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CONSTRUCTION ACTIVITY RECOGNITION FOR SIMULATION INPUT MODELING USING MACHINE LEARNING CLASSIFIERS

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ABSTRACT

Despite recent advancements, the time, skill, and monetary investment necessary for hardware setup and calibration are still major prohibitive factors in field data sensing. The presented research is an effort to alleviate this problem by exploring whether built-in mobile sensors such as global positioning system (GPS), accelerometer, and gyroscope can be used as ubiquitous data collection and transmission nodes to extract activity durations for construction simulation input modeling. Collected sensory data are classified using machine learning algorithms for detecting various construction equipment actions. The ability of the designed methodology in correctly detecting and classifying equipment actions was validated using sensory data collected from a front-end loader. Ultimately, the developed algorithms can supplement conventional simulation input modeling by providing knowledge such as activity durations and precedence, and site layout. The resulting data-driven simulations will be more reliable and can improve the quality and timeliness of operational decisions.

1 INTRODUCTION

Analysis of construction equipment activities with proper level of detail can help improve several aspects of construction engineering and management (CEM) such as productivity assessment (Joshua and Varghese 2010), safety management (Cheng and Teizer 2013), idle time reduction (Akhavian and Behzadan 2013c), emission monitoring and control (Ahn et al. 2013), and simulation input modeling (Akhavian and Behzadan 2013a). In most cases, however, manual observation of activities is very difficult, time consuming, and prone to error. Therefore, some automated field data collection techniques have been investigated as potential solutions to this problem (Ergen et al. 2007; Goodrum et al. 2010; Montaser and Moselhi 2012).

Simulation models used for decision-making in CEM can in particular benefit from realistic input data collected from field activities. There have been previous studies on localization of construction resources (Navon and Sacks 2007) and using simulation to predict the performance of a project (Martinez 2009) in order to reduce uncertainties in decision-making. However, to yield more accurate results, there is still a need to transform the current practice of relying on personal judgments and engineering assumptions in building simulation models (Gao et al. 2013). There is an abundance of cases where the use of such assumptions to create simulation models during the early planning of a project resulted in overestimation or underestimation of project performance indicators (Lu et al. 2007). Therefore, simulation input modeling is a domain that can benefit the most from an accurate assessment and benchmarking of activities performed by construction resources. This is especially the case given the intra-class variability of activity durations which requires several cycles of operations to be analyzed in order to develop a precise model describing a construction system (Golparvar-Fard et al. 2013).

To address this challenge, this paper presents a low-cost context-aware automated framework that can reliably detect construction equipment activities and extract their durations for simulation input modeling. Multi-modal data is acquired using ubiquitous built-in smartphone sensors including global positioning system (GPS) sensor, 3-axis accelerometer, and 3-axis gyroscope. Key time- and frequency-domain features are extracted from the collected data in windows of different sizes with 50% overlap. A subset of the extracted features is then selected using feature selection algorithms. Next, machine learning classifiers are employed to group the selected features into a number of distinct classes that represent construction equipment actions. The applicability and robustness of the presented framework is verified using real-world data collected from a front-end loader performing various actions.

2 RELATED WORK

2.1 Activity Recognition Using Micro-Electro-Mechanical Systems (MEMS) Inertial Sensors

Activity recognition using MEMS inertial sensors such as accelerometers and gyroscope has been the subject of previous studies in several fields including computer sciences, healthcare, and sports (Bao and Intille 2004; Ravi et al. 2005; Li et al. 2009; Altun and Barshan 2010). A three-dimensional (3D) accelerometer is a sensor that reruns values of acceleration, and a 3D gyroscope is a sensor that returns the rate of rotation (a.k.a. angular velocity) on x, y, and z axes (Li et al. 2009). Smartphone sensors are a class of MEMS inertial sensors that are widely used for activity recognition. For example, Kwapisz et al. (2011) evaluated identification of physical human activities by using accelerometer sensors embedded in mobile devices. They divided their 200 collected data points into 10-second segments and used over 40 features to describe certain motions. Finally, they used a few machine learning classifiers to evaluate the overall accuracy of their detection scheme. The same approach has been adopted in several other studies. For instance, Brezmes et al. (2009) investigated the feasibility of using conventional mobile devices for real-time pattern recognition in human activities. Li et al. (2009) used gyroscope and accelerometer data to propose a fall detection system. Using three accelerometers and one gyroscope, Motoi et al. (2003) developed a system for monitoring human posture and walking speeds in ambulatory subjects. Also, Namal et al. (2006) used wireless accelerometers to study movement patterns of soccer players.

