Integration of Imaging and Simulation for Earthmoving Productivity Analysis

Hongjo Kim[a,b], Seongdeok Bang[a], Hoyoung Jeong[a], Youngjib Ham[b], and Hyoungkwan Kim[a]

[a]School of Civil and Environmental Engineering, Yonsei University, Republic of Korea
[b]Department of Construction Science, Texas A&M University, United States
E-mail: hongjo@yonsei.ac.kr, bangdeok@yonsei.ac.kr, jhy0@yonsei.ac.kr, yham@tamu.edu, hyoungkwan@yonsei.ac.kr (corresponding author)

Abstract –

Earthwork productivity varies depending on a unique geologic condition, types of earthwork equipment, and an equipment allocation plan. For this reason, it is difficult to accurately estimate the productivity of an earthwork. To address this issue, this paper develops an imaging-to-simulation method in which a real jobsite data is automatically collected and used for analyzing the earthwork productivity. Object existence and its location in image data are identified by convolutional networks, and they are used to infer the earthwork context. The context information is transformed into the simulation input by the context reasoning processes. A productivity report is produced by using the WebCYCLONE simulation. The developed method was tested in a tunnel construction site, providing a new equipment allocation plan, which minimize the cost and time compared with the original plan.

Keywords –

Productivity Analysis, Vision-Based Monitoring, Simulation, Earthmoving, Context Reasoning

1 Introduction

Since earthwork in construction involves various types of construction equipment, establishing the optimal equipment allocation plan is a primary concern of site managers. Construction process simulation can be used to generate a productivity report to a given earthwork plan, thereby enabling comparison among different earthwork plans [1,2]. However, even with the simulation results, the optimal plan is not easily established due to a unique geologic characteristic and dynamic working conditions in jobsite. These issues cause the simulation input to deviate from the real jobsite working status. As a result, the reliability of the productivity report is degraded, because a small deviation of the simulation input significantly affects the simulation results. Previous studies proposed vision-based productivity analysis methods, which provides the cycle time of earthmoving [3-5] or concrete pouring operations [6]. Ham, et al. [7] presented an imaging-to-simulation framework to detect hazards related to strong winds. However, integration of construction simulation and vision-based monitoring for productivity analysis has not yet been proposed.

To address these issues, this study proposes an imaging and simulation integrated method to analyze an earthmoving process productivity, as shown in Figure 1. This method automates the process of jobsite data collection for productivity analysis, thereby improving the reliability of the simulation results. An earthmoving process in a tunnel construction site was selected for validating the proposed method. The initial idea of this study was presented in [8].

2 Vision-based context reasoning

A tunnel site, construction under the new Austrian tunneling method (NATM), was selected to apply the proposed method. In the tunnel construction site, the amount of muck produced daily was 680 m^3, and a closed-circuit television (CCTV) was installed at an elevated position to monitor muck-loading tasks by a single excavator and seven dump trucks. The maximum amount of muck that can be stored in the temporary

