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Vision-based Payload Volume Estimation for Automatic Loading

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In construction industry, the number of skilled workers is decreasing due to aging and avoidance of labor-intensive work. In addition, construction accidents take a large proportion of occupational accidents, about half of which are related to construction machinery such as excavators. To solve these problems, the need for studies on automation of excavator is increasing. Excavator work is largely divided into excavation and loading. Loading is important because it is a large part of excavator work and loading a large amount of payload in a single trip is an enormous gain across the entire job. Therefore, measuring volume of payload is essential to ensure high loading rate while preventing overloading. However, it usually depends on operators' observation based on their experience and can be challenging when the surface of payload is rough. In that sense, automatic volume estimation methods using pre-stored container model and multiple sensors have been developed, but they are not feasible to construction work. Therefore, this paper proposes payload volume estimation algorithm using a single depth camera. The proposed algorithm recognizes the truck dump body in RGB image using instance segmentation. With this information, we get the region of interest in dump body and estimate payload volume by processing point cloud. We use iterative closet point (ICP) and density-based spatial clustering of applications with noise (DBSCAN) algorithm to calculate the pose of dump body and improve the error of payload volume. Then, loading is executed according to the estimated payload. The algorithm is implemented and evaluated in RC excavator equipped with a depth camera under the boom and result of experiment show that the algorithm produces accurate estimation of payload volume.

1. Introduction

The construction industry is an important industry that has taken a large part in economic growth in many countries. The productivity of construction work varies greatly depending on the skill level of the workers. However, the number of skilled workers is decreasing due to an aging population and avoidance of dangerous and intensive construction work. Especially, in the case of excavators, it takes a long time to create skilled workers, and accidents related to construction machines such as excavators account for a large proportion of industrial accidents. In order to solve these problems, the need for automation research on excavators is increasing.

Previous studies have developed autonomous excavator. In 1999, autonomous loading system (ALS) was proposed [1]. ALS used laser scanners to recognize dump trucks and plan dig points and dump points. Other studies have also developed algorithms for automated excavators [2-4]. In addition, there have been studies on specific excavator operation [5-9]. For example, in [6], they obtained excavation data from experts and trained them to plan an appropriate excavation route according to the terrain. Studies on loading also have been developed. In [8, 9], loading system was proposed that use iterative learning control and normal distribution for soil shape to make the soil closer to desired shape. However, until now, the number of Studies on loading is minor compared to those of excavation studies. Loading is important in excavator work because it takes a large part of excavator work and loading lots of soil at once is directly related to the productivity of the entire job. This paper proposes loading algorithm that automatically estimate the volume of payload. We use single depth camera mounted on the excavator boom to acquire the data. Instance segmentation is used to recognize the dump truck from the RGB image and then convert it to point cloud pixels. Then, we align the dump body to the dump truck containing the soil using Iterative Closet Point (ICP) [10] algorithm and remove it to extract the soil. Outliers are removed from the point cloud of soil extracted by using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [11] algorithm. Finally, triangle mesh is created from the point cloud of the soil and the volume is estimated.

2. Literature Review

Measuring the volume of payload usually depends on human observation [12], and it can be challenging when the surface of payload is rough [13]. As mentioned before, measuring the volume of payload is vital to ensure high loading rate and prevent overloading that can damage to road during trip. However, performing the measurement of payload for themselves can be inefficient and make work more labor-intensive [13, 14].

Previous studies have proposed automatic methods for measuring the volume of payload in bucket or truck. In [1], laser rangefinders data of soil in truck are placed in a 2-D terrain map to plan the dump point. In [13], two lidars that mounted at top and road are used to reconstruct the truck and payload while truck is moving. Then, computer vision algorithms are used to estimate volume of payload. It achieved average percent error 4.41% relative to ground truth weight. In [15], the volume of payload in dragline bucket is estimated using lidar. Since the bucket of dragline is connected by ropes, sway and changes in the velocities of bucket are corrected. These studies depend on prepared models to recognize the target which are filled with soil. However, it is not practical in excavator work because dump trucks are constantly changed after loading. In addition, some studies used sensors that are not suitable in outdoor [16] and need high structure to install sensors [13, 14]. This paper use instance segmentation to recognize dump truck and install the stereo depth camera under the excavator boom.

3. Method

In this section, we describe the proposed algorithm for estimating the payload volume in dump truck while loading. We use single depth camera mounted to boom to acquire RGB images, depth map and point cloud. RGB images and depth map is used to convert pixels to point cloud, and point cloud is used to estimate the payload volume.

3.1 Dump body reconstruction

To estimate the volume of payload, we obtain the empty dump body model as a reference from the point cloud when the dump truck is empty. After acquiring the empty dump body data, dump body is segmented in the RGB image through our instance segmentation model, and the RGB image pixels labeled with the dump body are converted to point cloud coordinates address. Fig. 1 (a) shows the result of instance segmentation. Therefore, we can extract the empty dump body within the point cloud, and it becomes the dump body model.

