Productivity Analysis of Construction Worker Activities Using Smartphone Sensors

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Abstract:

Low productivity has been a longstanding issue in the construction industry. A comprehensive remedy to this problem not only does require the adoption of improved construction methods and resource utilization, but also calls for a robust, effective, and standard protocol to measure productivity especially in complex and dynamic construction jobsites. Research has shown that activity-level productivity analysis can serve as one of the most reliable decision support tools in construction operations. The backbone of such analysis is collecting and mining process-level data from construction entities on a jobsite. While manual data collection methods are prone to inaccuracy and inconsistency, and are almost always time consuming, automated data collection procedures have shown a promising prospect in construction industry research. This paper discusses a novel methodology for automated activity-level productivity measurement within the construction engineering and management context. In this methodology, pervasive smartphones provide the basis for data collection from construction workers. The collected data are then used as the input of machine learning classification algorithms to detect and differentiate between several classes of human activities. While recognizing the idle/busy state of the workers provides key information required for productivity analysis, the presented research further advances this information by extracting even more particular and accurate knowledge about different activities carried out by construction workers. For validation, results of various experiments including multiple construction activities are reported in this paper.

Keywords: Activity analysis, productivity, construction, workers, labor productivity, smartphone, machine learning, sensors

1. INTRODUCTION

Monitoring construction productivity by observing and analyzing activities enables project performance improvement (Pradhan et al., 2011). According to different research studies and based on industry data, construction productivity has had a track record of prolonged decline (Allen, 1985; Triplett & Bosworth, 2004). Monitoring productivity is not a trivial task in construction considering the dynamic nature of projects that involve a variety of inherently complex activities. However, the use of advanced technologies in managing resources on construction jobsites has shown promising prospects for productivity growth (Goodrum et al., 2010; D. Grau et al., 2009). While the application of cutting edge technologies results in higher productivity, it is essential to consider the effect of added cost to the project as well. In other words, the added cost of incorporating advanced tools should offset the project cost reduction as a result of productivity improvement. Nevertheless, when the technology is leveraged effectively and efficiently, significant value is gained in construction projects.

In order to improve labor productivity it has to be measured. There are various methods to measure productivity the majority of which depends on understanding how effectively time is utilized in the project. Data collection from the jobsite and tracking the resources have been extensively used to provide productivity measures and make improvement recommendations. However, a practical, sustainable, and feasible data collection methodology should not interfere with the actual work in progress. In addition, the specific characteristics of a typical construction jobsite in which the presence of dust, water, and debris is inevitable calls for a low maintenance data collection scheme. Also, when collecting data from a large number of entities, issues such as calibration of each sensor and synchronization of the whole data collection network, data storage, and data transfer -for real or near real time applications- might be prohibiting.

Considering the abovementioned factors, a data collection scheme that is cost effective, nonintrusive, low maintenance, and feasible in terms of calibration, data storage, and data transfer is desirable. Therefore, this paper discusses the use of smartphone sensors for automated data collection and productivity measurement. Specifically, pervasive smartphones are used to collect data from construction workers' activities. The collected data are then used to recognize activities performed by construction workers which in turn reveals the time spent on each activity. Using the determined activity durations and particularly the time periods during which workers were idle, measures for productivity analysis can be provided.

2. RESEARCH BACKGROUND

It is almost impossible to make a universal definition of construction productivity mainly because each company has its own definition and guidelines for productivity according to its unique project control system (Crawford & Vogl, 2006; Nasir et al., 2013). The heterogeneity of inputs and outputs make it very difficult to establish a fixed definition for productivity in construction. Nevertheless, factoring in the time and measuring productions over time makes it easier to compare productivity and determine its growth or decline (Nasir et al., 2013). Therefore, performance metrics of productivity often consider the time component. For example, in a study to assess the impact of automated identification and localization approach on craft productivity, labor productivity at a lay down yard was defined as time spent on specific tasks by lay down yard workers, and steel erection productivity was defined as weight of installed components per work hour (Grau et al., 2009).

