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Analyzing context and productivity of tunnel earthmoving processes using imaging and simulation

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ABSTRACT

This study presents an integrated method of construction-process simulation and vision-based context reasoning for productivity analysis of an earthmoving process in a tunnel. Convolutional networks are used to detect construction equipment in the tunnel CCTV video and the context of the earthmoving process is inferred by the context reasoning process. The construction equipment detection model exhibited enhanced performance, with a mean average precision of 99.09%, and the error rate of the estimated context information was only 1.6% of the actual earthmoving context measured by a human. The estimated context information was used as an input for the WebCYCLONE simulation to generate a productivity and cost analysis report. Sensitivity analysis regarding construction equipment provided a new equipment allocation plan that could reduce the cost of the current earthmoving process by 12.25%.

1. Introduction

Earthwork is performed using combinations of various construction equipment, and the optimal resource allocation plan for a specific earthwork process depends on the conditions and circumstances that are unique to the construction site. In general, construction-site managers decide the type and number of construction equipment for earthwork based on their experience. However, because earthwork is performed in a unique geologic environment, it faces various uncertainties during the earthwork process. In addition, the resource allocation plan established based on the manager's experience does not always provide optimal productivity.

Simulation can be utilized as an analytical method to determine earthwork productivity because simulation has the advantage of reflecting the uncertainty of earthwork (e.g., the duration of an earthwork task) and analyzing the productivity with various experimental conditions [1]. In particular, simulation shows the “productivity per unit time” and “productivity per unit dollar” related to a specific combination of the construction equipment, which is key information for cost reduction and schedule management. As an input for earthwork process simulation, all information related to the earthwork tasks is required such as the task duration and equipment cost. Task information is an important parameter that significantly affects the reliability of the simulation result. However, task information is mutable because the efficiency of an earthwork task may be different depending on the site due to different geologic properties, working environments, equipment types, and machine operators. Collecting task information through an interview with site managers is a common way to obtain simulation input; however, the accuracy and precision of the obtained information are not high compared with that obtained by directly observing the task.

Vision-based monitoring can be used to automatically extract earthwork task information by reasoning the context information from jobsite images. To infer earthwork context information using vision-based monitoring, construction equipment should be identified in images. Determining the class and location of construction equipment in images requires an object detection model that can properly recognize specific patterns in image regions. However, object detection is difficult for images taken in a tunnel because the objects are not fully visible due to the absence of natural light. In addition, heavy dust after a blasting task in a tunnel significantly degrades image quality.

To address these issues, this study proposes an automated productivity assessment method for an earthmoving process in a tunnel by integrating the vision-based context reasoning and construction-process simulation, as shown in Fig. 1. In vision-based context reasoning, the deep convolutional network identifies the class and location of target objects (excavators and dump trucks) in images, and the earthwork context is inferred from this visual information. Based on the earthwork context information, the probability distribution of a task duration is estimated for using it as an input to the WebCYCLONE simulation. The

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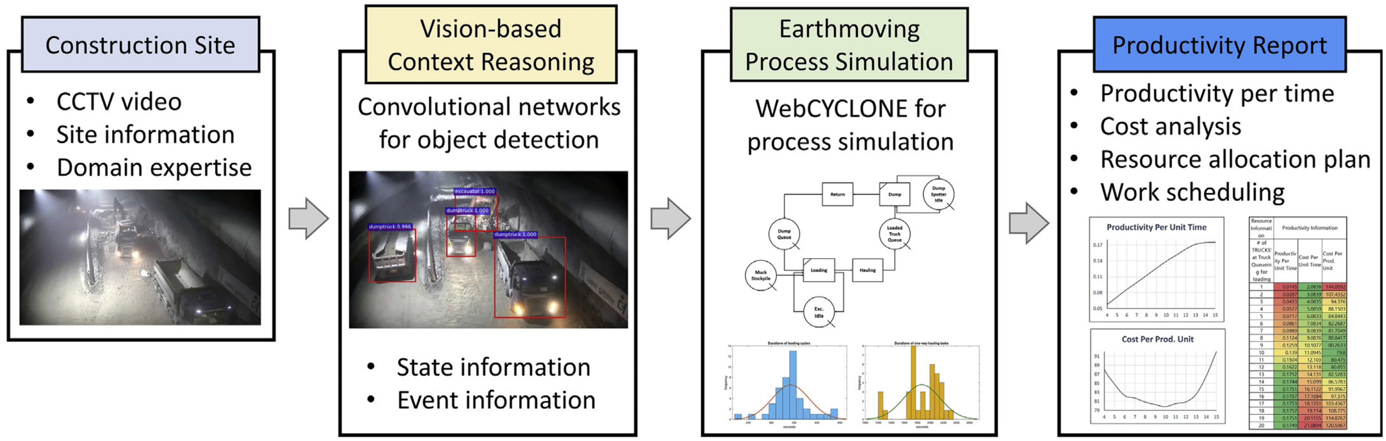

Fig. 1. Overview of the proposed method.

proposed method was validated by analyzing the actual earthmoving process in the tunnel construction site. The experimental results show that the detection model can detect excavators and dump trucks with high performance, and the estimated task durations were almost identical to the actual earthmoving context. Simulation results also show that the productivity of the earthmoving process can be significantly improved by changing the construction equipment allocation plan.

