Window-Warping: A Time Series Data Augmentation of IMU Data for Construction Equipment Activity Identification

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Abstract –

Automated, real-time, and reliable equipment activity identification on construction sites can help to minimize idle times, improve operational efficiencies, and reduce emissions. Many previous efforts in activity identification have explored different machine learning algorithms that use time-series sensor data collected from inertial measurement units mounted on the equipment. However, machine learning algorithms requires large volume of training data collection from the field, as inadequate and smaller amounts of data results in model overfitting. This study proposes an automatic and real-time activity recognition framework by using data from multiple IMUs attached to equipment's moving and articulated parts. In doing so, first a time-series data augmentation technique called *window-warping* (WW) is introduced to generate synthetic training data from a smaller volume of field-collected data. Two supervised machine learning algorithms, artificial neural network (ANN), and K-nearest neighbour (KNN) were trained and evaluated using the augmented training data to identify equipment activity. The developed data augmentation methodology is validated using a case study of an earthmoving excavator. The results show the potential for using time-series data augmentation in training machine learning algorithms for construction equipment activity recognition using minimal data collected from the field.

Keywords –

Data augmentation; Activity recognition; Time series; Construction equipment; Machine learning; IMU

1 Introduction

Automated, and real-time activity recognition of construction equipment plays an important role in construction operation analysis by enabling productivity monitoring [1-2], preparation of input for near real-time simulation [3–5], and automated cycle-time analysis [2-6]. It is also a key necessity for real-time safety applications on the construction site [7–9] and for automating environmental assessments [11-12]. Equipment activity identification can also enabled several applications in AR/VR visualization [12–15]. Despite being a necessary component for all the aforementioned applications, activity identification in construction site has historically been a manual effort. The manual approach of observing, recording, and analysing an equipment's action is prone to human error and requires excessive time, effort, and cost. In order to overcome these shortcomings, past efforts have investigated vision-based, as well as inertial measurement unit (IMU)-based activity recognition frameworks to automatically identify the activities that are performed by construction equipment in real-time or near real-time. Previous efforts in IMU-based frameworks have mostly used a single IMU attached to the equipment's cabin in order to capture the vibration of the equipment [9–11]. The vibration data were then used to train different machine learning algorithms that then classified an equipment actions. However, training machine learning algorithms requires a large volume of initial training data, which can be challenging to acquire from an active construction site due to the cost and effort inherent in such an endeavour that requires equipment and their operators to perform tasks that are extraneous to the work involved with their operation. Collecting data from an equipment during the course of its regular operations results in data that needs to be manually labelled and data that is non-uniformly distributed over the various activities that the equipment could be performing. These factors result in low-quality training data that result in poor performance of the training algorithm. Moreover, a small volume of training dataset poses a challenge in identifying a higher number of activities performed by the equipment as it creates an imbalance in the dataset. This paper describes a means for increasing the amount of training data for machine learning algorithms for equipment activity identification by using the technique of data augmentation.

In the machine learning domain, specifically in object recognition, handwriting recognition, and speech recognition, data augmentation is a popular technique to generate synthetic training data when only small training sets are available [17]. By augmenting training data, errors of the classifiers due to variance can be reduced. The issue of model overfitting due to a dearth of learning examples can be overcome by introducing synthetic data generated by data augmentation. Even though literature is rife with examples that have applied data augmentation techniques for images, handwriting, and speech, data augmentation of time series data for classification purposes has not be fully explored yet.

This paper thus presents a real-time and automatic activity recognition framework for construction equipment using augmented data from multiple IMUs that mounted to articulated parts of the equipment. A time series data augmentation technique called *window-warping* (WW) is introduced to generate synthetic training data, thereby eliminating the need for obtaining large volume of field data. The developed framework is validated by carrying out a case study using an excavator from an actual earthmoving site.

