	ANN	DT	KNN	RF	SVM
0.32s	Participant I	72.3	82.4	85.8	91.6	90.9	74.4	84.8	87.9	92.6	91.7
	Participant II	72.1	82.1	85.5	91.2	90.5	74.0	84.3	87.6	92.2	91.2
0.64s	Participant I	74.9	81.7	82.7	94.6	91.7	76.6	83.6	85.8	95.6	92.4
	Participant II	74.5	80.8	82.4	94.3	91.5	76.1	83.4	85.4	95.1	92.2
1.28s	Participant I	75.5	85.8	86.7	97.9	92.9	78.7	87.7	88.7	98.8	93.8
	Participant II	75.2	85.4	86.4	97.5	92.4	78.2	87.4	88.1	98.2	93.2
2.56s	Participant I	78.7	89.5	90.8	98.7	94.9	80.8	90.5	91.7	99.3	96.7
	Participant II	78.3	89.1	90.1	98.3	94.5	80.1	90.4	91.2	99.1	96.5

True class					
	1	92.2%	2.5%	1.1%	4.2%
	2	0.5%	98.6%	0.7%	0.2%
	3	0.1%	2.8%	96.4%	0.7%
	4	3.4%	1.6%	0.4%	94.6%
		1	2	3	4
		Predicted class			

(a) Participant I

True class					
	1	90.3%	1.4%	0.8%	7.5%
	2	0.9%	97.3%	1.4%	0.4%
	3	1.3%	3.1%	94.1%	1.5%
	4	4.5%	2.1%	0.7%	92.7%
		1	2	3	4
		Predicted class			

(b) Participant II

Fig. 5. Confusion matrix of the RF classifier for each participant using the best features with a 2.56s window size

Physical Intensity, Activity Duration and Frequency Estimation

Table 7 shows the actual and estimated physical intensity, activity duration and frequency of each participant in each category of activity. According to Table 7, the estimated physical intensity, activity duration and frequency results of the participant I were within ± 11.1%, ± 2%, and ≤ -15.4%, from the actual values respectively. On the other hand, the estimated physical intensity, activity duration and frequency results of participant II were within ± 25%, ± 5%, and ≤ -42.9%, from the actual values respectively. Based on these results, it could be concluded that the estimation of physical intensity, activity duration and frequency in participant I was slightly accurate as compared to participant II.

Table 7. Actual and Estimated Physical Intensity, Activity Duration and Frequency

Participant	Activity category	Physical intensity			Activity duration			Frequency		
		Actual (kg)	Estimated (kg)	Error	Actual (s)	Estimated (s)	Error	Actual	Estimated	Error
PI	1	14	13	7.1%	330	325	1.5%	20	23	-15.0%
	2	18	20	-11.1%	2305	2303	0.1%	63	70	-11.1%
	3	25	24	4.0%	3600	3594	0.2%	72	76	-5.6%
	4	19	17	10.5%	550	561	-2.0%	13	15	-15.4%
PII	1	15	16	-6.7%	338	355	-5.0%	22	27	-22.7%
	2	16	19	-18.8%	2315	2322	-0.3%	60	69	-15.0%
	3	26	30	-15.4%	3620	3628	-0.2%	68	72	-5.9%
	4	16	12	25.0%	570	542	4.9%	14	20	-42.9%

Ergonomic Risk Level Assessment

Following the evaluation of actual and estimated physical intensity, activity duration and frequency information of each participant, the corresponding ergonomic risk levels are calculated. These calculated values are based on risk levels of the category of activities as presented in Table 3. Table 8 summarizes the calculation of overexertion-related ergonomic risk levels. According to Table 8, all estimated risk levels are similar to actual risk levels in each participant. It was found that the difference between actual and estimated physical intensity is negligible compared to the difference between physical intensity for two adjacent risk levels (Table 8). Similarly, there was no significant difference between actual and estimated risk levels for either duration per shift or frequency per minute (Table 8). Given above, it is plausible to conclude that the proposed approach is feasible to calculate the actual and the estimated risk levels of each category of activity, which are within the same level of risk for each participant. Nath et al. (2018) reported similar findings for the actual and the corresponding estimated risk falls into the same level of risk by collecting time-stamped motion data from body-mounted built-in smartphone IMU sensors. Different from previous studies, the novelty of this study lies in estimating the physical intensity, activity duration, and frequency information for assessing the ergonomic risk levels of overexertion-related construction workers' activities by collecting acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system.

