CIB World Building Congress 2019
Hong Kong SAR, China
17 – 21 June 2019

Automated Recognition of Construction Workers' Activities for Productivity Measurement Using Wearable Insole Pressure System

Maxwell Fordjour Antwi-Afari,
Ph.D. Candidate, Dept. of Building and Real Estate, Hong Kong Polytechnic Univ., Room No. ZN1002, Hung Hom, Kowloon, Hong Kong Special Administrative Region
(Email: maxwell.antwiafari@connect.polyu.hk)
Heng Li,
Chair Professor, Dept. of Building and Real Estate, Hong Kong Polytechnic Univ., Room No. ZS734, Hung Hom, Kowloon, Hong Kong Special Administrative Region
(Email: heng.li@polyu.edu.hk)
JoonOh Seo,
Assistant Professor, Dept. of Building and Real Estate, Hong Kong Polytechnic Univ., Room No. ZN742, Hung Hom, Kowloon, Hong Kong Special Administrative Region
(Email: joonoh.seo@polyu.edu.hk)
Arnold Yu Lok Wong,
Assistant Professor, Dept. of Rehabilitation Sciences, Hong Kong Polytechnic Univ., Room No. ST512, Hung Hom, Kowloon, Hong Kong Special Administrative Region
(Email: arnold.wong@polyu.edu.hk)

Abstract

Continuous monitoring and automated recognition of activities performed by construction workers can help improve productivity measurements. However, manual methods are time-consuming and prone to errors; as such, they usually provide unreliable and inaccurate analyses. Therefore, an automated method can expedite the process of data collection and provide accurate analyses of activity recognition and productivity measurements. In this paper, a novel methodology is introduced to automatically recognize workers' activities for evaluating productivity measurement based on foot plantar pressure distribution data measured by a wearable insole pressure system. Four supervised machine learning classifiers (i.e., artificial neural network (ANN), decision tree (DT), *K*-nearest neighbor (KNN), and support vector machine (SVM)) were used for classification performance using a 0.32s window size. Cross-validation results showed that the SVM classifier (i.e., the best classifier) obtained a classification performance with an accuracy of more than 94% and sensitivity of each category of activities was above 95% using a sliding window size of 0.32s. The findings from this preliminary study have shown great potentials to use a wearable insole pressure system to collect foot plantar pressure distribution data for automated recognition of workers' activities and extract activity durations for evaluating productivity.

Keywords: Construction workers, Foot plantar pressure distribution, Productivity measurement, Supervised machine learning classifiers, Wearable insole pressure system

1. Introduction

Construction workplace is one of the most complex working environments because of its dynamic nature, and the combination of numerous resources and supply components (Behzadan et al. 2008). Despite these challenges in the construction industry, it is still crucial to promptly recognize construction activities in order to efficiently improve workers' productivity, project performance and safety (Hughes et al. 2004; Pradhan et al. 2011). With the advancement in mobile technologies, smartphones onboard inertial measurement units (IMUs) sensors have been employed to capture human motion related data for activity recognition (Joshua and Varghese 2010; Akhavian and Behzadan 2016a). Notably, wearable IMU sensors have been used extensively not only in monitoring patients and older adults (Mathie et al. 2004; Kang et al. 2010), but also in recognizing construction activities for preventing work-related musculoskeletal disorders (WMSDs) (Nath et al. 2017; Yan et al. 2017) and fall injuries (Dzeng et al. 2014; Fang and Dzeng 2017). Despite these great potential applications in recognizing activities and health monitoring, they are invasive and may interfere with construction activity, and thus may reduce productivity (Guo et al. 2017).

One common method used to measure a worker's productivity is work-sampling. This method evaluates the relative durations of time allocated by the workers in performing various categories of work activities during a specific time duration (Joshua and Varghese 2010). Although the work-sampling approach has been widely used to measure a worker's productivity, it has several inherent challenges during data collection. First, the manual methods (e.g., questionnaires, interview) of collecting data during specific activities are relatively tedious, time-consuming, subjective and susceptible to errors in analyses. Second, construction workers may feel uncomfortable in using wearable IMU sensors during a work-sampling activity since these sensors usually directly attached to the body by tapes or straps. Third, simultaneous real-time application and continuous monitoring of multiple workers may be difficult due to sensor calibration, synchronization, data storage, and data transfer. Given the limitations of these methods in work-sampling, it is necessary to develop a new method to monitor workers' activities and extract activity durations to quantify workers' productivity.

