IDENTIFICATION OF PARTIALLY-EXPOSED METAL OBJECT

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Abstract: This paper describes a method of automated type and pose (position and orientation) identification of partially exposed metal objects that makes excavation of hazardous materials safe and efficient. The object pose is estimated by matching a model of the object to the area that is extracted from the range image using the characteristics of metal objects. Experimental results show feasibility of type and pose identification of partially exposed objects.

Keywords: Automated Excavation, Vision System, Pose Identification, 3-D Data Analysis, Recognition of Object, Abandoned Munitions, Range Image.

1   INTRODUCTION

It is desired that removal of hazardous materials such as abandoned chemical weapons from burial pits should be completed safely in a short span of time. It is required to excavate metal objects safely and efficiently. Safe and quick excavation tasks make progress of plan of safe environment recovery projects [1-4].

In order to excavate metal objects, workers remove soil around the objects so that they identify the object shapes. According to the condition of the soil around the objects, and the pose of the objects, it takes large cost for removing the soil until the workers can identify the object shapes.

We have proposed an automated excavation system to excavate the metal objects quickly and safely [2]. To achieve the excavation task, the system removes soil around the metal objects safely and quickly at first. Next, the system identifies type and pose (position and orientation) of the metal object. After the identification, the manipulator excavates the metal object. Several metal objects are exposed partially since the soil around the objects and the other objects hide a part of the objects. Therefore, it is required to estimate the pose and type of the metal object by measuring hidden part of the object using a vision sensor and a metal finder.

This paper describes a method of automated pose identification of partially exposed metal objects in order to excavate hazardous materials safely and efficiently. This method extracts areas of the several objects from the captured three-dimensional range image. Type and pose of the metal object are determined by the matching the target area to the reference shape model of the object given beforehand.

This paper focuses on the pose estimation algorithm based on three-dimensional pattern matching in excavation and recovery system. Pose accuracy of the object influences the width of the area for scanning a hidden part of the object with a metal finder. This width of scanning area influences efficiency of the excavation task.

We have carried out the measurement of the object pose under the several conditions of the target object. Experimental results show feasibility of the type and pose identification of the partially exposed object.

2   SYSTEMS OVERVIEW

We introduce an overview of the automated excavation and recovery system. Buried metal objects have several characteristics shown as follows:
(1) The types of metal objects are several since an object is mass-product materials.
(2) Color of the object has changed for the long term by the corrosion and rust.
(3) Objects has deformed because of the corruption and the rust of the surface of the object.

These facts enable the automated identification and excavation system. From the characteristics (1), the automated pattern matching method is useful for identification of the type and pose of the metal object.

From the characteristics (2) and (3), it is difficult to use the color data and precise shape data for identification. In addition, color data is not useful

for this automated excavation system, since the change of light source influences this data strongly.

We use range data captured by a three-eye camera or a laser range finder for the data capture system of the automated excavation and recovery system. Figure 1 shows the overview of automated excavation system. The type and pose of the metal object are estimated using the three-eye camera. The robot arm manipulates and recovers the metal object using the sensory data. If the computer cannot determine orientation of the metal object since the area of the exposed object is small, the computer obtains the orientation data using the scanning around the candidates of the object pose by the metal finder. Then the manipulator removes the soil around the metal object.
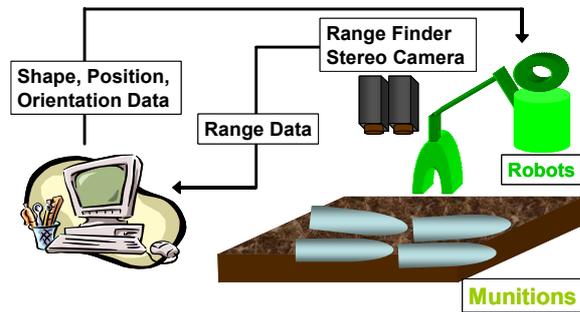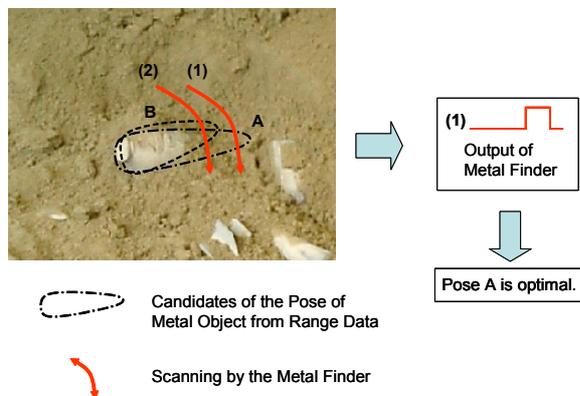

Figure 1: Systems overview.