Table 8. Calculation of Overexertion-Related Ergonomic Risk Levels

Item	Activity category	Physical intensity		Risk level	Duration/Shift			Risk level	Frequency per minute			Risk level
		Actual	Estimated		Actual	Estimated	Diff.		Actual	Estimated	Diff.	
PI	1	> 5 kg or high effort	> 5 kg or high effort	H	5%	5%	0%	L	0.18	0.20	0.02	L
	2	8-23 kg	8-23 kg	M	34%	34%	0%	M	0.56	0.62	0.06	L
	3	>23 kg	>23 kg	H	53%	53%	0%	H	0.64	0.67	0.03	M
PII	1	> 5 kg or high effort	> 5 kg or high effort	H	5%	5%	0%	L	0.19	0.24	0.05	L
	2	8-23 kg	8-23 kg	M	34%	34%	0%	M	0.53	0.60	0.07	L
	3	>23 kg	>23 kg	H	53%	53%	0%	H	0.60	0.63	0.03	M

Contributions, Potential Applications, and Practical Challenges

This section discusses the contributions, potential applications and practical challenges of the proposed approach. First, overexertion-related workers' activities were conducted in a controlled laboratory setting to examine the feasibility of automated activity recognition and ergonomic risk assessment using acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system. Cross-validation results showed that the RF classifier had the best classification accuracy of 98.3% and a sensitivity of each category of activities was above 95% with a 2.56s window size by using a combined data set of both participants. The results show that the proposed approach is reliable to autonomously and remotely monitor participants during simulated overexertion-related workers' activities. In other words, the results demonstrate that acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system show unique patterns for recognizing different categories of activities. Since the conducted experiments are generally peculiar to several construction workers (e.g., masons, carpenters, rebar workers) and other workers in industrialized sectors (e.g., manufacturing, agriculture), the proposed approach has a great potential application not only to be used as personal protective equipment for individualized construction workers but also in similar occupational trades. Second, the current study extends the authors' earlier works on automated detection and classification of awkward working postures (Antwi-Afari et al. 2018f) and loss of balance events (Antwi-Afari et al. 2018e). Specifically, the feasibility to automatically recognize overexertion-related workers' activities as a potential risk factor for developing WMSDs in construction was investigated in greater details in the current study. Despite the existing ergonomic risk assessment methods such as self-reported, observational-based, and vision-based methods that have some limitations, the proposed approach can allow researchers and safety managers to continuously and objectively evaluate overexertion-related activities that may lead to WMSDs among construction workers. The automated recognition of overexertion-related workers' activities may enable construction managers to accurately identify ongoing construction activities and easily share information with other project stakeholders. In addition, the novel method may help safety officers and construction managers to proactively identify potential risk factors for developing WMSDs in construction so as to implement effective interventions to minimize the occurrences of these risk factors on construction sites. Third, this is the first study to estimate the physical intensity, activity duration, and frequency information for assessing the ergonomic risk levels of overexertion-related workers' activities using a wearable insole pressure system. Our results found that the estimated ergonomics risk levels are similar to actual risk levels. As such, the proposed approach has a great potential application to replace subjective, time-consuming and interruptive approaches. The findings could be valuable for real-world implementations where it is possible to investigate whether the proposed approach (1) has the potential for recognizing and predicting workers' activities of new data collected in future instances to existing data storage; (2) is reliable and robust against the variability of movements among workers (e.g., directions of movement) while performing activities; (3) could be used to automate work-sampling process for evaluating workers' productivity.

