Automatic Analysis of Idling in Excavator's Operations Based on Excavator-Truck Relationships

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Abstract –

Excavators and trucks are important equipment for earthmoving work, which have major contributions to construction productivity. In order to control the work efficiency and productivity of earthmoving equipment, computer-vision (CV) methods have been proposed to monitor equipment operations from site surveillance videos. Existing methods can recognize equipment activities to estimate the working time and idling time; however, they are limited in analyzing the reasons behind the equipment idling and low productivity. Therefore, this research proposes a method to identify the main reasons that cause excavators and trucks idling by analyzing their interactive operations. In this method, the relationships between the excavator and the surrounding truck(s) in each group are analyzed to identify the potential reasons that cause the excavator's idling. The proposed method was validated with a video from construction site and the test results showed its effectiveness and efficiency.

Keywords –

Excavator; Interactive operation; Idling reasons

1 Introduction

Heavy equipment is one of three major resources in construction projects along with labor and material [1]. Efficient use of equipment is critical for construction cost control and time saving [2]. One way to increase the efficiency of equipment operation is reducing its idling time. When the equipment is idling, it has no contribution to production, and adds no value to the construction project. Therefore, minimizing idling time is important to improve the efficiency and productivity of construction equipment.

As cameras are recently installed to monitor construction sites, an increasing number of research studies have been focused on monitoring equipment work productivity by automatically analyzing surveillance videos with computer vision (CV)-based methods. Current research work has been focused on estimating equipment's productivity by identifying its states, such as working, moving and idling. However, existing methods did not fully consider the interactive relationships between different pieces of equipment, such as excavators and trucks, which is important for productivity analysis. This research aims to provide a CV-based method for identifying idling reasons of excavators based on the interaction analysis between excavators and trucks from construction surveillance videos. First, the activities of the excavators and trucks are identified using convolutional neural networks (CNN). Then, work groups of excavators and trucks are clustered. Finally, the relationships between each excavator and the surrounding truck(s) are analyzed to identify potential reasons that cause the idling. The proposed method has been tested in a case study and the results indicate that the average accuracy of the idling reasons identification is 93%.

2 Background

In recent years, CV technologies have been widely used for automatic construction equipment operation monitoring and efficiency measurement. In the early stage, researchers focused on developing methods to accurately detect and localize target equipment in video frames. Kim and Zou [3] used color space to detect and localize the excavator in video frames. Emarzadeh et al. [4] concatenated both HOG and the Hue-Saturation colors as descriptors, and used Support Vector Machine (SVM) classifiers to detect excavators, trucks and workers from site surveillance videos. In addition to the previous work of equipment detection and localization, researchers developed methods for equipment operation monitoring. For instance, some researches attempted to monitor the excavators' operations by recognizing their activities. Gong et al. [5] and Golparvar-Fard et al. [6] used motion features extracted from consecutive video frames, and classified the features with SVM to recognize excavators' activities, such as hauling, dumping, swinging, etc. Instead of using feature-classification-based activity recognition, other researchers developed activity recognition based on context information extracted from images. Kim et al. [8] considered the sequential relationship of the excavator's activities in its work cycle, and used CNN and Long-Short Term Memory (LSTM) network to recognize digging, dumping and hauling activities. Instead of using activity recognition, Soltani et al. [8] detected different components (e.g. dipper, boom and body), and extracted the excavator's 2-dimensional (2D) skeleton from the poses of the detected components. For the productivity estimation, Chen et al. [9] proposed a framework which integrated detection, tracking, and a 3D CNN to recognize multiple excavators' activities (e.g. digging, swinging, loading, and idling). By analyzing the activity information, the number of cycles and the productivity of the excavator are calculated.

The literature review shows that existing research mainly focused on excavator's productivity estimation and operation monitoring. Idling is one of the main factors that causes excavator's low productivity; However, deducing the potential reasons of idling has not been deeply investigated using CV. In order to reduce idling time of excavators and increase their productivity, it is necessary to identify the potential reasons that causes excavators idling. This paper aims to fill the research gap in existing works, and focuses on identifying the potential reasons of idling.