Figure 2: Pose estimation of metal objects using metal finder.

Figure 2 shows an example of pose estimation of a buried object that is exposed partially. The pose of buried object is ambiguous since the range sensor measures the data of only the exposed area. Thus, we obtain a precise pose of the object by searching for the buried part of the object using a metal finder.

We explain a method of the decision of the pose of the partially exposed object using a metal finder. The shapes expressed by the dashed line A and B in figure 2 are candidates of the pose of the metal object from the range data. The pose and type of the metal object is determined by the models of the metal object and the scanning data by the metal finder ((1) and (2) in figure 2). Since the metal finder replies on the trajectory (1), we consider that the candidate (A) is more suitable for the object pose.

In order to discuss the accuracy of the pose estimation of the object, we use only the range data captured by the three-eye camera in this paper. The width of the search area by the metal finder is decided by the pose accuracy of the object by the range data.

3   AUTOMATED IDENTIFICATION OF PARTIALLY EXPOSED METAL OBJECT

We describe a procedure of the automated identification of type and pose of a metal object using a three-eye camera system. The camera captures data about the metal object exposed partially and makes a range image of the exposed area of the object from the captured data. The computer estimates and detects a part of the target object using the range image data. The type and pose of the metal object are determined by the matching to the reference shape model of the object given beforehand. The procedure of this process is shown as follows:

(1) Obtain a range image data using the three-eye camera.
(2) Detect the area of the target object from the range data.
(3) Approximate the axis of the target object by the linear fitting by the least-squares method.
(4) Obtain the range data on the plural planes that are perpendicular to the approximated axis of the target object.
(5) Fit an ellipse to the range data on each plane, and estimate the axis of the target object using the center of the ellipses.
(6) Match the range image to the model of the target object along the estimated axis of the object. The position that is matched to the model the best regards as the estimated position of the target object.

4   EXPERIMENTAL CONDITIONS AND POSE IDENTIFICATION ALGORITHM

We explain the experimental condition of the pose identification of the metal object and pose identification algorithm. The detailed algorithm of pose identification is described using a part of the experimental result.

4.1   Experimental Setup

Figure 3 shows the experimental setup in our laboratory. Three-eye camera are fixed 700 [mm] above the target area vertically. The camera directs to the target area. We use Digiclops (focal range $f = 3.8$ [mm], the range of capturing is more than about 50 [cm]) as the three-eye camera. The distance to the

target area is obtained by the triangulation based on the stereo vision. The distance can be measured in the area that the view of at least two cameras are overlapped. The size of the image data for range image is 640×480 [pixels] and the distance is obtained by each pixel. The matching between the image pixels of each camera is obtained by correlation between the masks centering on the target pixel defined beforehand. The correlation is obtained based on the Sum of Absolute Difference (SAD) matching method. The size of the SAD mask is 15×15 [pixels].
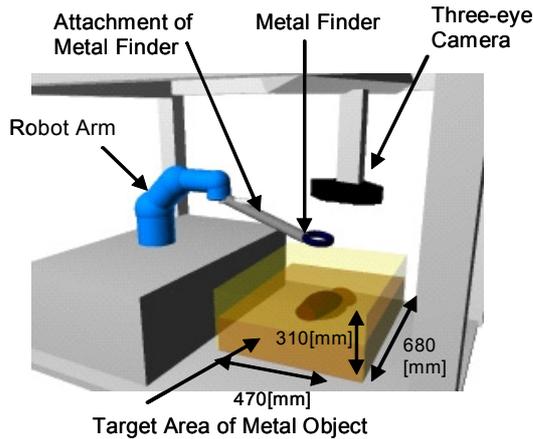

Figure 3: Experimental setup.

4.2 Obtain range image of target area

Figure 4 shows the image data and range image data captured by the three-eye camera. The range image data near a center is used in order to exclude the data of the container. The range data are transposed to the two-dimensional image. The light pixel indicates the near point, and the dark one indicates the far point. The image is called range image. The gradation of one degree of the range image indicates 1[mm]. The black pixel indicates that the distance of the pixel cannot be obtained. Figure 5 shows the image data of the target area that is plotted in three-dimensional volume. The white line of the figure 5 indicates the horizontal and vertical axis of the camera. An intersection of these lines indicates the center of the area of view.