Despite the aforementioned contributions and potential applications of the proposed approach, there are several practical challenges that need to be addressed when using it in a real-world setting. They include but not limited to (1) system design and development; (2) data collection, storage and processing; and (3) ethical and privacy issues. The effective use of a wearable insole pressure system on construction sites could be affected by design challenges from the hardware and software constraints arising from size and weight of the system, power efficiency and consumption. Due to the dynamic nature of the construction environment, the size and weight of pressure sensors must be small and lightweight to achieve a non-invasive and unobtrusive continuous monitoring of workers' activities. Compared to wearable IMU-based systems, wearable insole pressure system must be developed in different foot sizes to fit the safety boots of workers on site. The use of pressure sensor software programmes based on a desktop computer may interrupt with ongoing construction activities. As such, software manufacturers must incorporate it on smartphone, smartwatches or wrist band that can be easily worn by workers. With regards to power efficiency and consumption, a proposed method to address such issues is either by using a Bluetooth low energy (BLE), an ultralow-power technology for devices with limited battery capacity or Bluetooth 3.0 specification, which adopts the medium access control layers to a shared wireless medium (Soh et al. 2015). Unlike laboratory settings, collecting acceleration and foot plantar pressure data using a wearable insole pressure system at the workplace are expected to be affected by signal artifacts, missing data and high computational time issues. As such, filtering methods such as low pass filter, band-pass filter and notch filter need to be applied to remove signal artifacts from collected data from construction sites. To prevent missing data problems, data collection by using a wearable insole pressure system must be stored either on a flash memory device or in cloud software. For easy accessibility and to reduce computation time, raw sensor data need to be processed and transmitted through a short range of standardized wireless communication networks such as Wi-Fi, Bluetooth, ANT +, and ZigBee. Lastly, ethical and privacy issues are mostly related to personal data protection and user confidentiality. To overcome the practical challenges arising from these issues, safety managers and construction institutions could provide subsidies and performance incentives as well as clear guidelines on privacy, confidentiality and proper use of a worker's information.

Limitations and Future Directions

Despite the findings of this study, some limitations should be addressed in future studies. First, the number of student participants who participated in this study was relatively small either comparable to or larger than similar previous studies (Antwi-Afari et al. 2018c; Kong et al. 2018; Nath et al. 2018). As such, the limited sample size of this study may not be enough to reflect the diverse physiological characteristics of construction workers. Besides, all the experiments were conducted in a laboratory setting. Future research is warranted to validate our experimental protocol by using a larger sample of experienced construction workers at the jobsite to generate a more robust evaluation and recognition of overexertion-related workers' activities and ergonomic risk assessment. Second, the current study was limited to the only overexertion-related workers' activities in construction, and therefore the results may not be generalized to other construction activities (e.g., sawing, installing rebar, hammering)—future research should consider different types of construction workers' activities. Such future studies would invariably help to further validate the proposed approach. Third, automated activity recognition by using a wearable insole pressure system can be integrated with other types of sensors such as depth sensors and physiological sensors to expand to other applications for construction workers. As such, automated overexertion-related workers' activities based on a wearable insole pressure system can be enhanced by integrating it with either oxygen consumption or heart rate monitoring sensors for an in-depth understanding of workers' physical conditions.

Conclusions

The current study examined the feasibility of using acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system for automated recognition of overexertion-related workers' activities and assessing corresponding ergonomic risk levels. The proposed approach was tested in a laboratory setting by simulating overexertion-related workers' activities that may lead to developing WMSDs in construction. Cross-validation results found that the RF classifier had the best classification accuracy of 98.3% and a sensitivity of more than 95.8% for each category of activities using the best features of combined data set with a 2.56s window size. Moreover, the results showed that the accuracy of each participant's data sets was higher than the combined data set using the best features. Furthermore, the actual and the corresponding estimated ergonomic risk levels fall within the same level of risk.