Despite applications in other domains, there have been very few efforts in industrial and engineering settings where MEMS inertial sensors were used for activity recognition. For example, Lukowicz et al. (2004) developed a system for segmenting and recognizing typical user gestures in a wood workshop environment using body-worn microphones and accelerometers. In the prototype experiment that was conducted in a laboratory setting, they simulated the assembly of a simple wooden object to recognize specifically-designed activities. Using fast Fourier Transformation (FFT) for analysis, and Hidden Markov Models (HMMs) and Linear Discriminant Analysis (LDA) for recognition and classification, they reported a 84.4% overall detection accuracy.

2.2 Activity Recognition in CEM Domain

Within the CEM domain, different research groups studied methodologies for recognizing activities performed by construction resources (e.g. labor, equipment). Such approaches can be generally divided into two main categories: vision-based, and non-vision-based. However, none of the previous studies in this field has investigated the application of activity recognition for the purpose of simulation input modeling and to generate more accurate and reliable simulation outputs.

In one of the early computer vision studies in this area, Zou and Kim (2007) designed an image processing-based method for automatic quantification of idle times of hydraulic excavators. Their approach was able to only detect busy vs. idle states of hydraulic excavators. In another study, Gong et al. (2011) proposed an action recognition approach using visual learning techniques to classify subtle action categories in construction video segments. Although this study was one of the first works in classification, the use of unsupervised learning in classification for complex unstructured construction tasks is still subject to many challenges. Rezazadeh Azar et al. (2012) proposed another vision-based approach for dirt-loading cycles in earthmoving operations. Their approach is contingent upon the location of equipment which requires the algorithm to be modified for every new jobsite. In a more recent study, Golparvar-Fard et al. (2013) proposed a vision-based action recognition approach for earthmoving equipment that uses spatio-temporal features and support vector machines (SVM) for unsupervised machine learning classification. The limitation of most vision-based approaches, however, is that they usually need expensive cameras to be mounted in the jobsite. Also, the result is sensitive to moving backgrounds, illumination conditions, and occlusions. Moreover, video data processing and interpretation which is at best a computer-assisted manual reviewing process, prohibits the widespread use of video in construction (Gong and Caldas 2010).

Non-vision-based methodologies, on the other hand, do not require camera installation, nor do encounter challenges such as occlusion and the effect of ambient factors. However, the need for mounting sensors could be still a drawback of this approach. In the research presented in this paper, this shortcoming is rectified by using built-in smartphone sensors. Many research studies explored the potential of tracking technologies in construction. Examples include radio frequency identification (RFID) (Ergen et al. 2007; Montaser and Moselhi 2012), Ultra Wideband (UWB) (Teizer et al. 2007; Cheng et al. 2011), and GPS (Oloufa et al. 2003; Gong and Caldas 2008). Recently, there have been few studies that used accelerometer data in activity recognition for emission control and productivity assessment. Ahn et al. (2013) examined the feasibility of measuring operational efficiency of construction equipment using accelerometer data to classify three modes of an excavator operation: engine-off, idling, and working. Overall, their methodology showed a promising performance with a 93% accuracy in classification of these three classes. However, the level of detail in describing activities was limited to these three trivial modes. In another study, accelerometer-based activity classification was performed to automate the work-sampling process (Joshua and Varghese 2010). A case study was performed in an experimental setting where masonry activities were classified using data collected from accelerometers attached to the waist of a mason. Employing three type of classifiers, they concluded that a neural network classifier had the best performance with 80% accuracy.