This paper is organized as follows. First, a review of the state-of-the-art in IMU-based construction equipment activity recognition and data augmentation is provided to set the context for this research and highlight research gaps. Then, the methodology section discusses the main components of the proposed framework. Next, the results of the case study are presented. Finally, the results and main contribution of this work is summarized along with the limitations and future directions of this research.

2 Related Work

The framework presented in this paper consists of an activity recognition platform for construction equipment using multiple IMUs and a time-series data augmentation technique. This section provides a comprehensive literature review in IMU-based equipment activity recognition and data augmentation techniques in classification.

2.1 IMU-based Equipment Activity Recognition

IMU-based approaches for equipment activity recognition leverage the location and/or the vibration of the equipment in order to identify its activity at a specific time. El-Omari and Moselhi (2011) [18], and Ergen et al. (2007) [19] proposed a framework combining radio frequency identification (RFID) and global positioning system (GPS) technology for automated localization and tracking of construction equipment. Vahdatikhaki and Hammad (2014) [5] enhanced the performance of equipment state-identification approach by adopting a multi-step data processing framework combining location and motion data. Song and Eldin (2012) [20] developed an adaptive real-time tracking of equipment operation based on their location to improve the accuracy of project look-ahead scheduling. Although location-based operation tracking can identify the state and operation of construction equipment at a coarse level (e.g., *idle* and *busy* states), it is incapable of classifying the activities performed by equipment when it is stationary. Such limitations of location-based operation tracking have inspired researchers to explore the feasibility of both independent [10] and smartphone embedded [9 - 10] inertial measurement units (IMUs) for automated equipment activity recognition. Ahn et al. (2015) [10] used a low-cost accelerometer mounted inside the cabin of an excavator to collect operational data from an earthmoving worksite. Several classifiers were tested to classify three different states (i.e., engine-off, idle, and busy) of an excavator. Mathur et al. (2015) [6] utilized smartphone-embedded accelerometer by mounting it inside an excavator cabin to measure various activity modes (e.g., wheel base motion, cabin rotation, and arm movement) as well as duty cycles. Akhavian and Behzadan (2015) [16] adopted a similar approach by attaching a smartphone to the cabin of a front-end loader to collect accelerometer and gyroscope data during an earthmoving operation, upon which several classification algorithms (i.e., ANN, DT, KNN, LR, SVM) were tested. Their study also investigated the impact of different technical parameters such as level of details, segmentation window size, and selection of features on the performance of different classification algorithms. The same approach and technical parameters were further extended for construction workers [21].

2.2 Data Augmentation for Classification

Numerous data augmentation techniques have been tried and tested in computer vision [24–28] and speech recognition domain [29–31]. Charalambous and Bharath (2016) [24] introduced a simulation-based methodology which can be used for generating synthetic video data and sequence for machine/deep learning gait recognition algorithms. D'Innocente et al. (2017) [22] proposed an image data augmentation technique which zooms on the object of interest in an image and simulates the object detection outcome of a robot vision system. The goal of this paper was to bridge the gap between computer and robot vision, utilizing data augmentation. Most of the advanced object recognition algorithms utilizes various image augmentation techniques on images, such as flipping, rotating, scaling, cropping, translating, adding Gaussian noise etc. in order to generate synthetic data for training and testing machine/deep learning algorithms [25,26,30]. Moreover, in the speech recognition domain, studies have applied techniques such as vocal tract length normalization [27-28], speech rate, and frequency-axis random distortion [27], label-preserving audio transformation [29] to improve the performance of learning algorithms.

Despite the frequent implementation of data augmentation techniques in the computer vision and speech recognition domains, data augmentation in time series classification have not been deeply investigated yet [31]. Guennec et al. (2016) [32] proposed two time series data augmentation techniques; window slicing, and window-warping to train a convolutional neural network (CNN). In order to reduce the variance of a classifier, Forestier et al. (2017) [17] introduced dynamic time warping (DTW) for time series classification. Um et al. (2017) [31] proposed the most comprehensive set of time series data augmentation techniques in order to monitor Parkinson's disease patients using wearable sensors.

