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Smartphone-based construction workers' activity recognition and classification

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ABSTRACT

Understanding the state, behavior, and surrounding context of construction workers is essential to effective project management and control. Exploiting the integrated sensors of ubiquitous mobile phones offers an unprecedented opportunity for an automated approach to workers' activity recognition. In addition, machine learning (ML) methodologies provide the complementary computational part of the process. In this paper, smartphones are used in an unobtrusive way to capture body movements by collecting data using embedded accelerometer and gyroscope sensors. Construction activities of various types have been simulated and collected data are used to train five different types of ML algorithms. Activity recognition accuracy analysis has been performed for all the different categories of activities and ML classifiers in user-dependent and -independent ways. Results indicate that neural networks outperform other classifiers by offering an accuracy ranging from 87% to 97% for user-dependent and 62% to 96% for user-independent categories.

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1. Introduction

Effective and timely analysis and tracking of workforce activities are essential to overall productivity measurement, progress evaluation, labor training programs, and safety and health management [1–3]. The construction industry, as a major contributor to the U.S. economy, has traditionally suffered from low productivity and high inefficiency stemmed from misallocating resources resulting in under-utilizing or over-utilizing them in the project. Arguably, the first step in alleviating this problem is to accurately monitor and evaluate the time spent on interconnected construction tasks involving labor force, and compare the results with project benchmarks in order to improve the amount of time and resources spent on work packages involved in typical construction activities [4]. In addition to its benefits to productivity monitoring, the outcome of this analysis can be used for stochastic process simulation input modeling, work sampling, and integrated detailed assessment and continuous workflow improvement. For instance, the authors have designed and implemented a data-driven construction simulation framework by tracking construction entities [5,6]. Joshua and Varghese [7] adopted a similar approach to facilitate the manual process of work sampling in construction projects.

Process monitoring and control provides a solid basis for tracking and measurements required for activity analysis. Recent advancements in automated data collection to track resources and measure work progress have shown promising prospects for streamlining crew activity analysis compared to the conventional (manual) approaches such as direct observations and survey-based methods. This is mostly because manual methods involving human observers are tedious, time consuming, and error-prone. Furthermore, large amounts of data should be collected in order to maintain the statistical significance of observations.

However, automated technologies for data acquisition are still being assessed in terms of their reliability and feasibility in construction domain applications. In one hand, vision-based techniques have been proposed and investigated by a number of researchers for automated activity analysis [8]. On the other hand, wireless sensor-based methodologies have been examined to collect spatio-temporal activity data [9]. While vision-based methods are often prone to extant occlusions and illumination variability in construction jobsites, sensor-based techniques do not require a clear line-of-sight (LOS) and extensive computations and can provide relatively low cost solutions (compared to laser-scanning for instance). Despite their advantages, a longstanding challenge and impediment to the widespread use of sensor-based data collection schemes is that traditional sensor installation and maintenance in construction jobsites is not a trivial task (if not at all impossible) due to prohibitive ambient factors such as dust, adverse weather conditions, and harsh working environments.

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To remedy this situation, a relatively newer data collection technique has been trending which uses ubiquitous sensors that are readily available to and carried by most individuals on a daily basis. Such technologies are, for instance, provided through built-in sensors in most mobile phones. Mobile devices are advantageous over other activity recognition data collection platforms since they unobtrusively provide a self-sufficient data collection, computing, and storage scheme. Recently, several research projects within the construction domain have taken advantage of ubiquity of smartphones to design and prototype useful applications for construction workers on the jobsite [10,11]. Such applications in essence deliver information to the site personnel, while there is a great potential to infer information using the built-in sensors. A typical smartphone has an almost inclusive subset of these context-aware sensors including accelerometer, gyroscope, GPS, magnetometer, barometer, proximity sensors, light sensors, Bluetooth, Near Field Communication (NFC), and cameras [9]. In addition to academic endeavors, a number of construction equipment and tool manufacturers have started to produce rugged drop-proof, and dust- and water-resistant smartphones specifically designed for construction jobsites [12].

This paper presents a thorough evaluation of the performance of an activity analysis framework for recognition and classification of various construction worker activities using smartphone built-in sensors. In this research, data are collected from a variety of construction activities performed by construction workers and are annotated for feature extraction to train machine learning classifiers. Data-driven methodologies in activity recognition fall into one of the two major categories of generative or discriminative approaches. While in generative approach probabilistic models such as Baysian network are used to build a description of input, the discriminative approach models the mapping from inputs to outputs or data to activities [13]. Using generative models such as hidden Markov models (HMM) and dynamic Baysian network (DBN) is not within the scope of this research since they are not capable of capturing transitive dependences of the observations due to their very strict independence assumptions.

