

# Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers



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## ABSTRACT

Although activity recognition is an emerging general area of research in computer science, its potential in construction engineering and management (CEM) domain has not yet been fully investigated. Due to the complex and dynamic nature of many construction and infrastructure projects, the ability to detect and classify key activities performed in the field by various equipment and human crew can improve the quality and reliability of project decision-making and control. In particular to simulation modeling, process-level knowledge obtained as a result of activity recognition can help verify and update the input parameters of simulation models. Such input parameters include but are not limited to activity durations and precedence, resource flows, and site layout. The goal of this research is to investigate the prospect of using built-in smartphone sensors as ubiquitous multi-modal data collection and transmission nodes in order to detect detailed construction equipment activities which can ultimately contribute to the process of simulation input modeling. A case study of front-end loader activity recognition is presented to describe the methodology for action recognition and evaluate the performance of the developed system. In the designed methodology, certain key features are extracted from the collected data using accelerometer and gyroscope sensors, and a subset of the extracted features is used to train supervised machine learning classifiers. In doing so, several important technical details such as selection of discriminating features to extract, sensitivity analysis of data segmentation window size, and choice of the classifier to be trained are investigated. It is shown that the choice of the level of detail (LoD) in describing equipment actions (classes) is an important factor with major impact on the classification performance. Results also indicate that although decreasing the number of classes generally improves the classification output, considering other factors such as actions to be combined as a single activity, methodologies to extract knowledge from classified activities, computational efficiency, and end use of the classification process may as well influence one's decision in selecting an optimal LoD in describing equipment activities (classes).

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## 1. Introduction

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. During the

pre-construction phase, and due to the lack of data, it is customary to make engineering assumptions about the availability of tools, resources, information, materials, equipment, construction methods, and flow of activities [3]. Although a level of versatility is often considered for such assumptions, the dynamics involved in most projects as they enter the construction phase, makes it necessary to revise initial project plans and decisions, which may in turn result in potential delays and rework [3,6,7].

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 [8]. Therefore, computer simulation models capable of modeling uncertainties and stochastic events have become more relevant to the decision-making process especially when real world evaluation is difficult, expensive, or time-consuming. To achieve the best results, a simulation model

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should accurately represent the real engineering system through the integration of data that describe the real world resources and processes [5]. It is imperative that manual data collection techniques such as direct observations and field surveys are not efficient ways to obtain large volumes of high quality data in a timely manner [9]. Thus, automated data collection using sensors, vision-based systems, and laser scanners have gained credibility in quantitative analysis of construction activities.

Process-level data collection deals with data from construction resources (i.e. equipment, labor, material). Detailed resource activity recognition using these data has a great potential in discovering knowledge about activity durations and precedence, resource flows, and site layout. Among different types of process-level knowledge, activity duration is undoubtedly one of the most influential factors as there is always an uncertainty component to duration values that can propagate in time and/or space and consequently affect the outcome of the decision-making process [10,11]. Therefore, a systematic approach for action recognition that leads to precise activity duration extraction can boost the accuracy of decision-making tools such as simulation models. It has been widely discussed that inaccurate and unrealistic simulation models with static input data built upon expert judgments, secondary data (from past projects), and assumptions made on the basis of available resources and information during the pre-construction phase are major impediments that prohibit the widespread use of simulation models within the construction industry [8,12].

In an effort to address this challenge, the authors have been investigating the applicability of data-driven simulation for construction operations analysis [13,14]. In the authors' previous studies, a wireless network of sensors attached to different articulated parts of construction equipment was designed and implemented [13,14]. However, due to technical and practical difficulties associated with mounting sensors on construction equipment body parts (e.g. attachment and detachment of different sensors for every data collection session, construction site dust and noise) and data storage issues, a more pervasive data collection scheme is used in this study. This paper presents the latest findings on a critical component of an ongoing research, a ubiquitous data sensing and analysis system that captures multi-modal process data from construction equipment using mobile sensor nodes, and employs data mining and process reasoning methods to transform raw data into meaningful knowledge that can be ultimately incorporated into data-driven simulation models. In this paper, first, a comprehensive literature review is conducted to help identify the gaps in knowledge and practice, and put the presented work within proper context. Next, the requirements and necessary level of detail (LoD) and resolution in activity recognition is discussed, and the designed methodology is described. Finally, the experimental results of the developed methodology are presented and further discussion about the results is provided.

## 2. Previous work

The framework presented in this research consists of (a) an activity recognition architecture using built-in smartphone accelerometer, gyroscope, and positional sensors that is used to (b) detect distinct activities performed by construction equipment for (c) construction simulation input modeling. Therefore, this section provides a comprehensive literature review in each of these three domains.

### 2.1. Action recognition using accelerometer and gyroscope data

A three-dimensional (3D) accelerometer is a sensor that returns values of acceleration, and a 3D gyroscope is a sensor that returns the angular velocity about *x*, *y*, and *z* axes [15]. The idea of

recognizing activities using accelerometers have been around since the 1990s where researchers leveraged wearable devices to report instantaneous and sudden vibrations of human targets [16–18]. More recently, the use of gyroscope for the same purpose has also attracted the attention of researchers [15,19]. In particular, the adoption of such sensors in smartphones has facilitated the emergence of more context-aware applications.

Several fields including but not limited to computer sciences, healthcare, and sports have benefited from these Micro-Electro-Mechanical Systems (MEMS) inertial sensors [15,19–22]. For example, wireless accelerometers were used for the analysis of soccer players' movement patterns [23]. Using both accelerometer and gyroscope, Li et al. [15] presented a fall detection algorithm capable of detecting static postures and dynamic transitions. However, they stated that more environmental and physiological information is needed to distinguish between more complex actions. In a similar study, identification of physical human activities using mobile accelerometer sensors was evaluated [24]. Motoi et al. [25] proposed a human posture and walking monitoring system that works based on the speed of the ambulatory subjects.