2.3 Research Gaps and Point of Departure

Several machine learning approaches in IMU-based activity recognition for construction equipment have been explored in the recent past. Machine learning models usually benefit from larger training dataset because small and inadequate training data leads to model overfitting [33]. Moreover, small training dataset prevents a classification algorithm from learning parameters for identifying a higher number of classes due to an imbalance in data [16]. Furthermore from a practical standpoint, collecting large volume of IMU data from equipment operating in active construction sites poses challenges related to cost, time, and effort. In order to overcome these challenges, this paper aims to develop an equipment activity recognition framework which uses augmented training data, decreasing the effort of collecting large volume of field data. In doing so, a time-series data augmentation technique named *window-warping* (WW) is developed.

3 Methodology

The general architecture of the designed framework for data augmentation and classification is presented in Figure 1. In this methodology, accelerometer and gyroscope data are collected from multiple IMUs attached to different articulated elements of the equipment. The raw data is first divided into training and test data. The raw training data are used for data augmentation. The raw and augmented training data are combined together to train the machine learning algorithms. The trained models are then evaluated using the test data, separated at the beginning of the data processing.

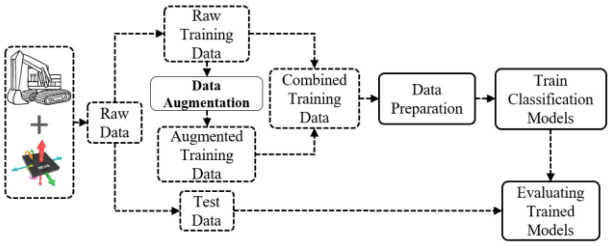

Figure 1. Developed framework for data augmentation and classification model

The following sections discusses the methodological details of data augmentation and model training.

3.1 Data Augmentation Using Window-Warping (WW)

Data augmentation can be regarded as an insertion of prior knowledge about the invariant properties of the data against certain transformations. The resulting augmented data can cover an unknown input space, prevent model overfitting, and increase the generalization capability of the classification model [31]. It is well known in the computer vision arena that minor changes (or augmentations) of the image in terms of jittering, scaling, warping, and rotating do not change the data labels as they can happen in real world observations. But not all data augmentation techniques implemented in computer vision domain are applicable to time-series data augmentation. This study utilizes a time-series specific data augmentation technique named *window-warping* (WW). Figure 2 provides a visualization of the WW augmentation technique proposed in this research. This data augmentation technique is implemented by warping the time-series data of each activity by speeding it up or down. This technique is logical in context of this research as the construction equipment can perform any specific