The findings from this study make significant contributions to research and practice. First, the current study shows that using acceleration and foot plantar pressure distribution data measured by a wearable insole pressure system is feasible for automated recognition of overexertion-related workers' activities. In particular, the proposed approach can continuously monitor and collect sensor data without interfering with ongoing activities on construction sites. In addition, it is non-intrusive and causes fewer constraints in body movement as well as minimizes discomfort. Furthermore, the outcome of using objective sensor data for recognizing overexertion-related workers' activities could help safety managers to reduce the shortcomings of existing activity recognition approaches. Second, a novel methodology to evaluate overexertion-related workers' activities which may lead to developing WMSDs in construction was presented. As a result, it extends the use of wearable sensing technologies for activity recognition and construction health and safety research. For example, it could be used to automate workers' productivity and safety hazards' detection. Third, this research study estimated the physical intensity, activity duration, and frequency information for assessing the ergonomic risk levels of different categories of activities. Consequently, the findings will enable a more comprehensive and meaningful analysis of ergonomic risks associated with overexertion. Overall, the findings would help develop a non-invasive wearable insole pressure system as a piece of personal protective equipment for continuous monitoring and activity recognition, which could assist researchers and safety managers in understanding the causal relationship between overexertion-related ergonomic risk and WMSDs among construction workers.

Data Availability Statement

All raw data and feature extraction codes generated or analyzed during the study are available from the corresponding author by request.

Acknowledgement

The authors acknowledged the support from the Department of Building and Real Estate of The Hong Kong Polytechnic University, the General Research Fund (GRF) Grant (BRE/PolyU 152099/18E) entitled "Proactive Monitoring of Work-Related MSD Risk Factors and Fall Risks of Construction Workers Using Wearable Insoles". Special thanks are given to Mr. Mark Ansah Kyeredey for assisting the experimental set-up and the participants involved in this study.

Declarations of Interest

None

References

Akhavian, R., and Behzadan, A. H. (2016) Smartphone-Based Construction Workers' Activity Recognition and Classification, Automation in Construction, Vol. 71, No. 2, pp. 198-209. DOI: https://doi.org/10.1016/j.autcon.2016.08.015.

Antwi-Afari, M. F., and Li, H. (2018g) Fall Risk Assessment of Construction Workers Based on Biomechanical Gait Stability Parameters Using Wearable Insole Pressure System, Advanced Engineering Informatics, Vol. 38, pp. 683-694. DOI: https://doi.org/10.1016/j.aei.2018.10.002.

Antwi-Afari, M. F., Li, H., Edwards, D. J., Pärn, E. A., Owusu-Manu, D., Seo, J., and Wong, A. Y. L. (2018a) Identification of Potential Biomechanical Risk Factors for Low Back Disorders During Repetitive Rebar Lifting, Construction Innovation: Information, Process, Management, Vol. 18, No. 2. DOI: https://doi.org/10.1108/CI-05-2017-0048.

Antwi-Afari, M. F., Li, H., Edwards, D. J., Pärn, E. A., Seo, J., and Wong, A. Y. L. (2017a) Effects of Different Weight and Lifting Postures on Postural Control During Repetitive Lifting Tasks, International Journal of Building Pathology and Adaptation, Vol. 35, No. 3, pp. 247-263. DOI: https://doi.org/10.1108/IJBPA-05-2017-0025.

Antwi-Afari, M. F., Li, H., Edwards, D. J., Pärn, E. A., Seo, J., and Wong, A. Y. L. (2017b) Biomechanical Analysis of Risk Factors for Work-Related Musculoskeletal Disorders During Repetitive Lifting Task in Construction Workers, Automation in Construction, Vol. 83, pp. 41-47. DOI: https://doi.org/10.1016/j.autcon.2017.07.007.