Despite the prevalent use of such context-aware systems in non-engineering domains, research on their applications in engineering fields has been relatively limited. For instance, in a driving safety application, Johnson and Trivedi [26] used accelerometers to detect, recognize, and record driving styles. In an industrial setting, Lukowicz et al. [27] developed a system for segmenting and recognizing typical user gestures in a wood workshop using body-worn microphones and accelerometers. In a prototype experiment that was conducted in a laboratory setting, they simulated the assembly of a simple wooden object to recognize specifically-designed activities. As discussed in more detail in the next Subsection, construction jobsites have unique characteristics that may prohibit the wide application of such pervasive mobile data collection techniques. Challenges include but are not limited to the unstructured arrangement of resources (i.e. equipment, labor, material) that creates technical and practical problems for installing and calibrating sensors, as well as storage of non-structured or semi-structured data. Moreover, unexpected and intermittent events such as equipment breakdowns, adverse weather, and human crew motion irregularities can also add to the difficulty of interpreting sensory data collected from construction jobsites.

### 2.2. Construction resource action recognition

Object recognition and tracking has been a major research direction of several ongoing efforts in the field of computer vision [28–30]. Unlike computer vision where almost all such studies target human action recognition and pose analysis, researchers in construction engineering and management (CEM) domain have applied similar algorithms mostly for vision-based construction resource recognition and tracking. For example, Brilakis et al. [31] proposed a framework for vision-based tracking of construction entities. Their methodology requires calibration of two cameras, recognition of construction resources and identification of the corresponding regions, matching the entities identified in different cameras, two-dimensional (2D) tracking of the matched entities, and finally calculation of 3D coordinates. This and similar vision-based approaches, although provide promising results for recognition and tracking of construction equipment, still require much computation in each one of the aforementioned steps. In another study, an image processing methodology was adopted for idle time quantification of hydraulic excavators [32]. The LoD of the framework, however, was limited to detection of only idle and busy states of a hydraulic excavator. For the purpose of learning and classification of labor and equipment actions, the concept

of Bag-of-Video-Feature-Words model was extended into the construction domain [33]. This technique uses unsupervised learning for classification, and only considers frequency of feature occurrence for classification. Another vision-based framework was proposed by Rezazadeh Azar and McCabe [34] for dirt-loading cycles in earthmoving operations that depends on the location of equipment which requires the algorithm to be modified for every new jobsite. In a more recent study aimed at vision-based tracking of construction equipment activities, spatio-temporal features were classified using support vector machines (SVM) [35]. Most such vision-based approaches, however, need installation of expensive cameras on the jobsite, are sensitive to ambient light conditions, visual occlusions, and moving backgrounds, and are computationally expensive due to the high volume of video data that need to be processed and interpreted [5].

Another category of object recognition and tracking methods uses sensors to collect data from target objects (e.g. equipment, labor). Compared to vision-based techniques, this approach does not require camera installation and direct line of sight, and is less prone to ambient factors. Yet, installing individual sensors is still an implementation challenge. In the CEM domain, different classes of sensors such as global positioning system (GPS) receivers, radio frequency identification (RFID), and Ultra Wideband (UWB) have been extensively used for productivity management, safety monitoring and control, and sustainability analysis [36–42].

### 2.2.1. Application of accelerometer sensors in construction and infrastructure

Accelerometer sensors have been previously used for bridge and structural health monitoring (SHM) [43–46] to detect and analyze defects, deflections, and deformations. In addition to SHM, construction labor activities have been analyzed by Cheng et al. [47] using a physiological status monitoring system containing an accelerometer. Construction labor activity classification was also investigated to automate the work-sampling process [48]. A case study was performed in an experimental setting where a mason's activities were classified using data collected from accelerometers attached to the mason's waist. Ahn et al. [49] 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 performed well in classifying these three classes. However, the LoD in describing activities was limited to these three classes that could be otherwise intuitively distinguished. In another study, Akhavian and Behzadan [50] used MEMS inertial sensors for updating the content of construction simulation models as well as creating a real time animation of the stationary activities of a front-end loader by mounting the sensors on equipment's articulated parts for tilt tracking.

## 2.3. Simulation modeling in construction

Computer simulation tools customized for construction operations have been in use for almost three decades since the introduction of CYCLONE by Halpin [51]. Several other simulation tools such as UM-CYCLONE [52] and Micro-CYCLONE [53] were designed based on CYCLONE. Later on, a new generation of computer simulation software came into life that provided object-oriented capabilities. STROBOSCOPE [54] and Symphony [55] are two examples of such modeling environments that are widely used by researchers due to their extensibility and added capabilities.

### 2.3.1. Data-driven simulation models

Several previous attempts have been made in non-CEM domains to develop real time data-driven simulation models. Some highlights include Dynamic Data-driven Application

Simulation (DDAS) tools for emergency management, contaminant tracking, enhanced chemical process design, and dynamic traffic signal control [56–59]. In a recent study, a railway simulation system was developed that employed a dynamic data-driven approach using real time measures [60]. Tannock et al. [61] used the concept of data-driven simulation to develop models for supply chain in aerospace engineering.

However, a review of the literature within the CEM domain reveals a dearth of research in simulation modeling paradigms that can incorporate and work with input data at execution phase from field activities. Recently, the authors have successfully designed and tested a methodology that integrated multi-modal (positional, angular, and payload) data collection, data mining and reasoning process, in order to update key parameters of construction simulation models using field data [13,14]. Results indicated that simulation models built upon the factual data outperformed the models created using static input data and engineering assumptions. In almost all other studies in CEM that used sensory data collection targeting simulation modeling, however, the only mode of data employed to extract process knowledge has been positional. For instance, Vahdatikhaki and Hammad [62] pursued a very similar methodology to Akhavian and Behzadan [14] for near real time simulation fine-tuning. Concrete production scheduling in a DES-based optimization system was updated in another study using GPS data streaming from vehicular onboard tracking system [63]. A real time simulation framework was proposed by Hammad and Zhang [64] to improve productivity and enhance safety considering the required spatio-temporal localization resolution. Song and Eldin [10] suggested real time tracking of construction equipment to update a dynamic simulation model for look-ahead scheduling. Although all such work provided more realistic input data for simulation models compared to the traditional techniques that use static input data, they only considered equipment location information to determine activity durations, which can potentially result in limited accuracy due to the existence of cases where data other than positional information may be necessary to describe an operation.