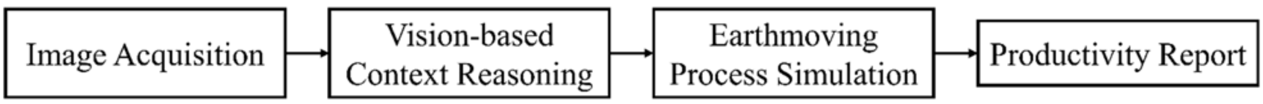

Figure 1. Overview of the proposed method

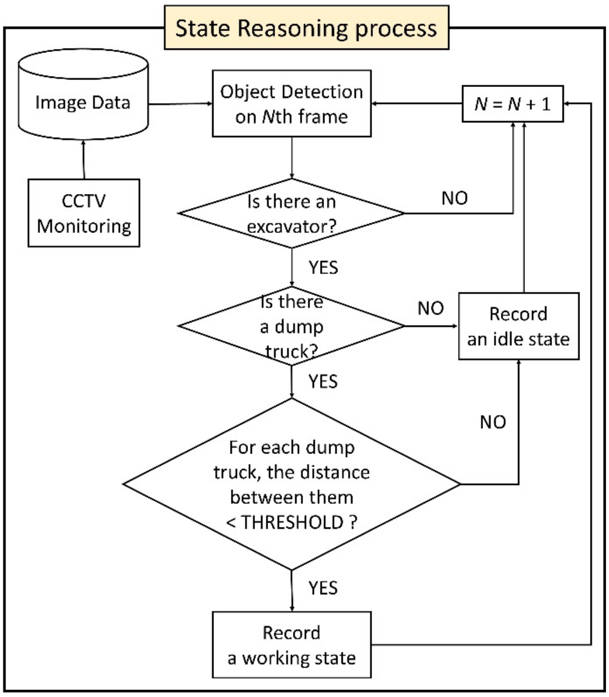

Figure 2. State reasoning process

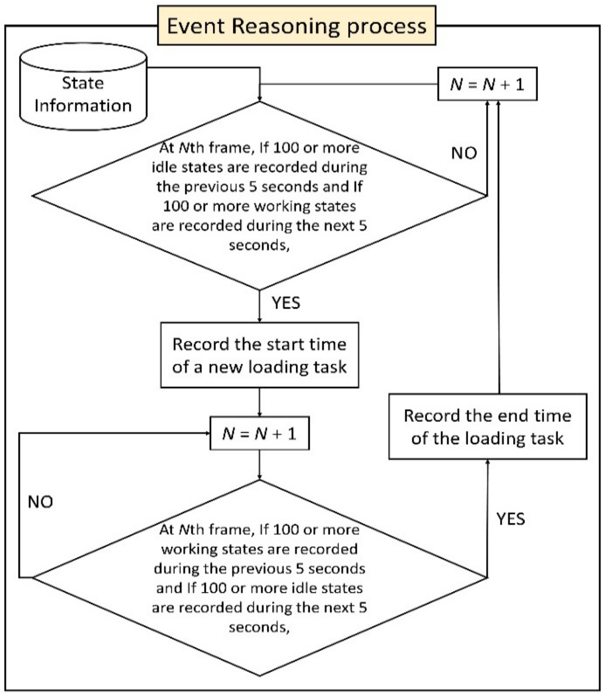

Figure 3. Event reasoning process

disposal area was 1,500 m^3. To detect the target objects in tunnel CCTV image data, a region-based fully convolutional networks (R-FCN) proposed by Dai, et al. [9] is utilized. Using R-FCN, construction equipment such excavators and dump trucks can be detected with the high accuracy at a short processing time [10]. R-FCN comprises three main modules for object detection, which are the feature extraction layers, region proposal network, and the position-sensitive score maps for determining the object class and location in image data. Refer to Dai, et al. [9]'s work for details.

For producing the simulation input, object class and location information from image data can be converted into the context information [3-6]. The context information includes the state and event information. The state information denotes a working or idle state of an excavator and dump trucks in regard to loading or hauling tasks. Figure 2 illustrates the state reasoning process. The event information denotes the time to complete a single loading or hauling task. It records the start and end time of a loading task, following the process illustrated in Figure 3. The start and end time of a hauling task is recorded by the site access information of a dump truck.

2.1 Earthmoving Process Simulation using WebCYCLONE

For the construction process simulation using the WebCYCLONE [11], the earthmoving process should be modelled as a form of discrete event elements used in WebCYCLONE such as NORMAL, COMBI, Q NODE, and ARROW. The target earthmoving process includes eight elements, which are "Loading", "Excavator Idle", "Hauling", "Loaded Truck Queue", "Dump", "Dump Spotter Idle", "Return", and "Dump Queue". The elements constitute the earthmoving process structure, representing loading and hauling cycles of an excavator and dump trucks.

3 Experiments and Results

The proposed method was performed on the Intel i7-6700 CPU and the GTX1080 8GB GPU with the Ubuntu 16.04 operating system. The R-FCN model [9] pretrained with the ImageNet data was re-trained using the AIMdataset [10] and the tunnel image data. The length of the tunnel video for the test was 8 h 11 m. The video resolution was 720 × 480. To evaluate R-FCN for object detection, the evaluation criterion of the PASCAL VOC [12] was used. The experimental results of object detection and vision-based context reasoning are shown in Table 1. R-FCN trained with the AIMdataset and the tunnel image data recorded the mean average precision (mAP) of 99.09% for detecting an excavator and dump trucks. The samples of the detection results are shown in Figure 4. The errors of the context reasoning processes were 0%, 1.6%, and 0.12% for estimating the number of task cycles, average duration of loading tasks, and average duration of hauling tasks, respectively.

Figure 2. Samples of the detection results

Table 1 Performance of equipment detection and vision-based context reasoning

Detection performance (mAP)		99.09%
Error rates of context reasoning	Number of task cycles	0%
	duration average of loading tasks	1.60%
	duration average of hauling tasks	0.12%

Table 2 Productivity report

Daily muck output	680m^3
Capacity of disposal storage area	1500m^3
Current resource allocation	1 excavator, 7 dump trucks
Current productivity	100.88 m^3/hour
Current unit cost	5.59 $/m3
Optimal resource allocation	1 excavator, 10 dump trucks
Optimal productivity	141.78 m^3/hour
Optimal unit cost	5.45 $/m^3
Cost savings (for 600 days)	$310,858

To validate the simulation model, the simulation result was compared to the actual earthmoving process. The deviation of the total working time between the actual earthmoving process and the simulation result was only 2.23% for the 44 task cycles, confirming that the simulation model was correctly modelled as the actual earthmoving process. The productivity report indicates that the current earthmoving process can be improved by changing the number of dump trucks to 10 from 7, as shown in Table 2. The equipment operation costs are $523.33 and $566.94 for each dump truck and excavator, respectively. The payload of a dump truck was 17m^3. With the new equipment allocation plan, the idle time of the excavator can be reduced to 21.12% from 43.97%. Moreover, the total earthmoving cost can be saved by $310,858 (12.25%) for 384 working days of earthmoving in the NATM process of 600 days.

4 Conclusion

This study presents an imaging and simulation integrated method for analyzing the earthwork productivity based on the actual jobsite data. Image data was process by R-FCN to identify the location and class of a target object. The context information was automatically interpreted by the context reasoning processes. By using the actual construction site data, the reliability of the construction process simulation results was enhanced. Integration of imaging and simulation enables rapid generation of a productivity report under changing geologic conditions. This capability allows site managers to optimize the resource allocation for the current geologic condition. Currently, the proposed model is suitable for analyzing a single earthmoving process. The developed model should be further improved to analyze a complex interaction among various jobsite work processes as well as the earthmoving process.

Acknowledgments

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