A Robust Framework for Identifying Automated Construction Operations

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Abstract –

Machine learning techniques have been successfully implemented for the identification of various construction activities using sensor data. However, there are very few studies on activity recognition in the automated construction of low-rise residential buildings. Automated construction is faster than conventional construction, with minimal human involvement. This requires high accuracy of identification for monitoring its operations. This paper discusses the development and testing of machine learning classifiers to identify normal automated construction operations with high precision. The framework developed in this work involves decomposing the activity recognition problem into a hierarchy of learning tasks in which activities at the lower levels have more details. The top recognition level divides the equipment states into two classes: 'Idle' and 'Operations'. The second recognition level divides the 'operations' into major classes depending on the top-level activities performed by the equipment. The third recognition level further divides the activities into subclasses and so on. Since the number of classes and the similarity between them increase with the recognition level, identification becomes extremely difficult. The identification framework developed in this study classifies operations belonging to the parent class at each level in the hierarchy. The efficacy of this framework is demonstrated with a case study of a top-down modular construction system. In this construction system, the modules of a structural frame are assembled and lifted starting with the top floor followed by the ones below. The accelerometer data collected during top-down construction is used to identify the construction operations. The proposed framework shows superior performance over conventional identification using a flat list of classes.

Keywords –

Automated Construction; Construction Monitoring; Machine Learning; Accelerometer

1 Introduction

Construction operations are monitored for several purposes like the determination of cycle time, productivity, fuel consumption, quality of work and possible failure conditions [1]–[3]. Identifying the activity with reasonable accuracy is sufficient for these purposes. However, for the development of a monitoring system to ensure safety, high accuracy of identification is necessary.

Automated construction is faster than conventional construction, with minimal human involvement. In a fast automated construction system, an undetected faulty operation might cause catastrophic accidents [4], [5]. Besides, the level of detail required in this activity recognition problem is also higher. If an operation is detected as faulty in ongoing automated construction, the details like which operation, the stage of construction in which it happens and its location, have to be identified to take appropriate corrective actions. Hence, the operation identification problem has to be carefully formulated to develop a monitoring system.

Existing studies on equipment activity recognition aim to improve the identification results by exploring advanced machine learning techniques, training options, hyperparameters, features extracted and also by carefully selecting the data [6]–[9]. The current study examines the significance of problem formulation in activity recognition.

The main objective of this study is to identify automated construction operations with high accuracy. A hierarchical operation recognition framework has been developed in this study which involves decomposing the activity recognition problem into a hierarchy of learning tasks. At the top level, equipment states, 'idle' and 'operations' are identified. The activities at lower levels have more details. The performance of this framework is compared with that of the conventional approach to operation recognition which involves a flat list of classes to be separated. The two approaches were evaluated using data from an automated construction system (ACS) prototype. Acceleration data collected from the structure is used for operation identification. Both approaches use artificial neural networks (ANN) as the learning algorithm.

2 Equipment activity recognition methods

Advancements in computing technology have opened a wide range of possibilities for automated activity recognition. There are mainly three methods for automated activity recognition: sensor-based methods, computer vision-based methods and audio-based methods [3]. In some cases, a combination of these methods is also adopted.

Sensor-based methods capture the characteristic signals associated with operations [10]. Accelerometers, gyroscopes, inertial measurement unit (IMU) and Global Positioning System (GPS) are some of the widely used sensors for activity recognition [6], [8], [11]. Sensor-based methods can be reliably applied to chaotic construction sites where equipment is often beyond the line of sight. A broad range of studies explored various supervised learning methods, starting from simple ANN, K-nearest neighbour (KNN), logistic regression, Support vector machine (SVM) to deep learning methods in recent times [7], [8], [12], [13].

Vision-based methods have the potential to identify any type of equipment if ambient conditions are favourable. Images or videos of the construction equipment are used for activity recognition. Initial studies used SVM and 2D motion descriptors for activity recognition from spatiotemporal data [14], [15]. More recent studies explore deep learning methods for automated labelling of activities in video data [2], [16]. Major limitations associated with the vision-based methods include high sensitivity to ambient conditions, obstructions, cost of implementation and need for large storage space.