## 3. Level of detail in equipment activity recognition

Supervised classification of construction equipment activities requires labeling different action classes to train the learning algorithm. The LoD or resolution required to successfully identify different classes from sensory data, however, may vary for each application. For instance, different mechanical degrees of freedom (DoFs) of a piece of construction equipment may have different levels of acceleration and/or angular velocity. In light of this, the hypothesis of this research is that data collection using built-in smartphone sensors enables activity recognition of construction equipment with appropriate LoD. Since the collected data are time-stamped, this can eventually lead to precise extraction of corresponding activity durations.

One major question in developing an activity recognition framework for simulation input modeling is what constitutes an “activity”? In other words, the extent to which each operation can be broken down (i.e. LoD) for modeling purposes defines the granularity of the activities modeled in the simulation. The significance of LoD in the context of modeling can be best seen in illustrative examples that use simulation results to create realistic replicas of engineering operations in visual environments such as simulation-based virtual or augmented reality [65–67]. In such environments, activities should be broken down to the most detailed level possible in order to render a smooth animation of the simulated operation. Consequently, if the final LoD does not include all mechanical DoFs, the resulting visualized scene appears unrealistic.

The state of a given piece of construction equipment can be broken down into further detailed actions. Here, action is defined as any process-level state of equipment that produces a distinctive sensory signal pattern. For example, Fig. 1 depicts a hierarchy of actions that can be performed by a front-end loader, a widely used construction equipment. As shown in this Figure, activities of a front-end loader can be broken down into different actions based on the defined LoD. In the coarsest breakdown (i.e. level 1), 2 classes are defined: Engine Off, and Engine On. Using the definition of action above, since these two classes produce two different sensory signal patterns, they can be treated as separate actions. In the next level, the Engine On class is further divided into the Idle and Busy classes. Therefore, the total number of possible classes in this LoD is 3 (i.e. Engine Off, Idle, and Busy). The action breakdown is continued to level 4, in which 5 classes are defined. If needed, this process can be continued even further. For example, Moving class may be divided into two subclasses of Going Forward and Going Backward. In most cases, the end application (purpose) of the activity recognition process can help determine the number of levels to which action breakdown should be continued.

As previously stated, the main focus of this study is to precisely extract activity durations. The occurrence of any action shown in an arbitrary level (referred to herein as level  $l$ ) of the hierarchy of Fig. 1 can imply that the parent action right above it (in level  $l - 1$ ) in the tree is occurring. However, depending on the circumstances, there may be two different interpretations. For instance, if the required LoD is level 4, given that an instance of Dumping action with duration  $t_1$  and an instance of Moving action with duration  $t_2$  are occurring, it can be concluded that two separate instances of Moving and Dumping action, with durations of  $t_1$  and  $t_2$  are taking place. On the other hand, if the required LoD is level 3, knowing that Moving and Scooping and Moving and Dumping actions are taking place with durations  $t_3$  and  $t_4$ , respectively, one should add up  $t_3$  and  $t_4$  to calculate the duration of a single instance of Busy state (e.g. dumping soil into a hauler) as  $t_3 + t_4$ . In any case, as a general rule, it is possible to derive the duration of actions in level  $l - 1$  given the duration of actions in level  $l$ , and not necessarily vice versa.

Although it is desirable to have as many levels as possible when describing equipment activities, depending on the structure of activity breakdowns, the performance of activity classifications and further, activity duration extraction methodologies varies over different levels due to three important reasons. Consider Fig. 1 as an example:

1. Training a classifier with a fixed dataset to distinguish between combined and coarser classes with similar movement characteristics (e.g. level 2) is expected to be more successful than dividing the same dataset into single more detailed classes (e.g. level 4). This is mainly because the more are the levels, the less will be the number of training data points in each class. Moreover, dividing some of the actions to more detailed actions and creating new classes may result in having imbalanced data. For example, if in a given operation, the breakdown of the collected data points in level 3 is 30% Engine Off, 30% Idle, 20% Moving and Scooping, and 20% Moving and Dumping, then in level 4, the number of data points in the last two activities will be further broken down into smaller portions, whereas other states such as Idle still have more data points for training the classifier.
2. Signal patterns to which classification is applied are expected to become more similar in each class when going down in the tree; meaning that for example, Scooping, Dumping, and Moving actions are more likely to have similar signal patterns within their individual classes than Moving and Scooping or Moving and Dumping. This makes it more difficult for the classifier to distinguish between different classes.
3. Automated extraction of activity durations from classified activities is performed by algorithms to detect separate instances of equipment activities and calculate the durations based on the data segmentation (i.e. window sizing). For example, if 10 segments in a row were labeled by the predictor model as the activity Scooping, but 1 or 2 segments are labeled Dumping, and right after them, again 8 segments are labeled as Scooping, the algorithm ignores the 1–2 Dumping segments and count them as Scooping, resulting in around 20 segments labeled as Scooping. Therefore, the accuracy of the activity classification algorithm (or trained model) which is defined by the ratio of correct predicted labels over actual labels in each class will be slightly different from the accuracy of activity duration extraction algorithm. This difference is obviously higher when having many classes with shorter durations rather than less classes (combined classes) with longer durations.