2.3 Construction Simulation Input Modeling

Recently, there have been a few attempts in building more reliable construction simulation models by improving the input data. The authors have previously investigated the application of multi-modal (positional, angular, and weight) data collection, fusion, and analysis for construction fleet process knowledge discovery and to update the corresponding simulation models (Akhavian and Behzadan 2012; Akhavian and Behzadan 2013b). In almost all other studies, however, the only mode of data used to extract process knowledge has been positional. For instance, Vahdatikhaki and Hammad (2014) pursued a very similar methodology to Akhavian and Behzadan (2013b) for near real-time simulation fine-tuning. However, the limitation of this approach is that collecting only positional data (UWB for indoors and GPS for outdoors) may cause uncertainty in the discovered knowledge since stationary equipment actions could not be readily detected using only position sensors. Zhang et al. (2013) proposed a Bayesian hybrid simulation approach to predict the time-varying probability of project completion. Their case study demonstrated that the updated simulation model (based on the actual data of one excavation cycle duration) provided more accurate predictions than those resulted from the original model. Song and Eldin (2012) proposed a look-ahead scheduling scheme using GPS data to update a simulation model. Concrete production scheduling in a DES based optimization system was updated in another study using GPS data streaming from vehicular onboard tracking system (Lu et al. 2007). However, since GPS data offers limited accuracy in reporting position, the use of a single mode of data (positional) in recognizing activities specially those performed in stationary states is subject to skepticism.

3 RESEARCH METHODOLOGY

In industrial engineering domain, the literature on using operational data in building data-driven simulation models is quite extensive (Darema 2005; Tannock et al. 2007; Huang et al. 2011). In contrast, within the CEM domain, previous work on this subject is scattered and has left many key research questions unanswered. Therefore, this study is an effort to derive and test a methodology that enables the integration of process data with simulation input modeling for CEM applications. The overall approach of this research is shown in Figure 1. As illustrated in this Figure, multi-modal data are collected using sensors embedded in mobile (smartphone) devices. In particular, accelerometer, gyroscope, and GPS data are collected and analyzed in the designed methodology and validation experiments. Accelerometer and gyroscope data are subject to major data processing effort, while GPS data is incorporated later on in the process to provide additional information for accurate knowledge extraction. Specifically, three main steps are pursued in the presented methodology: feature extraction, feature selection, and supervised learning and classification. These steps are described in detail in the following Subsections.

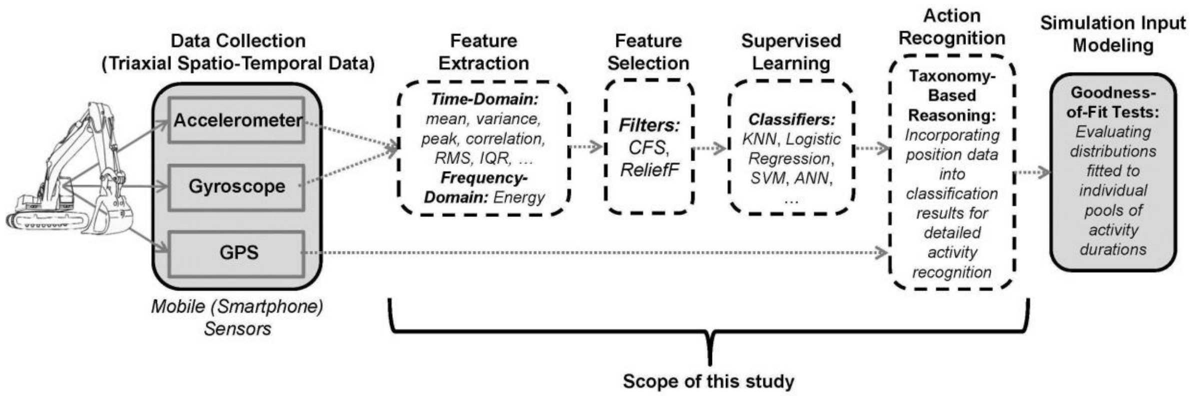

Figure 1: Developed system architecture for simulation input modeling.