Audio-based methods can be used to identify any equipment that generates sound. Numerous machine learning classifiers were implemented for sound classification. Some of the most popular classifiers are KNN, SVM, ANN, Hidden Markov model (HMM) and deep neural networks [17]–[20]. Microphones can capture the data from all directions without getting affected by visual obstructions [3]. This data is not biased by the skill level of the operator. However, not all equipment can be identified by this method. Data collecting for these methods can be challenging for noisy construction sites.

The current study attempts to identify operations of an ACS prototype for low-rise buildings. Acceleration data is used for activity recognition. ANN is one of the best performing machine learning classifiers for equipment activity recognition. Hence, ANN with a simple architecture (single hidden layer) is selected for the current study.

3 Methodology

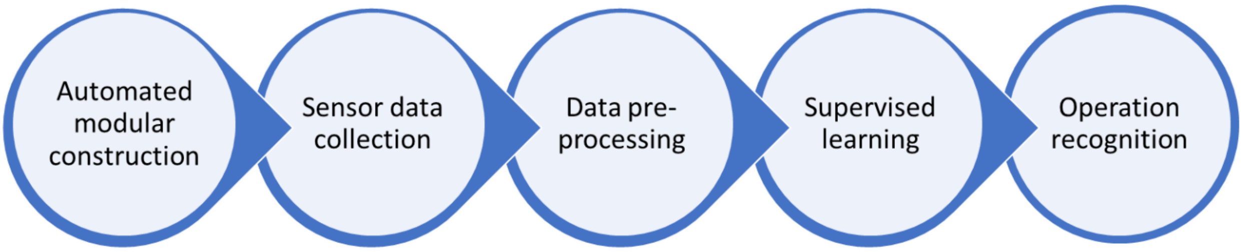

Figure 1. Methodology for operation recognition

Figure 1 shows the methodology adopted for this study. Acceleration data is collected during the modular construction of a structural frame using an Automated Construction System (ACS) prototype. After pre-processing, the data is supplied to the operation recognition framework. This machine learning-based framework identifies the operations that are organized hierarchically into 4 recognition levels (RL). Two approaches are compared: a) Conventional approach using a flat list of classes to be identified, and b) Hierarchical operation recognition framework. Each step of the research methodology is described in detail in the following sections.

3.1 Automated modular construction

The automated top-down construction method is adopted for the construction of the structural frame in this study [4], [5], [21], [22]. This method is mainly developed for the modular construction of low-rise buildings. For automated top-down construction, the main load-bearing parts of a structure are divided into smaller components. The modules of the beam and column are assembled sequentially, starting from the topmost parts of the structural frame. After the assembly of the first set of components, the completed structure is lifted to a certain height. The modules of the column are added to the existing structure and lifted it again in the next operation cycle. Since the structure is completed from top to bottom using an ACS, this method is called automated top-down construction.

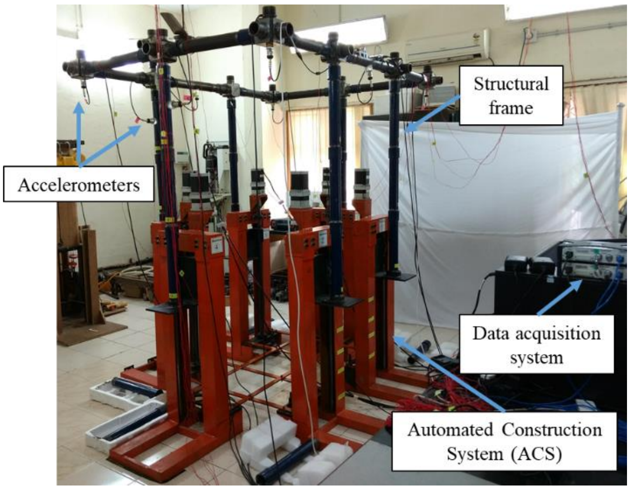

Figure 2. Data collection during automated modular construction

Figure 2 shows the laboratory prototype of the ACS and the structural frame developed for this study. The ACS consists of 6 lifting machines. Each of these machines is capable of operating individually for lifting or lowering of specific support and as a group for simultaneous lifting or lowering of all supports (coordinated lifting or coordinated lowering). The structural frame modules are made of standard steel pipe sections with external threading on both edges. They are connected by couplers and universal joints with internal threading. The structure has redundant columns to ensure stability during top-down construction. Each column of the structure is supported by a lifting platform of the ACS.