As a result, although a higher LoD is more desirable, the classifier may not necessarily perform well in the lower levels given the relatively large number of classes. This trade-off indicates that there should be an optimal level in the action hierarchy where a balance exists between the number of classes and the accuracy of the classification process and duration extraction.

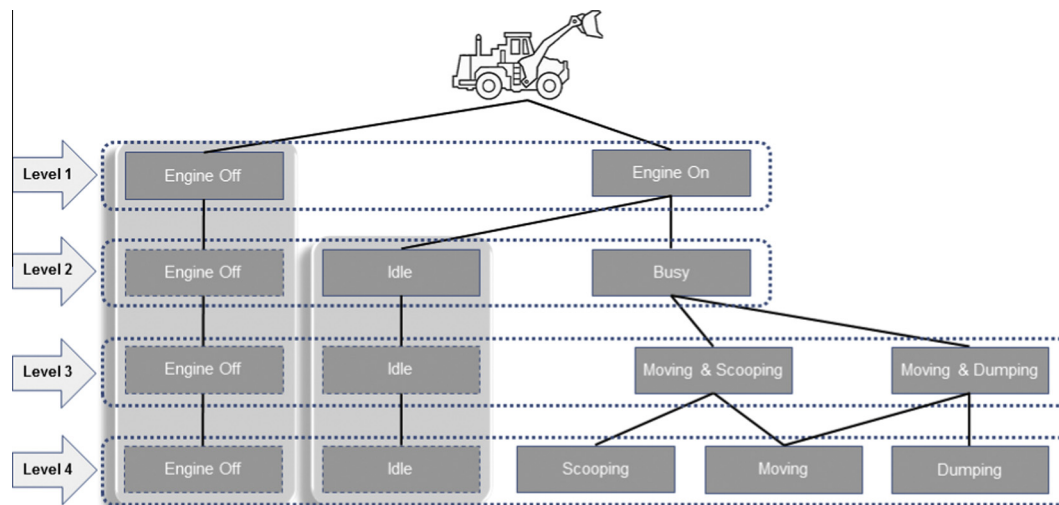


Fig. 1. LoD in activity breakdown of a front-end loader.



This issue will be further examined in this paper. It must be noted that Fig. 1 serves only as a demonstration example and a motivation case and each particular operation may require that a different action LoD hierarchy be constructed to best determine the relationship between the duration of child and parent actions for a specific operation. Likewise, the selection of the optimal point, where the number of classes vs. the LoD results in the best performance, may vary from case to case.

#### 4. Activity recognition methodology

The general architecture of the designed framework is depicted in Fig. 2.

In this methodology, multi-modal data is collected from different sensors (i.e. accelerometer, gyroscope, GPS) embedded in mobile (smartphone) devices placed inside construction equipment cabins. While GPS data is used later on to provide additional contextual information such as the proximity of two pieces of equipment (e.g. a front-end loader and a hauler) or work zone vicinity approximation [14], for accurate duration extraction (the focus of this study), mainly accelerometer and gyroscope data are subject to a major data processing effort. In particular, after collecting raw data, specific features should be extracted for classification. However, not all such features may contribute to the classification process, and thus a feature selection step needs to be taken. Selected features go through the training process