3.1 Feature Extraction

Raw data must be first represented in terms of specific features over a window of certain data points. In this research, mean, variance, peak, interquartile range (IQR), correlation, and root mean error (RMS) are the statistical time-domain features that are extracted from data. Moreover, signal energy was picked as the only frequency-domain feature that showed positive discrimination results in previous studies (Figo et al. 2010; Khan et al. 2011) for context recognition using accelerometer data. These 7 features were extracted for both accelerometer and gyroscope data corresponding to each of the x, y, and z axis. Since both sensors return triaxial values (x, y, z) a total of 42 (i.e. 7 features from 2 sensors in 3 axes) features were extracted. The size of the window depends on the sampling frequency and thus, varies for different applications. However, it should be selected in such a way that no important action is missed. This can be achieved by overlapping windows. Previous studies using accelerometer for context recognition have suggested a 50% overlap between windows (DeVaul and Dunn 2001; Darren Graham et al. 2005; Ahn et al. 2013). Time-domain features can be extracted using statistical analysis. However, the frequency-domain feature (i.e. signal energy) should be extracted from the frequency spectrum which requires signal transformation. In this study, FFT is used to convert the time-domain signal to the frequency domain. For computational efficiency, the FFT requires the number of data points in a window to be a power of 2.

3.2 Feature Selection

Feature selection is the process of picking a subset of originally extracted features to optimally reduce the feature space (Yu and Liu 2003). In other words, among the extracted features, there may be some that may not add to the accuracy of the classification. This might be due to the correlation that exists among the collected data and consequently extracted features, since many actions result in a similar pattern in different directions and/or different sensor types (i.e. accelerometer vs. gyroscope). Therefore, in order to reduce the computational cost and time of the classification process, and increase its accuracy, a subset of the discriminative features is selected by filtering out (removing) irrelevant or redundant features (Pirttikangas et al. 2006). In this study, two filtering approaches are used: ReliefF and Correlation-based Feature Selection (CFS). ReliefF is a weighting algorithm that assigns a weight to each feature and ranks them according to how well their values distinguish between the instances of the same and different classes that are near each other (Yu and Liu 2003). CFS is a subset search algorithm that applies a correlation measure to assess the goodness of feature subsets based on the selected features that are highly correlated to the class, yet uncorrelated to each other (Hall 1999).

3.3 Supervised Learning and Classification

A learning algorithm can be either supervised or unsupervised depending on whether or not different classes are labeled for training. Although unsupervised methods can be employed for equipment action recognition (Gong et al. 2011), supervised learning algorithms provide better performance for this purpose (Golparvar-Fard et al. 2013). This is mainly due to the fact that action classes of an equipment consist of some classes in which the number of instances are limited. This creates an imbalanced set of classes (caused by large differences between the number of instances in some classes) that can very likely lead to over-fitting in unsupervised learning classification. Among several supervised learning methods those that follow more complex algorithms may look more accurate in classification. However, the choice of learning algorithm is highly dependent on the characteristics and volume of data. As a result, a universal best classifier does not generally exists and each case requires unique evaluation of the learning algorithm through cross validation (Goldberg 1989). Therefore, a number of learning algorithms are tested in this research to compare their performance in classifying actions using sensory data.

4 EXPERIMENTAL ANALYSIS AND RESULTS

4.1 Experiment Setup

Figure 2 shows how smartphones are placed inside the equipment cabin for data collection. In this research, two smartphones were simultaneously used to guarantee the storage of data as well as evaluating potential differences between the sensory data collection mechanism in the iOS and Android operating systems. Data analysis indicated that data captured by iOS and Android devices were not different and therefore, the choice of the operating system does not affect the results.