At the beginning of the top-down construction, the top most beam and column modules are connected and supported by these lifting platforms. This idle condition before the beginning of the operation cycle is termed as 'Idle_CS0' where CS0 refers to Construction Stage 0. This is followed by the first operation cycle of top-down construction. The operations involved in one cycle are given below [21].

1. Coordinated lifting
2. Lowering support 1
3. Assembling module of column 1
4. Lifting support 1 till the load is transferred from column 1
5. Repeat steps (2) to (4) for other supports (support 2 to support 6)

One cycle of the top-down construction finishes one stage of construction (CS). Two cycles of operations were carried out for one set of experiments. Totally 6 sets of experiments were conducted for the study.

3.2 Data collection

Acceleration data was collected from 8 different locations on the structure during automated construction (Figure 2). Monoaxial piezoelectric accelerometers (measurement range: -5g to +5g, sensitivity: 1000 mv/g) were installed on the topmost beam-column assembly for this purpose. The data is acquired through HBM universal measuring amplifier (model: QuantumX MX840B) at 200 Hz sampling frequency. The timestamps of all operations were manually recorded in a time tracking excel sheet. These sheets were compared with the timestamps of the acquired data for generating operation labels required for supervised learning.

3.3 Data pre-processing

The acceleration data collected using HBM data acquisition software is exported to Microsoft Excel and MATLAB files for analysis. Based on the studies of equipment activity recognition, 5 time-domain features and 5 frequency domain features were extracted from the raw data [6], [11], [23]. The time-domain features include mean, variance, interquartile range, peak and root mean square error. The period of the signal and signal energy were extracted through autocorrelation of the signal. The other frequency domain features include the three prominent frequencies from the Fast Fourier Transform (FFT) of the signal. Totally 80 features (10 features x 8 sensor locations) were extracted from the raw acceleration data.

3.4 Supervised learning and operation recognition

In previous studies, supervised learning techniques have demonstrated superior performance compared to unsupervised learning techniques for unbalanced datasets [6], [14]. The current study adopts Artificial Neural Networks (ANN) for the classification of automated construction operations.

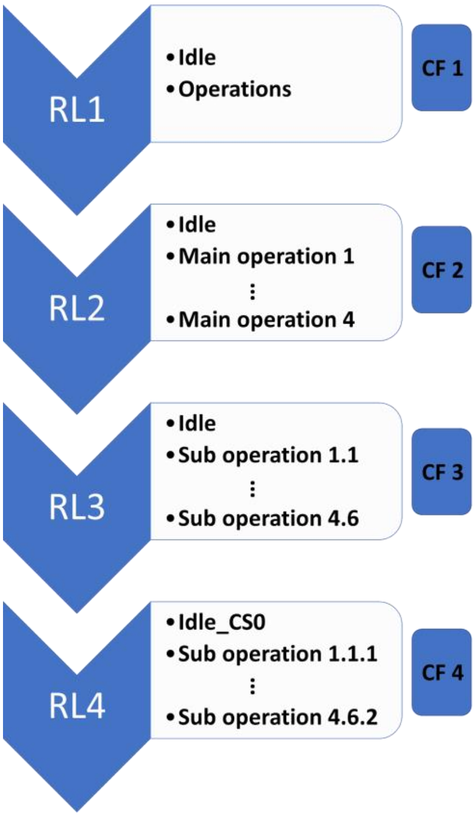

Figure 3. Conventional approach for operation recognition

The identification problem has 4 recognition levels (RL) as follows.

