

## **Visualization and Object Recognition in Construction Space using Dual 3D Laser Scanners Mounted on a Construction Vehicle**

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**Abstract:** Recently, ICT construction vehicles are used well in unmanned construction environments. However, using automated construction vehicles is difficult for cooperated operations with workers in dense urban areas. In our related studies, we have visualized the safety at construction sites with the recognition and identification of workers from horizontal laser scanning data acquired with a LiDAR mounted on a construction vehicle. However, the horizontal scanning data were insufficient to detect objects because the ranges of the vertical scanning angles were too narrow. Therefore, we proposed a methodology to integrate two-point clouds acquired by horizontally and vertically mounted LiDAR. We also proposed a method to recognize a backhoe bucket from the integrated point clouds. As a result, we confirmed that the point cloud data acquired from the backhoe during excavation work can be used to recognize the bucket. We also compared the integrated point clouds acquired with the vertical and horizontal LiDAR with the point clouds of the horizontal LiDAR to evaluate the performance of representation and object recognition in construction works.

**Keywords:** Point cloud, Object recognition, Point cloud registration, Laser scanning, Construction vehicle (5 Words Maximum)

### **1. INTRODUCTION**

In recent years, construction fields have had technical issues, such as project productivity improvement needs, need for accident reduction, and engineer shortage. Thus, various actions and projects are underway to develop and introduce advanced construction vehicles equipped with ICT technology and building information modeling (BIM). In large-scale construction spaces, experiments on construction using remotely operated unmanned construction vehicles are conducted to improve productivity and safety with the BIM/CIM framework. The remotely operated unmanned construction improves an operation environment with joystick-type remote controls and monitors to cover wide viewing angles to replace onsite backhoe operation (Kajita et al. 2017). Taisei Corporation has tested camera systems at Unzen Fugen-dake (Kondo et al. 2011). Onboard cameras mounted on the driver's seat of a construction machine are used to share an operator's perspective with a mobile remote-control room. Thus, the system support operators can quickly evacuate to a safe location in the case of an emergency such as mudslides. Kajima Corporation also has conducted experiments on construction vehicles with ICT technology at unmanned construction sites since 2005. Full-scale unmanned construction was implemented in 2018 at dam construction sites. Although construction

vehicles are not controlled remotely, instructions from the control room are sent to multiple construction vehicles to perform automated construction (Kajima Corporation, 2020).

Although various conventional ICT construction vehicles have been developed, several technical issues remain in working together with workers. In small construction sites in urban areas, construction vehicles need various kinds of assistance from workers to perform detailed tasks such as excavation and drilling works. Previous studies have attempted to visualize the safety of construction sites by object recognition and tracking from horizontal scanning data using multilayer LiDAR. However, horizontal scanning has problems such as difficulty in understanding the bucket behavior because of insufficient vertical scanning angle and insufficient scanning resolution and difficulty because of the occurrence of object detection omissions. Therefore, this study constructs a system (cross LiDAR) that combines horizontal LiDAR and vertical LiDAR, and develops an object recognition method using point cloud data acquired by vertical scanning. The purpose of this study is to develop a method of object recognition from point cloud data acquired by vertical scanning.

## 2. METHODOLOGY

The proposed methodology in this study is shown in Figure 1. The proposed methodology consists of ground surface estimation using the RANSAC algorithm, range image processing, and object recognition processing.