2. Related work

2.1. Vision-based monitoring in construction sites

The key task in generating information from image data is to detect objects for identifying the class and location of a target object. The general process for detecting objects is to extract features from an image and perform object classification based on the features in some regions in the image. In previous studies, histograms of oriented gradients (HOG) have been widely used as a visual feature to detect construction workers [2,3], hardhats [2], excavators [3–5], and dump trucks [3,5,6]. Park et al. [2] proposed a construction worker and hardhat detection method using HOG features. Memarzadeh et al. [3] combined HOG features with colors to detect workers, excavators, and dump trucks. Rezazadeh Azar and McCabe [4] presented a deformable object detection method based on HOG features to detect excavators with spatial-temporal constraints. Golparvar-Fard et al. [5] proposed an action recognition method to analyze the activities of earthmoving equipment using HOG features. Rezazadeh Azar and McCabe [6] presented a dump truck detection method using HOG features with Haar-like features or a background subtraction technique. However, the HOG feature has a disadvantage in that various views of an object cannot be represented in a single HOG feature, and it mainly represents the object shapes without texture information.

Vision-based tracking methods have been studied to track the moving path of the detected construction entities [7–10]. Kim and Chi [7] proposed a construction equipment tracking method integrating a detector and a tracker in an online learning fashion. Zhu et al. [8] utilized particle filtering, which mitigates occlusion problems, to track construction workers and equipment. Park and Brilakis [9] presented a detection and tracking integrated method to localize construction entities in consecutive video frames. Kim et al. [10] presented a tracking method for moving objects in construction sites using the Gaussian mixture model and morphological processing. The tracking information, which includes a trajectory of a target object, can be used to prevent collision accidents or to measure construction work and idle time. To analyze earthwork productivity in construction-site images, it is necessary to infer the context information from the detection or tracking results. The context information for the earthwork productivity analysis includes the work and idle time of a construction entity and the start and end time of each earthwork task. Gong and Caldas [11] analyzed a video containing a concrete-column pour operation to record cycle time and abnormal production scenarios. Rezazadeh Azar et al. [12] recorded the dirt-loading cycle time using an HOG-based object detection method with the parallel computing implementation for efficient processing. Bügler et al. [13] estimated the amount of removed soil using photogrammetry and analyzed the productivity based on dump truck activities.

2.2. Previous studies related to earthmoving processes

Many previous studies have been conducted to analyze earthmoving processes. Christian and Xie [14] investigated the factors affecting earthmoving operations that can be grouped into machine selections, production rates, and costs. Liu and Lu [15] presented a haul road network design method for effective earthmoving processes. Moselhi and Alshibani [16] proposed an optimization method for earthmoving operations using a combination of a genetic algorithm, linear programming, and a geographic information system.

Discrete event simulation has also been used to analyze an earthwork process, since it can reflect uncertainties in individual work tasks without formulating a complex mathematical model. The simulation technique allows construction engineers to evaluate the productivity of the construction operation to optimize the construction plans, including resource allocation and arrangement of various tasks. Previous researchers developed and applied simulation techniques, including CYCLONE (Cyclic operation network) [17], SIMPHONY [18], and STROBOSCOPE (State and resource based simulation of construction processes) [19], for productivity analysis in the construction domain. Smith et al. [20] determined the important factors for earthmoving processes using discrete event simulation. Han et al. [21] focused on productivity prediction of earthmoving through the combination of the simulation technique (CYCLONE) and a multiple regression or an artificial neural network. Ioannou and Martinez [22] compared the efficiency and effectiveness of two tunneling methods by using STROBOSCOPE. Lin et al. [23] used CYCLONE to predict the tunnel advancement rate of the new Austrian tunneling method (NATM); Touran and Asai [24] calculated the tunnel advancement rate in a tunnel site in which a tunnel boring machine was used, using CYCLONE. The simulation technique has also been used to analyze other construction operations. To name a few studies, Hong and Hastak [25] utilized CYCLONE to analyze the productivity and unit cost of installation processes of two different bridge deck panels made of a fiber-reinforced polymer and a precast concrete. Pantouvakis and Panas [26] developed a simulation platform containing seven different simulation templates of a floating caisson fabrication process based on