DATA-INFORMED DECISION MAKING IN CONSTRUCTION ENGINEERING USING SENSORS AND MACHINE LEARNING

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ABSTRACT

The "high volume, high velocity, and high variety information assets" or Big Data are finding their niche in decision-making process within the construction industry. Smart cities and internet of things, as two recent sensor-centric phenomena have been emerged to offer solutions for critical urban problems pertaining to energy efficiency, transportation planning, and risk mitigation. However, deployment of sensors, as the backbone of these innovative phenomena in design, planning, and construction of the smart cities' infrastructure has yet to be investigated by researchers in academia and industry. Automated activity recognition of heavy construction equipment as well as human crews can contribute to correct and accurate measurement of a variety of construction and infrastructure project performance indicators. Productivity assessment through work sampling, safety and health monitoring using worker ergonomic analysis, and sustainability measurement through equipment activity cycle monitoring to eliminate ineffective and idle times thus reducing greenhouse gas emission (GHG), are some potential areas that can benefit from the integration of automated activity recognition and analysis techniques. In light of this, this paper describes the latest findings of ongoing research that aims to design and validate a ubiquitous smartphone-based automated activity recognition framework using built-in inertial sensors.

Keywords: construction industry, data-informed, data-driven, decision making, machine learning.

INTRODUCTION

In the realm of the business process management, process mining as a relatively new research domain seeks to automatically discover a process model by observing activity records and extracting information. Process mining, in essence, requires substantial data analysis to discover trends and patterns. Thanks to the cost-effective, ubiquitous, and computationally powerful means of data collection and analysis, data-informed process mining and decision making have become prevalent. In the present era of data analytics, industries leverage the power embedded in the abundant data generated rapidly to improve procedures and facilitate decision making. The architectural, engineering, construction, and facility management (AEC/FM) industry as well, begins to realize the benefits of data-driven approaches. In this paper, recent trends in leveraging the power of data through the use of machine learning techniques in the AEC/FM industry are presented. Additionally, the future potentials of similar applications are evaluated and discussed.

LITERATURE REVIEW

According to the United States Department of Commerce, construction and infrastructure projects comprise a trillion dollar industry with a continuous annual increase in pace [1]. Although there have been many efforts to increase the productivity of construction and infrastructure projects in recent years, the industry is still suffering from low productivity growth [2–5]. There are several key factors that can influence productivity in construction and infrastructure industry, including the uncertain, dynamic, and transient nature of most construction projects. As infrastructure projects increasingly become larger and more complex in nature, traditional manual quantitative analysis methods mostly fail to effectively and accurately capture key project productivity performance indicators [6]. The basic concepts and existing techniques of multimodal data acquisition and fusion have been investigated in several research studies thst aimed at introducing solutions to specific problems within construction engineering. For example, [7] explored developing an experience database to fuse payload, temperature, and cycle-time data for the load activity in an earthmoving operation. In another study, as-design spatial information was fused with as-is laser scanner spatial data to detect construction defects [8]. Researchers also worked with positional data from global positioning system (GPS) and radio frequency identification (RFID) to estimate the coordinates of construction equipment and inventory items [9]. More recently, spatial (e.g., soil type) and temporal (e.g., weather) data were fused to support construction productivity monitoring [10].

Considering the dynamic and complex environment of most construction project sites, being able to control and measure the efficiency of construction resources is vital to the overall performance of the project in terms of time and financial resources. Moreover, by monitoring workers and equipment activities, catastrophes that include safety and health issues as well as many lawsuits could be prevented. [11] used ultra-wide band (UWB) and Physiological Status Monitors (PSMs) for productivity assessment. However, the LoD 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. In another set of research studies aiming at construction equipment activity analysis to support process visualization, remote monitoring and planning, queueing analysis, and knowledge-based simulation input modeling, the authors developed a framework by fusing data from ultra-wide band (UWB), payload, and orientation (angle) sensors to build a spatio-temporal taxonomy-based reasoning scheme for activity classification in heavy construction [12, 13, 14]. Sensor data can be used to train machine learning algorithms for classification and prediction problems. Example of such sensors that can be used for recognizing activities of construction resources such as workers or equipment are accelerometers and gyroscopes. Researchers have evaluated applications that include activity analysis of workers [15], safety of ironworkers [16], and equipment activity recognition [17]. In this paper, three main application areas of sensors-based systems that leverage machine learning power for process mining and activity recognition are discussed.