4.3 Extraction of metal object area

The computer extracts the area of the metal object from the obtained image data. The area of the metal object is extracted from the range image using the dynamical threshold based on the watersheds algorithm [5].
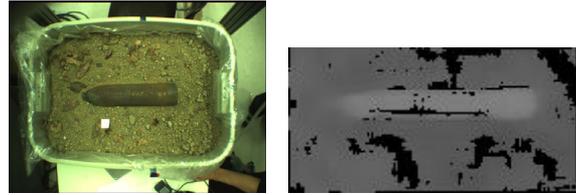

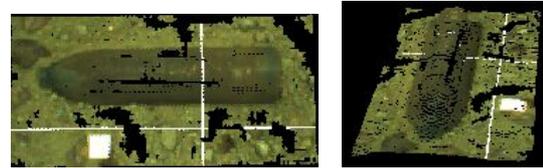
Figure 4 : Image and range data of the target area.

Figure 5 : Range Image (3-D volume).

The extraction process consists of the selection of the candidate of the metal objects and the segmentation of the range image based on the watersheds algorithm. The set of initial points of the candidates of the metal objects is selected from the histogram of the range image. The computer segments the range image into several areas of the metal object.

(1) Selection of the points that the target objects exist (initial points)

This process selects the candidates of the object areas from the histogram of range image and the labeled range image. The precisely procedure of the selection of the candidates of the target objects (initial points of the watersheds algorithm) is shown as follows:

1. Make a histogram about the distance from the range image.
2. The threshold of the range image is calculated from the histogram. The threshold extracts the domain of 20[%] of nearer ranks from the camera.
3. The range image is transferred to a binary image using the threshold. The binary range image is labeled. The large label, whose area is more than 150 [pixels], is considered as a target object. The centers of the gravities of the target objects are calculated.

These gravities are used as the set of the initial points of the watersheds algorithm.

(2) Area detection based on watersheds algorithm

Watersheds algorithm is a method of the segmentation of the image data. In this method, the brightness of the pixels regards as the altitude, and the image data regards as the geographical feature. Water is poured into positions with low altitudes, and the geographical feature is divided bordering on the watershed that divides a basin. This method divides the image data into the several areas such as the division of the watersheds. In this experiment, the set of the candidates obtained the procedure (1) is used as the initial points of each divided area. We apply the expansion task of the divided area from the initial point to the segmentation procedure. The precise

procedure of this watersheds algorithm is shown as follows:

1. The set of the centers of the gravities obtained procedure (1) is the initial points of the algorithm. The brightness of the pixel of the initial point is the initial level of the water.
2. Search for the eight-neighborhood of the pixel that belongs to the object area (x, y). The initial direction of the search process is rightward in the movement from the past position of the basis of search to the present position. The search direction is clockwise. If there is a point whose brightness (water level) is lower in the eight-neighborhood, the new position (x, y) of initial point is set the position (x', y') of the pixel whose brightness is the lowest, and the process 2 repeats recursively. If not, goes to process 3.
3. The amount of the increases of the area of the target object when a water level is gone up is calculated. If the amount of the increases is smaller than the threshold (1300), water level (base brightness) is gone up, and goes to process 2. If the amount is larger than the threshold, the expansion process is ended.

The area belong to the area that is obtained through this process is the object area, and the other area of the image is the background image. Through this method, we obtain the binary image of the object area. After smoothing and labeling of the binary image, the binary image are filtered about the area of the target object (threshold is that the area is more than 150). The each filtered label is considered as the area of the target objects. The extracted target object is shown in Figure 6. The range image referred to the area of the target object is shown in Figure 7.

Figure 6: Extracted target object.

Figure 7: Range image of the target object.

4.4 Estimation of axis of the object

This process estimates the rotary axis of the target object from the partially object shape. The form of the target object is approximated with a body of revolution and the rotary axis of the object is estimated from the three-dimensional shape of the object area. The target object is rotary symmetrical, and the axis of the object is called principal axis.

First, as the approximated axis of the target object, the inertial axis of the range data of the target object is calculated. Figure 8 shows the approximated principal axis on the range data.
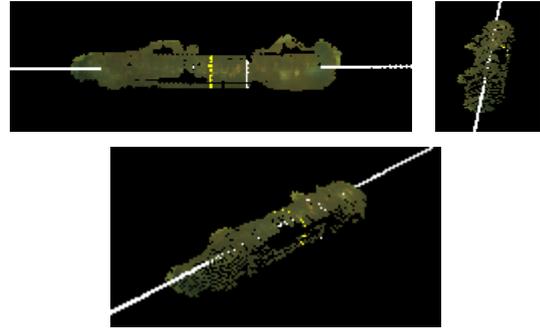

Figure 8: Approximated axis of the object.