3.2 Workspace dimension estimation

After segmenting the dump body from the background, we use empty dump body to calculate the workspace dimension. It is used to represent the workspace boundary as point cloud coordinates and estimate loading rate to ensure high productivity. By using the Random Sample Consensus (RANSAC) [17] algorithm to the point cloud of the empty dump body, the equation of the bottom plane and corresponding point cloud of dump body are obtained, and then we calculate the edge points of bottom. Height of the dump body is the

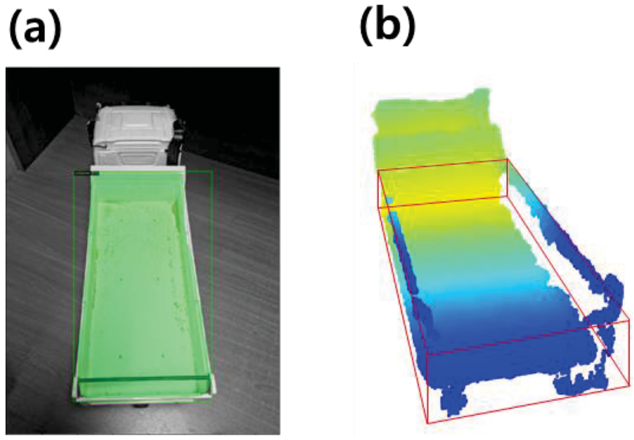

Fig. 1 (a) Result of instance segmentation, (b) Workspace represented in point cloud coordinate.

distance from the point on the side to the bottom plane. Through the edge points of the bottom and height of dump body, we can represent workspace as cuboid in point cloud coordinate (Fig 1. (b)) and obtain its volume.

3.3 Payload extraction

3.3.1 Dump body alignment

When we receive the point cloud data from depth camera after loading, we align the empty dump body model obtained in Section 2.1 with point cloud of the dump truck containing the payload. It is necessary because it allows to define the inner boundary of the payload and so, estimate the volume of the payload. To align the dump body, we calculate the transformation of the dump body using the ICP algorithm. Like other iteration methods, ICP require a good initial value (transformation) to improve approximate solutions. Since the truck does not move during the loading process and the pose of the excavator that acquires data does not change significantly, we can use the default transformation of ICP as an initial transformation and align the dump body with little errors. Fig. 2 (a) shows the result of aligning dump body to dump body.

3.3.2 Payload filtering

Once we align the dump body, next step is cropping the ROI through the bounding box of dump body and removing the dump body to extract the payload. Bounding box is the smallest cuboid that contains an entire object and specify the object location. We can crop the ROI by removing the points that are not in the bounding box and then remove the dump body from ROI. However, it is not possible to extract only the payload even if the pose is well estimated because we do not use the intact dump body model as a reference, therefore, outliers are remained. We use the DBSCAN algorithm to remove outliers by clustering the point cloud based on their density. Since the point cloud of payload has high density, outliers and soil can be distinguished effectively and the surface of the soil can be obtained (Fig. 2 (b)).

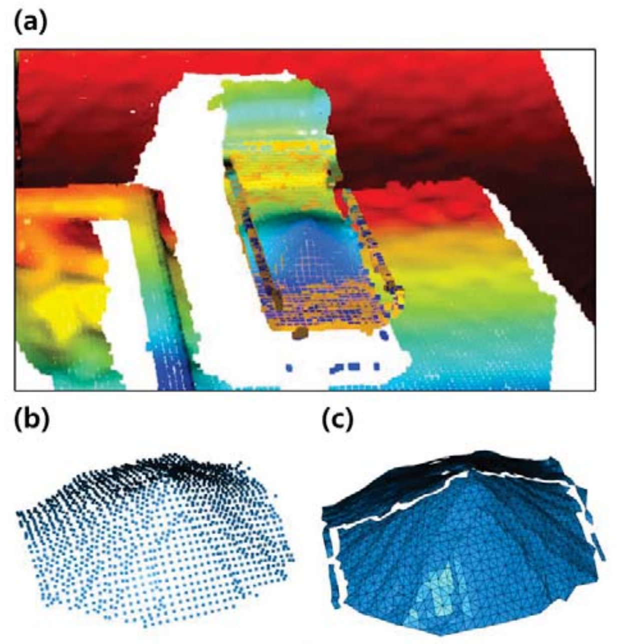

Fig. 2 (a) Result of alignment dump body, (b) Point cloud of payload, (c) Triangle mesh of payload.