Antwi-Afari, M. F., Li, H., Seo, J., and Wong, A. Y. L. (2018e) Automated Detection and Classification of Construction Workers' Loss of Balance Events Using Wearable Insole Pressure Sensors, Automation in Construction, Vol. 96, pp. 189-199. DOI: https://doi.org/10.1016/j.autcon.2018.09.010.

Antwi-Afari, M. F., Li, H., Seo, J., Lee, S., Edwards, D. J., and Wong, A. Y. L. (2018c) Wearable Insole Pressure Sensors for Automated Detection and Classification of Slip-Trip-Loss-Of-Balance Events in Construction Workers. Construction Research Congress, New Orleans, Louisiana, USA, April 2-5, 2018. DOI: https://doi.org/10.1061/9780784481288.008.

Antwi-Afari, M. F., Li, H., Wong, J. K. W., Oladinrin, O. T., Ge, J. X., Seo, J., and Wong, A. Y. L. (2019) Sensing and Warning-Based Technology Applications to Improve Occupational Health and Safety in the Construction Industry: A Literature Review, Engineering, Construction and Architectural Management. DOI: https://doi.org/10.1108/ECAM-05-2018-0188.

Antwi-Afari, M. F., Li, H., Yu, Y., and Kong, L. (2018f) Wearable Insole Pressure System for Automated Detection and Classification of Awkward Working Postures in Construction Workers, Automation in Construction, Vol. 96, pp. 433-441. DOI: https://doi.org/10.1016/j.autcon.2018.10.004.

Antwi-Afari, M. F., Yu, Y., Li, H., Darko, A., Seo, J., and Wong, A. Y. L. (2018b) Automated Detection and Classification of Construction Workers' Awkward Working Postures Using Wearable Insole Pressure Sensors. Proceedings of 1st Postgraduate in Applied Research Conference in Africa (ARCA), Accra, Ghana, February 21-23, 2018. Available via: https://www.researchgate.net/publication/323689588 (Accessed: March 2019).

Arndt, V., Rothenbacher, D., Daniel U., Zschenderlein, B., Schuberth, S., and Brenner, H. (2005) Construction Work and Risk of Occupational Disability: A Ten Year Follow Up of 14474 Male Workers, Occupational and Environmental Medicine, Vol. 62, No. 8, pp. 559–567. DOI: http://dx.doi.org/10.1136/oem.2004.018135.

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., and Amirat, Y. (2015) Physical Human Activity Recognition Using Wearable Sensors. Sensors, Vol. 15, No. 12, pp. 31314-31338. DOI: https://doi.org/10.3390/s151229858.

Barkallah, E., Freulard, J., Otis, M. J. D., Ngomo, S., Ayena, J. C., and Desrosiers, C. (2017) Wearable Devices for Classification of Inadequate Posture at Work Using Neural Networks, Sensors, Vol. 17, No. 9, pp. 2003. DOI: https://doi.org/10.3390/s17092003.

Breiman, L. (1984) Classification and Regression Trees, Wadsworth International Group, Belmont, CA. ISBN: 9780534980535.

Buchholz, B., Paquet, V., Punnett, L., Lee, D., and Moir, S. (1996) Path: A Work Sampling Based Approach to Ergonomic Job Analysis for Construction and Other Non-Repetitive Work, Applied Ergonomics, Vol. 27, No. 3, pp. 177–187. DOI: http://dx.doi.org/10.1016/0003-6870 (95)00078-X.

Bureau of Labor Statistics (BLS) (2016) Nonfatal Occupational Injuries and Illnesses Requiring Days Away from Work. Available via: http://www.bls.gov/news.release/osh2.toc.htm. (Accessed: March 2019).

Cates, B., Sim, T., Heo, H. M., Kim, B., Kim, H., and Mun, J. H. (2018) A Novel Detection Model and its Optimal Features to Classify Falls from Low-And High-Acceleration Activities of Daily Life Using an Insole Sensor System, Sensors, Vol. 18, No. 4, pp. 1227. DOI: https://doi.org/10.3390/s18041227.