3 Methodology

The methodology for idling reasons identification of excavators is shown in Figure 1, which contains three main steps. First, the excavators and trucks are detected and tracked to get their locations and activities in video frames. Second, excavators and trucks are clustered to analyze their interactive work states. Third, the idling reasons of the excavators are classified into four different cases based on the number, activities and locations of trucks, as well as the interactive work states of the excavators and trucks, which are calculated in the previous steps. The details of these three steps are introduced in the following sub-sections. The methodology of this paper is based on the assumption that the equipment does not have mechanical problems and all the operators have no health issues that may cause idling. These potential reasons of idling are beyond the scope of this paper.

3.1 Identification of excavators and trucks locations and activities

In the first step, detection and tracking methods are used to extract equipment's types and coordinates of bounding boxes in K video frames. YOLO-v3 [10] detector and multi-object deep Simple Online and Real-Time (SORT) tracker [11] are applied in this study for equipment detection and tracking, respectively. The YOLO-v3 and deep SORT are selected for their performance of high accuracy and speed in both CV and applications in the construction domain. Following the detection and tracking, the working and idling states of excavators and trucks are recognized using the method proposed by Chen et al. [9].

3.2 Excavator and truck clustering

The second step is to cluster excavators and trucks into different groups. In the real earthwork operations, excavators usually work with nearby trucks. Therefore, excavators and trucks are clustered based on their distances in video frames. First, the number of excavators M and trucks N are obtained from detection results. Second, the distance in pixels between each truck and each excavator in frame k (d_k) is calculated using Equation (1).

$$d_k = \sqrt{(y_k^e - y_k^t)^2 + (x_k^e - x_k^t)^2} \quad (1)$$

where (x_k^e, y_k^e), (x_k^t, y_k^t) are the centroid coordinates of excavator and truck in frame k, respectively. Accordingly, each truck is grouped with the nearest excavator. If the distance between the truck and the excavator is larger than the threshold, the truck will not be included in the group. The threshold is calculated using Equation (2).

$$Threshold\ (\mu) = 0.5 \times (w_k^e + w_k^t) \quad (2)$$

where w_k^e, w_k^t are the widths of bounding boxes of excavator and truck, respectively, in frame k.

3.3 Idling reasons identification

The third step is to identify the potential reasons why excavators are idling. These reasons are summarized into four cases, as shown in Table 1. For each idling excavator, the number of trucks n in the same group is calculated. If there is no truck in the group, the reason of the idling is classified into Case 1, which indicates that the excavator is waiting for a truck.