Many research studies evaluated the application of automation and information technology in monitoring and potentially increasing construction productivity. For example, Pradhan et al. (2011) demonstrated that monitoring construction productivity needs multimodal data fusion from multiple data sources for different queries from project engineers. Their approach enables automated and efficient multi-source data fusion. In another research, it was found that at the activity level, equipment technology in general has caused a great long-term improvements in labor productivity (Goodrum & Haas, 2004). The relationship between automation and construction productivity has been extensively explored by Zhai et al. (2009) where they concluded that information technology has had positive impact on productivity of construction projects and the trend is likely to be similar in the future. It was also stated that both automation and integration of project information systems can lead to better construction labor productivity performance (Zhai et al., 2009).

Automated data collection from jobsites using radio frequency based positional and/or identification sensors, such as global positioning system (i.e. GPS) and radio frequency identification (i.e. RFID), for automated resource tracking are extensively used to analyze construction operations (Hildreth et al., 2005; Navon & Sacks, 2007). For example, Navon and Goldschmidt (2003) have previously attempted to automatically determine the activity a worker is engaged in by knowing their location. This was done with the simplifying assumption of considering work envelope (WE) which is the volume, normally in the vicinity of a building element, where a worker, working on that element, should be located. Admittedly however, relying merely on WE cannot result in absolute determination because workers could be outside the WE of an element and still be engaged in adding value to an activity associated with it or be inside and not adding value (Navon & Goldschmidt, 2003). That is why determining the type of the work performed using more accurate and deterministic activity duration methods are preferable to such reasoning-based framework.

Among other techniques that have been previously employed for activity recognition of workers in construction environment is vision-based systems. Wireless video cameras, Microsoft Kinect, and 3D range image cameras are some of the technologies that researchers used to monitor and detect specific activities (Gonsalves & Teizer, 2009; Han & Lee, 2013). Specifically for the purpose of productivity analysis, Gong and Caldas (2010) developed a video interpretation model to automatically interpret videos of construction operations into productivity information. However, requiring multiple cameras or vision sensors, having short operational range, and the need for a direct line of sight are among the challenges one encounters when implementing such systems. Another school of thought in data collection for activity recognition in construction is using microelectromechanical sensors (i.e. MEMS). The authors have previously explored using sensors for simulation input modeling, evaluation of queuing systems, and equipment fuel consumption monitoring (Akhavian & Behzadan, 2013a, 2013b, 2014). Specific towards productivity assessment, Cheng et al. (2013) used a data fusion approach to integrate ultra-wide band (UWB) and Physiological Status Monitors (PSMs) data to facilitate real time productivity assessment.

This research benefits from employing smartphone onboard accelerometer and gyroscope sensors for productivity assessment using machine learning classifiers. To date, research efforts have not extensively explored the potential of this mobile sensor fusion technique. While the application of accelerometer in construction for work sampling has been explored in one research study in a limited scope only for a single bricklayer in a controlled environment, gyroscope data has never been fused to increase the accuracy, and the wired sensor limited the worker's freedom of movement (Joshua & Varghese, 2010). One of the most important reasons for lack of comprehensive studies on this subject is the complexity of activities in the dynamic environment of a construction project. There is a great deal of research studies on recognizing human activities in areas other than construction, but almost all of them are limited to detection of daily and routine human movements. In particular to using smartphone sensors for human activity recognition, one study 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 (Reddy et al., 2010). 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 support vector machines (SVMs), Kim et al. (2013) classified daily activities to basic classes of sitting, walking up- and downstairs, biking, and having no motion. As it was mentioned before, all such studies attempt to recognize activities within the limit of daily routine work, while activities performed in construction jobsites by nature have more layers of complexity.

3. RESEARCH METHODOLOGY

As stated before, there is no common definition for construction productivity that is acceptable and approved by the industry and academia. What is used frequently though is the ratio of production output over the input. However, it is very difficult to define the input and output because they are always dependent on the scope of the measure and availability of data (Crawford & Vogl, 2006). Labor productivity, however, is one of the most reliable and frequently used metrics for evaluating project productivity, according to the Construction Industry Institute (CII) and the Organization for Economic Co-operation and Development (OECD) (CII, 2010; OECD, 2010). This method of calculating productivity is formulated in equation 1.

$$Labor\ Productivity = \frac{Unit\ of\ Physical\ Output}{Work\ Hours} \quad (1)$$

There are other productivity measurement methods that rely heavily on the labor work hours. For example, performance ratios is a measure that is used to evaluate the project overall productivity. This measure compares the total number of work hours required to complete a given quantity of work by a certain date to the scheduled work hours that was considered to complete the work (Gong & Caldas, 2011). Another method that is very common in measuring productivity in construction is work sampling. Work sampling evaluates the productivity by measuring how time is utilized by the labor force (Thomas, 1991). The actual and exact procedure to perform work sampling and its effectiveness however, is a subject of debate in construction productivity assessment. Therefore, a modern version of work sampling has been recently introduced by a team of researchers from academia and the industry (CII, 2010; Gouett et al., 2011). Similar to all the aforementioned methods, activity analysis deals with how workers use their time on a jobsite and tries to quantify how craft workers spend their time.