3.4 Volume estimation

If the soil is extracted from the dump truck, then the volume of the soil is measured. However, since the point cloud of payload is its surface, several processes are required to measure the volume. The point cloud of the payload is reconstructed into a mesh by connecting three nearby points to create triangular faces, which is called triangle mesh (Fig. 2 (c)). Also, using the transformation computed by the ICP in Section 2.3, the bottom plane of the dump body in Section 2.2 is transformed and it is used as a reference plane for the height of payload. The volume of each face is area projected on the bottom plane multiplied the height of each face. Projected area is the face area multiplied cosine of angle between bottom plane and face, and height is the distance between the center of gravity of face and bottom plane. Total volume is the sum of the volume that each face has.

4. Result and Discussion

The algorithm using Intel® realsense™ Depth camera d455 (Resolution: 640 × 480) was implemented with Python and Labview on the computer with Intel® Core™ i7-10700F CPU and NVIDIA GeForce GTX 1060 GPU. In addition, we used RC model of excavator and dump truck that is 1:14 scaled and evaluated the algorithm.

When we acquire the data, if there are bucket in depth camera's data, it is hard to recognize dump body and estimate payload volume. Therefore, to remove the bucket from data, we lift the arm and bucket when the data is acquired (Fig. 3 (a)), and data acquisition is performed when the dump truck is empty (beginning of the loading) and after dumping the payload. We evaluated the workspace dimension first. Table 1 shows the estimated volume, actual volume

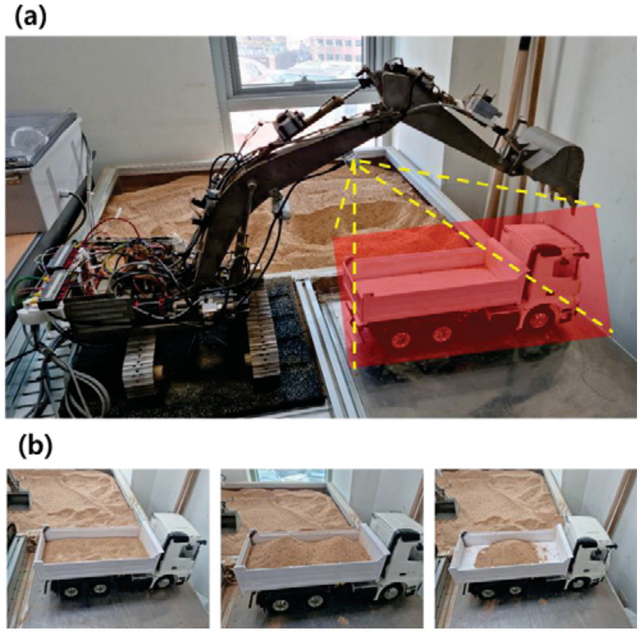

Fig. 3 (a) Excavator pose of data acquisition (b) Datasets of payload (from left to right: flat, dumpy, ridge)

and relative error for dump truck. Actual volume was calculated by measuring the length, width and height of the dump truck. We evaluated the payload volume next. Table 2 shows the estimated volume, estimated weight, ground truth weight and relative error for each payload sample. Three types of payload shapes (Fig.3 (b)) are used to evaluate the algorithm. We measured the weight to evaluate the data since it is hard and not accurate to measure the payload volume directly. Estimated payload weight is computed by using the average density of payload (1.31kg / m^3) that we measured.

The algorithm achieved a relative error of 0.038 for workspace and mean relative error 0.05 for payload. Table 2 shows that results are varied depending on the type of payload shape. Among the datasets, flat payload achieved the low error while bumpy payload achieved high error. It is mainly caused by the blind spot of depth camera which become bigger when the payload is bumpier.

Table 1 Evaluation of workspace dimension.

	$V_{est}(10^{-3}m^3)$	$V_{act}(10^{-3}m^3)$	Error
Workspace	3.937	3.791	0.038

Table 2 Evaluation of payload weight computed using volume estimated by the algorithm.

Dataset	$V_{est}(10^{-3}m^3)$	W_{est}(kg)	W_{gt}(kg)	Error
Flat_1	1.144	1.499	1.540	0.027
Flat_2	2.039	2.75	2.845	0.033
Bumpy_1	1.449	1.898	2.025	0.063
Bumpy_2	1.309	1.714	1.880	0.088
Ridge_1	0.374	0.490	0.515	0.049
Ridge_2	0.940	1.232	1.285	0.041
			Average	0.05

5. Conclusion

We proposed new algorithm for estimating the volume of payload in dump truck during loading. The stereo depth camera is used to acquire the data. With depth camera's data, the dump body is recognized and the point cloud of payload in dump truck is extracted. The point cloud of payload is reconstructed to triangle mesh and the volume is estimated from the mesh. We achieved the error 0.038 for workspace and the mean error 0.05 for payload. It indicates that the algorithm is successfully estimate the volume of workspace and payload. The algorithm is deployed and implemented in RC model that is scaled 1:14. Future work need to include experiments in real environments of loading work.

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