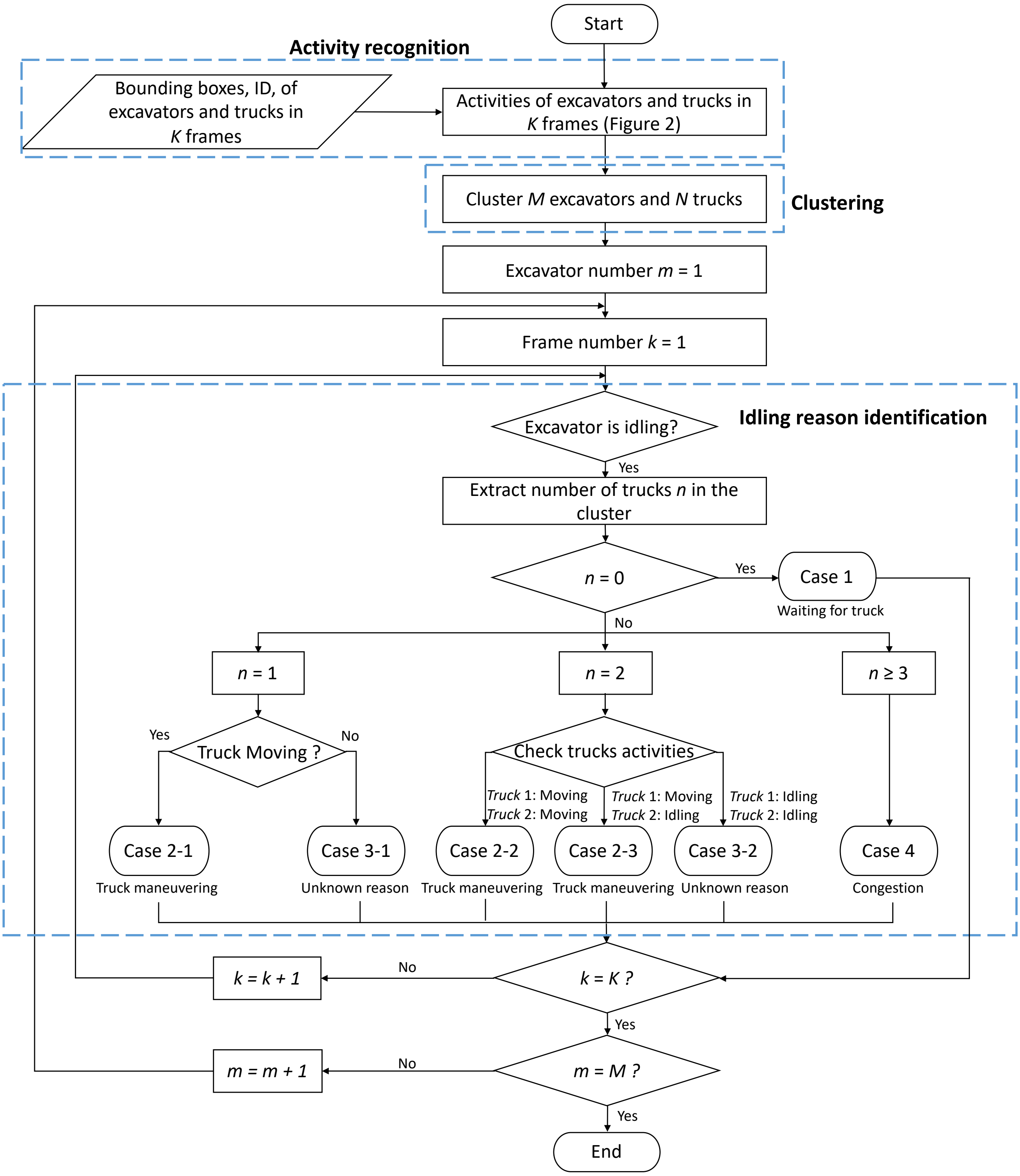


Figure 1. Flowchart of the proposed methodology

When there is only one truck in the group, the idling reason is determined by the activity of the truck. If the truck is moving, the reason is classified to into Case 2, which indicates that the excavator is waiting for the truck maneuvering to the loading position. Otherwise, there could be different reasons that cause excavator's idling as explained above. Therefore, in this condition, the reason of excavator's idling is classified into Case 3 (unknown reason). For Case 2 and Case 3, there are subcases depending on the number of trucks. When there are two trucks identified in the group, the activities of trucks have three conditions: both trucks are moving, one is moving and the other is idling, or both trucks are idling. These different conditions of trucks' activities could lead to two reasons of excavator's idling. If at least one of the two trucks is moving, the reason is classified into Case 2 (i.e. truck maneuvering). If both trucks are idling, the reason of excavator's idling is unknown, which is Case 3. When there are more than three trucks in the group, the idling of the excavator is classified into Case 4, which indicates too many trucks causing site congestion around the excavator.

Table 1. Potential reasons of the excavator idling

Case		Potential reasons
Excavator idling	Case 1	Excavator is waiting and there is no truck
	Case 2	Several trucks are maneuvering
	Case 3	Unknown reasons (e.g. operator, mechanical problem, safety issue)
	Case 4	Congested site with many trucks

4 Implementation and case study

In this section, the implementation of the proposed method is introduced, and three case studies are provided to demonstrate the performance of the proposed method. A computer with two NVIDIA GeForce GTX 1070 GPUs @ 3.4 GHz, 64 GB DDR, and Windows 10 system was used for the implementation.

