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OVEREXERTION-RELATED CONSTRUCTION WORKERS' ACTIVITY RECOGNITION AND ERGONOMIC RISK ASSESSMENT BASED ON WEARABLE INSOLE PRESSURE SYSTEM

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Work related activities that led to overexertion are a major cause of work-related musculoskeletal disorders (WMSDs) among construction workers. However, existing risk assessment methods (e.g., self-reported and observational-based methods) have failed to fully recognize these activities and assess the corresponding risk level exposure to mitigate WMSDs. This study examines the feasibility of using acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system for automated assessment of construction workers' activities and overexertion risk levels. The accuracy of five types of supervised machine learning classifiers was evaluated with different window sizes to investigate individual participant performance and further estimate physical intensity, activity duration and frequency information. The results showed that the Random Forest classifier with 2.56s window size achieved the best classification accuracy of 94.5% and 94.3% and a sensitivity of more than 90.1% and 88.4% for each category of activities. Overall, the proposed approach provides a non-invasive method and objective assessment of ergonomic risk level based on acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system which could help other researchers and safety managers to: understand the level of workers' risks; and provide an effective intervention to mitigate the risk of developing WMSDs among construction workers.

Keywords: activity recognition; construction workers; overexertion risk; supervised machine learning classifiers; wearable insole pressure system; work-related musculoskeletal disorders

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INTRODUCTION

Work-related musculoskeletal disorders (WMSDs) are a leading cause of nonfatal occupational injuries within the construction industry (Eaves et al., 2016). In the United States, WMSDs account for 32% of all injuries and illness cases that result in absenteeism throughout industry (Bureau of Labor Statistics, 2015). WMSDs (e.g., low back pain) impose substantial direct and indirect costs, schedule delays and lost time claims to the industry (Umer et al., 2017a). To prevent WMSDs, the potential risk factors must be identified in order to provide practical interventions to mitigate the risk. Among the various biomechanical risk factors (e.g., awkward postures, overexertion, repetitive motions), overexertion (i.e., force exertion) has been identified as the leading cause of WMSDs among construction workers (BLS, 2016).

Previous studies have successfully demonstrated the use of wearable inertial measurement units (IMUs) for activity recognition and risk assessment (Akhavian and Behzadan, 2016; Nath et al., 2018; Ryu et al., 2018). For instance, 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. Despite the inherent advantages of wearable IMU-based systems, these approaches are intrusive and require multiple sensors to be attached to a construction worker's body. Consequently, they are often uncomfortable to wear and/or instigate epidermal irritation. In addition, little research has been conducted to automatically recognize overexertion-related work activities and evaluate the amount of physical intensity (i.e., grip effort), activity duration and frequency information. Against this contextual backdrop, this paper proposes a non-invasive wearable insole pressure system for recognizing overexertion-related work activities and assessing ergonomic risk levels.

LITERATURE REVIEW

There are four thematic groupings of ergonomic risk assessment methods for identifying the development of WMSDs, namely: i) self-reported methods; ii) observational-based methods; iii) vision-based methods; and iv) direct measurement methods. Self-reported methods are relatively straightforward to implement and have an initial low cost as workers are asked to provide self-assessment risk-related data. However, researchers have stated that workers' self-assessments on exposure levels are often imprecise, unreliable and biased (Wang et al., 2015a). Observation-based methods involve real-time assessment or analysis of recorded video footage. However, these methods are mostly impractical due to the substantial cost, time and technical knowledge required for post-analysis of large amounts of non-heterogeneous data (David, 2005). Vision-based methods use depth sensors or stereo camera systems to capture human motion data (Han et al., 2013; Han and Lee, 2013). These methods provide accurate, non-invasive and automated human motion data for analyzing workers' safety behaviors or unsafe actions (Han et al., 2013). Despite the advancements in automation, these methods still require a direct line of sight to register human movements (Han and Lee, 2013). Direct measurement methods use wearable sensor-based systems to collect human motion-related data and provide accurate and reliable data for identifying WMSDs' risks (David, 2005; Akhavian and Behzadan, 2016; Antwi-Afari et al., 2017b;

Antwi-Afari et al., 2018a). 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. However, these methods require sensors to be attached to the workers' skin which may cause irritation and discomfort (Antwi-Afari et al., 2017b). To overcome the aformentioned challenges, this study proposes a wearable insole pressure system to recognize overexertion-related construction worker activities and assessing corresponding ergonomic risk levels.

