# Automated Material Separation Activity Identification for Sustainable Demolition Operations

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## ABSTRACT

The reusability and recyclability of demolition waste are significantly affected by demolition operations, particularly material separation activities, which are largely driven by productivity considerations. As such, investigating the productivity of demolitions operations is key to understanding the decision-making processes affecting the reusability and recyclability of demolition waste. Traditional approaches for tracking the duration of demolition operations and thereby monitoring their productivity are costly, time consuming, and prone to human errors. To enable more effective and efficient demolition productivity monitoring, this study presents an automated approach for identifying demolition waste material separation activities using the motion data of demolition machinery. As proof of concept, small-scale heavy equipment is used to simulate demolition operations. Inertial measurement unit (IMU) sensors are attached to different moving members of the small-scale heavy equipment to collect angular and linear acceleration data. Collected time-stamped sensor data are preprocessed and subsequently used to train and test an activity recognition model using various supervised machine learning classification algorithms. The output of the developed model facilitates the delivery of actual productivity information, which can be used to optimize demolition planning and decision-making in a way that increases the recycling and reuse of demolition waste.

## INTRODUCTION

Globally, the construction industry is one of the largest contributors to resource depletion and waste generation, accounting for more than 30% of natural resource extraction and 25% of solid waste generation (Benachio et al. 2020). The majority of the waste generated by the construction industry is associated with the demolition activities that occur during the end-of-life phase of structures (Çimen 2021). Demolition waste is typically composed of significant quantities of inert materials such as metals, brick, concrete, wood, and asphalt. When properly processed, nearly 90% of said waste can be recycled (Hyvärinen et al. 2020). Despite this potential, a considerable portion of demolition waste, at least 35% globally (Menegaki and Damigos 2018), is sent to landfills. As urbanization and economic growth continue to accelerate, coupled with elevated concerns about raw material supply disruptions and depletion of available landfill space (Hill et al. 2023), sustainable harvesting of demolition waste is becoming increasingly needed.

The feasibility of recycling and reuse of demolition waste is largely dependent on the effective implementation of material separation during demolition operations (Hyvärinen et al. 2020). This implementation, however, can be complicated by productivity concerns. Since demolition projects are usually directly followed by new construction projects, there is often a sense of urgency to rapidly complete the demolition process in order to reduce the construction project's completion time, which can consequently impede material separation activities. Considering this inherent tradeoff between sustainability and productivity in demolition operations (Jalloul et al. 2022), investigating the productivity of the demolition process is key to understanding the decision-making processes impacting the reusability and recyclability of demolition waste.

Material separation during the demolition process is conducted by means of heavy construction equipment, particularly excavators. Monitoring the productivity of heavy construction equipment has traditionally been conducted through manual time monitoring. Such a labor-intensive process is tedious, costly, and prone to human errors (Kim et al. 2018). As the tasks performed by heavy construction equipment involve a series of repetitive actions, each with a distinct time duration, prior research studies (Chen et al. 2022) have focused on automatically recognizing these actions to facilitate productivity monitoring. Nonetheless, all of these studies were limited to earthmoving operations, with no investigations carried out in relation to demolition operations. Given the distinct nature of demolition activities, particularly with regards to material separation, relevant previous research efforts are not applicable to automatically recognizing material separation activities and thereby tracking the productivity of heavy equipment during the sorting and separation of demolition waste.

This study aims to address the current knowledge gap by focusing on enabling automated identification of material separation activities performed by excavators during demolition operations. The proposed approach uses motion data of excavators, particularly linear and angular acceleration, collected using inertial measurement unit (IMU) sensors. As proof of concept, the proposed activity identification model is developed and tested using small-scale simulations of material separation operations during demolition. The potential of the developed model for enabling low-cost, efficient, and effective demolition productivity monitoring is discussed, with the ultimate goal of optimizing demolition decision-making in a way that increases the recycling and reuse of demolition waste.