Accordingly, this paper develops a novel method that can non-intrusively and continuously collects foot plantar pressure distribution data measured by wearable insole pressure sensors. Also, the proposed method not only is feasible for data calibration, data storage, and data transfer but also collects more objective and reliable data. In addition, it provides engineering control to minimize job site hazards by continuous monitoring of unsafe surface environmental conditions. Therefore, the main objective of this paper was to investigate the feasibility of using foot plantar pressure distribution data measured by a wearable insole pressure system for automated recognition of workers' activities and productivity measurements. Recognizing workers' activities are essentially a data mining approach that uses supervised machine learning classifiers for data training and validation. Antwi-Afari et al. (2018e; 2018f) proposed a method for automated detection and classification of workers' loss of balance events and awkward working postures by using a wearable insole pressure system to illustrate the concept of collecting foot plantar pressure distribution data in their preliminary study. Ultimately, these authors showed the potentials of accurately detecting and classifying loss of balance events and awkward working postures by using time domain, frequency domain and spatial temporary data features. This paper extends their previous works to develop a systematic methodology for the automated recognition of workers' activities, which may help estimate the time spent on each category of activity. By using the estimated activity durations, the productivity of each analysis can be measured.

2. Literature Review

The construction industry is one of the most labor-intensive industries and hazardous occupations which involves several physically demanding activities such as repetitive lifting, pushing, carrying and pulling (Seo et al. 2016; Antwi-Afari et al. 2017b; 2018a). Consequently, construction workers' are at high risk of developing WMSDs, which may reduce workers' productivity (Gatti et al. 2014). In order to measure workers' productivity, work-sampling is one of the simplest and most efficient data collection method, which is based on statistical sampling theory (Thomas et al. 1984). However, the data collection procedures are time-consuming, tedious, and prone to error since work sampling greatly depends on the subjective judgment of observers (Golparvar-Fard et al. 2013). As a result, there is a demand for an objective and automated work-sampling process for an efficient measurement of workers' productivity.

Several methods have been demonstrated to recognize workers' activities. Vision-based methods have been previously investigated for activity recognition of workers in the construction realm. These approaches use pictures and videos from either a single or multiple cameras to evaluate workers' productivity and to identify potential risk factors for WMSDs (Ray and Teizer 2012; Yan et al. 2017). In fact, marker-based optical motion tracking systems have been widely used because of their precision (Hwang et al. 2009). Similarly, markerless optical motion tracking systems have been investigated using either video cameras or depth cameras due to their non-invasiveness (Ray and Teizer 2012). Peddi et al. (2009) proposed a human pose analyzing algorithm, using a video camera for construction productivity estimation. While these methods have been proven to be useful in recognizing workers activities, they are limited by the fact that a direct line of sight is required to register the movements (Han and Lee 2013).

Recently, wearable IMUs based sensors are gaining its popularity in recognizing workers' activities. Joshua and Varghese (2010) clustered acceleration data into several patterns and identified specific activities from these patterns using accelerometers attached to the waist of a worker (i.e., mason). Similarly, Ryu et al. (2016) classified activity by analyzing wrist-worn accelerometer data and achieved high levels of accuracy. In addition, smartphone-based construction workers' activity recognition method, which is an integration of accelerometer and gyroscope sensors, has been shown to be feasible (Akhavian and Behzadan 2016b). Akhavian and Behzadan (2016b) captured body movements via smartphones and used the collected data to train machine learning algorithms to simulate various activity types, where activity recognition was performed by machine learning classifiers. However, since they are relatively intrusive, workers are unwilling to attach them to their bodies while performing a task.