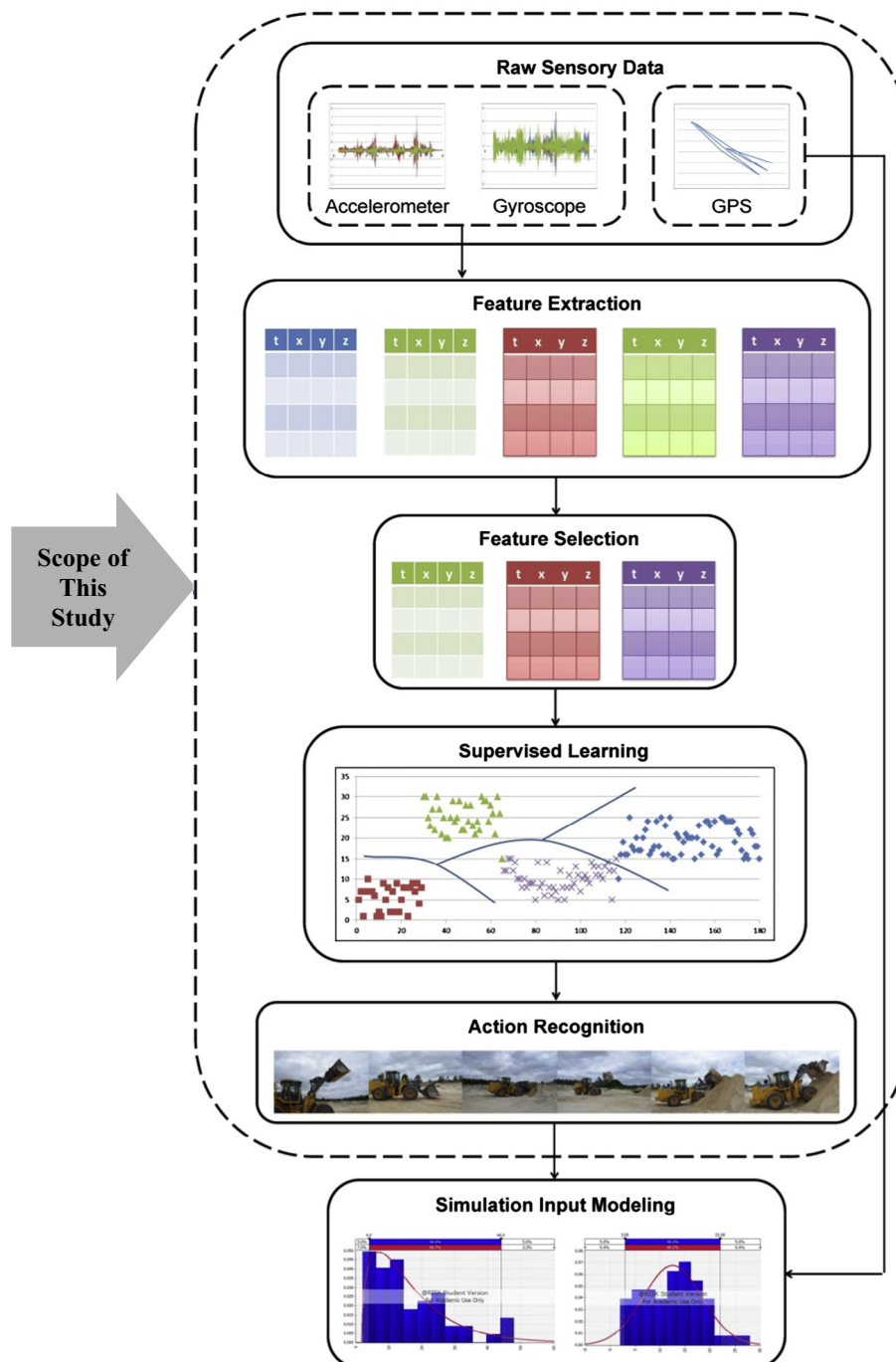


Fig. 2. Developed system architecture for simulation input modeling.

and then new actions are recognized at the LoD specified in the training phase. Each one of these steps is described in detail in the following case study where real world data was used.

#### 4.1. Experiment setup

In all experiments conducted in this study, smartphones were placed inside the equipment cabin for data collection. For each scenario, two smartphones were simultaneously used to guarantee the uninterrupted storage of data. It must be noted that since data collection and feature extraction is done using tri-axial data, results do not depend on the placement orientation of the data collection device. Moreover, potential significant correlation between each pair of axes is reflected in three of the extracted features, thus guaranteeing capturing any distinguishable feature related to the placement orientation of the data collection devices. In order to fully automate the process of data collection, low-cost near field communication (NFC) RFID smart tags were also used [68]. 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 was placed in the holder. A JOHN DEERE 744 J front-end loader was employed for data collection. All experiment operations were fully videotaped for later activity annotation and labeling, and visual validation. Fig. 3 shows how data collection devices were mounted and secured inside the target equipment cabin.

#### 4.2. Data collection and logging

Data was collected using commercially available data logger applications for iOS and Android devices. The sampling frequency was set at 100 Hz. Among different modes of data collected in this study, it was observed that acceleration (i.e. vibration) values resulted from different equipment motions had the highest degree of volatility. Several sensor manufacturers have recommended that a bandwidth of 50 Hz be used for normal-speed vibration and tilt sensing applications. Therefore, in this research, and considering the Nyquist criterion in signal processing [69], the sampling frequency was set at twice this value or 100 Hz. This bandwidth guaranteed that no significant motion was overlooked and at the same time, the volume of recorded data was not prohibitively large. Data was stored with comma separated value (CSV) format for processing in Microsoft Excel. The logger applications provided time-stamped data which facilitated the synchronization of data and video recordings. As mentioned earlier, GPS data is not directly used in data mining processes employed in this study and was only collected to demonstrate the potential of acquiring high accuracy positional data for such context-aware applications. Fig. 4 visualizes part of the collected accelerometer, gyroscope, and GPS data.

#### 4.3. Data processing

##### 4.3.1. 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 were extracted from data. Moreover, signal energy was picked as the only frequency-domain feature since it had already shown positive discrimination results in previous studies [70,71] for context recognition using accelerometer data. These 7 features were extracted from both accelerometer and gyroscope data corresponding to each of the  $x$ ,  $y$ , and  $z$  axis. Since both sensors return tri-axial values ( $x$ ,  $y$ ,  $z$ ), a total of 42 (i.e. multiplication of 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 consecutive windows. Previous studies using accelerometer for context recognition have suggested a 50% overlap between windows [49,72,73]. 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, fast Fourier transform (FFT) was used to convert the time-domain signal to the frequency-domain. In order to be computationally efficient, FFT requires the number of data points in a window to be a power of 2. Data was initially segmented into windows of 128 data points with 50% overlap. Therefore, given a sampling frequency of 100 Hz, each window contained 1.28 seconds of the experiment data. A sensitivity analysis presented in Section 5 provides more detail about the process of selecting the proper window size. The entire data analysis process including feature extraction was performed in Matlab.

##### 4.3.2. Feature selection

Feature selection is the process of picking a subset of originally extracted features to optimally reduce the feature space [74]. In other words, among all extracted features, there are 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 [75]. 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



Fig. 3. Smartphones mounted inside the front-end loader cabin.