In this research, an automated methodology is introduced, implemented, and verified that uses activity recognition to assist in concrete understanding of how time is spent by various workers. Different components of this framework are depicted in Figure 1.

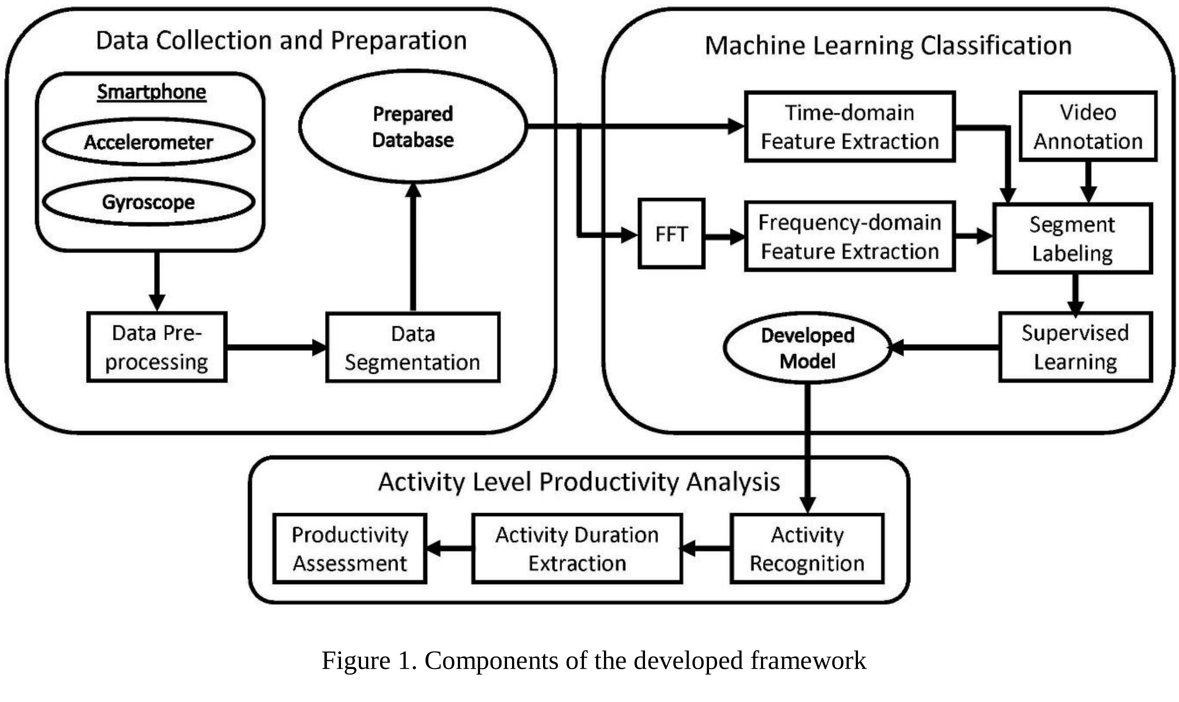

Figure 1. Components of the developed framework

As shown in Figure 1, accelerometer and gyroscope sensors of smartphone are used to collect raw data. This data is collected in three dimensions so that a fixed orientation for the smartphone during data collection would not be mandated. The accelerometer sensor measures the acceleration of the device while gyroscope measures its angular velocity. When the mobile device is attached to a human body involved in different activities, these two sensors generate different and unique patterns of signal.

The collected data should go through a series of data preprocessing steps to be prepared for the next phases. For example, there might be some missing data points that if not handled properly, could cause data synchronization between the two sensors to be erroneous. Also, accelerometer sensors are sometimes characterized by a drift in their data collection process and this is another reason why preparation of the data to account for such drifts is recommended. After data are pre-processed, they should be segmented into windows with certain size (i.e. number of data points) to prepare data for feature extraction. The frequency of100 Hz for both accelerometer and gyroscope was used in the research experiments. Also, windows of 128 data points were segmented and 50% overlap between windows were considered.