To address these issues, this study proposes a novel and non-intrusive method for automated recognition of workers' activities and productivity measurements based on foot plantar pressure distribution data measured by a wearable insole pressure system. Our proposed approach is characterized by its ubiquity, unobtrusiveness, cheap installation procedure and the ease of usability. Notably, the proposed approach has been widely used in other applications such as rehabilitation, sports, and clinical fields (Queen et al. 2007; Sawacha et al. 2009; Mickle et al. 2011; Harle et al. 2012). Different from previous studies, this research used a wearable insole pressure system to measure workers' productivity and recognize workers' activities—which are characterized as dynamic and physically demanding such as upright holding, carrying, lifting, lowering, pulling and pushing that may lead to WMSDs. To achieve this, the authors extended our previous developed methodology to automatically recognize and evaluate workers' productivity of various construction activities. Ultimately, the findings of this research will have significant practical implications in the construction domain since the proposed method can be used as an objective measurement for workers' productivity by simply inserting a wearable insole pressure system into workers' safety boots.

3. Research Methods

Fig. 1 illustrates the framework for construction activity recognition and productivity measurements based on foot plantar pressure distribution data as measured by a wearable insole pressure system. All data processing and machine learning classification were performed using Toolbox in MATLAB 9.2 software (Matlab, The MathWorks Inc., MA, USA). The following sections discuss the detailed steps in Fig. 1.

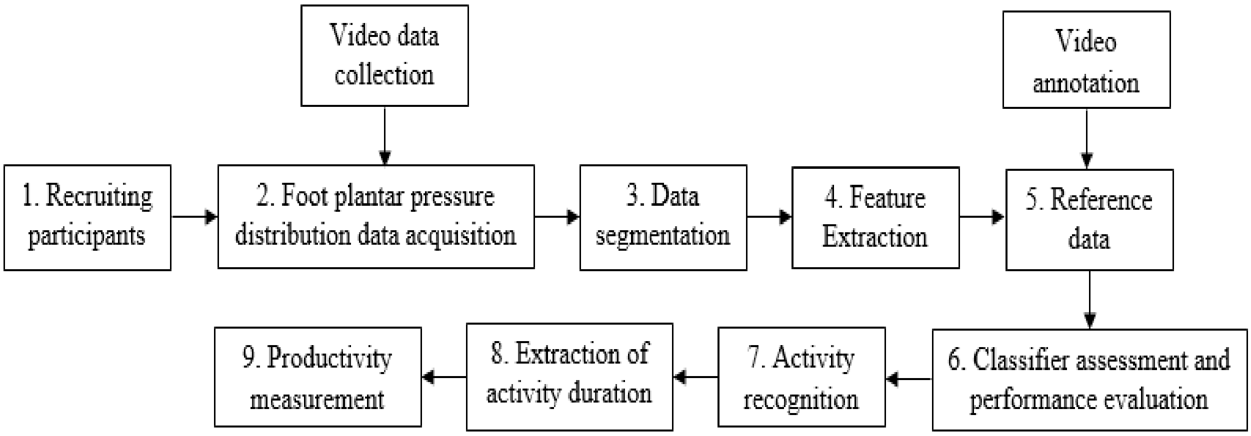

Figure 1. Framework for Construction Worker Activity Recognition and Productivity Measurement Using a Wearable Insole Pressure System

3.1 Participants

Four healthy male participants were recruited from a student population at The Hong Kong Polytechnic University. The participants mean age, weight, and height were 27.75 ± 3.40 years, 73.25 ± 3.30 kg, and 1.71 ± 0.04 m, respectively. All participants had no history of mechanical upper extremities or back pains, or lower extremities injuries. All 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).

3.2 Foot plantar pressure data acquisition

An OpenGo system (Moticon GmbH, Munich, Germany) that contained 13 capacitive pressure sensors within a single wearable insole was used for measuring foot plantar pressure distribution. Each insole system incorporates a flash memory of 16 MB and a wireless module for data transmission. A detailed description of proposed wearable insole pressure system has been reported in previous research (Antwi-Afari and Li 2018g).