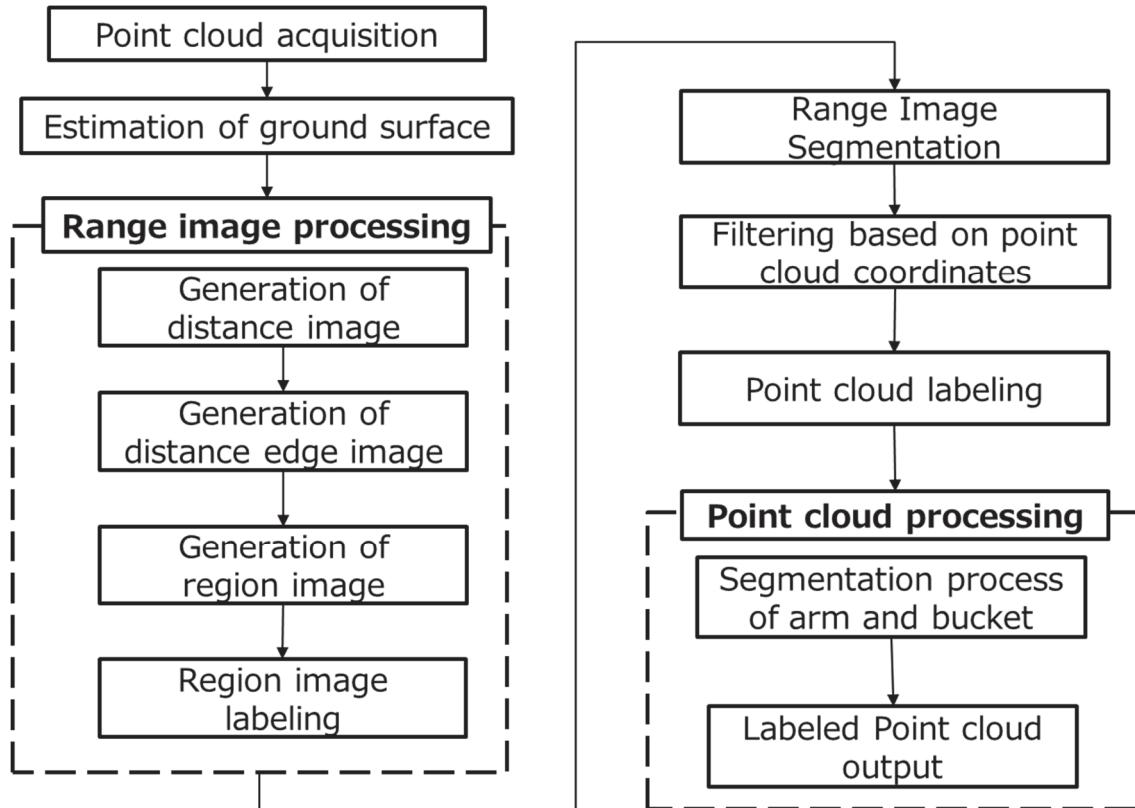


Figure 1. Proposed methodology

The integration of the horizontal and vertical LiDAR point clouds consists of LiDAR time synchronization, point cloud rotation processing, and alignment using offset values. Figure 2 shows

an overview of the proposed methodology.

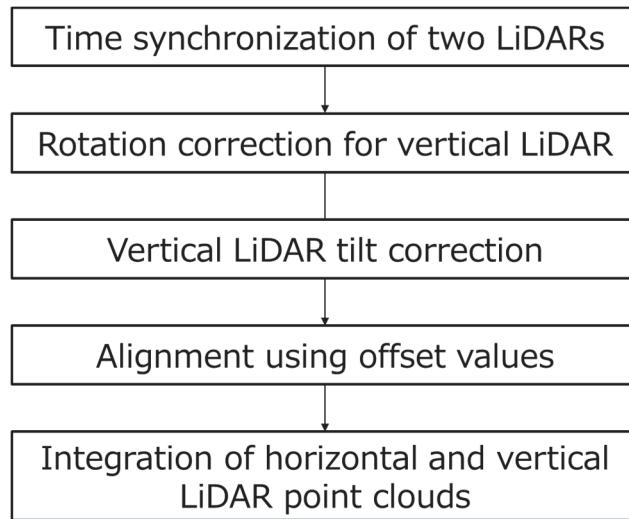


Figure2. Point cloud integration methodology

The object recognition process first estimates the ground surface using the RANSAC algorithm as a preprocessing step. Next, range image processing is used to label each object. Then, to extract only the point cloud of the bucket of the construction vehicle, the arm and the bucket of the construction vehicle are segmented.