Figure 2: NFC smart tags and smartphones are attached to the side window in the front-end loader cabin.

In order to fully automate the process of data collection, low-cost near field communication (NFC) RFID smart tags were used (Want 2006). NFC tags were glued to the device holder (i.e. suction cup attached to the side window of the cabin) to automatically launch the data logger application once the smartphone is placed in the holder. A JOHN DEERE 744J front-end loader was employed for data collection. Experiments were conducted in two modes: controlled (i.e. instructed), and normal (uninstructed). Both modes were fully videotaped for later activity annotation and labeling. In the controlled mode, the equipment operator was given instructions to perform certain actions with start and stop signals and a few second gap in between consecutive actions for distinct action annotation using the video. Figure 3 shows the equipment performing activities in controlled environment and normal mode.

(a) **(b)**

Figure 3: Equipment actions in (a) instructed (controlled) and (b) uninstructed (normal) modes.

4.2 Data Collection and Logging

The interface for data collection was iOS and Android data logger applications. The sampling frequency was 100 Hz. Data was stored in comma separated value (CSV) format that can be analyzed in Microsoft Excel. The logger applications provided time-stamped data that facilitated synchronization of data and video recordings. Figure 4 visualizes part of the collected accelerometer, gyroscope, and GPS data.

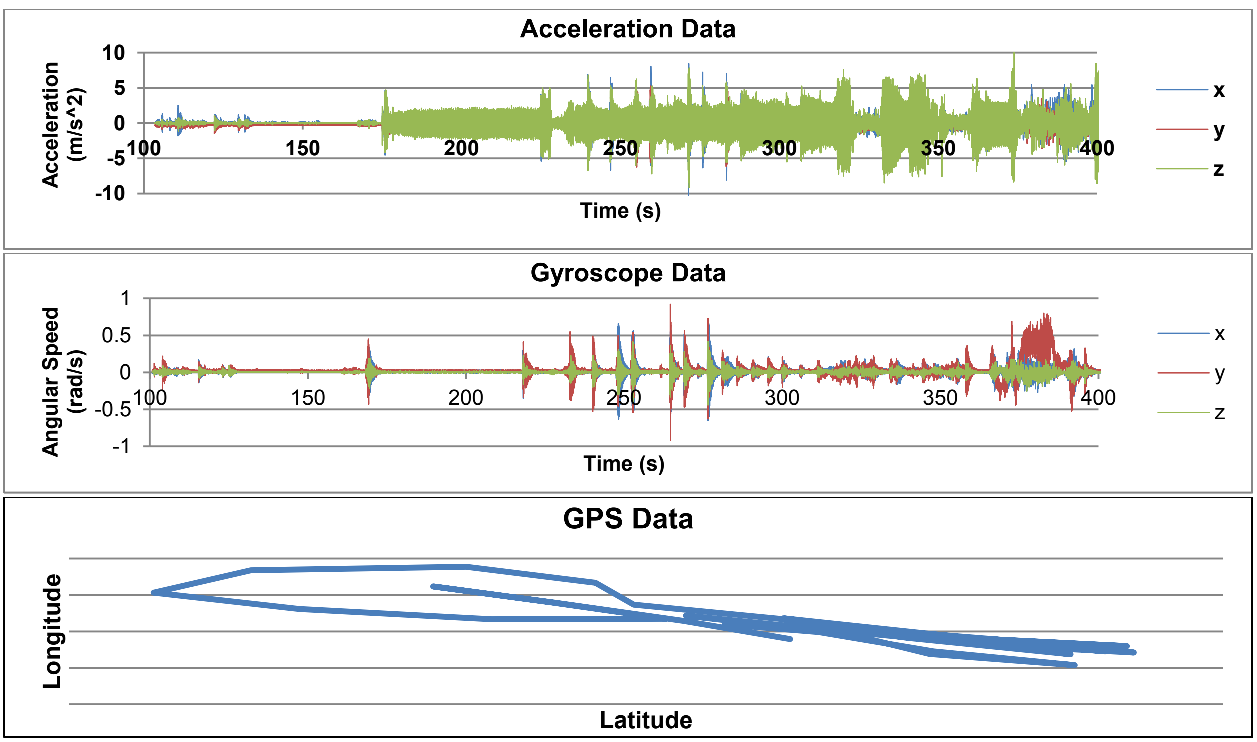

Figure 4: Snapshot of the collected accelerometer, gyroscope, and GPS data.

4.3 Data Analysis