This study involved a single visit in a controlled laboratory setting (Fig. 2). Each participant wore a hard hat, and a safety boot. Generally, our participants conducted laboratory simulated manual material handling activities performed by workers in the construction workplace. They included upright holding, carrying, lifting, lowering, pulling and pushing (Fig. 2). In this study, these activities were performed in three different categories. The first category of activity only included an upright holding task (Fig. 2a). The second category involved lifting (Fig. 2b), carrying (Fig. 2c), and lowering tasks (Fig. 2d). In the third category, participants conducted pulling (Fig. 2d) and pushing tasks (Fig. 2e). In each category of activities, the goal of activity recognition was to differentiate between the time the participant spended in conducting each activity and when they were standing (i.e., idle). In all activities, a weight of 15 kg was loaded into a wooden box (measuring 30 × 30 × 25 cm). Prior to data collection, the participants were allowed to practice twice with each activity. The experiments were recorded using a video camcorder to provide video data annotation. The procedure of our experimental protocol was fully explained to the participants. Next, the participants provided their demographic data, informed consent, and were allowed to train each activity. The participants performed each category of activities for ten repetitive trials. In order to reduce fatigue, the participants were allowed to rest for 3 minutes between two successive trials.

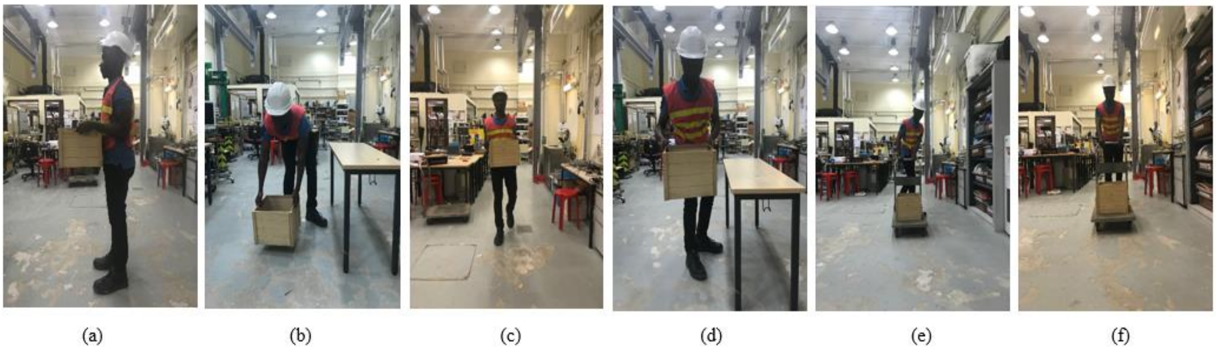

Figure 2. Laboratory Experimental Setup: (a) Upright Standing; (b) Lifting; (c) Carrying; (d) Lowering; (e) Pulling (f) Pushing

3.3 Data segmentation

The sliding window technique was used to divide raw foot plantar pressure distribution data into smaller data segments (Preece et al. 2009). The sampling frequency was set at a rate of 50 Hz and then digitized by a 16-bit analog to digital (A/D) converter. A window size data segment of 0.32s, which correspond to 16 (2^4) data sample was used. This window size was chosen 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 2016b). A 50% overlap of the adjacent windows was considered in this research (Ravi et al. 2005).

3.4 Feature extraction

In order to provide input variables for the classifiers, features extraction was performed. Common time domain and frequency domain feature extractions have been adopted from activity classification in the literature (Akhavian and Behzadan 2016b; Antwi-Afari et al. 2018e; Antwi-Afari et al. 2018f). Specifically, mean pressure, variance, maximum pressure, minimum pressure, range, standard deviation, and kurtosis comprised the seven time domain features. Spectral energy and entropy were the two frequency domain features extracted (Bao and Intille 2004). Additionally, the current study used a spatial-temporal feature known as pressure time integral (Antwi-Afari et al. 2018e; Antwi-Afari et al. 2018f).

3.5 Classifier assessment and performance evaluation

Supervised machine learning classifiers require dataset for training and validation. To this end, class labels were provided to the classifiers to generate a model that matched the input (extracted features) to output variables (activity category) (Ravi et al. 2005). A multilayer perceptron artificial neural network (ANN), decision tree (DT), *K*-nearest neighbor (KNN), and support vector machine (SVM) (Preece et al. 2009; Akhavian and Behzadan 2016b; Antwi-Afari et al. 2018e) were the four classifiers adopted for performance evaluation. The performance of the classifiers was made by the stratified 10-fold cross-validation method (Cawley and Talbot 2003). The performance indicators used to evaluate the classifiers were the accuracy and sensitivity (i.e., correct detection of positive instances).