RESEARCH METHODS

Fig. 1 shows the schematich framework for overexertion-related ergonomic risk assessment. The detailed description of each step is provided in the following sections.

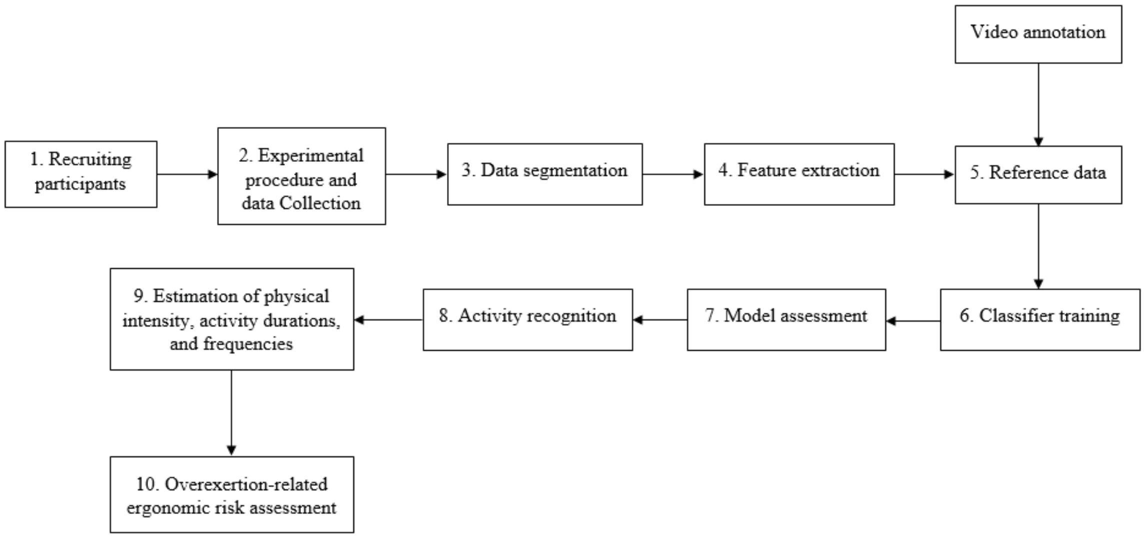

Fig. 1. Schematic framework for overexertion-related ergonomic risk assessment

Participants

Two asymptomatic male participants were recruited from the student population of the Hong Kong Polytechnic University. The participants mean age, weight, and height were 27.6 ± 3.01 years, 72 ± 3.75 kg, and 1.65 ± 0.17 m, respectively. Both participants had no medical history of mechanical upper extremities or back pains, or lower extremity injuries. Participants provided their informed consent in accordance with the procedure approved by the Human Subject Ethics Subcommittee of The Hong Kong Polytechnic University (reference number: HSEARS20170605001).

Experimental procedure and data collection

An OpenGo system (Moticon GmbH, Munich, Germany) that contained 13 capacitive pressure sensors within each pair of a wearable insole was used for measuring acceleration and foot plantar pressure distribution data (cf. Antwi-Afari and Li 2018g). A cross-sectional study design was adopted during a single visit. All participants were asked to wear personal protective equipment such as a pair of safety boots and a hard hat during the testing sessions. The participants were shown representative videos of overexertion-related construction workers' activities which were performed by workers on site. Participants then performed the following seven overexertion-related construction workers' activities viz: (i) load a wooden box (measuring 30 × 30 × 25 cm) with dumbbell weights and hold it in a static standing position to receive further instruction from the experimenter; (ii) walk while carrying the weighted box along a set path to a preset destination on the floor; (iii) lift the weighted box from the floor level onto a table at waist level for inspection; (iv) lower the weighted box from the table at waist level onto a four-wheeled dolly; (v) walk while pushing the dolly on a set path to another preset destination; (vi) wait while the experimenter offload the dumbbell weights from the wooden box; and (vii) walk while pulling the dolly to a specific preset location in the laboratory. The entire experiment was conducted for 20 cycles for two participants. It was recorded using a video camcorder in a laboratory setting. These activities were grouped into four different categories of activities, namely (cf. Jaffar et al., 2011): (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. In addition, these activity categories can be assessed by three different sets of rules that limit the physical intensity, activity duration and frequency information (as summarized in Table 1) that can lead to developing WMSDs (OSHA, 2012).