4.1 Training and testing

First, to get the locations of the excavators and trucks in video frames, the YOLO-v3 detection model was trained to detect excavators and trucks in the video frames. A dataset containing 1,191 images of excavators and trucks (1,071 excavators, 871 trucks) was created to train the detector. In the training process, the learning rate is set to 0.1, and an Adam optimizer was used to adjust the learning rate during each epoch. The batch size was set to 6. It took about 10 hours with the validation loss not decreasing after 350 epochs. Then, the detection model was tested on the test dataset with 300 images (362 excavators, 421 trucks). The test results are shown in Table 2. The average accuracy of the detection is 82%, which shows that the model has a good ability to identify excavators and trucks in video frames.

Table 2. Detection results

Confusion matrix	Predict class			Model performance		
	Excavator	Truck	None	Precision (%)	Recall (%)	Accuracy (%)
Excavator	337	2	23	98	93	
Truck	6	303	112	99	72	
Average						82

4.2 Case study

In this section, a video of about 62 min of earthmoving work was used for testing. The video has the resolution of 1920 × 1080 pixels and the frame rate of 30 fps (110,914 image frames). In this video, one excavator has 2,645 s idling time and 1,052 s working time. The idling and working states of the excavator and trucks were identified based on the method explained in Section 3.1. The step of the sliding window was selected as 100 frames for both excavators and trucks idling states identification. The thresholds α and μ of the excavator were selected as 7 pixels and 2% of average bounding box areas. The threshold of trucks was selected as 10 pixels without considering the bounding box's area changing. The comparison of ground truths and estimated results are shown in Figure 2. The estimated idling and working times are 2,612 s and 2,085 s, respectively. The error rates are 1.2% and 3.1%.

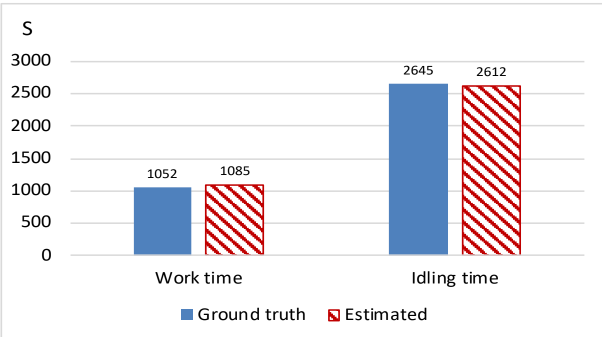


Figure 2. Estimated excavator idling and working time with ground truth

The idling time of the excavator was further analyzed to identify the reasons that caused excavator's idling. In this video, there are three kinds of reasons of excavator's idling: Case 1, Case 2 and Case 3. The accuracy of the estimated results of these three cases are 99%, 82%, and 98%, respectively as shown in Figure 3.

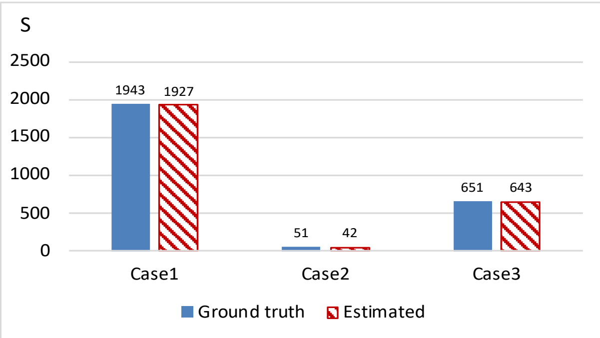


Figure 3. Results of idling reasons analysis with ground truth

The results show that the identification of Case 2 has the maximum error rate of 18%. The errors are mainly due to the failure of detection of partial appearances of trucks as can be seen in Figure 4. This case appeared from time T = 2,535 s to T = 2,540 s and T = 3,153 s to T = 3,156 s, which decreased the estimated moving time of trucks. If the errors of the detection results are excluded, the accuracy of these Cases 1-3 are 100%, 97%, and 99%, respectively.