## REVIEW OF RELATED WORK

Prior research efforts on developing automated methods for recognizing the activities performed by heavy construction equipment for productivity monitoring purposes can be generally categorized into two groups based on their primary source of information: vision-based and sensor-based approaches. Vision-based activity identification methods analyze visual information collected by means of video recordings of heavy construction equipment operations on-site. Advancements in computer vision technology, particularly in terms of object detection and tracking, along with the availability of low-cost cameras for visual data collection, have increased the popularity of these methods (Chen et al. 2022). For instance, Gong et al. (2011) utilized the Bag-of-Words computer vision model, which represents visual content as a collection of words, and integrated it with Bayesian network learning models to classify backhoe states. Golparvar-Fard et al. (2013) adopted a different methodology by utilizing the Histogram of Oriented Gradients to represent the spatiotemporal features extracted from video data and then employing a Support Vector Machine to learn and classify different activities performed by excavators and trucks during earthwork operations. More recent research on vision-based activity identification has predominantly relied on spatiotemporal neural networks (Chen et al. 2022). One example is the work conducted by Chen et al. (2020) during which three convolutional neural networks were used to detect, tract, and classify three types of excavator actions, namely digging, swinging, and loading. Although vision-based approaches have exhibited significant potential in identifying heavy construction equipment activities, they remain highly dependent on the field view captured by on-site cameras, which can be impacted by object obstructions, moving backgrounds, and changes in light conditions (Rashid and Louis 2020). These limitations are not present in sensor-based approaches that do not depend on visual data.

With the advancement and widespread availability of various sensors in the market, sensor-based approaches have been increasingly utilized for automated identification of heavy construction equipment activities. One such category of sensors used in productivity monitoring applications are location sensors, such as global positioning systems (GPS) and radio frequency identification (RFID). These sensors, however, are limited to tracking and identifying nonstationary activities performed by heavy construction equipment, as they mainly rely on changes in equipment location (Kim et al. 2018). To overcome such limitations, motion sensors, particularly inertial measurement unit (IMU) sensors, have been employed to analyze the motion information of heavy equipment motion and, thus, automatically identify its performed activities. This is based on the assumption that different equipment activities result in unique patterns in the linear and angular acceleration measured by the motion sensors. Ahn et al. (2015) were the first to utilize the linear acceleration data of an excavator in an earthmoving site, collected using a low-cost accelerometer mounted inside the excavator cabin, to train and test several machine learning algorithms in order to recognize three types of activities: working, idling, and engine-off. Mathur et al. (2015) extended their work by using both linear and angular acceleration data captured by an IMU sensor embedded in a smartphone, which was similarly placed in the cabin of the excavator, to classify its operation as idle, wheel base motion, arm/bucket movement, or cabin rotation. A similar methodology was employed by (Kim et al. 2018) and Akhavian and Behzadan (2015), with the latter aiming to recognize slightly different classes of excavator earthmoving activities, such as engine off, idle, moving, scooping, and dumping. Rashid and Louis (2020) pointed out a limitation in the aforementioned studies, highlighting that the vibration of the cabin of the excavator is impacted by the site conditions, the properties of the excavator itself (e.g., condition of the engine and suspension quality), and the skill-level of the operator. They argued that this limitation can result in activity identification models that are not transferable to other excavators and may not be applicable to the same excavator operating in different site conditions. To address this limitation, Rashid and Louis (2020) relied on the motion data collected by IMU sensors attached to three different moving parts of an excavator, namely the boom, arm, and bucket, in order to automatically identify the activities performed by the excavator in an earthmoving site.

Given that none of the existing literature on automated activity identification pertains to demolition operations, this study focuses on automatically identifying material separation activities performed during such operations. It specifically employs the methodology proposed by Rashid and Louis (2020), utilizing the motion data of different moving members of an excavator.

## METHODOLOGY

The study follows a three-step methodology consisting of data collection, data preprocessing, and action recognition (Figure 1). Each step is explained in detail in the following subsections.

