A Productivity Forecasting System for Construction Cyclic Operations Using Audio Signals and a Bayesian Approach

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ABSTRACT

A large portion of the expenses in a construction project are allocated towards the capital and operating costs of heavy equipment. Most of construction heavy equipment and tools carry out activities in the form of repetitive cycles (e.g., a cycle of digging, swinging, loading). Precisely estimating cycle times for those operations is a crucial step toward productivity analysis, cost estimation, and scheduling of a construction project. The traditional approaches for estimating cycle times of construction cyclic activities are twofold: 1) based on direct observations and recordings; 2) using available graphs and approximate formulas for estimations. The first approach is time consuming and labor intensive and the second one might not be sufficiently accurate and realistic. To tackle the above-mentioned issues, this paper proposes an automated, Bayesian system for estimating cycle times of construction heavy equipment. Considering that construction equipment usually produces distinct acoustic patterns while performing various tasks, the main input for the system is recorded audio data. The presented system includes a de-noising algorithm for enhancing the quality of audio data as well as a Short-Time Fourier Transform (STFT) and Support Vector Machines (SVM) for classifying various activities in a primary stage. A Markov chain model for activity transitions is calculated from ground truth data and used to code an adaptive filter that converts SVM-labeled time-frequency bins into higher-level labels of the full period for each activity. Preliminary results show that, through this system, the accuracy of predicting cycle times could be as high as 90%.

INTRODUCTION

Project managers usually perform a financial estimate for site work activities (e.g., foundation excavation and site cleaning) based on job type, material quantity, site conditions, contractual and legal constraints, and safety factors. Given that a significant fraction of the budget is allocated toward the capital and operating costs of construction equipment, type and quantity must be selected optimally. This is usually based on an expected production rate obtained from historic data, manufacturer's manual, or guides (Peurifoy et al. 2010; Caterpillar 2017). Nonetheless, projected productivity seldom matches actual productivity.

While most non-farming labor efficiency has at least doubled since the 1960s, statistics show that 70% of construction projects are over budget and delivered late (Lean Construction Intitute 2017). This low performance can be attributed in part to the fact that the construction industry lacks an automated performance monitoring system that may allow for real-time waste reduction and labor management. A pressing necessity considering that construction industry contributes to at least 10% of the gross national product (Navon 2005). One of the major obstacles to developing an automated performance monitoring system for the construction environment is that projects are diverse and that the activities within them are hard to classify, even during different stages of the same project. Regardless of the nature of the project; however, it is likely that it involves machinery performing cyclic activities. For earthmoving operations, productivity is calculated in terms of volume of displaced material or finished surface area. Tractors, loaders, excavators, and graders are the principal machinery used to execute these tasks. All this equipment has in common that productivity is inversely proportional to cycle time, which is generally obtained from direct observation or estimated from historic data. Direct observation is time-consuming, expensive in terms of labor cost, and prone to human error, while statistical estimations might not effectively characterize complex operations under varying conditions, e.g., operator skill, weather conditions, and maneuverability. Other parameters for calculation like bucket capacity, fill factor, and blade size, are fairly constant because they depend on equipment design and type of material being worked with. Thus, an attempt for real-time monitoring of construction equipment must focus on calculating cycle times accurately in a timely manner.

A line of research into the use of audio signals for activity analysis of heavy equipment and construction site productivity estimation has been recently initiated by the authors of this paper and other scholars (Cheng et al. 2017; Cho, Lee, and Zhang 2017). Taking the output of the previously devised activity analysis audio framework as direct observation data and using historic data to design Markov-chain-based filter, we propose an optimal cycle time forecasting system.