Features that are used in this research are of two types, statistical time-domain, and frequency domain. In order to obtain the frequency-domain features, the fast Fourier transform (FFT) procedure is applied on the time-domain features. Once the features are extracted, each time window will be associated with a label that characterizes an instance of an activity. This process is facilitated by mapping the activity labels to the recorded video of the activities performed during data collection. The extracted features associated which each time window and their corresponding labels will then be used to train a supervised machine learning algorithm. Previous research conducted by the authors showed that artificial neural network (ANN) and k-nearest neighbor (KNN) result in successful activity recognition (Akhavian & Behzadan, 2015). Therefore, both algorithms are trained with the collected data in this research and an ensemble of them is used. Bootstrap aggregation or Bagging is the ensemble algorithm used in this research. Using this algorithm, T training data subsets each containing m training examples are selected randomly with replacement from the original training set of m examples. The classification result of the ensemble is determined through plurality voting (Lin et al., 2003). Here, the number of training dataset is T = 20.

The ANN used for training had one hidden layer. The input layer consisted of 54 input units that was the total number of features extracted. The hidden layer consists of p = 25 units. The number of units for the output layer is equal to the number of activity classes. Given the large feature space and in order to prevent overfitting, regularization was used. Using a regularization parameter, the magnitude of the model weights decreases, so that the model will not suffer from high variance to fail to generalize to the new unseen examples (Haykin et al., 2009). The activation function (i.e. hypothesis) used for minimizing the cost function in the training process is a Sigmoid function, as shown in Equation 2,

$$h_{\Phi}(x) = \frac{1}{1+e^{-\Phi x}} \tag{2}$$

in which $h(x)$ is the activation function (i.e. hypothesis), Φ is a matrix of model weights (i.e. parameters), and x is the features matrix. In this study, in order to minimize the cost function, the most commonly used neural network training method, namely feed-forward backpropagation is used. Considering a set of randomly chosen initial weights, the backpropagation algorithm calculates the error of the activation function in detecting the true classes and tries to minimize this error by taking subsequent partial derivatives of the cost function with respect to the model weights (Hassoun, 1995).

In the KNN algorithm, training examples identified by their labels are spread over the feature space. A new example is assigned to a class that is most common amongst its K nearest examples considering the Euclidean distance that is used as the metric in this research, as shown in Equation 3,

$$D = \sqrt{(x_i^{(1)} - x_{new}^{(1)})^2 + (x_i^{(2)} - x_{new}^{(2)})^2 + \cdots + (x_i^{(d)} - x_{new}^{(d)})^2} \tag{3}$$

in which D is the Euclidean distance, x_i is an existing example data point which has the least distance with the new example, x_{new} is the new example to be classified, and d is the dimension of the feature space.

The trained developed model is now ready for recognizing unseen activities. In particular, the unseen activities produce new raw data that will go through the same process that was used for training. This means that the same features will be extracted from each dataset of new and unseen activities. This time, however, the labels are predicted according to the model that is developed. Once the recognized and classified activity labels are generated, the duration of each activity is computed. The process, however, is not as straightforward as counting the number of segments detected to be associated with specific label. During each instance of detected activity, segments might be detected incorrectly that do not belong to that activity. A heuristic process is used here to detect such window labels and replace them with the correct label. For example, few instances of class C_2 classified after many instances of class C_1 followed by other instances of class C_1 are considered as class C_1. The exact numbers followed by this heuristic algorithm depends on the sampling frequency, window size, and rough approximation of the activity durations. As a result of this procedure, activity duration extraction will be further improved, thus leading to higher accuracy in activity recognition.