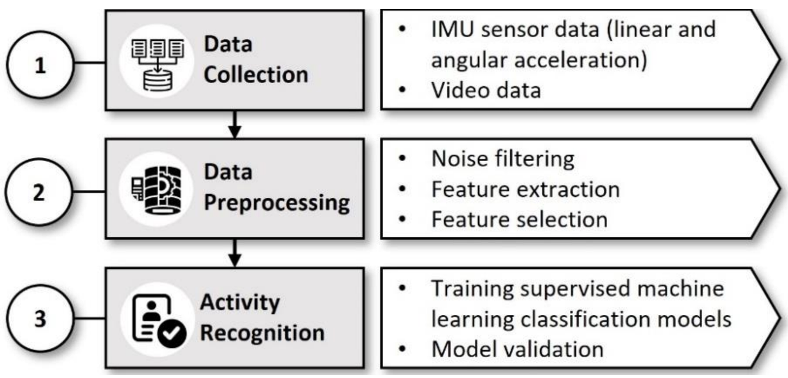


**Figure 1. Research methodology.**

**Data Collection.** Material separation activities during demolition operations were simulated in a lab setting using a small-scale, 1:14 remote control excavator equipped with a grapple bucket, operating on a mix of color-coded cement and metal debris. An excavator was specifically selected for this experiment since it is typically employed for separating various types of materials present in demolition debris and arranging them in different piles. Three IMU sensors, each equipped with a 3-axis accelerometer and a 3-axis gyroscope (Figure 2a), were used to collect linear and angular acceleration data of different moving parts of the excavator during its operation. Each IMU sensor is powered using a 2000 mAh lithium-ion battery of 3.7 volts and furnished with a microSD card for the purpose of logging data. The IMU sensors were specifically attached to the (1) boom, (2) arm, and (3) bucket of the excavator (Figure 2b).

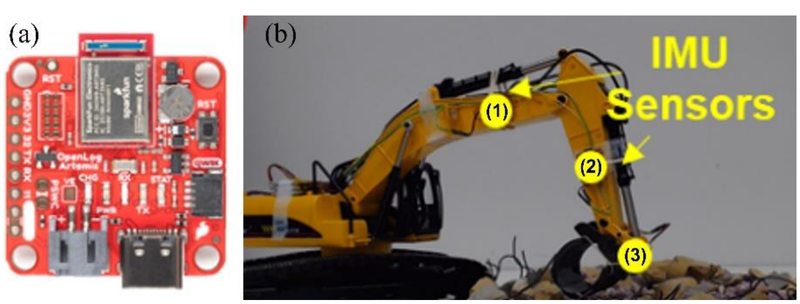


**Figure 2. Experimental setup: (a) IMU sensor and (b) sensors' placement on the excavator.**

Sensor data was collected for a total duration of 35 min at a sampling frequency of 80 Hz. The entirety of the experimental operations was recorded on video for data labeling purposes. Specifically, the collected time-stamped sensor data were synchronized with the video data and, subsequently, manually labeled into five classes of demolition waste material separation activities: (1) leveling, (2) grabbing, (3) swinging, (4) dropping, and (5) moving (Figure 3).

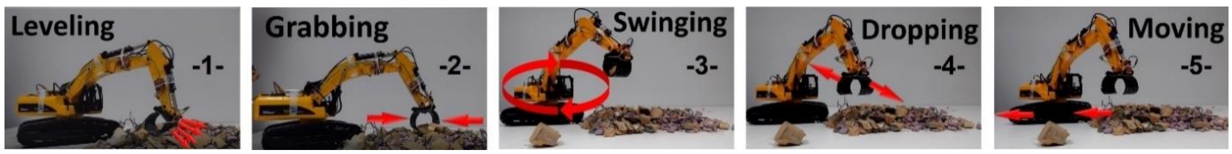


**Figure 3. Classes of demolition waste material separation activities.**

**Data Preprocessing.** The collected data was stored in a structured query language (SQL) database for preprocessing and analysis using Python. Data preprocessing involved filtering out any noise in the data, extracting features from the data, and selecting the most useful features for activity recognition.