Next, we suppose the several planes that are perpendicular to the approximated axis of the target object. We suppose that the range data on each plane are the data obtained from the surface of the target object, and fit the ellipse to the data set on the plane. In the experiment, the range data that are neighborhood of the plane consider as the range data on the plane. The fitting algorithm is conic fitting method developed by Kanatani [6]. If the result of conic fitting to the data on the plane is not an ellipse, the fitting result is not used.

Figure 9 shows the result of conic fitting to a set of the range data on a plane. The origin of the figure indicates the approximated principal axis of the object. The pixels illustrated by the circle indicate the range data of the object. The estimated center of the ellipse indicates the square in the figure.
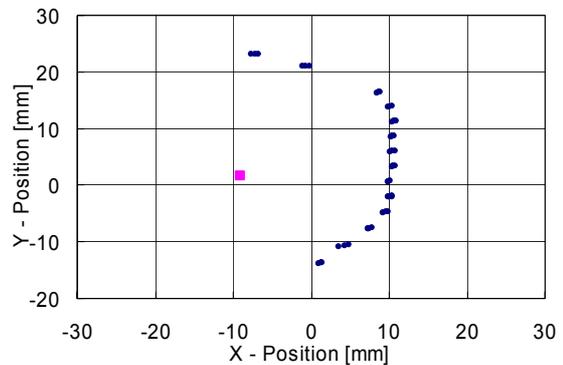

Figure 9: Estimation of center of ellipse.

The set of the range data on the perpendicular plane to the center axis for the ellipse fitting, the computer selects the range data to improve the accuracy. We suppose a circle whose center is the point that is nearest to the camera, and the radius of the circle is that of the target object. The range data that are in the circle are selected. The inertial axis of the center of the ellipse obtained by the plural planes is calculated, and we suppose the principal axis of the target object. Figure 10 shows the principal axis of the object. We set the perpendicular planes by 8 [mm].
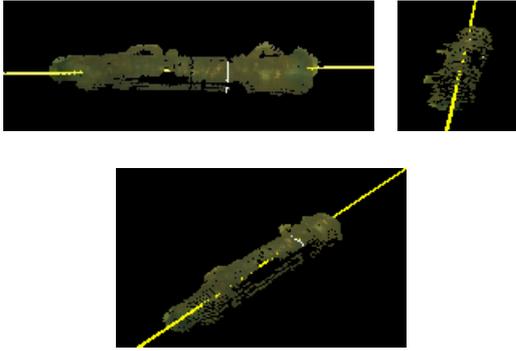
Figure 10: Principal axis of the target object.

4.5 Object matching along the principal axis

This process matches the model of the object to the range image along the estimated principal axis of the target object. The distance between the model and the range image data is calculated. The distance between the model data and image data is calculated about each displacement along the principal axis of the target object. The displacement that the distance between the model and the range image is minimum value is the estimated displacement along the principal axis of the object. Therefore, the position of the target object is obtained. Figure 11 shows the pose estimation result of the target object. The white dots indicate the fitting result of the target model to the range image data.
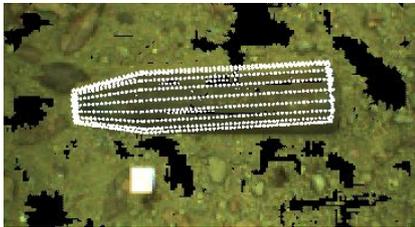

Figure 11: Pose estimation result.

5 EXPERIMENTAL CONDITIONS

We carry out the pose estimation experiment under several conditions about types and poses. The experiment conditions are type, ratio of the exposed area, depth of the object, and relationship of between two objects.

(1) Ratio of the exposed area of the target object
    The ratio of the exposed area of the target object are defined as the area ratio of the model projected to the X-Y plane shown in Figure 12. This ratio of the exposed area is 1 if the object is on the plane.
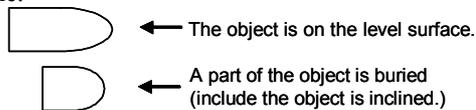

Figure 12: Ratio of the exposed object area.