Center to Protect Workers' Right (CPWR) (2018) The Construction Chart Book: The Center for Construction Research and Training. Available online via: https://www.cpwr.com/sites/default/fles/publications/The_6th_Edition_Construction_eChart_Book.pdf (Accessed: March 2019).

Cortes, C., and Vapnik, V. (1995) Support-Vector Networks, Machine learning, Vol. 20, No. 3, pp. 273-297. DOI: https://doi.org/10.1007/BF00994018.

David, G. C. (2005) Ergonomic Methods for Assessing Exposure to Risk Factors for Work-Related Musculoskeletal Disorders, Occupational Medicine, Vol. 55, No. 3, pp. 190–199. DOI: https://doi.org/10.1093/occmed/kqi082.

Han, S., and Lee, S. (2013) A Vision-Based Motion Capture and Recognition Framework for Behavior-Based Safety Management, Automation in Construction, Vol. 35, pp. 131–141. DOI: http://dx.doi.org/10.1016/j.autcon.2013.05.001.

Han, S., Lee, S., and Peña-Mora, F. (2013) Comparative Study of Motion Features for Similarity-Based Modeling and Classification of Unsafe Actions in Construction, Journal of Computing in Civil Engineering, Vol. 28, No. 5, pp. A4014005. DOI: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000339.

Haykin, S. (2009) Neural Networks and Learning Machines, 3rd Edition, Pearson Education, Upper Saddle River, New Jersey. ISBN: 978-0-13-147139-9.

Jaffar, N., Abdul-Tharim, A. H., Mohd-Kamar, I. F., and Lop, N. S. (2011) A Literature Review of Ergonomics Risk Factors in Construction Industry, Procedia Engineering, Vol. 20, pp. 89–97. DOI: https://doi.org/10.1016/j.proeng.2011.11.142.

Jahanbanifar, S., and Akhavian, R. (2018) Evaluation of Wearable Sensors to Quantify Construction Workers Muscle Force: An Ergonomic Analysis, In Proceedings of the 2018 Winter Simulation Conference, pp. 3921-3929, IEEE Press. ISBN:978-1-5386-6570.

Joshua, L., and Varghese, K. (2010) Accelerometer-Based Activity Recognition in Construction, Journal of Computing in Civil Engineering, Vol. 25, No. 5, pp. 370-379. DOI: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000097.

Ke, S. R., Thuc, H. L. U., Lee, Y. J., Hwang, J. N., Yoo, J. H., and Choi, K. H. (2013) A Review on Video-Based Human Activity Recognition, Computers, Vol. 2, No. 2, pp. 88–131. DOI: https://doi.org/10.3390/computers2020088.

Kim, H., Ahn, C. R., and Yang, K. (2016) Identifying Safety Hazards Using Collective Bodily Responses of Workers, Journal of Construction Engineering and Management, Vol. 143, No. 2, pp. 04016090. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001220.

Kong, L., Li, H., Yu, Y., Luo, H., Skitmore, M., and Antwi-Afari, M. F. (2018) Quantifying the Physical Intensity of Construction Workers, A Mechanical Energy Approach, Advanced Engineering Informatics, Vol. 38, pp. 404-419. DOI: https://doi.org/10.1016/j.aei.2018.08.005.

Li, K. W., and Yu, R. (2011) Assessment of Grip Force and Subjective Hand Force Exertion Under Handedness and Postural Conditions, Applied Ergonomics, Vol. 42, No. 6, pp. 929–933. DOI: https://doi.org/10.1016/j.apergo.2011.03.001.

Mcatamney, L., and Corlett, N. E. (1993) RULA: A Survey Method for the Investigation of Work-Related Upper Limb Disorders, Applied Ergonomics, Vol. 24, No. 2, pp. 91–99. DOI: http://dx.doi. org/10.1016/0003-6870 (93)90080-S.