LITERATURE REVIEW: BAYESIAN MODELS

The major strength of Bayesian statistics is its ability to include historical data to perform calculations based on degrees of belief. Bayesian methods have taken an increasingly important role in cycle time and productivity estimation and other situations requiring stochastic modeling. In fact, the Metropolis Algorithm for Monte Carlo has been listed by the IEEE Journal Computing in Science and Engineering as one of the "10 algorithms with the greatest influence on the development and practice of science and engineering in the 20th century" (Dongarra and Sullivan 2000). Using random processes and probabilistic simulations derived from a fraction of the typically-required samples, this algorithm offers an efficient way to pursue answers to problems that are too complex to solve exactly.

Bayesian Models in Manufacturing

There is some notable research relating to Bayesian models for productivity estimation in manufacturing. Chen, George, and Tardif (2001) proposed a Bayesian approach to model cycle time mean and variance at different levels of work-in-progress. They used Markov Chain Monte Carlo (MCMC) methods, namely the Gibbs sampling and the Metropolis-Hastings algorithms, to partition and parametrize cycle time mean vs. work in progress linear piecewise function and obtained promising results when comparing their model with a typical non-linear model. Abdoli and Choobineh (2004) conducted a simulation experiment of a resource-sharing, multi-class production environment to compare the performance of Bayes and empirical Bayes methods applied to different flow time forecasting models. Their results strongly suggest that simpler models consistently yield better forecasts than complex models with carelessly-selected parameters. More recently, Shen (2008) developed a Bayesian network model for cycle time estimation in the LCD screen defect detection process. Since defect detection is usually carried by human visual inspection, common practice for cycle time estimation is conveyed through complex frequentist statistical models. Nevertheless, Bayesian models, once again, provided a relatively simple and reliable solution.

Bayesian Models in Construction

Due to the complex nature of the construction environment, many construction scholars and engineers have relied on Bayesian statistical methods in a variety of applications including: modeling workflow for productivity forecasting, analyzing structural resistance to natural forces, and analyzing safety hazards.

For productivity estimation, MCMC-based models have been particularly relevant. Semaan (2016) performed a stochastic productivity analysis of a ready mix concrete batch plant using a queuing model based on Markov chains and a simulation model based on Monte-Carlo-based MicroCyclone modeling software. These results showed that the MicroCyclone simulations effectively evaluate idleness and yield novel insight into the impact on plant productivity resulting from changing truck size and quantity. The findings of this study led to MicroCyclone being used to model numerous activities including: tunneling, paving, bridge construction, bridge redocking, and several other construction operations (Halpin and Riggs 1992; Pang, Zhang, and Hammad, 2006). In structural analysis, specifically Performance Based Design (PBD), Bayesian models are useful to determine the amount of stress that a structure will be subject to when considering natural phenomena. Adeli et al. (2011) published insightful remarks after performing a probabilistic seismic demand analysis using MCMC methods to simulate the effects on structural performance from parameters with known prior distribution, but no correlation (i.e., earthquakes and economic factors).

Safety in the construction industry deeply relies on providing proper proximity warnings and understanding the workers' responses to such warnings. Looking forward to creating a proactive collision warning system, Zhu et al. (2016) utilized Kalman filtering to predict movement of construction equipment and workers in a construction job site. Location estimates from a computer vision framework were provided as input to the filter. Then, the filter generated its own estimates and a corrected location was determined using Kalman gain as a degree of belief. The filters were continuously adjusted based on historical position data and showed incremental effectiveness as more data became available. Luo et al. (2016) conducted a field experiment to gather location-based data on workers' response rates to different levels of safety hazard warnings. Considering that construction job sites are constantly evolving depending on various factors, like complexity and urgency, they applied a Bayesian model founded on MCMC methods to get realistic and versatile response rate estimates from simulation.

This research aims to benefit from the proven versatility of Bayesian models to a field that had been disregarded despite its potential for application: cycle time modeling of construction equipment with real-time audio-based activity information.

RESEARCH METHODOLOGY

The process followed for cycle time estimation can be divided into four steps, as depicted in Figure 1. The authors have designed and implemented Markov chains for productivity estimation as an addition to the audio framework presented in previous publications.