Construction Safety

Construction companies pay a substantial amount of money for expenses directly or indirectly related to their workers' injuries. Records from National Academy of Social Insurance (NASI) show that in 2013 employer costs for workers' compensation were $88.5 billion for 129.6 million covered workers [18]. Previous research indicates that construction labors have the highest rate of Work-related Musculoskeletal Disorders (WMSDs) among all industries [19]. One way to prevent WMSD injuries is to use wearable sensors to detect unsafe activities. A team of researchers used EMG-based model to evaluate muscle force that affects spinal and lumbar [20]. Other studies used both accelerometer and gyroscope data from worker's motions and construction equipment to auto-recognize and categorize construction tasks through activity recognition [21, 22]. Such used supervised machine learning algorithms to train computers for classifying unseen activities (i.e. those not presented in the training phase). In other words, the computer should understand the nature of the activity and its category through the collected and labeled data to be able to prepare them for an assessment of the safety level of the activity. Inertial Measurement Unit (IMU) sensors as one of the most accurate activity recognition tools have helped researchers to collect and transfer data from any moving subjects [23]. The data from these type of sensors can translate into a host of information that can help more thorough analysis of the activity.

Construction Productivity

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 [24, 25]. 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 [26]. 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 [27, 28]. Specifically for the purpose of productivity analysis, [29] 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).

Sustainable Construction

According to the Environmental Protection Agency (EPA), construction industry is ranked third just behind the “oil and gas” and the “chemical manufacturing” sectors in terms of contributing to greenhouse gas (GHG) emission [30]. Extensive use of energy-intensive equipment, in particular, produces high levels of emission. EPA states that if diesel fuel consumption reduces by only 10%, CO_2 emission will decrease by 14.8 million pounds or approximately 5% of the entire energy consumption in the construction sector [31]. [32] developed a model for construction equipment emission rates in which various modes of equipment duty cycles including the idle mode accounted for different fuel use and emission rates. In another study, equipment activity durations and idle time were extracted to update a data-driven simulation model in real time [33]. [34] used vibration signal analysis to monitor the operational status of construction equipment involved in different activity modes (working or idling). Although all such work highlighted the role of idling as one of the duty cycle modes of construction equipment that contributes to the overall equipment emission in a non-productive manner, none of the previous work in this area investigated the prospect of detecting idling instances to provide solutions for idling and emission reduction.

METHODOLOGY AND RESULTS

IMU data can be collected using smartphones. In this section, three similar frameworks that use smartphone IMU sensors to detect activities are presented. Each framework serves a different purpose and application area within the construction engineering and management domain.

Construction Safety

Data collection phase of this study was conducted in an engineering research lab (i.e. a controlled environment). All the experiments were videotaped to assist in labeling and cross-referencing the collected data and performed activities. A 25 years old male Construction Management graduate student (i.e. the simulated worker) conducted the experiments who provided written informed consent to participate in the study. BTE Simulator II used to simulate construction physical activities includes a series of 21 attachments that can be mounted on its exercise head in multiple positions to facilitate simulation of several activities and movement combinations. The simulator can be connected to a computer that allows selection of the desired resistance and measures performance by quantifying the force exerted, work done, and power output while the task is being performed. Figure 1 shows a snapshot of the actual experiment as well as the experimental design of the developed methodology.

A total number of 10 experiments were conducted each of which with a relatively fixed level of power consumed as reported by the BTE Simulator II. Each experiment lasted for around 20 seconds. An approximation of the net force (F) exerted was achieved using Equation (1)

$$F = \frac{P \times t}{d} \tag{1}$$

in which F is the net force exerted in Newton (kg.m/s^2), P is the power displayed by the BTE Simulator II in Watt (kg.m^2/s^3), "t" is the duration of the experiment in seconds, and "d" is the displacement of the simulated worker's arm in meter. For example, using Equation 1, for a measured power level of 2.5 Watt in one experiment that lasted for 20 seconds with a measured distance of 1 Meter, the force is calculated as 50 Newton.