Mickle, K. J., Munro, B. J., Lord, S. R., Menz, H. B., and Steele, J. R. (2011) Gait, Balance and Plantar Pressures in Older People with Toe Deformities, Gait & Posture, Vol. 34, No. 3, pp. 347-351. DOI: https://doi.org/10.1016/j.gaitpost.2011.05.023.

Nath, N. D., Akhavian, R., and Behzadan, A. H. (2017) Ergonomic Analysis of Construction Worker's Body Postures Using Wearable Mobile Sensors, Applied ergonomics, Vol. 62, pp. 107-117. DOI: https://doi.org/10.1016/j.apergo.2017.02.007.

Nath, N. D., Chaspari, T., and Behzadan, A. H. (2018) Automated Ergonomic Risk Monitoring Using Body-Mounted Sensors and Machine Learning, Advanced Engineering Informatics, Vol. 38, pp. 514-526. DOI: https://doi.org/10.1016/j.aei.2018.08.020.

Occupational Safety & Health Administration (OSHA) (2012) University of Massachusetts Lowell, Ergonomics for Trainers. Available online via: https://www.osha.gov/sites/default/files/2018-11/fy12_sh-23543-12_ErgoforTrainers-TTTProgram.pdf (Accessed: March 2019).

Occupational Safety and Health Administration (OSHA) (2017) Worker Safety Series: Construction, United States Department of Labor. Available via: https://www.osha.gov/Publications/OSHA3252/3252.html. (Accessed: March 2019).

Pavey, T.G., Gilson, N. D., Gomersall, S. R., Clark, B., and Trost, S. G. (2017) Field Evaluation of a Random Forest Activity Classifier for Wrist-Worn Accelerometer Data, Journal of Science and Medicine in Sport, Vol. 20, No. 1, pp. 75–80. DOI: https://doi.org/10.1016/j.jsams.2016.06.003.

Preece, S. J., Goulermas, J. Y., Kenney, L. P., Howard, D., Meijer, K., and Crompton, R. (2009) Activity Identification Using Body-Mounted Sensors—A Review of Classification Techniques, Physiological measurement, Vol. 30, No. 4, R1–R33. DOI: https://doi.org/10.1088/0967-3334/30/4/R01.

Queen, R. M., Haynes, B. B., Hardaker, W. M., and Garrett Jr, W. E. (2007) Forefoot Loading During 3 Athletic Tasks, The American Journal of Sports Medicine, Vol. 35, No. 4, pp. 630-636. DOI: https://doi.org/10.1177/0363546506295938.

Reme, S. E., Dennerlein, J. T., Hashimoto, D., and Sorensen, G. (2012) Musculoskeletal Pain and Psychological Distress in Hospital Patient Care Workers, Journal of Occupational Rehabilitation, Vol. 22, No. 4, pp. 503–510. DOI: https://doi.org/10.1007/s10926-012-9361-5.

Ryu, J., Seo, J., Jebelli, H., and Lee, S. (2018) Automated Action Recognition Using an Accelerometer-Embedded Wristband-Type Activity Tracker, Journal of Construction Engineering and Management, Vol. 145, No. 1, pp. 04018114. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001579.

Sazonov, E. S., Fulk, G., Hill, J., Schutz, Y., and Browning, R. (2011) Monitoring of Posture Allocations and Activities by a Shoe-Based Wearable Sensor, IEEE Transactions on Biomedical Engineering, Vol. 58, No. 4, pp. 983-990. DOI: https://doi.org/10.1109/TBME.2010.2046738.

Simoneau, S., St-Vincent, M., and Chicoine, D. (1996) Work-Related Musculoskeletal Disorders (WMSDs): A Better Understanding for more Effective Prevention, IRSST, Québec. Available via: https://www.irsst.qc.ca/en/publications-tools/publication/i/100698 (Accessed: March 2019).