4. Results and Discussion

4.1 Category 1 activities

The accuracy of activity recognition for this category of activities was 99.60% (SVM) followed by the 98.60% (KNN), 97.80% (DT), and 97.10% (ANN). The mean of the discovered activity duration for 10 trials of 5 participants during upright holding task was 120.44 seconds while the ground truth obtained from the recorded video of the experiment was 120.40 seconds. Moreover, the sensitivity of classifying the time spent during the idle and upright holding tasks was more than 99% in each case. In addition, discovered activity durations showed that the participants spent 70.13% in upright holding task and was idle in the remaining time (Fig. 3). On the other hand, the ground truth for this category 1 activities was 70.07% during upright holding (Fig. 3).

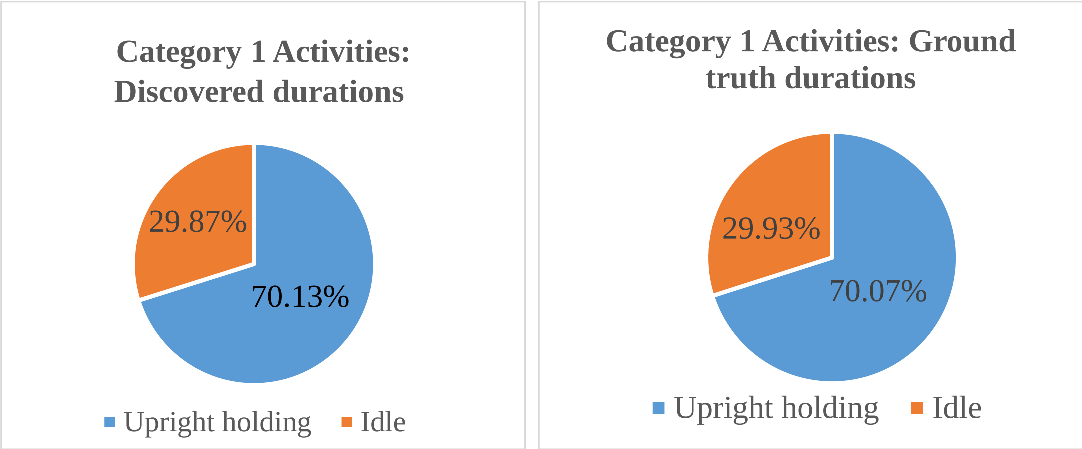

Figure 3. Discovered and Ground Truth Durations Allocation Proportion in Category 1 Activities for Productive Measurement

4.2 Category 2 activities

The accuracy of activity recognition for this category was 94.40% (SVM) followed by 92.10% (KNN), 91.50% (DT), and 87.90% (ANN). Although these accuracies were lesser than category 1 activities, the results may still be considered desirable considering the dynamic nature and body movements of the category 2 activities. Notably, our results may be attributed to the fact that category 2 activities were conducted with similar movements with little changes in foot plantar pressure distribution data. The sensitivity of classifying the time spent during category 2 activities was more than 95% in each case. The mean of the discovered activity duration and ground truth for ten trials of 5 participants are presented in Table 1. Moreover, Fig. 2 depicts the time allocation proportions in percentages using our developed method and the ground truth. Overall, the results showed that our developed method was feasible for recognizing dynamic activities and the discovered durations. This is an important leap for automating the process of work sampling, which traditionally relies on manual observations.

Table 1. Mean Durations in Category 2 Activities

Category 2 Activities	Discovered durations	Ground truth durations
Lifting	89.98	89.06
Lowering	122.82	122.01
Carrying	203.97	203.10