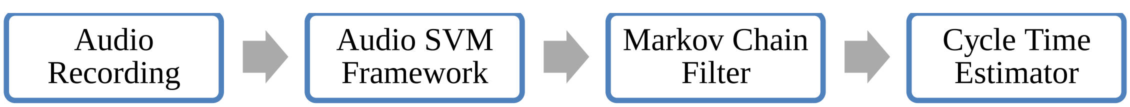

Figure 1: Cycle time estimation framework.

Audio Recording

Individual pieces of construction heavy equipment were recorded performing cyclic activities. In separate work, the authors have studied optimal hardware placement and type thoroughly (Cheng, Rashidi et al. 2017). Thus, the XMOS xCORE-200 multichannel array microphone was placed on site, less than 10 meters away from the sound source of interest. Video was recorded simultaneously for manual activity labeling.

Audio SVM Framework

Audio recordings were processed in MATLAB through an audio activity labeling framework. The audio framework consists of four major steps: first, audio recordings were enhanced through a de-noising algorithm to isolate the signal of interest; second, frequency magnitude and phase features were extracted through the Short-Time Fourier Transform (STFT) to obtain a time-frequency representation of the audio signal; third, a Support Vector Machine (SVM) supervised machine learning algorithm was used for library generation and posterior activity classification; and, finally, time frequency bins of classified activities were converted to higher order labels through a two-step window filter. Essentially, the window filter scans through continuous bins of labeled data and labels a greater potion of the audio signal if the percentage of bins over the window is greater than a specific threshold. This percentage can be taken as the accuracy over the window filtering process.

Markov Chain Filter

The output from the audio SVM framework was not sufficiently smooth to estimate cycle times accurately. Therefore, Markov chains were incorporated to include ground truth statistical data into activity labeling. To design a suitable Markov model, the concepts of decisions per activity and calls for activity were devised. The number of time-frequency bins in one second of audio is given by the equation below.

$$BPS = \frac{Sampling\ Frequency}{STFT\ Window\ Size - STFT\ Overlap}$$

In this study, the audio sampling frequency is 44100 Hz, the STFT window size is 512 samples, and the STFT overlap is 256 samples. Thus, the number of bins per second is 172.26. The SVM classifier labels each bin so the number of seconds elapsed in each class multiplied by the number of bins per second represents decisions taken during each activity. The number of calls for activity refers to the number of transitions from one activity to the other.

Table 1: Ground truth data for JD 700J.

Activity	Start (sec)	Elapsed Time	Call Act 1	Call Act 2	Act 1 Time	Act 2 Time	Decisions 1	Decisions 2
Pushing soil with blade	0	35	NA		35		6029	
Reversing	35	13		1		13		2239
Pushing soil with blade	48	25	1		25		4306	
Reversing	73	13		1		13		2239
Pushing soil with blade	86	44	1		44		7579	
Reversing	130	28		1		28		4823
Pushing soil with blade	158	23	1		23		3962	
Reversing	181	16		1		16		2756
Pushing soil with blade	197	46	1		46		7924	
Reversing	243	23		1		23		3962
Pushing soil with blade	266	31	1		31		5340	
Reversing	297	16		1		16		2756
Pushing soil with blade	313	27	1		27		4651	
Reversing	340	14		1		14		2412
Pushing soil with blade	354	5	1		5		861	
End	359							
TOTAL			**7**	**7**	**236**	**123**	**40653**	**21188**

A typical arrangement of ground truth data for Markov chain calculation is depicted in Table 1. The total time that the construction equipment spent on performing major activities (Act 1) and minor activities (Act 2) was manually labeled using video recordings as reference. This is indicated in the columns Act 1 Time and Act 2 Time. Multiplying these by the number on bins per second produces the values in columns

Decisions 1 and Decisions 2. The number of calls for each activity is simply the number of transitions from Act 1 to Act 2, and vice versa. The probability of the state changing to Act 2 given that it is Act 1 is equivalent to the calls for Act 2 divided by the number of decisions taken while in Act 1. The probability of the state being Act 1 and keep being Act 1 is the complement. Using data from Table 1, the values for a Markov model are calculated below:

- While in Act 1,

$$P(Act\ 2 \mid Act\ 1) = \frac{Calls\ for\ Act\ 2}{Decisions\ for\ Act\ 1} = \frac{7}{40653} = 0.00017219 \rightarrow 0.017\%$$

$$P(Act\ 1 \mid Act\ 1) = 1 - P(Act\ 2 \mid Act\ 1) = 0.99982781 \rightarrow 99.983\%$$

- While in Act 2,

$$P(Act\ 1 \mid Act\ 2) = \frac{Calls\ for\ Act\ 1}{Decisions\ for\ Act\ 2} = \frac{7}{21188} = 0.000330 \rightarrow 0.033\%$$

$$P(Act\ 2 \mid Act\ 2) = 1 - P(Act\ 1 \mid Act\ 2) = 0.999670 \rightarrow 99.967$$

The Markov chain matrix for the JD 700J dozer using the state-dependent probability distributions is depicted in Table 2. A graphical representation of the Markov process is depicted in Figure 2.

Table 2: Markov matrix for JD 700J.

John Deere 700J		Next State	
		Act 1	Act 2
Current State	Act1	0.999828	0.000172
	Act2	0.000330	0.999670

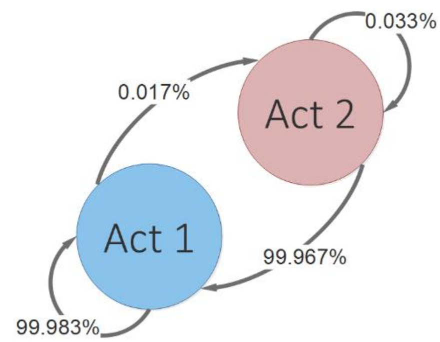

Figure 2: Two-state Markov process for JD 700J.

The process flow diagram of the Bayesian filter is shown in Figure 3. The audio portion (sensor data) is depicted in blue, the Markov chain portion is depicted in red, the current state is depicted in green, and decision blocks are depicted in grey. The predicted state for the Markov chain is the one with highest probability in the Markov process. The accuracy for the prediction is the probability by which it was predicted. Likewise, the accuracy for the SVM-predicted state is taken as the percentage over the widow filter by which it was determined. The next state is the one with greater accuracy, either the SVM-predicted state or the Markov process state. The exponent (n) of the Markov process is reset if the current state diverges from the previous state. Otherwise, the Markov matrix is elevated to the next power (n+1) for the following step. This algorithm was coded for MATLAB implementation.