## 2.1 Range Image Processing

The point cloud can be treated as an image by converting it into a range image, facilitating the labeling of the point cloud used for bucket extraction. In this research, a range image is generated by arranging LiDAR channel information in rows and scan directions in columns. Each point cloud contains information such as x, y, and z coordinate values and reflection intensity values, and by projecting this information as an image, a range image is generated in which each pixel of the image contains the information of the point cloud. The information handled by the range image in this study is the result of processing using the coordinate values of the point cloud to generate the range image (Figure 3). The range image processing in this study consists of generating a distance image from the LiDAR center, generating a distance edge image using the difference in distance measurement values between adjacent pixels, segmenting the distance image into regions using the distance edge image, and generating a label image by labeling the result of the region segmentation process.

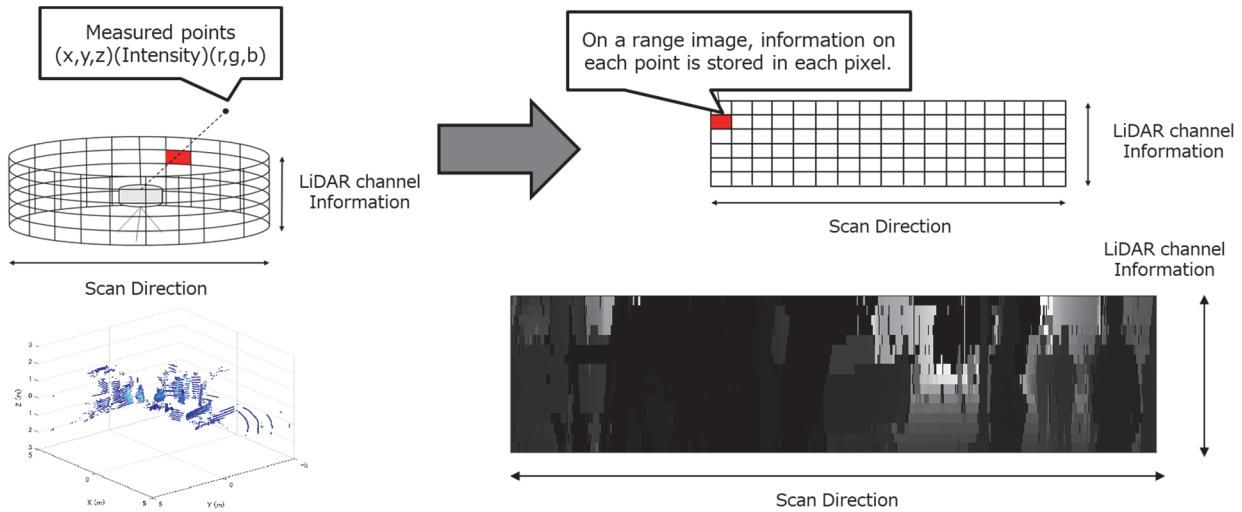


Figure3. Overview of range images

## 2.2 Labeling of Point Cloud

On the label image generated by range image processing, the point cloud is labeled in conjunction with the distance image, thus displaying the distance values of each point from the coordinate values of the point cloud at each pixel, but the point cloud is not labeled with labels for land objects. Therefore, labels for geographic objects are added using the relative positional relationship with the construction vehicle. In this section, we categorize the objects into three types: objects below the machine's travel surface (e.g., buried pipes and steel sheet piles), objects in front of the machine (e.g., bucket and arm of the machine), and other objects (e.g., workers, dump trucks and buildings). Figure 4 shows a conceptual diagram of the target area of the point cloud in front of the construction vehicle. In this study, the area to be extracted as a point cloud in front of the construction machine was 0-5[m] in front of and 2[m] to the left and right of the onboard LiDAR, and -2 to 5[m] in relative height from the LiDAR.