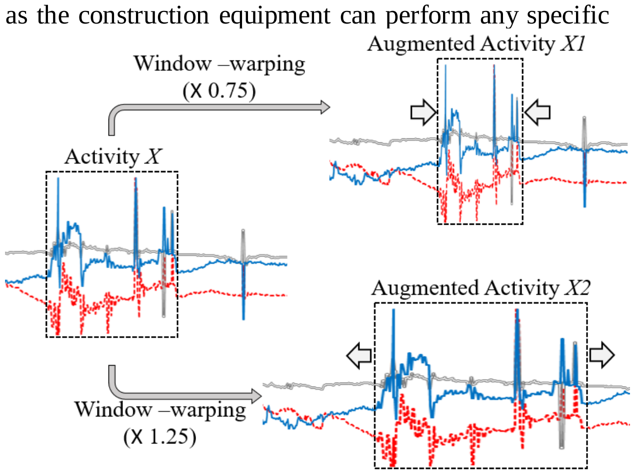

Figure 2. Window-warping (WW) data augmentation

activity at slightly different speeds. Thus, synthetic data can be generated, which generalizes IMU data for different operational speeds of the equipment. In this paper, warping ratios of $1/2$, $3/4$, 1.25 and 1.5 were considered. In other words, the raw training data are speeded up to 1.25, and 1.5 times and slowed down up to $1/2$, and $3/4$ times. Figure 2 illustrates the WW technique with warping ratio $3/4$ (top), and 1.25 (bottom) for a specific activity *X*, which generates two augmented activities; *X1*, and *X2*. Applying four different warping ratio, training data are increased 5-fold, considering raw training data as 1-fold. This method generates training data of different lengths, which cause difficulties in training the machine learning algorithm. This issue is dealt with segmenting all training data (i.e., raw training data and augmented training data) with sliding window technique of fixed length and 50% overlap. More specifics about the data preparation and classification model training are discussed in following section.

3.2 Data Preparation

The data preparation step of the methodology includes data segmentation and feature extraction from the field-collected data. A single data point of the IMU sensor does not provide useful information about the activity of the equipment, since it just represents a momentary position of the equipment, similar to a snapshot image. In contrast, the activities of equipment consists of sequential motions distributed over a period of time, similar to a sequence of images or a video. Thus, data streams containing individual data points are segmented into data windows (i.e., consecutive time-series data points). In this paper, data windows of 1 second fixed length is considered with a 50% overlap between adjacent windows. After segmenting the time-series data into windows, a set of time-domain statistical features are extracted from each window. These features represent the pattern of the signal in the corresponding window and are eventually used as inputs in the classification algorithms. In this paper, 12 statistical features are extracted from each window, and they *are mean, maximum, minimum, standard deviation, mean absolute deviation, interquartile range, skewness, kurtosis* and, *4th order autoregressive coefficients*. Using these features as inputs, classification models are trained as discussed in the next section.

3.3 Training and Evaluation of Classification Model

Activity recognition frameworks are developed using both supervised and unsupervised classification models. However, since supervised learning algorithms provide better performance for equipment activity recognition [34], a network-based learning algorithm, *Artificial Neural Network* (ANN), and a distance based classification algorithm, *K-Nearest Neighbour* (KNN), are considered for training. Both ANN and KNN models are trained using the combined (raw and augmented) training data. After each model is trained, they are evaluated with the test data, which were separated from the raw data before the data augmentation phase. The performance of the model is evaluated using *accuracy*, *precision*, *recall*, and *F-1 score*. Confusion matrices are also generated in order to analyse inter-activity confusion of the trained model. The following section discusses the results of the case study carried out in this research, using motion data captured from an excavator.

4 Case Study and Results

In the case study, three IMUs were attached to the bucket, stick, and boom of an excavator. The excavator was operating on an earthmoving site, loading trucks with soils and levelling the ground. In addition to IMU data, video data were also collected for 2 hours for labelling purpose. The entire operation of the excavator was divided into 9 different classes: *Engine Off*, *Idle*, *Scooping*, *Dumping*, *Swing Loaded*, *Swing Empty*, *Moving Forward*, *Moving Backward*, and *Ground Levelling*. Raw data from the IMUs were labelled using the video, with numeric numbers (1 to 9) being assigned for each activity. Next, the raw data was separated into training and testing data with 50-50 ratio. Raw training data were used for the *window-warping* (WW) data augmentation, generating 4-fold augmented training data (with warping ratio of $1/2$, $3/4$, 1.25, and 1.5), thus increasing the volume of the training data 5- fold (4-fold augmented data plus raw training data). Table 1 summarizes the number of instances of each of the activity in raw and augmented dataset in the case study.