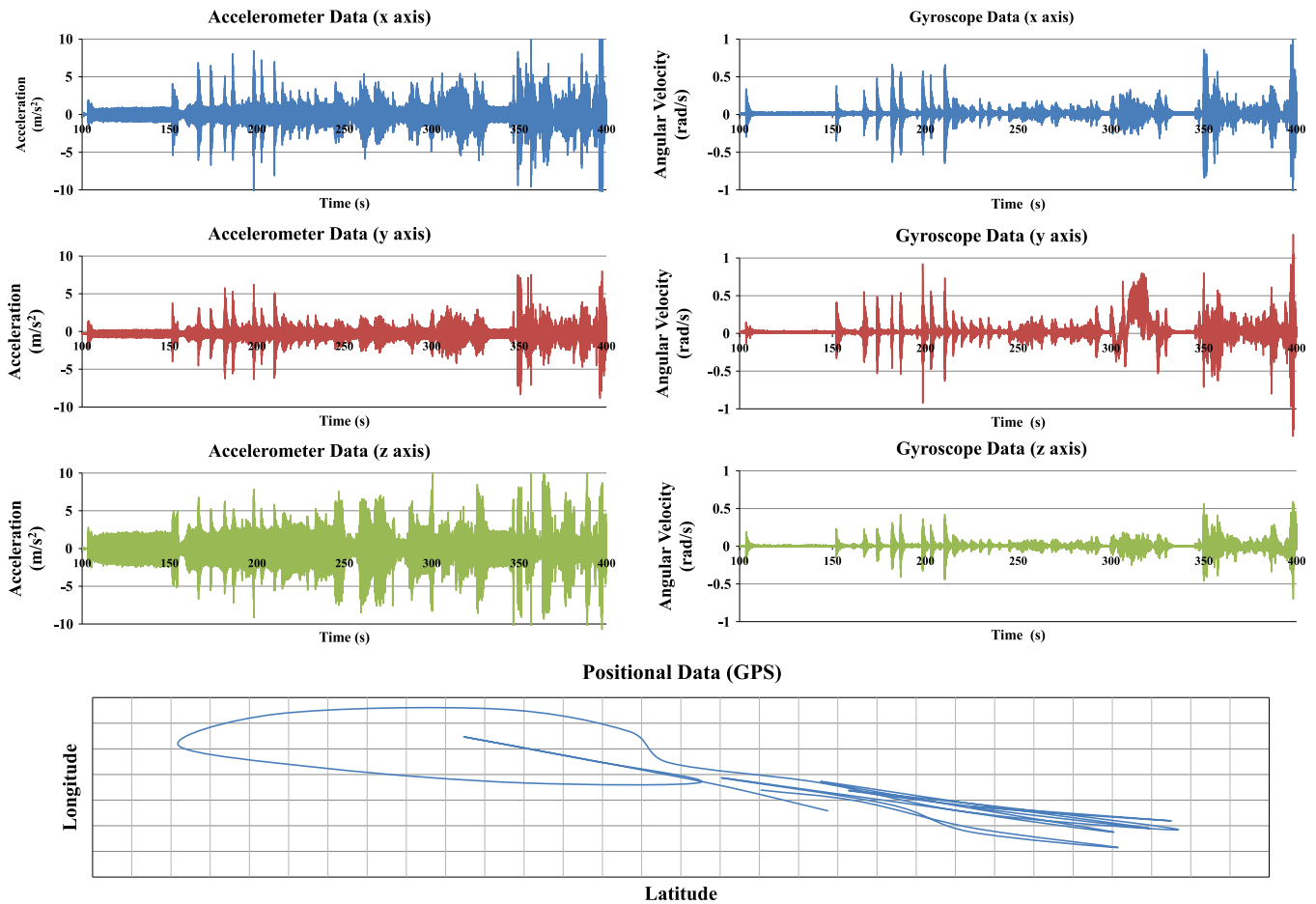


Fig. 4. Snapshots of collected sensory data.

the instances of the same and different classes that are near each other [74]. 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 [76].

Using CFS, irrelevant and redundant features were removed which yielded 12 features (out of 42). These features were then ranked by ReliefF 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 methods were ultimately chosen as the final feature space. Table 1 shows the selected features by each filter as well as their intersection.

#### 4.3.3. Supervised learning and classification

A learning algorithm can be supervised or unsupervised depending on whether or not different classes are labeled for training. Although unsupervised methods can be employed for

equipment action recognition [33], supervised learning algorithms provide better performance for this purpose [35]. This is mainly due to the fact that action classes of a piece of equipment consist of some classes with limited number of instances. 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 seem more accurate in classification. However, the choice of the learning algorithm is highly dependent on the characteristics and volume of data. As a result, a “single” best classifier does not generally exist and each case requires unique evaluation of the learning algorithm through cross validation [77]. Therefore, a number of learning algorithms are tested in this research to compare their performance in classifying actions using sensory data.

As per the discussion of LoD in breaking down the activities in Section 3, in this experiment, classification was performed by labeling the classes in different LoDs. Following the same hierarchy of actions presented in Fig. 1, and starting from level 2 (since level 1 is too coarse for the purpose of this study) the first set of training and classification algorithms is applied to three classes namely Engine Off, Idle, and Busy. Next, the Busy class is broken down into two subclasses of Moving and Scooping, and Moving and Dumping, and so on for level 4.

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. Using different classifiers reduces the uncertainty of the results that might be related to the classification algorithm that each classifier uses.

**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
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_mean_z A_iqr_z A_peak_x

## 5. Results and discussion

Starting from level 2, for each LoD, five classifiers were trained. Training and testing were performed through stratified 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. Moreover, in the stratified  $k$ -fold cross validation, each fold contains almost the same proportions of classes as in the whole dataset. The mean accuracy is reported as the accuracy of each class. Result of the classification performance for each case (i.e. LoD) is presented in Table 2 in terms of overall classifier accuracy.

As shown in Table 2, Neural Networks had the best relative overall accuracy among all five classifiers in all the LoDs. Moreover, although in level 2 with 3 classes the accuracy gets to as high as 98.59%, the highest accuracy in level 3 with 4 classes is 81.30% which is less than that of level 4 with 5 classes, which is 86.09%.

As stated earlier, construction equipment activity recognition has been previously explored through vision-based technologies. Gong et al. [33] reported an overall accuracy of 86.33% for classification of three action classes of a backhoe. In a more recent study, Golparvar-Fard et al. [35] achieved 86.33% and 76.0% average accuracy for three and four action classes of an excavator, respectively, and 98.33% average accuracy for three action classes of a dump truck. Although the target construction equipment are different in each case and action categories varies in these studies, the developed framework in this study that uses IMUs for the first time for construction equipment action recognition shows promising results when compared to existing vision-based systems that have been the subject of many research studies for the past few years.

