AN OBJECT DETECTION ALGORITHM FOR 3D TERRAIN DATA COLLECTED VIA LASER SCANNING

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ABSTRACT: The intelligent excavating system (IES) aims for the full-scale automation of the excavation process that includes a series of tasks such as movement, excavation, and loading. The core elements of the IES include excavating robots, 3D modeling of surrounding terrains, and the technology for detecting objects accurately (i.e., for detecting the location of nearby loading trucks and humans as well as of obstacles positioned on the movement paths). These are absolutely necessary in ensuring the performance quality and safety of the equipment. This study was conducted to detect the terrains and objects near the location of the intelligent excavating robot via a 3D laser scanning system and to ensure the quality and safety of automated excavation. Moreover, an algorithm for estimating the location, height, width, and shape of objects in the 3D-realized terrain that surrounds the location of the excavator was proposed. The performance of the algorithm was verified via tests inside an actual earthwork field.

Keywords: Object, Detection, Earth Work, 3D, Excavation

1. INTRODUCTION

The excavator is among the most important equipment used in earthwork operations. Since the 1990s, the United States and Japan have actively led research on the teleoperation and fully autonomous control of excavators. In Korea, the development of the intelligent excavating system (IES) took off in 2006 with the support of the Ministry of Land, Transport and Maritime Affairs (formerly the Ministry of Construction and Transportation). The IES project aims to fully automate earthwork operations that consist of a series of tasks that include movement, excavation, and loading. The automation of excavation particularly necessitates a technology for accurately modeling the terrain in which the excavating robot operates. The said task also requires error-proof detection of objects such as loading trucks and humans approaching the excavating robot and the obstacles positioned on its path. Furthermore, the technology for accurately detecting terrains and objects is a core element of the development of the intelligent excavating robot to ensure its performance quality and safety.

In this study, a 3D laser scanning module was used to carry out accurate 3D modeling of the IES's surroundings. The previous review of related studies showed that laser scanning systems had been used to detect objects in the earthwork fields, though the fields were narrow and the types of objects were limited. Thus, there seemed to have been a limitation in the application of the conventional methods to the testing of vast, irregularly-shaped earthwork fields.

This study was conducted to: (a) develop an object detection algorithm using the terrain data that were collected via the 3D laser scanning module of the IES, which were considered the basic information needed for the estimation of the location, height, width, and shape of the objects near the IES; and (b) test the algorithm against actual earthwork fields and verify its performance level.

2. OBJECT DETECTION FOR IES

The IES collects terrain data via the 3D laser scanner module, in which a 2D laser scanner (SICK LMS-151) is set to rotate at a steady speed via a motor (Figure 1). The module creates polar coordinates and gathers terrain data

composed of $D_{i,j}$ (the distance between two survey points), Φ_i (the motor rotation angle), and θ_j (the inner scan angle). Then an internal processor converts $D_{i,j}$ into $P_{i,j}$, which is a point on the 3D cartesian coordinates.



Fig. 1 3D laser scanner module of IES

Characteristically, the shape of earthwork fields varies considerably. Furthermore, it is irregular, unlike the shape of road surfaces and construction sites that are more level. In this study, attention was given to the shadows of objects, and such information was used to accurately measure the location of objects that are found in irregular terrains. A shadow area is created behind any object that is found to exist on the scan line. For the purpose of this study, the boundary points of the shadow area were estimated to isolate the object.

The boundary of the shadow area can be detected by differentiating the 2D distance of $P_{i,j}$. With $D_{i,j}$ defined as the 2D distance between $P_{i,j}$ and a point in the scanner, differentiating D against Φ (the scanner rotation angle) would enable the detection of the two points at which the area of the object begins and ends (Fig. 2). Here, $\Delta\Phi$ (the interval of Φ) remains the same for as long as the scanner rotates at a steady speed, and may be called a constant. As far as θ_j (the inner scan angle) is concerned, the longer the distance is from the point in the sensor, the smaller the mean density of the data is. Furthermore, a scale error is created whereby the mean value of D and the mean of the differential values increase.