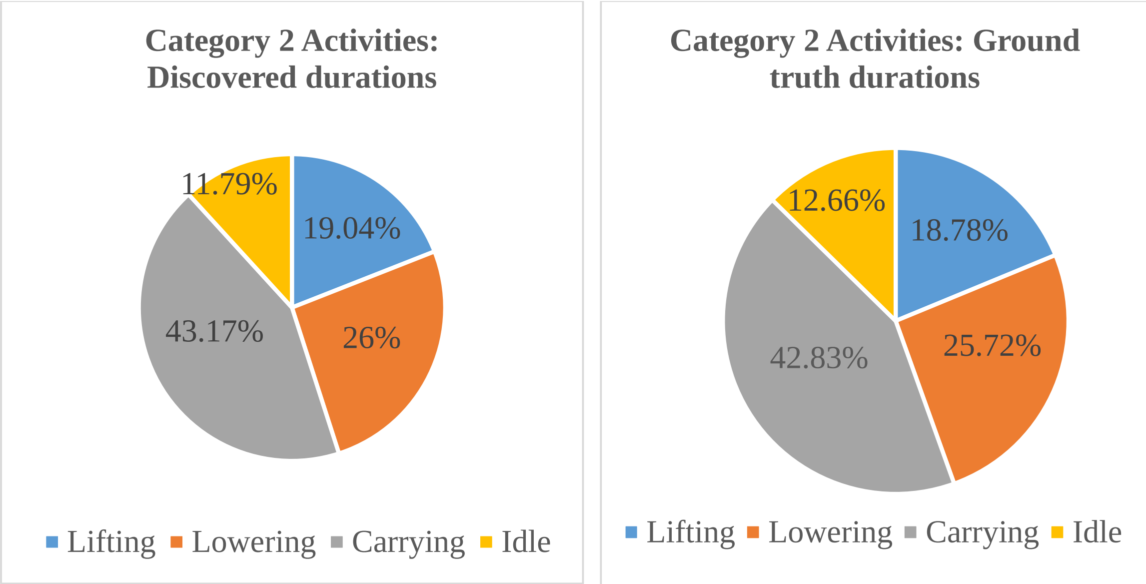

Figure 4. Discovered and Ground Truth Durations Allocation Proportion in Category 2 Activities for Productive Measurement

4.3 Category 3 activities

The accuracy of activity recognition for this category was 97.30% (SVM) followed by 95.20% (KNN), 93.60% (DT), and 90.80% (ANN). Although these accuracies were lesser than category 1 activities, they were higher than category 2 activities. Additionally, the sensitivity of classifying the time spent during category 3 activities was more than 97% in each case. Again, our results might be attributed to the fact that category 3 activities were involved similar movements with little changes in foot plantar pressure distribution data. Table 2 presents the mean of the discovered activity duration and ground truth for the 10 trials of 5 participants. Further, Fig. 3 illustrates the time allocation proportions in percentages using our developed method and the ground truth. Collectively, the high accuracies achieved by the classifiers and the discovered durations substantiate that each category of activities creates unique patterns of foot plantar pressure distribution data that could allow the estimation of productivity.

Table 2. Mean Durations in Category 2 Activities

Category 3 Activities	Discovered durations	Ground truth durations
Pulling	130.86	130.26
Pushing	120.84	120.22