***Noise Filtering.*** IMU sensors are subject to random and deterministic noise, such as static bias resulting from imperfections during sensor manufacturing (Nirmal et al. 2016). To reduce any imbedded noise in the data collected by the IMU sensors, a median filter with a window size of 3 was utilized. Median filtering is a signal processing technique that entails moving a window across the data and replacing the value at the center of the window with the median of the original values in the window, which helps remove noise from the signal while preserving its structure (Justusson 1981).

***Feature Extraction.*** Analyzing the collected sensor data sampled at a frequency of 80 Hz (i.e., 80 data points per second) can be computationally expensive. Given that each material separation activity takes place over a specific time period rather than a single point in time, the collected sensor data can be segmented into windows of data points whose statistical features can be used to represent the pattern of the corresponding motion data. Data segmentation can be implemented either using a sliding window of a fixed size with a designated overlap percentage or based on the actual start and end times of each activity performed. Given that activity-defined data segmentation has yielded the highest activity recognition accuracy in the previous work performed by Rashid and Louis (2020), it was adopted in this study.

Following the segmentation of the data into windows, a group of time-domain statistical features that have been commonly used in previous literature (Ahn et al. 2015; Akhavian and Behzadan 2015; Kim et al. 2018; Mathur et al. 2015; Rashid and Louis 2020) were computed for each window. Specifically, for each of the linear and angular acceleration data, the following features were extracted: resultant, mean (x, y, z), standard deviation (x, y, z), mean absolute deviation (x, y, z), maximum (x, y, z), minimum (x, y, z), interquartile range (x, y, z), correlation (x, y, z), zero crossing rate (x, y, z), kurtosis (x, y, z), skewness (x, y, z), and fourth-order autoregressive coefficients (x, y, z). Overall, a total of 86 features were extracted per IMU sensor.

***Feature Selection.*** Given the large number of features extracted, selecting the most relevant and informative features for activity recognition is important to avoid model overfitting and reduce computational complexity. As such, the ReliefF algorithm was employed for feature selection. ReliefF is a widely used feature selection algorithm, particularly for classification problems, that scores the importance of features based on how well they discriminate between instances that are close to each other in the feature space (Robnik-Šikonja and Kononenko 2003). The number of the top-ranked features by the ReliefF algorithm to select was determined by evaluating the performance of activity identification models built using different subsets of the top-ranked features.

**Activity Recognition.** The preprocessed data were used in the training and evaluation of material separation activity recognition models using supervised machine learning. Previous literature on automated equipment activity recognition (Golparvar-Fard et al. 2013) has shown that supervised learning outperforms unsupervised learning methods in this regard. Further, since different supervised machine learning classification models may have varying performance on a specific task (Amancio et al. 2014), multiple classifiers were trained and evaluated in this study. Specifically, seven different categories of supervised classifiers were employed: (i) K-Nearest Neighbor (KNN) – an instance-based learning model, (ii) Gaussian Process Classifier (GPC) – a probabilistic model, (iii) Relevance Vector Machine (RVM) – a Bayesian model, (iv) Classification and Regression Tree (CART) – a tree-based model, (v) Random Forest (RF) – an ensemble learning model, (vi) Support Vector Machine (SVM), and (vii) Artificial Neural Network (ANN). As the performance of each of these classifiers is affected by its hyperparameters, various hyperparameter values were used for each classification algorithm, as specified in Table 1. Hyperparameter tuning was conducted to optimize the classification performance.

Each of the seven classifiers was trained and tested using 5-fold cross-validation. This involves dividing the dataset into five equal-sized subsets and training and testing the classifier five times, with each subset being used once as the test set and the remaining four subsets as the training set (Akhavian and Behzadan 2015). The final performance score is obtained by averaging the scores across the five evaluations. Accuracy was used as the classification scoring metric, which measures the proportion of correct predictions made by the classifier across all classes of demolition waste material separation activities.