In the aforementioned case, estimating two points by applying certain thresholds is impossible. Hence, a variable (S_j) that indicates the differential values in a scale is needed. With θ_j serving as the scan angle, S_j represents the density of average points and can be calculated as shown in Figure 2 using Equation (1), assuming the terrain is completely level. Moreover, the differential value of $P_{i,j}$ is

defined in Equation (2), wherein $D_{i,j}$ (the distance from the starting point) is differentiated against S_i and not against Φ .

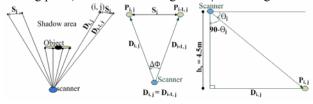


Fig. 2 Object piece detection at θ_i

$$\begin{aligned} D_{i,j} &= h_s \cdot \tan\left(90 - \theta_j\right) \\ S_j^2 &= 2 \cdot D_{i,j}^2 - 2 \cdot D_{i,j}^2 \cdot \cos(\Delta \phi) & (based \ on \ law \ of \ cosines) \\ S_j &= D_{i,j} \cdot \sqrt{2 \cdot (1 - \cos(\Delta \phi))} \\ &= h_s \cdot \tan\left(90 - \theta_i\right) \cdot \sqrt{2 \cdot (1 - \cos(\Delta \phi))} \end{aligned} \tag{1}$$

 h_s : sensor height (4.5m)

 $\Delta \Phi$: packet interval (360/No. Packet) $Differential (i,j) = \frac{D_{i,j} - D_{i-1,j}}{c}$ (2)

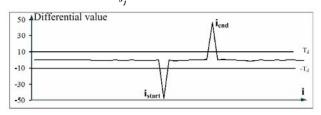


Fig. 3 Differential graph of θ_i

Figure 3 shows the differential graph for Equation (2). In the graph, i_{start} (the starting point of the object) and i_{end} (the ending point of the object) form a pair of values with opposite signs. They can be estimated using T_d (the threshold) as the reference value. The section between i_{start} and i_{end} becomes an object piece, which creates the shadow area. T_d can be calculated using Equation (3), as shown in Figure 4, by incorporating h_o (the minimum height) of the object that is being detected.

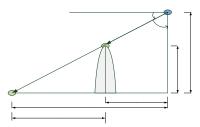


Fig. 4 Principle of derivation of T_d

$$\begin{split} D_{i,j} - D_{i-1,j} &= h_o \cdot \tan\left(90 - \theta_j\right) \\ T_d &= \frac{D_{i,j} - D_{i-1,j}}{s_j} = \frac{h_o \cdot \tan\left(90 - \theta_j\right)}{h_s \cdot \tan\left(90 - \theta_j\right) \cdot \sqrt{2 \cdot (1 - \cos(\Delta\phi))}} \\ &= \frac{h_o}{h_s \cdot \sqrt{2 \cdot (1 - \cos(\Delta\phi))}} \end{split} \tag{3}$$

 h_s : sensor height (4.5m)

h_o: object height

 $\Delta \Phi$: packet interval

Object pieces, which can be detected with scan lines, are grouped to form a single object via the clustering process. For this study, the grassfire algorithm was used. As shown in Figure 5, the boundary of the three sides of a single object, i.e., $\min(j)$, $\min(i_{start})$, and $\max(i_{end})$, can be detected. On the contrary, detecting $\max(j)$, where the object meets the surface and where the boundary in between is vague, using partial differentiation is infeasible. Therefore, 3D analysis using elevation must be used instead.

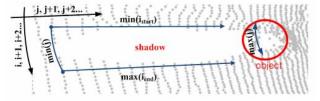


Fig. 5 Boundary of the shadow area

Figure 5 shows the tendency of the object to have a smaller projection as the proximity to max(j) increases. The actual location of max(j) is decided on as shown in Figure 6, when no more projection is detected off the ground line. The data that indicate the shape of the object can be estimated by grouping the previous projection points for the object.