2. Literature review

2.1. Automated recognition of construction worker activities

Previous research for activity recognition and classification of construction workers mainly falls into the vision-based category. Microsoft Kinect, for example, was employed by some researchers for vision-based activity recognition in indoor and controlled environments [14,15]. In another set of studies, 2D videos are used to collect visual data for action recognition in construction sites. For example Favela, Tentori, Castro, Gonzalez, Moran and Martínez-García [3] used a wireless video camera to extract human poses from video to recognize construction workers' actions. In a different study, 3D range image camera was used for tracking and surveillance of construction workers for safety and health monitoring [16]. Gonsalves and Teizer [16] indicated that if their proposed system is used in conjunction with artificial neural network (ANN), the results would be more robust for prevention of fatal accidents and related health issues. In their study on construction workers' unsafe actions, Han and Lee [17] developed a framework for 3D human skeleton extraction from video to detect unsafe predefined motion templates. All of these frameworks, although presented successful results in their target domain, require installation of multiple cameras (up to 8 in some cases), have short operational range (maximum of 4 m for Kinect), and require a direct LOS for implementation. Such shortcomings have served as a major motivation to investigate alternative solutions that can potentially alleviate these problems.

Recently, researchers in construction engineering and management (CEM) have investigated the applications of senor-based worker activity analysis. For example, a data fusion approach using ultra-wide band (UWB) and Physiological Status Monitors (PSMs) for productivity [4] and ergonomics [18] analysis was proposed. In these studies, UWB and PSM data were fused and the result was categorized using a spatio-temporal reasoning approach. However, the level of detail in recognizing the activities was limited to identification of traveling, working, and idling states of workers and could not provide further insight into identified activities. Prior to this study, the integration of UWB, payload, and orientation (angle) data with spatio-temporal taxonomy-based reasoning was adopted by the authors for construction equipment activity analysis to support process visualization, remote monitoring and planning, and knowledge-based simulation input modeling [19–21]. More recently, the authors have used smartphone-based data collection and activity recognition for data-driven simulation of construction workers' activity by extracting process knowledge and activity durations [22]. Joshua and Varghese [7] were among the first researchers who explored the application of accelerometer in construction for work sampling. However, the scope of their work was limited to only a single bricklayer in a controlled environment. Moreover, their proposed framework used accelerometer as the sole source of motion data. Also, the necessity of installing wired sensors on the worker's body may introduce a constraint on the worker's freedom of movement.

2.2. Activity recognition using cellphone sensors

Detection and classification of human activities using wearable inertial measurement units (IMUs) consisting of accelerometer and gyroscope gained traction among computer science researchers in mid-2000′s with applications in different fields such as healthcare and sports [23–25]. In all such studies, data pertaining to human physical movements are captured using IMUs and different postures and dynamic transitions are detected by training classifiers. However, recent studies are mostly geared toward leveraging the ubiquity, ease of use, and self-sufficiency of mobile phones for human activity recognition [26–29]. In one study, Reddy, Mun, Burke, Estrin, Hansen and Srivastava [30] used decision tree and dynamic hidden Markov model (DHMM) to classify activities such as standing, walking upstairs, biking, driving a car, and jumping using accelerometer and GPS data. In another research, Sun, Zhang, Li, Guo and Li [28] used support vector machines (SVMs) to build a human daily physical activity recognition system using mobile phone accelerometers. More recently, mobile phone gyroscope has been also employed in addition to accelerometer for activity recognition. For example, using accelerometer and gyroscope data and hierarchical SVM, Kim, Cho and Kim [31] classified daily activities to sitting, walking up- and downstairs, biking, and having no motion. Moreover, Martín, Bernardos, Iglesias and Casar [32] used decision table, decision tree, and naïve Bayes to classify data from various smartphone sensors such as accelerometer and gyroscope to classify daily activities into standing, sitting, jogging, and walking upstairs.

Despite its great potential for construction automation, and considering the existing interest in construction workers' activity recognition, the application of such emerging data collection platforms has not been fully investigated within the CEM domain. In the research presented in this paper, signature patterns observed in the signals received from wearable IMUs of ubiquitous smartphones are analyzed to recognize activities performed by different construction workers.

3. Research objectives and contributions to the body of knowledge

As stated in the previous Section, existing work on activity recognition within the CEM domain has primarily focused on vision-based systems while a very limited number of studies aimed at developing multi-modal sensor-based data collection schemes. Hence, the presented study in this paper contributes to the body of knowledge by investigating construction worker activity recognition through (1) using the sensors embedded in mobile phones to (2) identify complex activities that consist of more than one task by (3) deploying combined features of

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