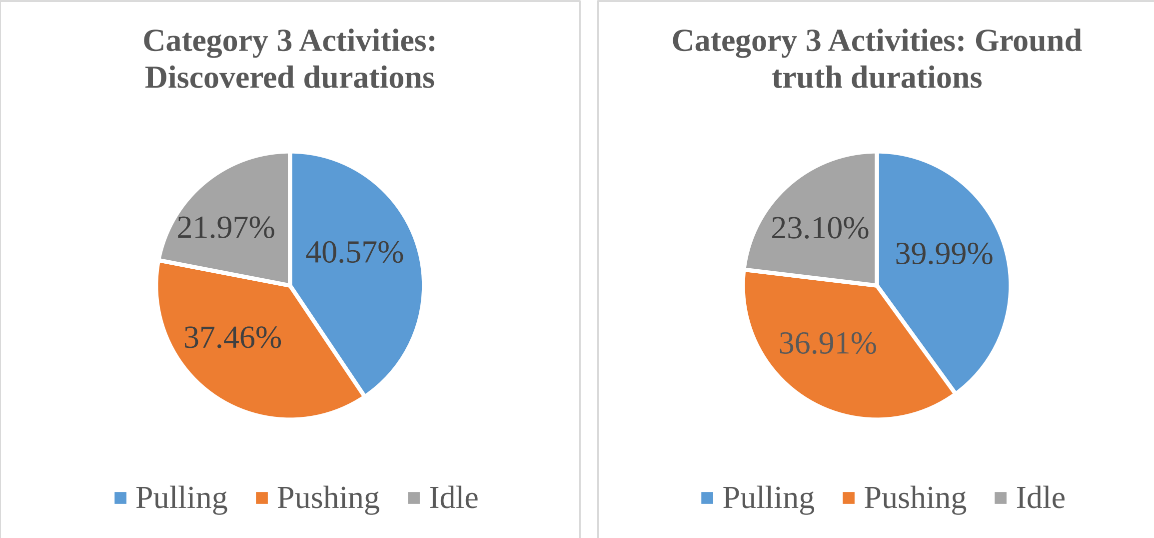

Figure 5. Discovered and Ground Truth Durations Allocation Proportion in Category 3 Activities for Productive Measurement

5. Conclusions

This paper examined a novel and non-intrusive methodology for automated recognition of construction activities for productivity measurements. The developed approach used a wearable insole pressure system to quantify foot plantar pressure distribution. Simulated laboratory experiments were conducted to test the feasibility and reliability of the proposed methodology by using four types of supervised machine classifiers (i.e., ANN, DT, KNN, and SVM) at 0.32s window sizes. Our results showed that the SVM classifier obtained the best results with an accuracy of more than 94% and sensitivity of each category of activities above 95% using a sliding window size of 0.32s. Moreover, it was found that the time allocation proportions between the activity durations discovered using the developed methodology and the ground truth conducted during the experiment demonstrated excellent agreements. The main contribution of this research is the development of a novel methodology for continuous monitoring and automated recognition of construction activities that can improve the process of productivity measurements. Future research should focus on investigating ways to apply the developed methodology for automated identification of frequencies and intensity factors (in addition to durations) for ergonomic risks analyses.

Acknowledgements

The authors acknowledge the Department of Building and Real Estate of The Hong Kong Polytechnic University for funding this research. Special thanks to Mr. Mark Ansah Kyeredey and Mr. Wong Chun Fai for assisting the laboratory study set-up and all our participants.

References

Akhavian, R. and Behzadan, A. H., 2016a. Productivity analysis of construction worker activities using smartphone sensors. *In Proc., 16th Int. Conf. Comput. Civil Building Eng.*

Akhavian, R. and Behzadan, A. H., 2016b. Smartphone-based construction workers' activity recognition and classification. *Automation in Construction*, *71*(2), pp.198-209.

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*, *38*, pp. 683-694.

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, 18*(2).

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, 83*, pp. 41-47.

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, 96*, pp. 189-199.

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, 96*, pp. 433-441.

Bao, L. and Intille, S. S., 2004. Activity recognition from user-annotated acceleration data. *In: Ferscha, A., Mattern, F. (Eds) Pervasive Computing, Pervasive 2004, Lecture Notes in Computer Science*, 3001, Springer, Berlin, Heidelberg.

Behzadan, A. H., Aziz, Z., Anumba, C. J. and Kamat, V. R., 2008. Ubiquitous location tracking for context-specific information delivery on construction sites. *Automation in Construction, 17*(6), pp. 737-748.

Cawley, G. C. and Talbot, N. L., 2003. Efficient leave-one-out cross-validation of kernel fisher discriminant classifiers. *Pattern Recognition, 36*(11), pp. 2585-2592.

Dzeng, R. J., Fang, Y. C. and Chen, I. C., 2014. A feasibility study of using smartphone built-in accelerometers to detect fall portents. *Automation in Construction, 38*, pp. 74-86.

Fang, Y. C. and Dzeng, R. J., 2017. Accelerometer-based fall-portent detection algorithm for construction tiling operation. *Automation in Construction, 84*, pp. 214-230.

Gatti, U. C., Migliaccio, G. C., Bogus, S. M. and Schneider, S., 2014. An exploratory study of the relationship between construction workforce physical strain and task level productivity. *Construction Management and Economics, 32*(6), pp. 548-564.

Golparvar-Fard, M., Heydarian, A. and Niebles, J. C., 2013. Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers. *Advanced Engineering Informatics, 27*(4), pp. 652-663.

Guo, H., Yu, Y. and Skitmore, M., 2017. Visualization technology-based construction safety management: a review. *Automation in Construction, 73*, pp. 135–144.