For the purpose of feature extraction, data was segmented into windows of 128 data points with 50% overlap. Therefore, given a sampling frequency of 100 Hz, each window contains 1.28 seconds of the experiment data. The entire data analysis process including feature extraction was performed in Matlab. Also, as stated earlier, CFS and Reflief F filtering algorithms were used for feature selection. CFS removed the irrelevant and redundant features and yielded 12 features (out of 42) while ReliefF ranked them using their weight factors. The first 12 features selected by ReliefF were compared to those selected by CFS and the 7 common features in both were ultimately chosen as the final feature space. Table 1 shows the selected features by each filter as well as their intersection.

Table 1: Selected features by CFS and ReliefF and their intersection (A= Accelerometer, G = Gyroscope).

Filter	Selected Features	Common Selected Features
CFS	A_mean_x, A_mean_y, A_mean_z, A_peak_x, A_iqr_y, A_iqr_z, A_correlation_z, A_rms_z, G_mean_x, G_mean_y, G_mean_z, G_variance_x	G_mean_z A_mean_x G_mean_x A_mean_y A_mean_z A_iqr_z A_peak_x
ReliefF	G_mean_z, A_mean_x, G_mean_x, A_peak_z, A_mean_y, A_correlation_y, A_correlation_x, A_mean_z, A_iqr_z, A_peak_x, A_peak_y, G_rms_z	

A total of seven classes were considered for the actions of the front-end loader. These classes include engine off, forward and backward moving, stationary idling, lowering the boom, raising the boom, scooping, and dumping. Also, actions that served the same task were merged into one. For example, lowering the boom (in most cases) was accompanied by lifting the bucket. Therefore, lowering the boom and lifting the bucket were merged into one class. Figure 5 shows a sample of features grouped by their classes in a scatter plot matrix. All data points are grouped by their corresponding classes according to the legend.

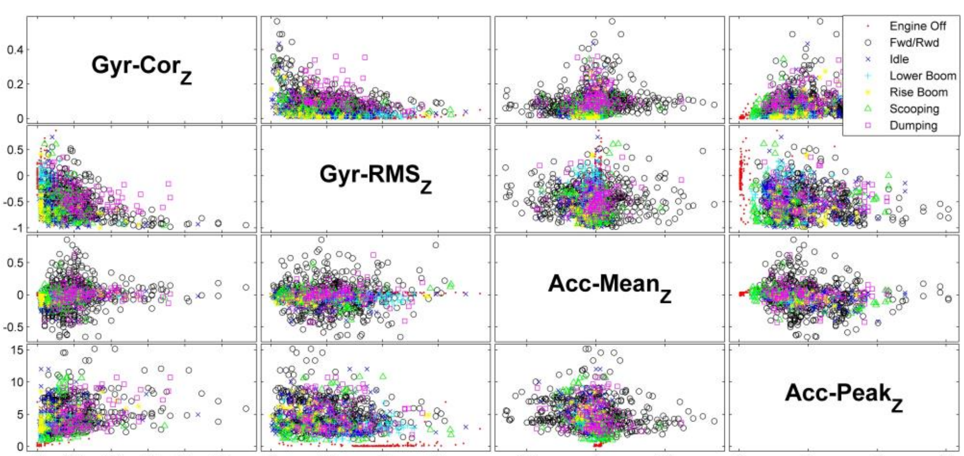

Figure 5: Scatter plot matrix of a sample of the extracted features grouped by action classes.