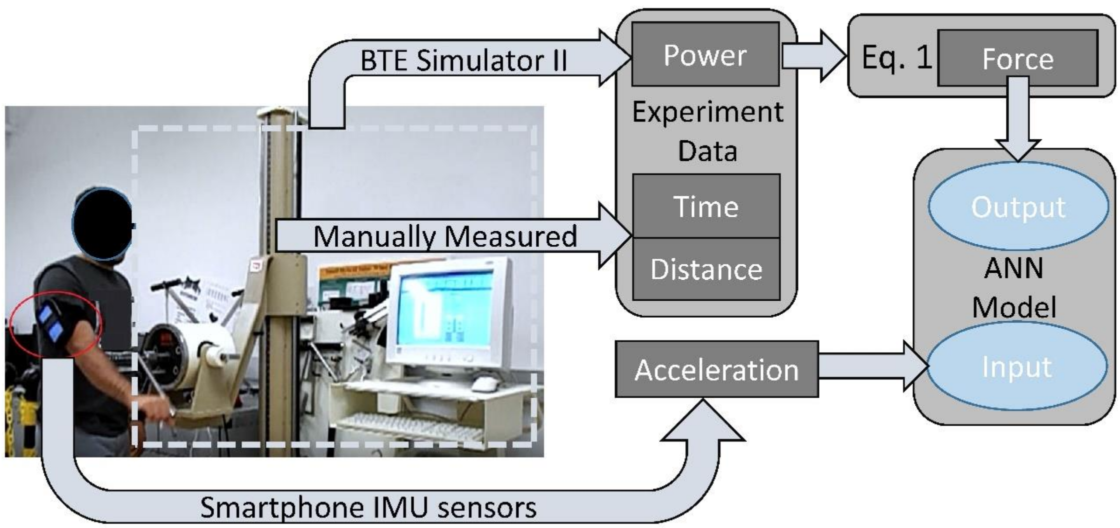

Figure 1: Experimental design of the developed methodology.

A smartphone was affixed to the simulated worker's arm with a sports armband to capture acceleration data in three dimensions using its IMU sensors. Sensor Log smartphone application was employed which is a commercially available smartphone app for iOS and Android operating systems. This application reports a variety of signals including Acceleration, Gyroscope data, Core Location, Device Motion, Decibels, Pedometer Data, and Pressure from different sensors of the smartphone. The data collection frequency was set at 35 Hz using the Sensor Log application interface. This ensures collecting enough data for model training as well as capturing all the body movements. The recorded data from this application was extracted in Comma Separated values (CSV) format. Before analyzing the collected data, a data preparation step is required to assure data quality and cleanliness. Toward this goal, the raw data were plotted in Microsoft Excel and cross-referenced against the recorded video. Outliers and redundant data points captured during the transition periods between the experiments were removed. Finally, the prepared data was imported to Python software for the analysis stage.

Artificial Neural Network (ANN) was employed in this study to develop a model trained by the acceleration data as the input and measured forces as the output. The ultimate goal is to prepare a model capable of predicting unseen force levels using acceleration data provided to it. ANN is a machine learning method which works similar to the way brain neurons process information and develops relationships for classification and prediction purposes. The hidden layers of an ANN network collect the input and process them to generate the output [35, 36].

A total of 10 experiments were conducted with different power (force) values. Approximately 66% of the data was used to train the ANN model. The ANN structure included two hidden layers to make the connection between the input layer (i.e. acceleration data) and the output layer (i.e. net forces). Gradient decent was used as the optimization algorithm within the ANN model training using a feedforward backpropagation method.

ANN model training and testing was performed in Python and training and testing results were recorded. In ANN training, the weights of the parameters in the cost function need to be updated and this updating process has to happen more than once since gradient decent is an iterative process. When the dataset is passed through the neural network it is called one epoch.

The result of the model training and testing is shown in Figure 2. After around 2 epochs, an accuracy of slightly higher than 87% was achieved. As the number of epochs increased, the accuracy converged to around 87.5%.

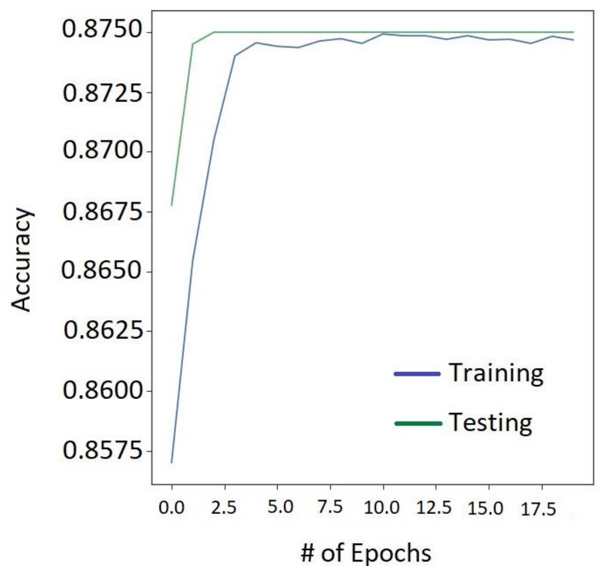

Figure 2: Results extracted from python for ANN.

Construction Productivity

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 [37, 38]. 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) [39, 40]. This method of calculating productivity is formulated in equation 1.

$$Labor\ Productivity = \frac{Unit\ of\ Physical\ Output}{Work\ Hours} \qquad (2)$$

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 3. As shown in Figure 3, 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.