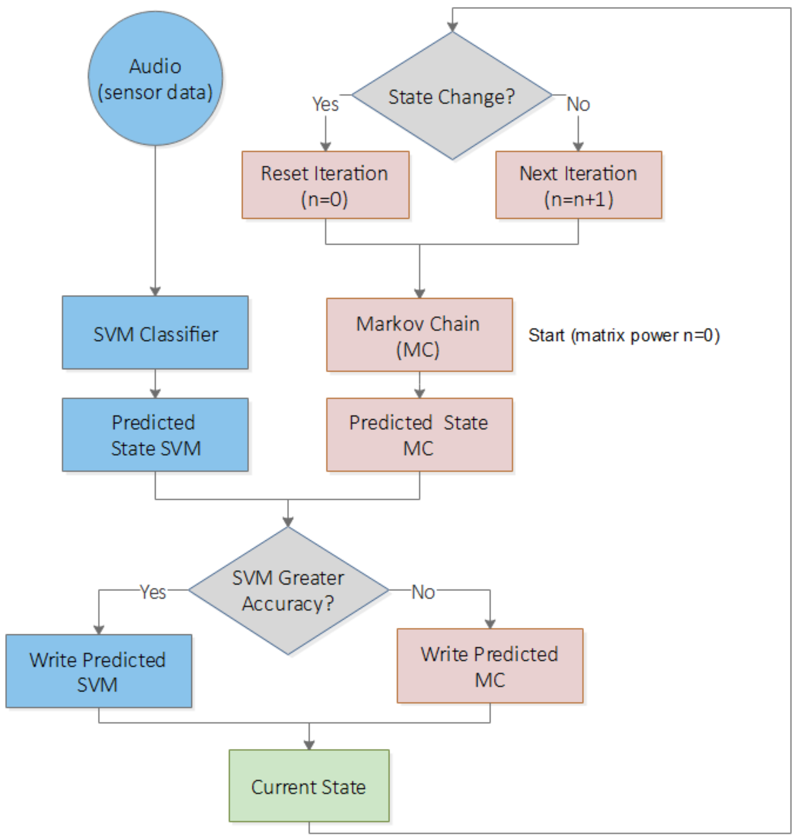

Figure 3: Adaptive filter process diagram.

Cycle Time Estimator

If cycle time for a specific action can be accurately measured, then it can be used along with manufacturer data to determine the equipment productivity. A machine work cycle is a succession of major and minor activities, as shown in Table 1. Cycle time is the time elapsed during such succession. Therefore, the cycle time estimator was designed in MATLAB to scan through the labeled audio signal, count continuous activities by type, and determine the average time elapsed on each cycle.

Table 3: Typical actions performed by heavy equipment.

Equipment	Action	Typical Activity Sequence	Type
Excavator/ Loader/ Dozer (dozer less effective)	Excavating/ Moving material/ Backfilling/ Truck loading	Digging	Major
		Swinging or maneuvering	Minor
		Dumping	Major
		Swinging or maneuvering	Minor
Excavator/ Loader	Compacting/ Demolishing	Compressing with bucket	Major
		Swinging or maneuvering	Minor
Grader/ Dozer/ Loader (loader less effective)	Grading/ Ripping/ Clearing/ Blending	Pushing material with blade/bucket	Major
		Reversing or maneuvering	Minor

RESULTS

To assess the accuracy of the cycle time estimation framework, it was tested with audio data for three pieces of equipment. For each machine, one audio signal was separated into two portions. The first portion was used for SVM framework training and Markov process design and an independent portion was used to test the accuracy of cycle estimation framework.

An example of labeled audio signal for a JCB 3CX backhoe loader clearing surface material is depicted in Figure 4. The top part of the figure shows the predicted labels over the spectrogram of the audio signal and the bottom part shows manually labeled activities (ground truth data). A high position represents a major activity and a low position represents a minor activity. From the predicted sequence, an average cycle time of 49.70 seconds has been estimated. The observed average cycle time was 50.77 seconds, which yields an estimation error of 2.11%.

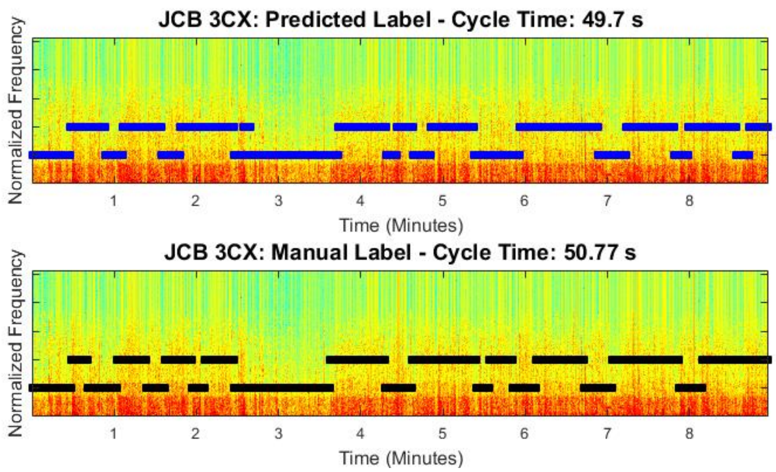

Figure 4: Labeled activities for a JCB 3CX clearing surface material.