Prior to conducting a detailed analysis of results, one more sensitivity analysis was performed to confirm that the intuitively selected window size of 1.28 seconds is actually the best option. Considering that FFT uses windows that are sized as a power of 2, window sizes of 0.64 seconds and 2.56 seconds were selected for this sensitivity analysis. A window size smaller than 0.64 seconds (e.g. 0.32 seconds) is too small, while a window size larger than 2.56 seconds is too large given the type of activities observed in the experiment from the annotated videotaped data. The sensitivity analysis was performed for the best classifier (i.e. the Neural Networks) and the highest number of classes (i.e. 5 classes) that required the most computation and has the least numbers in some classes. Table 3 shows the result of the sensitivity analysis. According to Table 3, a window size of 1.28 seconds that corresponds to 128 data points has the best accuracy among the all three window sizes and thus is used for further analysis.

**Table 2**  
Overall accuracy of classifiers for each LoD.

	Classifier	Accuracy (%)
Level 2	ANN	98.59
	DT	97.40
	KNN	97.65
	LR	96.93
	SVM	96.71
Level 3	ANN	81.30
	DT	81.21
	KNN	80.51
	LR	77.58
	SVM	78.03
Level 4	ANN	86.09
	DT	73.78
	KNN	84.20
	LR	84.42
	SVM	78.58

**Table 3**

Accuracy of the trained neural networks for different window sizes.

Window size (Sec.)	0.64	1.28	2.56
Accuracy (%)	82.03	86.79	82.45

Next, confusion matrices for classification performance for each class within a LoD are constructed. In a confusion matrix, row labels represent actual (real world) classes while column labels represent predicted classes (from sensory data patterns). Therefore, the percentage value shown in each cell in a row indicates the accuracy of the classifier in identifying the class corresponding to that row. With the same token, diagonal elements of the matrix represent classes that were classified correctly (predicted vs. actual), while non-diagonal elements represent misclassified instances. Table 4 shows the number of segments of each activity within each class and the number of instances in each equipment action category.

Figs. 5–7 show the confusion matrices for classification of classes in levels 2, 3, and 4, with 3, 4, and 5 classes, respectively, using Neural Networks.

Following activity recognition and classification, activity durations should be extracted for simulation input modeling. Detected instances of each activity have a certain number of classified windows. Since each window is 1.28 seconds with 50% overlap with the previous window (i.e. 0.64 seconds), the duration of each instance is calculated using Eq. (1):

$$t \text{ (seconds)} = (n + 1) \times 0.64 \quad (1)$$

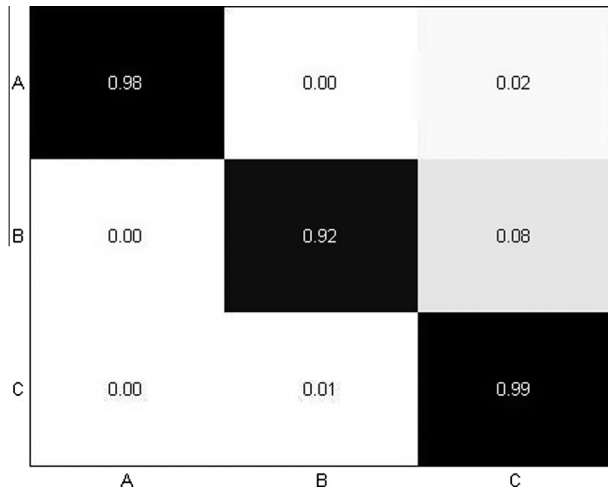
in which  $n$  is the number of detected windows of each class in each instance, and  $t$  is the duration of that instance of the target class. In order to find the LoD which results in the most accurate activity duration extraction, normal root mean squared errors (NRMSEs) of the actual activity durations and extracted ones are calculated and tabulated in Table 5.

Since the Busy state recognized as one of the classes in level 2 is not an actual activity, it is not considered in the discussion of activity durations extraction. However, for levels 3, and 4, as shown in Table 5, the NRMSE results indicate that in level 3 with 4 classes, the extracted activity durations were more accurate than those in level 4 with 5 classes. This is while classification accuracy was higher in level 4. There are two important factors that explain these results. First, combining multiple classes to build a single coarser class of activity for simulation input modeling (i.e. extracting activity durations) should be in a way that different classes that are combined to form a new class are adjacent to each other, thus summing the activity durations is meaningful when combining

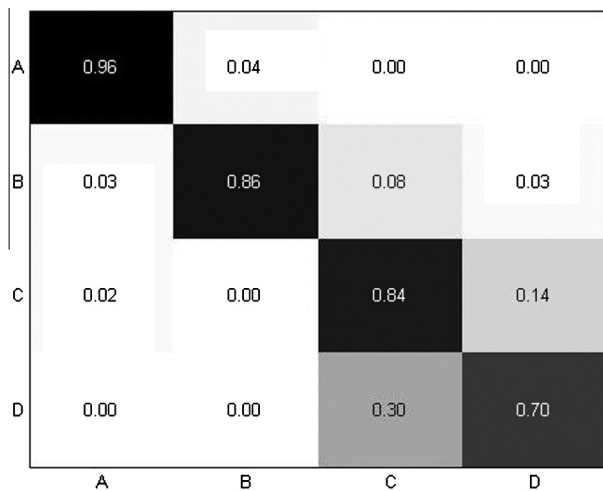
**Table 4**  
Number of segments and instances for each activity within each class.