**Table 1. Summary of the employed classifiers and their hyperparameter values.**

| Classifier | Hyperparameter Values |
|---|---|
| KNN | Number of neighbors = [1, 10, 100] |
| GPC | Kernel = radial basis function (RBF) |
| RVM | Kernel = [linear, polynomial, RBF] |
| CART | Maximum depth = [4, 6, 8, 15]; minimum cost-complexity pruning is then applied |
| RF | Number of trees = 100 |
| SVM | Kernel = [linear, polynomial, RBF] |
| ANN | Number of hidden layers = [50, 100, 150, 200, 250, 300] |

## RESULTS

The selected classifiers were first trained and tested using the motion data from each of the three employed IMU sensors individually. The aim was twofold: firstly, to compare the performance of the different classifiers in identifying demolition waste material separation activities, and secondly, to identify the optimal IMU sensor placement on an excavator if only one sensor is to be utilized for collecting motion data. Table 2 summarizes the classification accuracies of the seven classifiers for each of the three IMU sensor placements (i.e., boom, arm, and bucket). Across all three sensor placements, KNN and CART demonstrated the poorest performance, yielding the lowest classification accuracies. Among the remaining classifiers, GPC achieved the highest classification accuracy when using the IMU sensor attached to the boom, while RF exhibited the best classification performance for both IMU sensors attached to the arm and bucket. Regarding sensor placement, the IMU sensor attached to the boom achieved the highest classification accuracy of 81.6%, followed by the IMU sensor attached to the arm with a slightly lower maximum accuracy of 81.3%. Meanwhile, the IMU sensor attached to the bucket resulted in notably lower classification accuracies, with the highest being 77.6%.

**Table 2. Performance of each classifier based on data from a single IMU sensor.**

| Classifier | Boom Sensor Accuracy (%) | Arm Sensor Accuracy (%) | Bucket Sensor Accuracy (%) |
|---|---|---|---|
| KNN | 75.5 | 72.3 | 70.7 |
| GPC | 81.6 | 76.1 | 73.0 |
| RVM | 79.9 | 75.6 | 73.0 |
| CART | 71.6 | 73.4 | 71.3 |
| RF | 80.5 | 81.3 | 77.6 |
| SVM | 80.5 | 76.1 | 74.6 |
| ANN | 81.0 | 80.2 | 75.7 |

Next, the impact of utilizing more than one IMU sensor on the achieved activity recognition accuracy was investigated. Towards this end, the selected classifiers were trained and tested using the motion data from various combinations of IMU sensors. Their resulting performance is presented in Table 3. Among the seven classification algorithms, RF and ANN were found to be the top-performing. Specifically, RF yielded the highest classification accuracy for both combinations of (i) boom and arm and (ii) arm and bucket IMU sensors, while ANN had the highest classification accuracy for (i) the combination of arm and bucket sensors and (ii) when all three sensors (i.e., boom, arm, and bucket) were utilized. The results indicate that when utilizing two IMU sensors, attaching them to either the boom and bucket or the boom and arm yields the best performance, with the highest achieved classification accuracy being 83.8% and 83.5%, respectively. When employing all three IMU sensors (i.e., on boom, arm, and bucket), the maximum achieved classification accuracy reaches 84.1%, which is the highest compared to using a single or a pair of IMU sensors. These findings suggest that including motion data from additional moving parts of an excavator can improve the accuracy of automated recognition of demolition waste material separation activities.