For action classification, five supervised learning methods were used: 1) Logistic Regression, 2) K-Nearest Neighbor (K-NN), 3) Decision Tree, 4) Neural Network (feed-forward backpropagation), and 5)

SVM. Extracted features were used as the input attributes for the supervised classifiers, and annotated action classes were used as the labeled training data.

4.4 Results

Figures 6 through 10 show the results in form of confusion matrices obtained for each class following the training of classifiers and examining them through 10-fold cross validations. In a k-fold cross validation the dataset is divided into k sets of equal sizes, and classifiers are trained k times, each time they are tested on one of the k folds and trained using the remaining $k-1$ folds. The mean accuracy is reported as the accuracy of each class. Confusion matrix is used to assess the predictions of a classifier based on the actual classes. In the confusion matrices, each row contains the percentages of the class labeled on the row (actual class) that is predicted as the class labeled on each column. Diagonal elements of the matrix represent the classes that classified correctly (predicted vs. actual) while all non-diagonal elements represent misclassified instances. In addition to the accuracy of classification in each class, the overall accuracies (using all classes) were evaluated and are presented in Table 2. As shown in this Table, all classifiers have an overall accuracy of more than 73%.

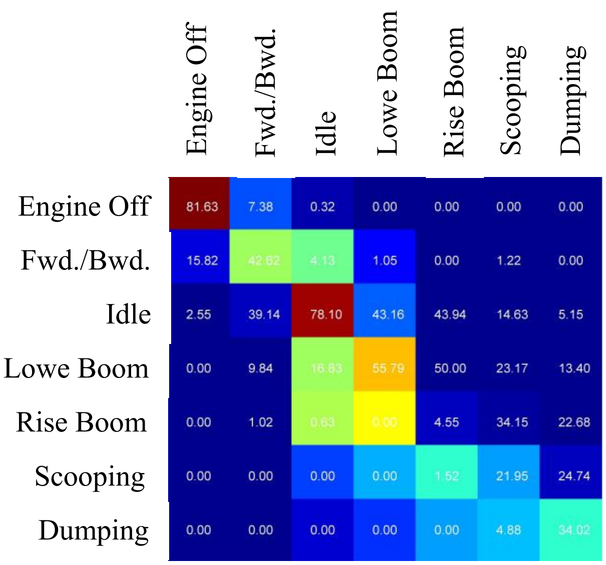

Figure 6: Confusion matrix for Neural Network classifier.

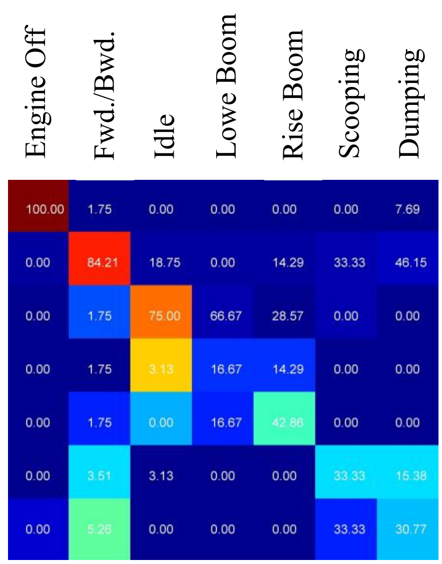

Figure 7: Confusion matrix for Decision Tree classifier.