Table 1. No. of instances of raw and augmented data

		No of Instances				
Label	**Act. Name**	**Raw data**	**Raw testing data**	**Raw training data**	**Augmented training data (4-fold)**	**Combined training data (5-fold)**
1	Eng. off	166	83	83	332	415
2	Idle	34	17	17	68	85
3	Scooping	78	39	39	156	195
4	Dumping	81	40	41	162	203
5	Swi. Loaded	80	40	40	160	200
6	Swi. Empty	87	43	44	174	218
7	Mov. For.	5	2	3	10	13
8	Mov. Bac.	7	3	4	14	18
9	Grnd. Level.	17	8	9	34	43

For example, *Scooping* activity happened total 78 times during data collection, 39 of them were separated for testing, and 39 for training. 39 training instances were used for 4-fold WW augmentation, generating total 195 training instances for *Scooping*. Next, two supervised classifiers (i.e., ANN, and KNN) were trained for 9 classes of activities using combined 5-fold training data. Finally, the models were tested using the 50% raw test data.

Figure 3 and Figure 4 illustrates the effect of WW data augmentation by comparing the use of 1-fold raw training data vs. 5-fold combined training data. From both the figures, we see that training the models with 5-fold augmented data improves their performance substantially from just training with raw training data. For example, the accuracy, precision, recall, and F-1 score of KNN improves from 51.7% to 97.9%, 49.5% to 96.4%, 44.2% to 96.8%, and 45.6% to 96.6% respectively by training the model with augmented data. It can also be observed that, improvement in the performance indices (i.e., accuracy, precision, etc.) is higher for KNN than ANN.

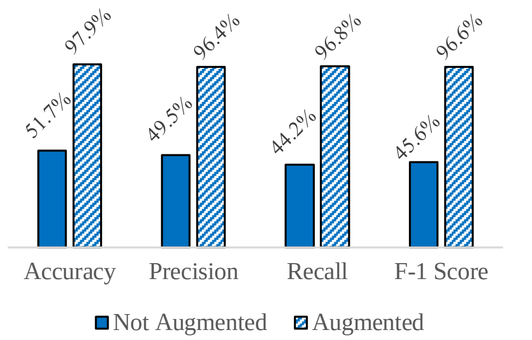

Figure 3. Performance measures of KNN

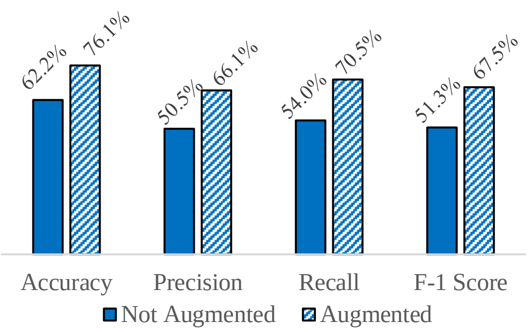

Figure 4. Performance measures of ANN

Next, a sensitivity analysis was conducted using different volume of training dataset (e.g., 1-fold, 2-fold, etc.) for the model training. KNN was trained with raw training data (i.e., 1-fold), 2-fold, 3-fold, 4-fold, and 5-fold augmented training data. Figure 5 illustrates that F-1 score of KNN increases with the volume of augmented training data. We see that KNN performs best for 5-fold training data, and worst for 1-fold training data.

Figure 6, and Figure 7 are confusion charts of KNN with 1-fold, and 5-fold training data, respectively. The confusion charts are generated to explore the improvement of inter-class confusion of the trained