4. EXPERIMENTS AND RESULTS

In order to implement the developed framework, several experiments were designed and conducted. Data was collected from human subjects simulating typical activities performed in construction jobsites. These activities included sawing, hammering, turning a wrench, loading sections into wheelbarrows, pushing loaded wheelbarrows, dumping sections from wheelbarrows, and returning with empty wheelbarrows. Activities were performed in 3 different categories. The first category included only one activity; sawing. In this case, the goal of activity recognition was to differentiate between the time workers were sawing and the time they were not sawing (i.e. they were idle). The second category included hammering and turning a wrench as it was observed that this two activities produce similar movements on the upper arm, where smartphones were worn by workers for data collection. Finally, the third category included a number of activities with different levels of vibration produced on a worker's body. These activities included loading sections into a wheelbarrow, pushing a loaded wheelbarrow, dumping sections from a wheelbarrow, and returning with an empty wheelbarrow.

4.1 Category 1 Activities

Figure 2 shows a worker performing the activity in category 1 (i.e. sawing) while data is being collected using the smartphone on his upper right hand arm. The accuracy of activity recognition for this category was 99.28%. The mean of the discovered activity duration for 30 instances of sawing was 27.97 seconds while the ground truth obtained from the recorded video of the experiment was 27.95 seconds. Moreover, discovered activity durations showed that the worker was sawing 69.79% of the total time of the experiment and was idle in the remaining time. The ground truth for this category was 69.72%.

Figure 2. Worker performing category 1 activity

4.2 Category 2 Activities

Figure 3 shows a snapshot of category 2 activities (i.e. hammering and turning a wrench). The smartphone can be seen on the worker's upper left arm. In this case, the accuracy of activity recognition was 92.97% which is less than the result achieved in the first category. This is primarily because the number of activities increased, and the two activities were producing similar movements of the arm. Nevertheless, ~7% error is still considered a reliable result considering the complex nature of such activities. The mean of the discovered activity duration and ground truth for 30 instances of hammering and turning a wrench are compared in Table 1. In addition, Table 2 compares the time allocation percentages discovered using the developed data analysis methodology and the ground truth.

Figure 3. Worker performing category 2 activities

Table 1. Activity analysis result in terms of the mean of activity durations in category 2

Activity	Discovered Duration (s)	Ground Truth Duration (s)
Hammering	17.59	17.05
Turning the Wrench	13.44	13.39

Table 2. Activity analysis result in terms of time allocation proportions of activity durations in category 2

Activity	Discovered (%)	Ground Truth (%)
Hammering	44.6	41.7
Turning the Wrench	35.1	34.2
Idling	20.3	24.1

4.3 Category 3 Activities

A snapshot of the activities performed by the worker in this category is shown in Figure 4. This category included activities such as loading sections into a wheelbarrow, pushing a loaded wheelbarrow, dumping sections from a wheelbarrow, and returning with an empty wheelbarrow. The accuracy achieved in this case for activity recognition was 90.09%. The most important reason for achieving an accuracy less than the other two categories is the increased number of activities. However, again the error is less than 10% which is very promising for productivity assessment purposes. Table 3 tabulates the discovered and ground truth activity durations, and Table 4 shows the time allocation percentages discovered using the developed data analysis methodology and the ground truth.

Figure 4. Worker performing category 3 activities

Table 3. Activity analysis result in terms of the mean of activity durations in category 3

Activity	Discovered Duration (s)	Ground Truth Duration (s)
Loading	9.24	8.96
Pushing	14.14	14.02
Unloading	13.53	13.18
Returning	11.39	11.33

Table 4. Activity analysis result in terms of time allocation proportions of activity durations in category 3

Activity	Discovered (%)	Ground Truth (%)
Loading	15	14.6
Pushing	23	21.9
Unloading	21	21.5
Returning	19	19.7
Idling	22	22.3

5. CONCLUSIONS

Previous research studies have shown that construction activity analysis has a high potential to evaluate productivity and to design strategies to improve productivity (Cheng et al., 2013; Gouett et al., 2011). The presented research in this paper introduced an activity analysis framework built upon automated activity recognition. The hardware component of the developed framework consisted of onboard sensors of ubiquitous smartphones. The analysis component was a supervised machine learning process that was trained and developed to assist in recognizing construction activities. It was shown that analysis of time spent on different activities conducted by workers plays an important role in assessing productivity in construction. Further, it was discussed and verified that the time allocated to different activities can be obtained using the developed activity recognition technique. The framework was validated through a series of experiments. In these experiments, the accuracy achieved for activity recognition was over 90% which shows a very close agreement between activity durations discovered using the developed framework and the ground truth observed in the experiments. The future work in this research encompasses the application of the activity recognition system for safety and ergonomics analysis and improvement.

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