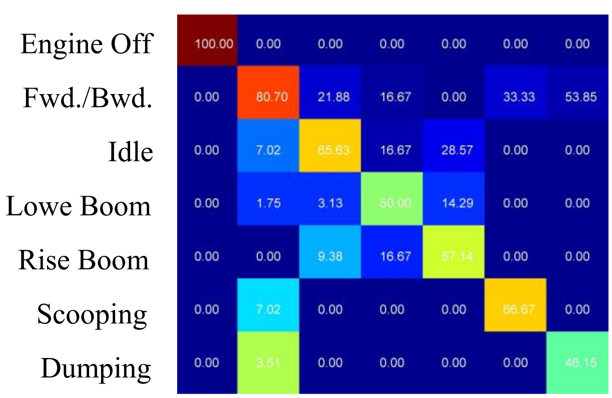

Figure 8: Confusion matrix for K-NN classifier.

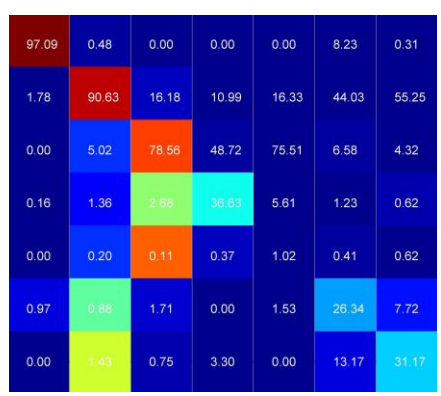

Figure 9: Confusion matrix for Logistic Regression classifier.

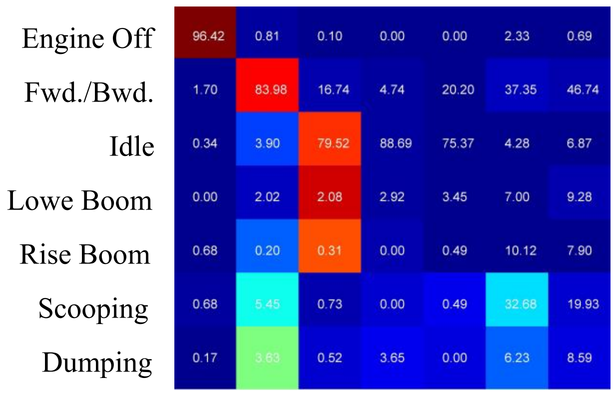

Figure 10: Confusion matrix for SVM classifier.

Table 2: Classification accuracies based on 10-fold cross validation.

Classifier	10-Fold Cross Validation Accuracy
K-NN	73.61
Decision Tree	73.47
Logistic Regression	72.29
SVM	66.5
Neural Networks	53.29

5 DISCUSSION AND CONCLUSIONS

In this paper, the process of extracting process knowledge for construction simulation input modeling was described. In particular, the applicability of built-in smartphone sensors and machine learning classifiers for equipment action recognition was evaluated using the example of a front-end loader. Results indicated that different equipment actions generate distinct data patterns (i.e. signatures) in sensory data. As soon as the start and end times of each action are detected, the corresponding duration can be calculated and used for simulation input modeling. Careful examination of the confusion matrices showed that although overall, the K-NN method outperformed other classification methods and Neural Network had the poorest performance, certain actions could not be properly classified in any of the classifiers. More specifically, almost all of the classifiers did a satisfactory job in detecting engine off, forward and backward moving, and to the most extent, idling, whereas in activities such as dumping, scooping, and to some extent, lowering and raising the boom, almost all classification methods performed poorly. This can be explained by the challenge of learning from imbalanced data in the machine learning domain. Based on the collected data and extracted features, there were 532 instances of the forward and backward moving class while in the scooping class for example, there were only 88 instances. It is known that if the class distribution is imbalanced, machine learning algorithms perform poorly in detection of the minority class (Van Hulse et al. 2007). Moreover, this also explains why the K-NN and Decision Tree methods perform better, as their procedure to classify different classes (compared to Neural Network or SVM) is not that sensitive to imbalanced classes (Maloof 2003). Future work in this study will include improving the performance of classifiers for imbalanced data, designing robust methods to detect data anomalies, and extracting potential spatio-temporal and/or time-series properties of resulting process knowledge.

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