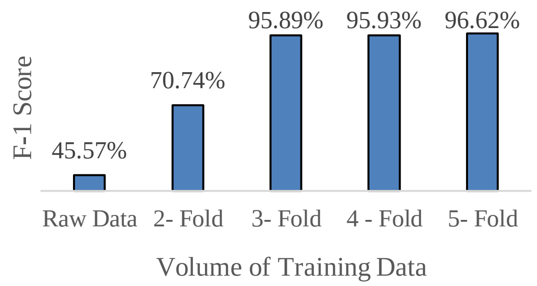

Figure 5. Performance of KNN for different volume of training data

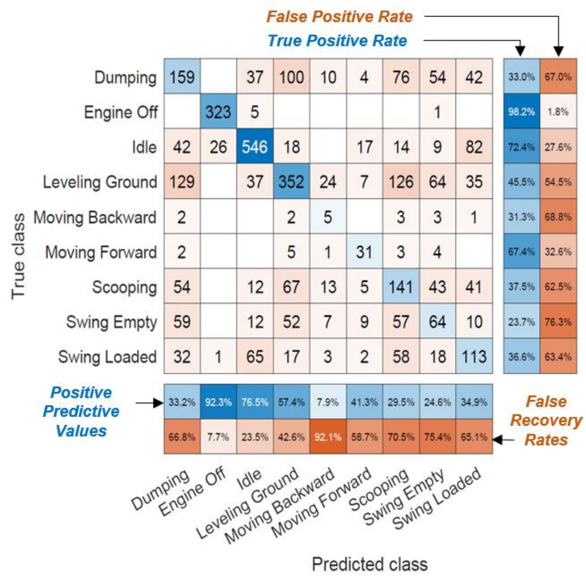

Figure 6. Confusion chart of KNN with 1-fold training data

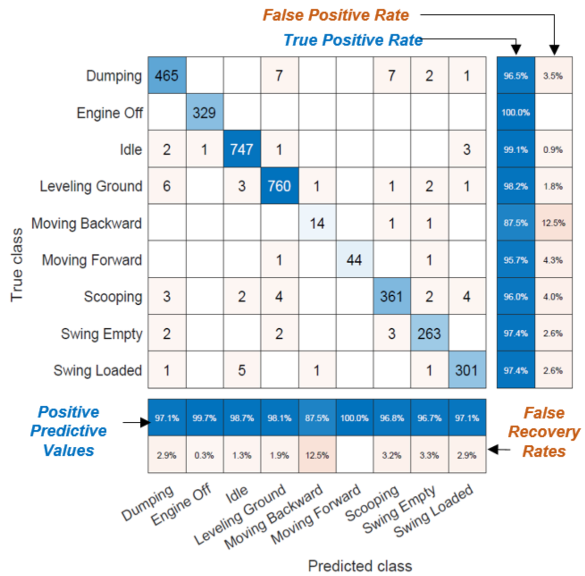

Figure 7. Confusion chart of KNN with 5-fold training data

model before and after data augmentation is implemented. Training the model without any augmented data (Figure 6) results in significantly higher percentages of error. Moreover, the KNN confuses in predicting activities with similar type of signal patterns such as, *Moving Forward* and *Moving Backward*, *Swing Empty* and *Swing Full*, *Scooping* and *Ground Levelling*, *Dumping* and *Ground Levelling* etc. On the other hand, error of the model decreases significantly while augmented data is used for the training (Figure 7). Also, the KNN can successfully identify similar kind of activities.

5 Conclusions and Future Work

Automated and accurate recognition of construction equipment's activity can help to improve productivity, safety, fuel use, and overall management and monitoring of the construction operations. To this end, this study presents an activity recognition framework for construction equipment using multiple IMUs. Moreover, as machine learning algorithms performs better for large volume of training data, a time series data augmentation technique, *window-warping* (WW) is proposed to generate synthetic training data. The methodology was validated using a comprehensive dataset collected from an excavator from a real construction site. The result of this study shows significant improvement in classifier's performance while using augmented training data. Specifically, data augmentation results in 51% and 16.2% increase in F-1 score for KNN, and ANN respectively. This indicates the potential of adopting data augmentation methods in equipment activity recognition which eliminates the necessity of collecting large volume of data from the field.

Future works of this study include testing the methodology for multiple types of equipment, such as loader, hauler, dump truck etc. Moreover, other types of time series data augmentation techniques will be explored to see their effect on the classification algorithms. Deep learning methods such as, convolutional neural network (CNN), recurrent neural network (RNN) will also be explored to analyse time series sequences for higher accuracy.

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