Construction Equipment Emission Modeling and Activity Analysis Using Deep Learning

Reza Akhavian
Department of Civil, Construction, and Environmental Engineering
San Diego State University
San Diego, United States
Email: rakhavian@sdsu.edu

***Abstract*—Automated activity recognition and modeling of heavy construction equipment can contribute to the correct and accurate measurement of a variety of project performance indicators. Productivity assessment and sustainability measurement through equipment activity cycle monitoring to eliminate ineffective and idle times thus reducing Greenhouse Gas (GHG) Emission, are some potential areas that can benefit from the integration of automated activity recognition and analysis techniques. In light of this, this idea paper describes design and development of a deep-learning framework that uses accelerometer data to detect activities of construction equipment and consequently estimates the emission produced corresponding to various activities.**

Keywords-construction equipment; machine learning; emission; modeling; sensors .

I. Introduction

Thanks to the cost-effective, ubiquitous, and computationally powerful means of data collection and analysis, data-informed process mining and decision making have become prevalent. The Architectural, Engineering, Construction, and Facility Management (AEC/FM) industry as well, begins to realize the benefits of such approaches.

Monitoring construction resources, such as heavy equipment enables not only improvements in productivity but also increased awareness of emissions produced as a result of fuel consumption. Studies conducted by the United States Environmental Protection Agency (EPA) demonstrate that heavy-duty construction equipment is one of the major contributors of emissions from diesel engines [1].

In order to reduce emissions, it is practical to reduce the time that construction equipment spends doing non-value-adding activities and/or idling. Research indicates that although using newer equipment, using well-maintained equipment, and using clean fuels can improve exhaust emissions, reducing engine idling time and enhancing equipment operating efficiencies results in improved outcomes [2][3]. Therefore, timely evaluation and monitoring of key construction activities may significantly contribute to foresee potential failures prior the project execution phase.

The ultimate goal of this line of research is to develop a model that enhances sustainability measures of construction projects by monitoring the operational efficiency and environmental performance of working equipment. Direct means of measurement, such as portable emission measurement equipment systems (PEMS) provide a reliable means of quantifying emissions. While PEMS provide direct and reliable measurements, use of PEMS in routine emissions assessments is questionable since they require time-consuming setup, calibrations, and data collection.

This idea paper explores the feasibility of developing an automated system for construction equipment analysis that helps monitor activities by leveraging sensors, such as inertial measurement units (IMUs) and deep learning technologies. The ultimate goal is to provide a detailed equipment operational analysis smart enough to detect idle times and the performance of no-value added activities. This approach is less time consuming, expensive, and error-prone compared to the manual methods.

The rest of this paper is structured as follows. In Section II, the methodology adopted is introduced and Section III discusses the conclusion and future directions of this work.

II. Proposed Methodology

Previous work by the author has shown that end-to-end deep learning models can learn to accurately classify the activities of construction equipment based on vibration patterns picked up by accelerometers attached to the equipment [4]. The work proposed here extends this prior work in two ways: (1) it introduces a new architecture that simplifies the previous approach while improving activity classification performance and (2) it explicitly studies relationships between the equipment activities and the emissions that they generate.

A. Data

Two of the datasets mentioned in this work for comparison purposes were collected and originally studied in a prior work led by the author [4]. These datasets study a BOMAG BW 145PDH-3 compactor performing six different activities and a CAT 328D excavator (Excavator 1) performing seven activities. In each experiment, the equipment was outfitted with two 3-axis accelerometers mounted at different locations, which produced six channels worth of vibration patterns. The data were manually labeled with their corresponding activity classifications according to video taken of the experiments, separated into disjoint training and validation sets, segmented into smaller sequences using sliding windows, and used to train two deep learning models.