Han, S. and Lee, S., 2013. A vision-based motion capture and recognition framework for behavior-based safety management. *Automation in Construction, 35*, pp. 131–141.

Harle, R., Taherian, S., Pias, M., Coulouris, G., Hopper, A., Cameron, J., Lasenby, J., Kuntze, G., Bezodis, I., Irwin, G. and Kerwin, D. G., 2012. Towards real-time profiling of sprints using wearable pressure sensors. *Computer Communications, 35*(6), pp. 650-660.

Hughes, S. W., Tippett, D. D. and Thomas, W. K., 2004. Measuring project success in the construction industry. *Engineering Management Journal, 16*(3), pp. 31-37.

Hwang, S., Kim, Y. and Kim, Y., 2009. Lower extremity joint kinetics and lumbar curvature during squat and stoop lifting. *BMC Musculoskeletal Disorders, 10*(1), pp. 15.

Joshua, L. and Varghese, K., 2010. Accelerometer-based activity recognition in construction. *Journal of computing in civil engineering, 25*(5), pp. 370-379.

Kang, D. W., Choi, J. S., Lee, J. W., Chung, S. C., Park, S. J. and Tack, G. R., 2010. Real-time elderly activity monitoring system based on a tri-axial accelerometer. *Disability and Rehabilitation: Assistive Technology, 5*(4), pp. 247-253.

Mathie, M. J., Coster, A. C., Lovell, N. H. and Celler, B. G., 2004. Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. *Physiological Measurement, 25*(2), pp. R1.

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, 34*(3), pp. 347-351.

Nath, N. D., Akhavian, R. and Behzadan, A. H., 2017. Ergonomic analysis of construction worker's body postures using wearable mobile sensors. *Applied ergonomics*, *62*, pp. 107-117.

Peddi, A., Huan, L., Bai, Y. and Kim, S., 2009. Development of human pose analyzing algorithms for the determination of construction productivity in real-time. *In Construction Research Congress 2009: Building a Sustainable Future*, pp. 11-20.

Pradhan, A., Akinci, B. and Haas, C. T., 2011. Formalisms for query capture and data source identification to support data fusion for construction productivity monitoring. *Automation in Construction, 20*(4), pp. 389-398.

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, 30*(4), R1–R33.

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*, *35*(4), pp. 630-636.

Ravi, N., Dandekar, N., Mysore, P. and Littman, M. L., 2005. Activity recognition from accelerometer data. *In Proceedings of the 17th International Conference on Innovative Applications of Artificial Intelligence*, Pittsburgh, PA, USA, 9-13 July 2005, 5(2005), pp. 1541–1546.

Ray, S. J. and Teizer, J., 2012. Real-time construction worker posture analysis for ergonomics training. *Advanced Engineering Informatics*, *26*(2), pp. 439–455.

Ryu, J., Seo, J., Liu, M., Lee, S. and Haas, C. T., 2016. Action recognition using a wristband-type activity tracker: Case study of masonry work. *In Construction Research Congress 2016*, pp. 790-799.

Sawacha, Z., Gabriella, G., Cristoferi, G., Guiotto, A., Avogaro, A. and Cobelli, C., 2009. Diabetic gait and posture abnormalities: a biomechanical investigation through three dimensional gait analysis. *Clinical Biomechanics, 24*(9), pp. 722-728.

Seo, J., Lee, S. and Seo, J., 2016. Simulation-based assessment of workers' muscle fatigue and its impact on construction operation. *Journal of Construction Engineering and Management, 142*(11), pp. 04016063.

Thomas, H. R., Guevara, J. M. and Gustenhoven, C. T., 1984. Improving productivity estimates by work sampling. *Journal of construction engineering and management*, *110*(2), pp. 178-188.

Yan, X., Li, H., Li, A. R. and Zhang, H., 2017. Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention. *Automation in Construction*, *74*, pp. 2–11.

Yan, X., Li, H., Wang, C., Seo, J., Zhang, H. and Wang, H., 2017. Development of ergonomic posture recognition technique based on 2D ordinary camera for construction hazard prevention through view-invariant features in 2D skeleton motion. *Advanced Engineering Informatics, 34*, pp. 152-163.