- RL1: Recognizes whether the ACS is 'idle' or 'operating'
- RL2: Recognizes the major operation categories
- RL3: Recognizes the sub-operation categories
- RL4: Recognizes stage of construction

The conventional approach for operation recognition uses a flat list of classes to be separated. However, in order to test the performance of this approach at different recognition levels, the identification problem is divided into 4 different identification tasks, one task per RL (Figure 3). An ANN classifier is assigned to each identification task. The classifiers are named as CF 1, CF 2, ..., CF 4, represented by blue boxes in figure 3. The operation categories identified are given as a list next to it. The actual operation categories identified by the classifiers are given in Table 1. The complexity of the identification problem seems to increase from RL1 to RL4 in this approach.

Hierarchical operation recognition framework is developed by considering the hierarchical relationship among the operations (Figure 4). If the major category of an operation is identified with high accuracy, the further identification task can be simplified by exploring the subcategories of that operation. This idea is the basis of the hierarchical operation recognition framework. The main

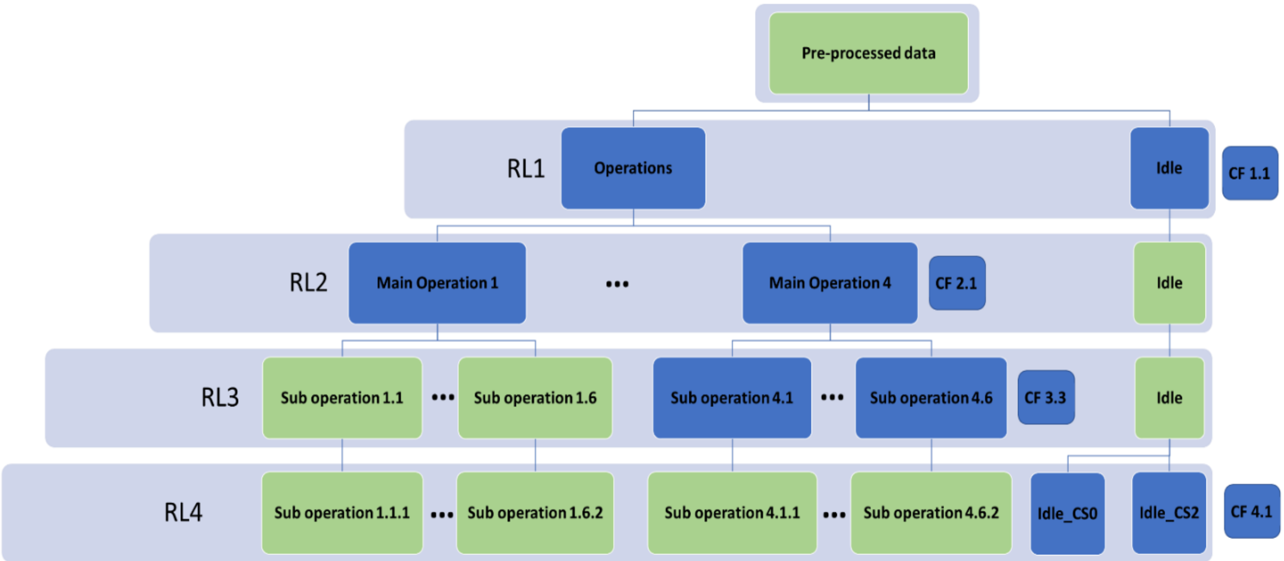

Figure 4. Hierarchical operation recognition framework

Table 1. Classifiers in operation recognition frameworks

Recognition Level	Classifiers in conventional approach	Classifiers in hierarchical operation recognition framework	Name of Classes
1	CF 1	CF 1.1	Idle
			Operations
2	CF 2		Idle
		CF 2.1	Coordinated Lifting
			Lowering Support
			Assembling Column Module
			Lifting Support
3	CF 3		Idle
			Coordinated Lifting
		CF 3.1	Lowering Support 1 ... Lowering Support 6
		CF 3.2	Assembling Column Module Step 1 … Assembling Column Module Step 6
		CF 3.3	Lifting Support 1 … Lifting Support 6
4	CF 4	CF 4.1	Idle_CS0
			Idle_CS2
		CF 4.2	Coordinated Lifting_CS0
			Coordinated Lifting_CS1
			Coordinated Lifting_CS2
		CF 4.3	Lowering Support 1_CS1 Lowering Support 1_CS2
		…	…
		CF 4.8	Lowering Support 6_CS1 Lowering Support 6_CS2
		CF 4.9	Assembling Column Module Step 1_CS1 Assembling Column Module Step 1_CS2
			…
		CF 4.14	Assembling Column Module Step 6_CS1 Assembling Column Module Step 6_CS2
		CF 4.15	Lifting Support 1_CS1 Lifting Support 1_CS2
			…
		CF 4.20	Lifting Support 6_CS1 Lifting Support 6_CS2

the identification problem is divided into a hierarchy of simple identification tasks across the RLs. Hence, there can be more than one identification task per RL. The classifiers are named as 'CF RL.n' where the first index RL represents recognition level and n denotes the number of the classifier in that RL. For clarity, only one classifier is shown per RL in figure 4 The classifier and the operations classified are shown in blue boxes. This figure is also for the representation of the concept of hierarchical operation recognition framework. The actual details of the framework are given in Table 1.

The performance of all classifiers is assessed through k-fold cross-validation. This avoids the problem of overfitting to the given data. The classifiers in RL1 to RL3 are 10-fold cross-validated and those in RL4 are 5-fold cross-validated for both identification frameworks. The predicted class labels were compared with the digital record of actual class labels to estimate the accuracy of identification. The accuracy is computed as given in equation 1.