This work uses the same approach to data collection as these previous studies, but this time a CAT 305D CR excavator (Excavator 2) performing seven different activities was studied and, in addition to the accelerometer readings, emissions data for various gases were collected using a PEMS. In total, 377,808 accelerometer readings were collected at a sampling rate of 100 Hz. Because the PEMS operated at a sampling rate of 1 Hz, its readings were upsampled to 100 Hz to match those of the accelerometers. The first 324,579 readings (85.9%) were used as training data while the remaining 53,229 readings (14.1%) were used for validation of the results. This split was chosen so as to ensure similar activity distributions in the training and validation sets.

The emissions signals collected and studied include carbon monoxide (CO), nitrogen oxides (NO_x), and carbon dioxide (CO_2). Because the carbon dioxide emissions were much larger, they are reported on a percentage scale, while the other signals are reported in parts-per-million (ppm). Figure 1 plots the emission signals vs. time below.

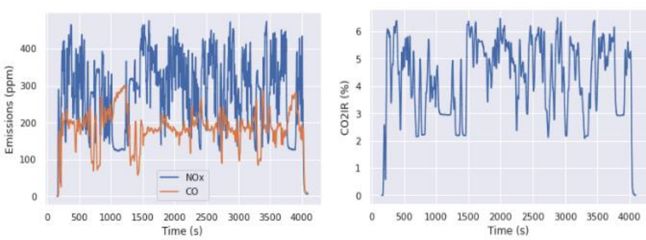

Figure 1. CO, NO_x, and CO_2 emissions vs. time.

B. Predicting Equipment Activities from the Accelerometer Readings

The author applied the same data processing techniques as in prior work. That is, the readings in each sensor channel were normalized to fall into the range [0, 1] and segmented into training examples 200 time steps x 6 sensor channels each using an overlapping sliding window process. Each frame was labeled according to the activity at the last time step so as to structure the problem as follows: given the 200 most recent accelerometer readings across six channels, predict the activity label at the 200^{th} time step.

C. Linking Equipment Activities to Emissions

For each emissions signal considered, the readings were separated by activity and plotted as histograms in order to estimate their true distributions. The training and validation subsets of the data were considered separately.

D. Deep Learning Architecture

A *BaselineCNN* and a *DeepConvLSTM*, two models adapted for construction equipment activity recognition based on models of the same names originally developed for human activity recognition by [5] are investigated. Both *BaselineCNN* and *DeepConvLSTM* begin with four layers of convolutional filters meant to automatically extract features from the accelerometer time series. *BaselineCNN* then uses two fully-connected layers to interpret these extracted features and make a classification while *DeepConvLSTM* uses two Long Short-term Memory (LSTM) layers to interpret the extracted features and make its own classification. LSTMs are a particularly popular and performant kind of recurrent neural network (RNN), which are a broad class of networks that deal with sequence data.

Temporal convolutional networks (TCNs) are another kind of network designed to deal with sequence data. Traditional convolutional networks (CNNs) are suited to extracting locally correlated features but not suited to interpreting features that are distant from each other in space or time. This is because the receptive field of a convolutional network scales linearly with its number of layers. In order to achieve a larger receptive field that scales exponentially with the number of convolutional layers, the concept of dilated convolutions to CNNs is applied.

III. Conclusion and Future Work

This Idea Paper proposes the use of deep learning algorithms for activity recognition of construction equipment as well as quantifying the emission attributed to activities. Preliminary analysis reveals promising results to predict the emission associated with activities. It was seen, across all of the measurements taken, that the new *TCN* model is at least competitive with the previous reigning champion, *DeepConvLSTM*. In fact, it beats *DeepConvLSTM* in terms of validation accuracy every time, despite training much faster and being simpler to explain. In the first excavator experiment, *DeepConvLSTM* managed a validation accuracy of 82.5%, but the *TCN* managed to achieve 83.4% validation accuracy regardless of whether the *Various* label was present. In the second excavator experiment the *TCN* achieved a validation accuracy of 78.8%. The ongoing and future directions of this work include extending the deep learning model created for activity recognition to also predict the emission levels.

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