The results of Case Study 1 show that during 62 min earthmoving work, the excavator's idling time is 60% of total operation time. The proportion of each case is shown in Figure 5. Among these three cases, Case 1 consumes 74% of the total idling time, which indicates a limited number of trucks were arranged to work with the excavator. By observing the video, it could be noticed that the average cycle time of trucks is about 20 min, and Loading time per truck is about 4 min. In the earthmoving work, more trucks should be arranged to cooperate with the excavator to reduce its idling time, since the utilization cost of the excavator is higher than truck. Therefore, to keep the excavator working at capacity, more trucks are required.

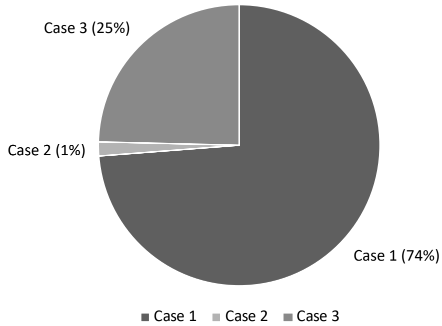


Figure 5. Percentage of the reasons for idling

Case 3 consumes 25 % of the total idling time. From the video time $T = 51$ s to $T = 520$ s, it can be observed that the operator of the excavator left the equipment, as shown in Figure 6(a). From $T = 3,159$ s to $T = 3,358$ s, it can be observed that two persons were talking near the excavator, and the excavator started to work after they left, as shown in Figure 6(b).