$$Accuracy = \frac{Number\ of\ samples\ correctly\ identified}{Total\ number\ of\ samples}\ x\ 100\ \% \quad (1)$$

4 Results and discussion

Table 2. Summary of operation recognition results

Recognition level (RL)	Conventional approach for operation recognition		Hierarchical operation recognition framework	
	Classifiers	Overall accuracy per RL (%)	Classifiers	Overall accuracy per RL (%)
1	CF 1	99.58	CF 1.1	99.58
2	CF 2	99.18	CF 2.1	100.00
3	CF 3	95.92	CF 3.1 - CF 3.3	99.07
4	CF 4	84.56	CF 4.1 - CF 4.20	99.19

The operation recognition results are summarized in Table 2. For comparing the performance of the two approaches, the prediction accuracy of all classifiers in the hierarchical framework is combined to estimate the overall accuracy per RL. The classifier CF 1 and CF 1.1 are assigned with the same identification task: classifying ‘idle’ and ‘operations’. Hence the accuracy of identification is also equal. At RL 2, the hierarchical framework performs slightly better than the conventional approach with 100% accuracy. Meaning all main operations were identified correctly. CF 2.1 removes the ‘idle’ from the classes. This is the reason for improved accuracy.

RL 3 onwards there is a significant difference in the problem formulation. The hierarchical framework has focused classifiers for the identification of sub-operations at RL3. Hence the operations were better identified in this framework. At RL 4 where the construction stage is to be identified, there is a significant difference in performance between two recognition frameworks.

While the hierarchical framework consistently delivers accuracy close to 100%, the performance of the conventional approach continuously declines with the increase in the recognition level. Even though both approaches use the same machine learning algorithm, their performances are different. The results emphasize the importance of problem formulation in activity identification.

5 Conclusions

This study proposes a robust framework for identifying automated construction operations with high accuracy. The hierarchical operation recognition framework formulates the identification problem into a hierarchy of learning tasks. The performance of this framework is compared with the conventional approach to operation recognition using a flat list of classes representing activities.

Both approaches use ANN as the learning algorithm. Even though their performances are comparable at the top level, the hierarchical framework outperforms the conventional approach while identifying operations with minute levels of details. Most previous activity recognition studies have attempted to improve the performance by carefully selecting data, and exploring learning algorithms, training options, parameter selection and features extracted. This study shows that the problem formulation can make a tremendous difference in the performance.

Acknowledgement

The project is funded by the Department of Science and Technology (DST), India through the grant DST/TSG/AMT/2015/234.

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