The ground line takes into consideration the terrains that surround the shadow area. With the boundary of the shadow area ranging between $\min(i_{start})$ and $\max(i_{end})$, the terrains under consideration (G1 and G2) are converted into coordinates that correspond to $[\min(i_{start})-1, \max(j)]$ and $[\max(i_{end})+1, \max(j)]$, respectively. A linear function for i of the assumed ground line ($\overline{G1G2}$) that passes through G1 and G2 is calculated. If the z value is found to be greater than the straight line ($\overline{G1G2}$) by T_h at the minimum, the terrain will be isolated as the object. Here,

 T_h refers to the threshold that separates the terrain from the object. It was set at 0.15 m in this study. GL(i), the linear function for i of $\overline{G1G2}$, is defined in Equation (4). Table 1 summarizes the location, width, and height of the object.

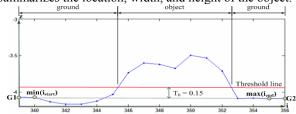


Fig. 6 Object separation via thresholding ($T_h = 0.15 \text{ m}$)

$$GL(i) = a \cdot i + b$$

$$a = \frac{(z_{G2} - z_{G1})}{\{\max(i_{end}) + 1\} - \{\min(i_{start}) - 1\}}$$

$$b = z_{G2} - a \cdot \{\max(i_{end}) + 1\}$$
 (by linear equation)

Table. 1 Object information formula

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Item	Formula			
Object No.	Clustered Number			
Location : (x-y) coordinates of P(i, j)	$i = \left\{\frac{\min(i_{start}) + \max(i_{end})}{2}\right\}, j = \max(j)$			
Width	$\left\{\max(i_{end}) - \min(i_{start})\right\} \times S_{\max(j)}$			
Height	max(z)-min(z)			

3. FIELD TEST RESULTS

The data that were to be used for the site testing were collected from an actual earthwork field. The ability of IES to detect objects was tested with the target objects, i.e., trucks, humans, and dirt pile. Figure 7 shows the results of the object detection ($T_d = 5$), and the data are summarized in Table 2.

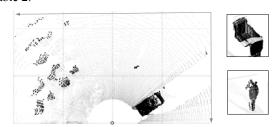


Fig. 7 Detection result of the earthwork filed (T_d=5)

All the trucks, humans, dirt pile, and equipment at the site were detected without omissions. With the heaped dirt pile, the layers were treated as a single object for the detection. The data on the shape of the trucks and humans were manipulated such that the obtained values represented those that were 15 cm above the surface. This was done to ensure the isolation. Being elevated objects, the trucks formed the shadow area that extended all the way up to the end of the terrain data. Detection would still have been possible if the truck location veered 15 m away from the scan radius. Due to the distance, however, the scanner was unable to cover the entire truck. Moreover, the accuracy of the estimated shape was compromised.

Table. 2 Object information

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Object information					
57					
46					
.25					
.38					
81					

Table 3 summarizes the T_d values that were changed for the same terrain data. The bigger the T_d value was, the higher the object under detection was. By the same principle, modifying the T_d values allowed adjustment of the height of the object under detection.

Table. 3 Detection result based on T_d value

T_{d}	Detection Result				
	Truck	Dirt Pile	Human	Equipment	
5	О	О	О	О	
15	О	О	0	X	
25	0	X	X	X	

4. CONCLUSION

In this study, an algorithm in which the shadow area boundary was obtained from terrain data using a rotating laser scanner was proposed, and the shape data of various objects were estimated. The proposed algorithm was tested at a site where earthwork operations were underway. It detected all the humans, trucks, and dirt pile that were found at the site without any omission. According to the test results, the distance that enabled the estimation of the truck shape was found to have had a radius of about 15 m. The results also indicated that the reference height of the object under detection could be adjusted by changing the $T_{\rm d}$ values.

The findings from this study offer a broad range of applicabilities, considering that object detection technology is a core element of IES as well as of automated construction equipment and tele-operated equipment using laser scanning modules.

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