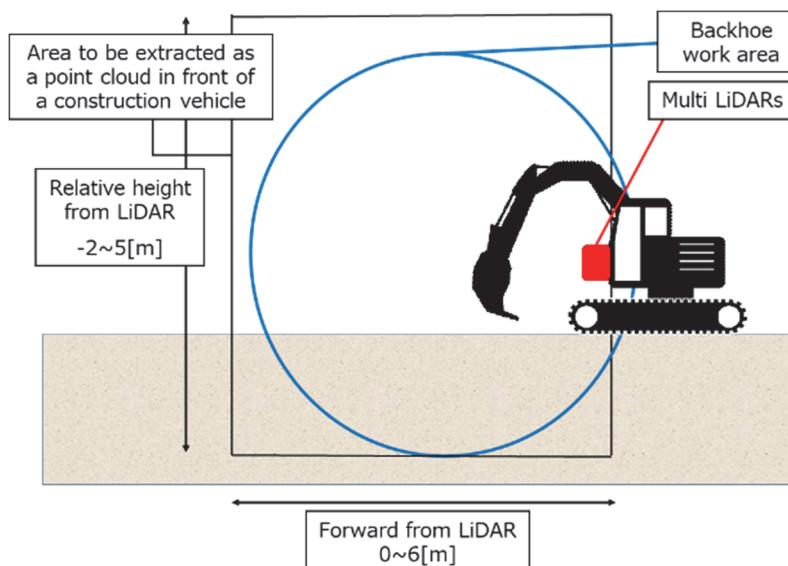


Figure 4. Target area of the point cloud in front of a construction vehicle

## 2.3 Segmentation Processing of Arm and Bucket of the Backhoe

Among the point clouds labeled as geographic features in front of the construction vehicle, the arm and bucket are resegmented from the point clouds at close range. Because the arm and bucket are connected objects and treated as a single label in the label image, the arm and bucket are divided using the manually labeled point cloud data. The point cloud data used to divide the bucket are obtained by extracting only the point cloud of the bucket from the experimental data. In this study, the model fitting using the iterative closest point (ICP) algorithm is applied to the bucket segmentation using the point cloud labeled as a bucket to extract the bucket region (Figure 5). The bucket geometry data and the point cloud extracted as the point cloud in front of the construction vehicle are used to align the point clouds. Then, only the point cloud of the bucket is extracted from the point cloud in front of the construction vehicle from the point cloud of the bucket after alignment. Because the accuracy of point cloud positioning using the ICP algorithm is highly dependent on the initial position, this study uses the point cloud extracted as a bucket in the previous scene for positioning.