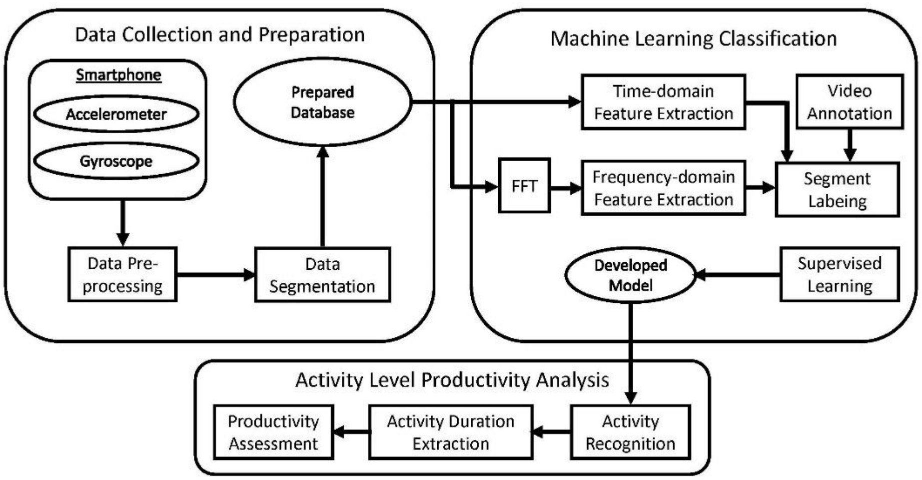

Figure 3: Components of the developed framework

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 [15]. 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 [41]. Here, the number of training dataset is T = 20.

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. Figure 4 shows some snapshots of the experiments.

Figure 4: Worker performing activities in 3 categories with data collection device (i.e. smartphones) affixed on their arms

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%. In Category 2, 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. Category 3 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 1 and 2 present the results for categories 2 and 3.

Sustainable Construction

Recent research has made significant progress in developing activity recognition frameworks using machine learning algorithms. More recently, deep learning neural network models have made such frameworks even more accurate. Data is collected from real-world activities performed by construction equipment such as excavators and loaders. The goal of this project is to use sensor data and machine learning methods to evaluate the fuel use and greenhouse gas (GHG) emission of construction equipment.

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 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

The data is used to train and evaluate the performance of deep feed-forward networks (DNN) and recurrent networks that rely on Long Short-Term Memory cells (LSTMs). The preliminary results indicate the superiority of recurrent networks in terms of accuracy, precision, and recall. The long-term objective of this project is to enable accurate prediction of activities for equipment emission estimation. Different discrete even simulation (DES) models are developed to simulate heavy civil construction operations such as grading, compacting, material delivery, and earthmoving. Additionally, a novel framework based on the equipment activity cycle is proposed to predict emission. The emission output is then compared to Environmental Protection Agency (EPA)'s NONROAD model, the California Air Resources Board's (CARB) OFFROAD model, and a modal model proposed in the literature. Results indicate that the developed framework in this research provides more accurate emission estimation compared to all the three models. Figure 5 shows the overall framework. Detailed results of this part of the research will be presented in the WDSI 2019 conference.

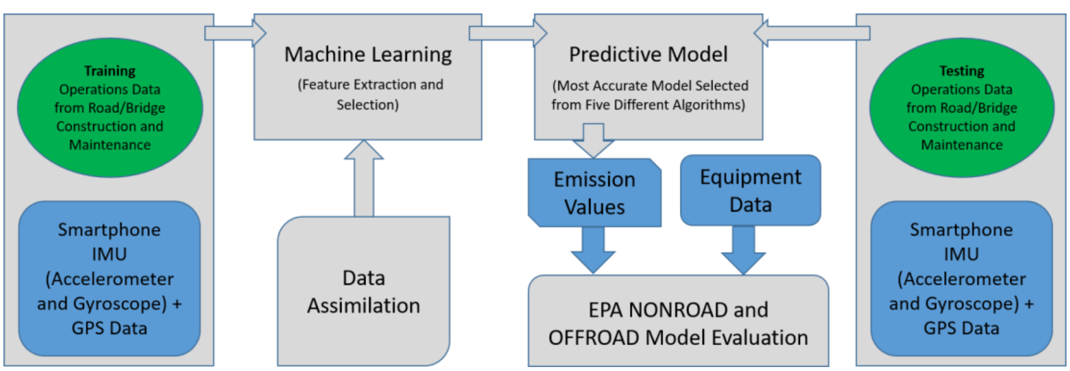

Figure 5: Sustainable construction (i.e. equipment emission estimation) framework

REFERENCES

References available upon request.