Data segmentation

The sliding window technique was used to divide the collected data into smaller data segments; where the sampling frequency per second was set at 50 Hz (Banos et al., 2014). The window sizes of 0.32s, 0.64s, 1.28s and 2.56s were used because the conversion of the time domain to frequency domain using fast Fourier transforms (FFT) in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA) required the window size to be a power of 2 (Akhavian and Behzadan, 2016). A 50% overlap of the adjacent windows was considered in this research (Antwi-Afari et al., 2018f).

Feature extraction

Three groups of features were extracted in this study, namely: (1) time-domain features such as mean, variance, maximum, minimum, range, standard deviation, root mean square, kurtosis, skewness, standard deviation magnitude, sum vector magnitude and signal magnitude area; (2) frequency-domain features such as spectral energy and entropy spectrum; and (3) spatiotemporal features such as pressure-time integral, anterior/posterior centre of pressure and medial/lateral centre of pressure. Overall, previous studies indicated better classification performance from these groups of features in human activity recognition (Antwi-Afari et al., 2018f; Ryu et al., 2018).

Reference data

A class label for each of the four categories of activity was assigned to each window size with the assistance of the video data to serve as the ground truth to evaluate the performance of the classifiers (Antwi-Afari et al., 2018e).

Classifier training

Five different types of supervised machine learning classifiers were examined, 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). All data processing of the classifiers were performed using Toolbox in MATLAB 9.2 software.

Model assessment

The performance of the classifiers (i.e., accuracy and sensitivity) was assessed by the stratified 10-fold cross-validation method (cf. Attal et al., 2015).

Activity recognition

Once the model was trained, and its parameters are finalized, it can be used for recognizing activities for which it has been trained. The overexertion-related workers' activities involved in this study can be allocated into four categories of activities that may lead to developing WMSDs among construction workers.

Estimation of physical intensity, activity duration and frequency

The physical intensity was calculated by subtracting the participant's self-weight from the total ground reaction force (Yu et al., 2018). The activity 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 (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 was determined by counting all the instances of that category (Simoneau et al., 1996).

Overexertion-related ergonomic risk assessment

Table 1 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). 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. In this study, a shift is the total duration of the experiment.

Table 1. 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 < 5s at once	Gripping 5 – 30s at once	Gripping > 30s 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	Nil	Nil	Nil	Nil

RESULTS AND DISCUSSION

The classification performance of the proposed approach was based on an individualized participant evaluation. Table 2 illustrates the classification accuracy using individualized data of each participant. The highest accuracies of participant I and participant II (based on the RF classifier at 2.56s window size) were 94.5% and 94.3%, respectively. The best accuracy achieved from the RF classifier demonstrates that both acceleration and foot plantar pressure distribution data captured by a wearable insole pressure system show unique patterns according to the categories of activities. In addition, the results suggest that the larger window size provides better classification results when compared to a smaller window size in recognizing overexertion in workers' activities. With regards to the different types of classifiers and window sizes, participant I had higher accuracies compared to participant II. The confusion matrices of the best classifier (i.e., RF) at 2.56s window size of participant I and participant II are presented in Fig. 2a and Fig. 2b respectively - the sensitivity of each category of activity was more than 90% and 88% respectively. This result suggests that there are between-participant variations among the two participants although they performed the same activities. Also, the most misclassified category of activities was 4.8% in participant I (Fig. 2a) and 8.1% in participant II (Fig. 2b).