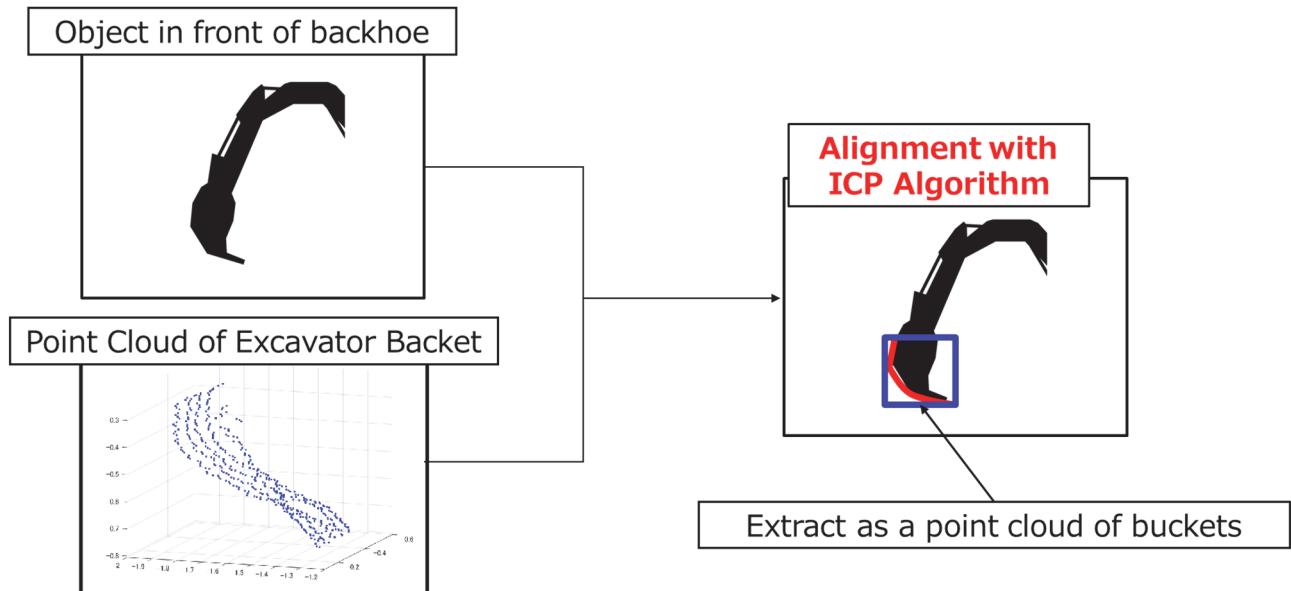


Figure 5. Extraction of a bucket from the point cloud of a construction vehicle

## 2.4 Integration of Horizontal and Vertical LiDAR

To integrate the point clouds acquired by horizontal and vertical LiDAR, time information is recorded by GPS and used to synchronize the two LiDAR systems. To perform vertical scanning, the LiDAR is mounted at a 90° tilt (Figure 7), and the amount of rotation of the LiDAR is corrected. After the rotation is corrected, the point clouds are merged using the offset values between the LiDARs measured when the LiDARs were mounted.

### 3. EXPERIMENT

In a simulated construction space (Figure 6), where excavation, piping, and backfilling operations by a backhoe and workers are reproduced, point clouds of 4000 scenes (about 7 minutes) were acquired using a multilayer LiDAR mounted on a construction vehicle. A horizontal LiDAR (VLP-32C, Velodyne) was mounted in front of the backhoe at a ground level of 1.0[m], and a vertical LiDAR (VLP-16, Velodyne) was mounted at a ground level of 1.2[m]. The threshold for distance edge extraction was set at 0.2[m].



Figure 6. Simulated construction space

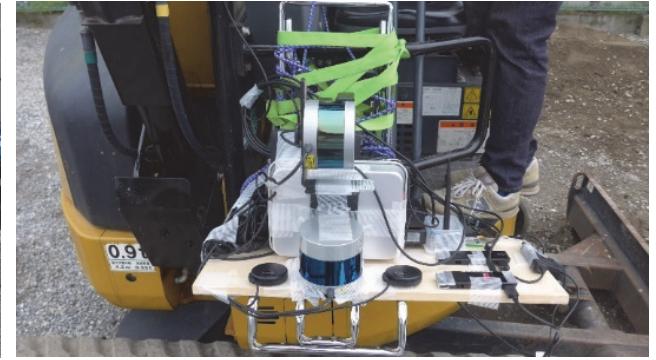


Figure 7. Mounted LiDAR

### 4. RESULT

The range image processing results for an arbitrary scene are shown in Figure 8.