## TOWARDS EFFICIENT DEMOLITION PRODUCTIVITY MONITORING

Rather than relying on manual methods, the automated approach for identifying demolition waste material separation activities presented in this study offers a low-cost and effective solution for monitoring the productivity of demolition operations, particularly demolition material separation. This productivity generally refers to the production rate at which excavators sort demolition debris in a demolition site (Kim and Chi 2020). Specifically, it is the ratio of the total output to the total input required, where the amount of demolition debris to be sorted represents the total output, and the sorting duration represents the total input. The amount of demolition debris is typically estimated based on the total demolition area and the type of the structure that is demolished (i.e., to determine the corresponding debris generation rate) (Wu et al. 2014). As for the demolition debris sorting duration, it should be determined based on the actual activities performed by the excavator in order to avoid accounting for typical work interruptions and non-productive time (e.g., idle or engine off) during demolition operations. As such, the sorting duration can be computed as the sum of the time required to complete the value-adding excavator activities (i.e., leveling, grabbing, swinging, dropping, and moving) when sorting a specific amount of debris. Using the developed automated activity identification model, these activities can be automatically recognized and, subsequently, their durations can be easily extracted given the start and end time of the motion data window associated with each recognized activity.

**Table 3. Performance of each classifier based on data from multiple IMU sensors.**

| Classifier | Boom & Arm Sensors | Boom & Bucket Sensors | Arm & Bucket Sensors | Boom, Arm, & Bucket Sensors |
|---|---|---|---|---|
| | Accuracy (%) | Accuracy (%) | Accuracy (%) | Accuracy (%) |
| KNN | 75.7 | 75.2 | 74.0 | 75.4 |
| GPC | 78.5 | 80.2 | 78.0 | 79.3 |
| RVM | 78.8 | 81.9 | 76.5 | 79.9 |
| CART | 73.5 | 75.1 | 72.6 | 75.4 |
| RF | 83.5 | 83.5 | 81.0 | 82.7 |
| SVM | 78.2 | 80.4 | 80.2 | 80.7 |
| ANN | 83.5 | 83.8 | 80.7 | 84.1 |

The ability to efficiently obtain actual demolition productivity information can eliminate the uncertainty inherent in demolition planning as well as facilitate continuous performance measurement in a demolition project. During the planning stage, demolition contractors can utilize demolition productivity information in order to maximize the amount of recyclable demolition waste, and thereby maximize the profits earned from selling said waste to recycling markets, all while ensuring the completion of the demolition project within the set time constraints (Jalloul et al. 2022). During the operational stage, continuous monitoring of the productivity of the demolition operations enables the assessment of the actual project performance with respect to its plan. Accordingly, heavy equipment operators can implement any necessary measures (e.g., expediting the demolition waste material separation activities), while project managers can make more informed decisions (e.g., allocating additional resources).

## CONCLUSION

Given that the sustainability of demolition operations is often largely impacted by productivity considerations, effective and efficient demolition productivity monitoring is crucial to investigate the decision-making processes affecting the reusability and recyclability of demolition waste. Toward this end, this study introduced an automated sensor-based approach for identifying demolition waste material separation activities. It leverages the motion data of different moving members of demolition machinery collected by means of IMU sensors. Based on a small-scale demonstration of the proposed approach, results have shown that the IMU sensor placement on the excavator impacts the accuracy of activity recognition. Specifically, if only one IMU is used, the highest activity recognition accuracy is achieved when the sensor is attached to the boom. When two IMU sensors are employed, the accuracy is highest when they are attached either to the boom and bucket or the boom and arm. Lastly, utilizing three IMU sensors (i.e., on boom, arm, and bucket) has demonstrated the best performance for automated activity recognition. The effectiveness of the proposed approach in identifying demolition waste material separation activities within a simulated setting provides a foundation for future testing on full-size demolition equipment, while employing more advanced deep learning models to further increase the resulting classification accuracy. This future work will facilitate (i) monitoring the productivity of demolition operations for time and cost savings by using automated approaches as compared to manual ones, (ii) investigation of the resulting improvements in the sustainability of demolition operations, and (iii) verification of the adopted small-scale simulation's ability to capture the regularity of real-world demolition operations.

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