Classification	Activity	Number of segments	Number of instances
Level 4 (5 classes)	Engine Off	55	2
	Idle	36	2
	Scooping	32	4
	Moving	180	8
	Dumping	57	4
Level 3 (4 classes)	Engine Off	55	2
	Idle	36	2
	Moving & Scooping	142	4
	Moving & Dumping	127	4
Level 2 (3 classes)	Engine Off	55	2
	Idle	36	2
	Busy	269	1

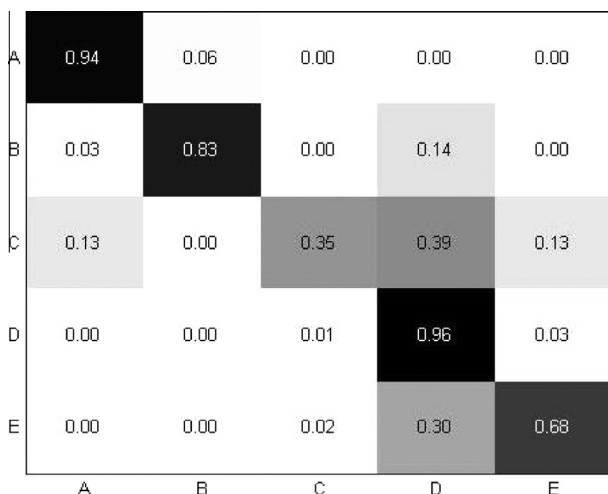




**Fig. 5.** Neural network confusion matrix for level 2 (A: Engine off, B: Idle, C: Busy).



**Fig. 6.** Neural network confusion matrix for level 3 (A: Engine off, B: Idle, C: Moving and Scooping, D: Moving and Dumping).



**Fig. 7.** Neural network confusion matrix for level 4 (A: Engine off, B: Idle, C: Scooping, D: Moving, E: Dumping).

**Table 5**

NRMSEs of extracted activity durations compared to the real activity durations.

Classification	Activity	NRMSE of durations (%)
Level 4 (5 classes)	Engine Off	2.9
	Idle	4.5
	Scooping	44.1
	Moving	6.5
	Dumping	23.4
Level 3 (4 classes)	Engine Off	2.6
	Idle	4.4
	Moving & Scooping	3.8
	Moving & Dumping	5.5
Level 2 (3 classes)	Engine Off	2.5
	Idle	3.6
	Busy	0.0

them. For example, from level 4 to level 3, the classes Scooping and Dumping cannot be combined because they did not actually occur following each other (i.e. a loader first scoops, then moves, then dumps) and thus, their durations cannot be added up. Therefore, the classification accuracy may not be as high as the lower detailed level since now two different activities (with some different signal patterns) are combined. Second, classification accuracy per se is not sufficient to know what is the best combination of classes for activity duration extraction, because there might be a few misclassified windows within each detected instance that although affect the classification accuracy negatively, but are ignored in duration extraction because they last as short as one or two window sizes (0.64 or 1.28 seconds) in an instance that is on average 10 seconds. For example, the observed average of dumping activity in the conducted experiments was around 10 seconds and in an instance, two consequent windows were labeled as scooping. Therefore, the algorithm for extracting durations easily ignores 1.92 seconds of scooping in the middle of 10 seconds of dumping. As a result of these two important issues, the classification accuracy may not always be the same as the activity duration extraction accuracy. This was observed in the experiments conducted with different number of classes. Therefore, such a thorough study is important to understand the theoretical and working principles of the framework targeting simulation input modeling using activity recognition and classification.

## 6. Conclusions

The goal of this research was to investigate the prospect of using built-in smartphone sensors as ubiquitous multi-modal data collection and transmission nodes in order to detect detailed construction equipment activities. The discovered process-level knowledge can provide a solid basis for different applications such as productivity improvement, safety management, and fuel use and emission monitoring and control. In addition, this methodology can serve as a basis for activity duration extraction for the purpose of construction simulation input modeling. A case study of front-end loader activity recognition was used to describe the methodology for action recognition and evaluate the performance of the developed system. In doing so, several important technical details such as selection of discriminating features to extract, sensitivity analysis of data segmentation window size, and choice of classifier to be trained were investigated.

In summary, results indicated that different equipment actions generate distinct data patterns (i.e. signatures) in accelerometer and gyroscope data. In particular, using smartphone built-in sensors demonstrated a perfect success (i.e. classification accuracy of over 98%) in recognizing the engine off, idle, and busy states of construction equipment. This can be the basis of future studies targeting automated state recognition of construction equipment for

sustainability and safety purposes. Careful examination of the classification confusion matrices in the highest LoD showed that the classification of activities was successfully performed (i.e. around 90% classification accuracy) in detecting some classes such as engine off, idle, and moving, whereas in activities such as dumping, and scooping, lower accuracies were achieved. It is worth mentioning that the classes that have higher classification accuracy have more distinctive vibration and angular velocity features as well. Therefore with more sensing devices and technologies, the results can improve even further. Having said that, as indicated in Table 5, the lower classification accuracy for some levels/classes does not necessarily translate into a low accuracy in activity duration estimation, which is the ultimate goal of integrating process sensory data for activity classification and creating more accurate simulation input models.

Another key contributing factor to classification performance is what was referred to in Section 3 as the problem of having imbalanced data for classification. It was observed that performance is much better when dealing with better balanced data. The results of the presented study compared the performance of different classifiers, number of classes, and window sizes in recognizing construction equipment activities. However, as discussed in the previous Section, proper attention should be paid to the fact that the accuracy of activity duration extraction is contingent upon a variety of interconnected factors.

## 7. Future work

Some of the directions for future work on this topic include the investigation of algorithms that suit classification of imbalanced data. The authors will explore a number of methodologies that can potentially handle this situation, including under-sampling and over-sampling [78], and cost-sensitive analysis (i.e. giving weights to data according to the number of data points) [79]. In addition, it was observed in the case study that some classifiers showed a better performance in classifying certain classes. Therefore, one possible solution to improve the overall classification accuracy is to use multiple classifiers in conjunction with one another. To this end, ensemble methods [80] and meta-learners [81] can be used to combine different classifiers. The authors will also broaden the application area of the designed methodology to cover more diverse operations with multiple types of equipment and labor crews. Moreover, further research is needed to evaluate the performance of similar frameworks for various activities performed by different types of construction equipment. Ultimately, the discovered process-level knowledge will be fused into process simulation models and is sought to increase the accuracy and quality of simulation results in support of better project decision-making and control.

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