Soh, P. J., Vandenbosch, G. A., Mercuri, M., and Schreurs, D. M. P. (2015) Wearable Wireless Health Monitoring: Current Developments, Challenges, and Future Trends, IEEE Microwave Magazine, Vol. 16, No. 4, pp. 55-70. DOI: https://doi.org/10.1109/MMM.2015.2394021.

Su, X., Tong, H., and Ji, P. (2014) Activity Recognition with Smartphone Sensors, Tsinghua Science and Technology, Vol. 19, No. 3, pp. 235–249. DOI: http://dx.doi.org/10.1109/ccnc.2013.6488584.

Tang, W., and Sazonov, E. S. (2014) Highly Accurate Recognition of Human Postures and Activities through Classification with Rejection, IEEE Journal of Biomedical and Health Informatics, Vol. 18, No. 1, pp. 309-315. DOI: https://doi.org/10.1109/JBHI.2013.2287400.

Umer, W., Antwi-Afari, M. F., Li, H., Szeto, G. P. Y., and Wong, A. Y. L. (2017a) The Global Prevalence of Musculoskeletal Disorders in the Construction Industry: A Systematic Review and Meta-Analysis, International Archives of Occupational and Environmental Health, pp. 1–20. DOI: https://doi.org/10.1007/s00420-017-1273-4.

Umer, W., Li, H., Szeto, G. P. Y., and Wong, A. Y. L. (2017b) Low-Cost Ergonomic Intervention for Mitigating Physical and Subjective Discomfort During Manual Rebar Tying, Journal of Construction Engineering and Management, Vol. 143, No. 10, pp. 04017075. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001383.

Valero, E., Sivanathan, A., Bosché, F., and Abdel-Wahab, M. (2016) Musculoskeletal Disorders in Construction: A Review and A Novel System for Activity Tracking with Body Area Network, Applied Ergonomics, Vol. 54, pp. 120–130. DOI: http://dx.doi.org/10.1016/j.apergo.2015.11.020.

Wang, D., Dai, F., and Ning, X. (2015a) Risk Assessment of Work-Related Musculoskeletal Disorders in Construction: State-Of-The-Art Review, Journal of Construction Engineering and Management, Vol. 141, No. 6, pp. 1–15. DOI: http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000979.

Yang, K., Ahn, C. R., Vuran, M. C., and Aria, S. S. (2016) Semi-Supervised Near-Miss Fall Detection for Ironworkers with a Wearable Inertial Measurement Unit, Automation in Construction, Vol. 68, pp. 194-202. DOI: https://doi.org/10.1016/j.autcon.2016.04.007.

Yang, K., Ahn, C. R., Vuran, M. C., and Kim, H. (2017) Collective Sensing of Workers' Gait Patterns to Identify Fall Hazards in Construction, Automation in Construction, Vol. 82, pp. 166-178. DOI: https://doi.org/10.1016/j.autcon.2017.04.010.

Yang, Z., Yuan, Y., Zhang, M., Zhao, X., and Tian, B. (2019) Assessment of Construction Workers' Labor Intensity Based on Wearable Smartphone System, Journal of Construction Engineering and Management, Vol. 145, No. 7, pp. 04019039. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001666.

Yu, Y., Li, H., Yang, X., and Umer, W. (2018) Estimating Construction Workers' Physical Workload by Fusing Computer Vision and Smart Insole Technologies. In Proceedings of the International Symposium on Automation and Robotics in Construction, Vol. 35, pp. 1-8. IAARC Publications. Available via: https://www.researchgate.net/profile/publication/326825634.pdf (Accessed: March 2019).

Zhang, M., Chen, S., Zhao, X., and Yang, Z. (2018) Research on Construction Workers' Activity Recognition Based on Smartphone, Sensors, Vol. 18, No. 8, pp. 2667. DOI: https://doi.org/10.3390/s18082667.