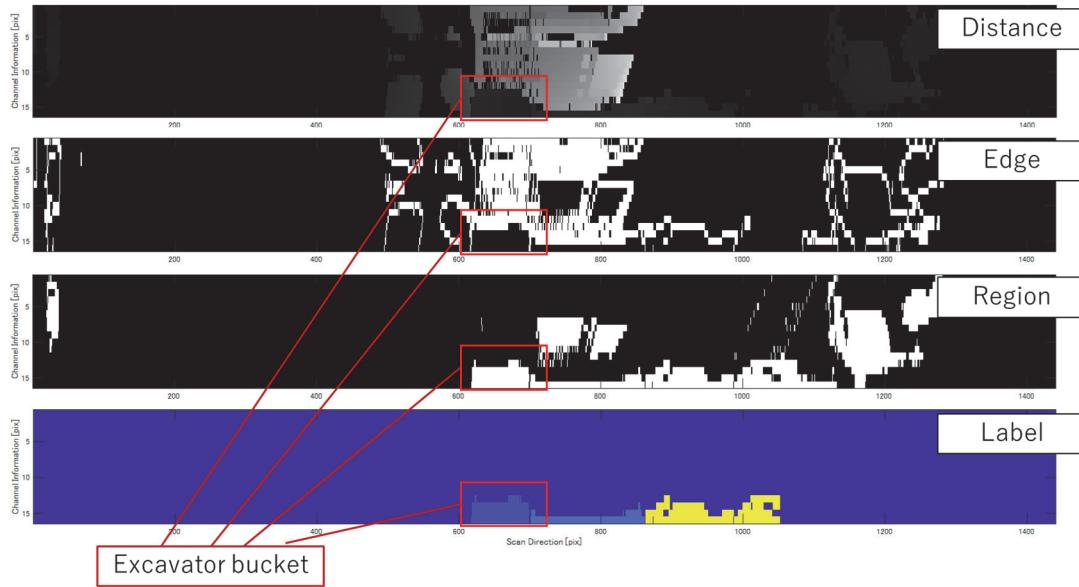


Figure 8. Range image processing results

(from top to bottom: distance image, distance edge image, region image, and region label image)

Figure 9 shows the point clouds of an arbitrary scene acquired by horizontal LiDAR and vertical LiDAR in this experiment. Figure 10 shows the classification results of the point clouds.

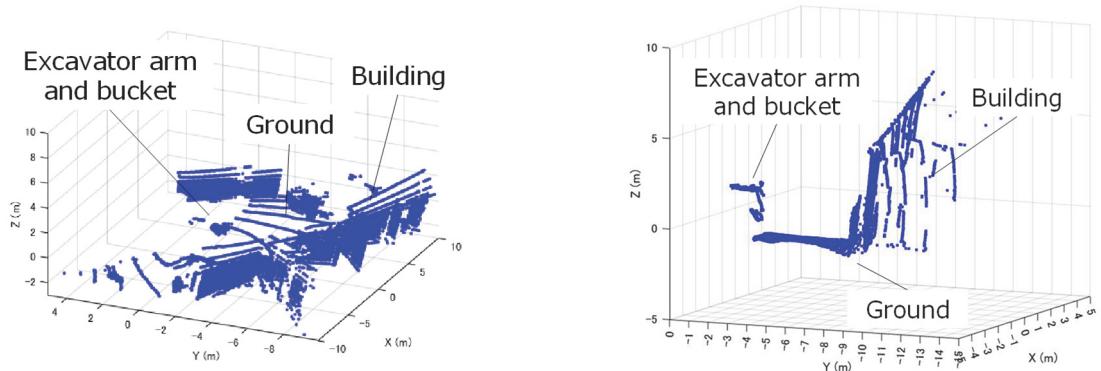


Figure 9. Acquired point cloud (Left: horizontal LiDAR, Right: vertical LiDAR)

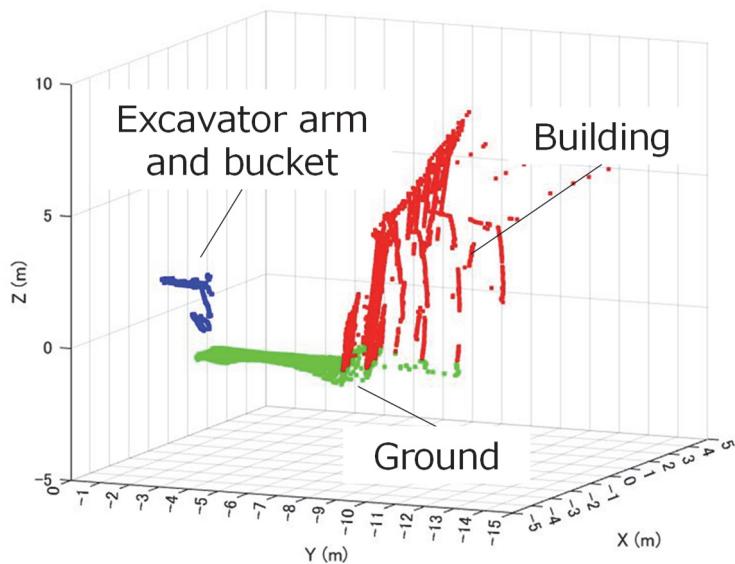


Figure 10. Point cloud classification results

Figure 11 shows the results of the integration of the horizontal and vertical LiDAR point clouds.