Table 2. Classification accuracy (%) for each participant

Window size		ANN	DT	KNN	RF	SVM
0.32s	Participant I	65.2	71.6	75.2	80.6	77.5
	Participant II	64.9	71.1	74.8	80.2	77.1
0.64s	Participant I	67.5	73.9	78.8	85.5	80.6
	Participant II	66.9	73.4	78.3	85.3	80.2
1.28s	Participant I	69.4	76.7	83.7	90.8	88.6
	Participant II	68.8	76.4	83.2	90.5	88.1
2.56s	Participant I	72.1	79.6	86.9	94.5	91.7
	Participant II	71.5	79.2	86.1	94.3	91.4

True class	1	90.1%	3.6%	1.5%	4.8%
	2	1.1%	96.6%	1.3%	1.0%
	3	0.3%	3.8%	94.5%	1.4%
	4	4.3%	2.3%	0.6%	92.8%
		1	2	3	4
		Predicted class			

(a) Participant I

True class	1	88.4%	2.6%	0.9%	8.1%
	2	1.6%	95.6%	1.9%	0.9%
	3	1.4%	3.8%	92.5%	2.3%
	4	4.9%	3.1%	1.8%	90.2%
		1	2	3	4
		Predicted class			

(b) Participant II

Fig. 2. Confusion matrix of the RF classifier for each participant at a window size of 2.56s in all category of activities

Table 3 presents the actual and estimated physical intensity, activity duration and frequency of each participant in each category of activity. Table 3 illustrates that the estimated physical intensity, activity duration and frequency of the first participant were within ± 5, ± 2.2%, and < -2, from the actual values respectively. Conversely, the estimated physical intensity, activity duration and frequency of the second participant were within ± 5, ± 3.8, and < -4, from the actual values respectively. These findings suggest that the estimated values in participant I was slightly accurate as compared to participant II. Table 4 illustrates the calculation of overexertion related ergonomic risk levels (where these values are based upon the risk levels presented in Table 1). All estimated risk levels are similar to actual risk levels in each participant. Given above, it is plausible to conclude that the proposed approach is feasible to calculate all the actual and the estimated risk levels, which are within the same level of risk for each participant.

Table 3. 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	15	14	1	226	221	2.2%	21	23	-2
	2	17	22	-5	2168	2164	0.2%	52	55	-3
	3	28	25	3	3128	3120	0.3%	64	69	-5
	4	20	18	2	430	435	-1.2%	11	14	-3
PII	1	14	17	-3	218	225	-3.2%	20	28	-8
	2	15	20	-5	1230	1235	-0.4%	56	60	-4
	3	27	24	3	2586	2642	-2.2%	62	79	-7
	4	18	15	3	345	332	3.8%	12	16	-4

Table 4. 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	4%	4%	0%	L	0.23	0.25	0.02	L
	2	8-23 kg	8-23 kg	M	39%	39%	0%	M	0.57	0.60	0.03	L
	3	>23 kg	>23 kg	H	57%	57%	0%	H	0.70	0.75	0.05	M
PII	1	> 5 kg or high effort	> 5 kg or high effort	H	5%	5%	0%	L	0.30	0.41	0.11	L
	2	8-23 kg	8-23 kg	M	30%	30%	0%	M	0.83	0.88	0.05	L
	3	>23 kg	>23 kg	H	64%	64%	0%	H	0.92	1.16	0.24	M

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 assessment of construction workers' activities and overexertion risk levels. The results found that the RF classifier (with 2.56s window size) provided the best classification accuracy of 94.5% (PI) and 94.3% (PII) and a sensitivity of more than 90.1% (PI) and 88.4% (PII) for each category of activities. In addition, all actual and the corresponding estimated ergonomic risk levels fall into the same level of risk. The study's findings illustrate 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. Overall, the findings could help develop a non-invasive wearable insole pressure system as a piece of personal protective equipment for continuous monitoring and activity recognition. Such a tool could assist researchers and safety managers in understanding the causal relationship between overexertion-related ergonomic risk and WMSDs among construction workers. Despite these promising findings, the number of study participants was small and all the experiments were conducted in a laboratory setting vis-à-vis actual construction site. Future research should therefore be undertaken to validate our experimental protocol by using a larger sample of experienced construction workers on site to generate a more robust evaluation and recognition of overexertion related workers' activities and ergonomic risk assessment.

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