A summary for the initial assessment is presented in Table 4. Preliminary results showed an error of less than 10% for cycle time estimation. Nonetheless, typical machine operation is carried under varying work conditions (e.g., location accessibility, weather conditions, and operator skill). Thus, additional experimentation was performed to evaluate the accuracy of the cycle estimation framework over several days of operation.

Table 4: Cycle time estimation accuracy.

Machine	Operation	Observed cycle time	Predicted cycle time	Error
JCB 3CX	Clearing	50.77	49.70	2.11%
CAT 320E	Excavating	9.30	9.96	7.10%
JD 700J	Grading	50.22	50.56	0.68%

Figure 5: Simultaneous audio and video recording.

A Komatsu PC200 excavator was monitored during 4 days while crushing and moving demolition material (Figure 5). For each day, a 12 to 30-minute audio signal was processed and the estimated cycle time was compared against the observed cycle time obtained from manually labeled activities. The predicted average cycle time and observed average cycle time for each day are plotted in Figure 6 (top). It can be observed that estimation error is less than 8%, as depicted in Figure 6 (bottom). From these results, it can be concluded that a robust cycle time estimation model can be achieved through audio signal analysis and the inclusion of statistical information.

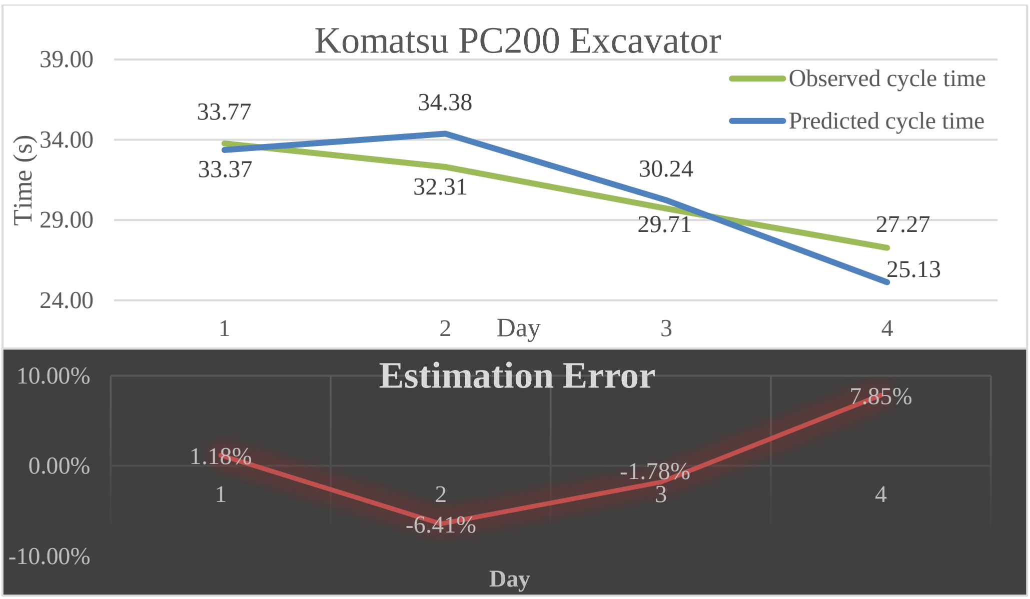

Figure 6: Komatsu PC200 - Observed cycle time vs. predicted cycle time (top). Cycle time estimation error (bottom).

CONCLUSION

This paper presented a novel, automated forecasting system for construction cyclic activities through audio signal analysis and the application of a Markov chain filter, designed from a small portion of statistical data. Preliminary evaluation shows promising accuracy for estimating cycle time of single machines under various work operations and conditions. The authors plan to further contribute into this line of research in the following key aspects:

- Testing the current model with additional equipment operating for several days under various work conditions.
- Calculating cycle time under more realistic environment that involves multiple machines working simultaneously.

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