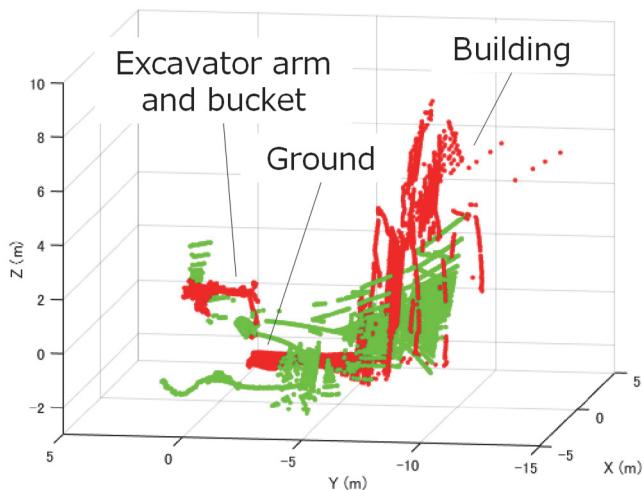


Figure 11. Point cloud integration results

Processing time (CPU: Intel Corei7-1165G7, 2.80 GHz, and MATLAB) is shown in Tables 1 and 2.

Table 1. Processing time (bucket extraction)

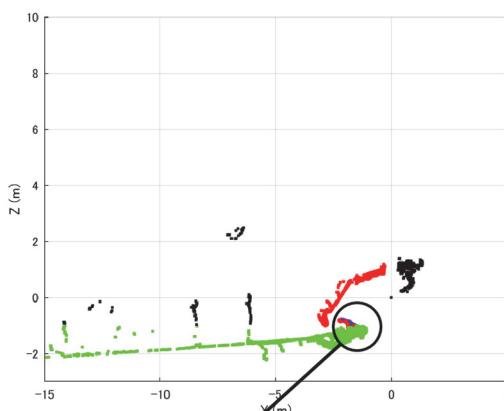
	Processing time[sec]	Processing time per scene[sec]
Ground surface extraction	347.19	0.09
Range image processing	356.14	0.09
Extraction of construction vehicle	138.64	0.03
Extraction of bucket	86.94	0.02

Table 2. Processing time (point cloud integration)

	Processing time[sec]	Processing time per scene[sec]
Rotation correction for vertical LiDAR	6.56	0.002
Tilt correction	6.05	0.002
Alignment using offset values		

## 5. DISCUSSION

Figures 10 and 11 show that the object can be recognized from the vertical LiDAR point cloud. The results also confirmed that there were frames in which the bucket was not detected (Figure 12). One of the reasons the bucket was not detected is that the point cloud of the bucket could not be acquired when the bucket moved outside the LiDAR field of view (e.g., into a pit) during excavation. In addition, we confirmed that the integration of the horizontal and vertical LiDAR point clouds can complement the point cloud, which is difficult to measure and acquire independently of either of the LiDARs.



The bucket is aligned with the area that could not be extracted as a ground surface.

Figure 12. Example of failed bucket extraction

## 6. CONCLUSION

In this study, we developed an object recognition method using point clouds acquired by vertical scanning from a construction vehicle. Through experiments, we confirmed that it is possible to label point clouds using range images output from the coordinate values of the point clouds and to extract buckets by object recognition. We also confirmed that the combination of horizontal LiDAR and vertical LiDAR can acquire point clouds of the bucket behavior and the bucket work area, which are difficult to acquire only by horizontal scans. Future work is needed to add a recognition and identification function for the operator.

## ACKNOWLEDGMENTS

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