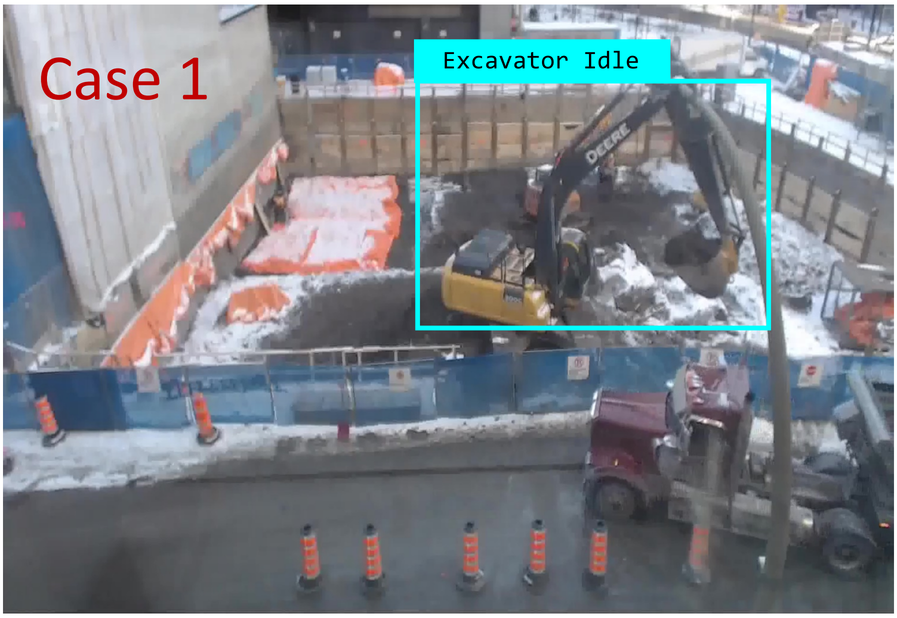
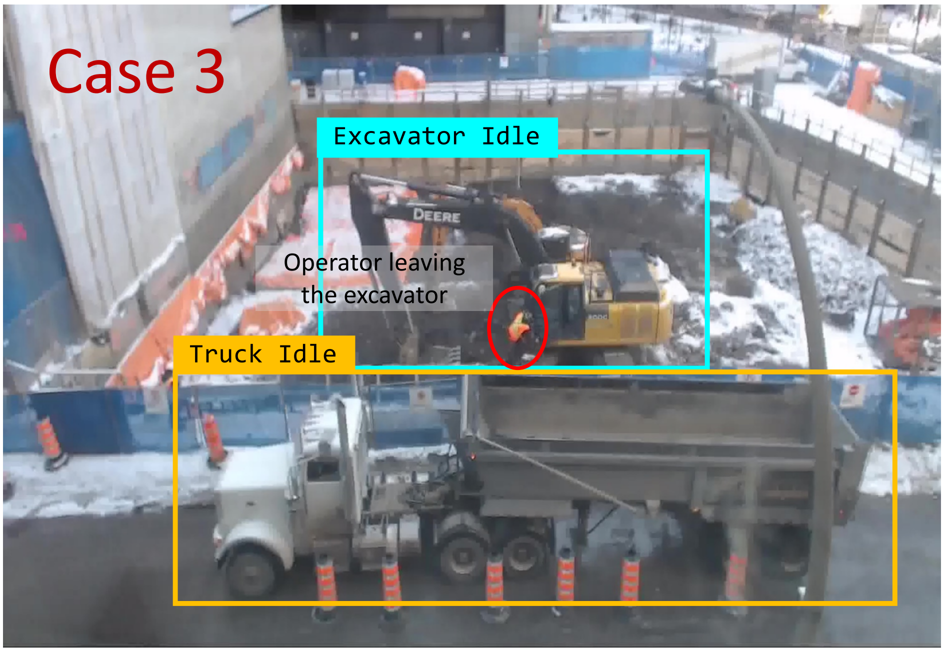
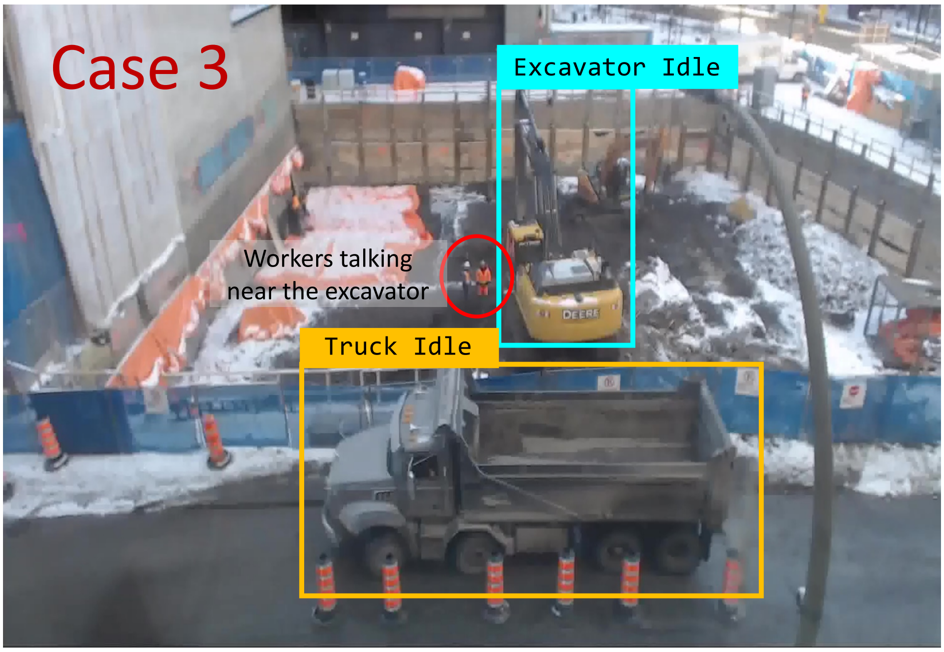


Figure 4. Example of lost detection for the partial truck



(a) Operator leaving the excavator



(b) People talking near the excavator

Figure 6. Examples of Case 3

5 Conclusion and future work

This paper developed a novel CV-based method to automatically identify the idling reasons of excavator and truck based on their interactive work states. To the best knowledge of the authors, this is the first attempt to classify the reasons of equipment's idling into detailed categories using CV. The proposed method provides an efficient solution to explore the reasons of low productivity from site surveillance videos, which could contribute to the better understanding of the earthmoving productivity under complex construction site conditions.

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