(2) Depth of the object position
    The depth of the target object is compared in the case the target object is exposed partially. In partial buried case, the depth of the lowest point of the object as shown in Figure 13(a), and the depth of the highest and lowest point of the object as shown in Figure 13(b). Since the metal finder is not used in this experiment, the pose estimation of the perfectly buried object is not carried out.
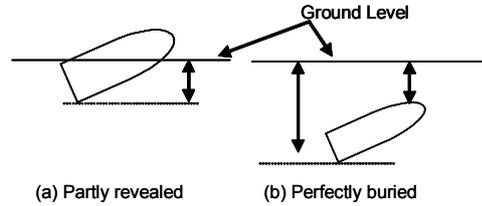

Figure 13: Depth of the object position.

(3) Type of the target object
    The type of the target object is 75[mm] and 90[mm] object.
(4) Vertical orientation of the object
    The vertical orientation is defined as the angle about the horizontal direction. In this experiment, the conditions of the vertical orientation are set 0, 30, 60, and 90 [deg].
(5) Position of the neighborhood objects
    The number of the neighborhood object is one. The relative relationships between each object are defined three parameters d, , and h shown in Figure 14 and 15.
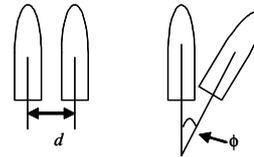

Figure 14: Relationship of between two objects in horizontal plane.
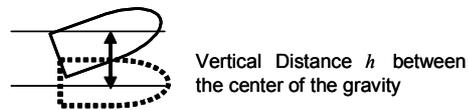

Figure 15: Relationship of between two objects in vertical plane.

6 EXPERIMENTAL RESULTS

We have estimated pose of the metal object under several conditions of the object shown in Figure 16. Experiment Condition are shown as follows: (1) $\theta = 0$ [deg], exposed rate about object area: 100[%]. (2) $\theta = 0$[deg], exposed rate 70[%]. (3) $\theta = 30$[deg], exposed rate 50[%]. (4) $\theta = 30$[deg], exposed rate 40 [%]. (5) $\theta = 60$ [deg], exposed rate 50[%]. (6) $\theta = 90$[deg], exposed rate 20[%], (7) Horizontal rotation between

two objects. ϕ = 0 [deg], both θ = 0 [deg], exposed rate 100[%]. (8) ϕ = 30[deg], θ = 0[deg], exposed rate 100[%]. (9) Objects are set vertically. Upper object: θ= 30[%], exposed rate 50[%].

The estimation result is shown in Table 1. In the case of (4) and (6), the principal axis of the object is not obtained. From the table, when the target object is horizontally oriented, we obtain the object pose accurately. On the other hand, the object is inclined in some extent, the axis is estimated inaccurately, and then no accurate model matching can be achieved.
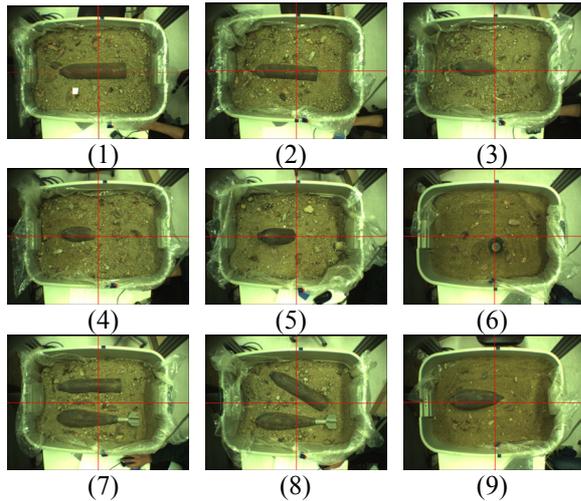

Figure 16: Experimental condition.

Table 1: Experimental result of pose estimation.

Experiment Condition	Position Error [mm]			Orientation Error [deg]	
	x	y	z	ϕ	θ
(1)	-0,5	-12,8	-11,2	-3,5	2,0
(2)	2,4	-20,9	-18,0	4,2	2,0
(3)	40,4	17,5	-125,8	4,4	-30,0
(5)	-58,7	-36,5	-175,1	-11,1	-38,3
(7)	45,4	9,0	-22,6	2,6	-0,4
	28,8	19,7	-30,0	4,7	-1,1
(8)	4,2	-0,6	-5,5	1,6	2,1
	20,4	37,7	-28,2	7,6	-1,1
(9)	90,9	-24,7	-62,7	-5,3	-18,2

From this result, the error of the direction of the orientation is large, in the case the object inclines about the horizontal plane along the vertical axis. Failure of ellipse fitting of the range data to the perpendicular plane about the initial rotary axis is one of the reasons of the error of the object. On the other hand, if the objects are on the level surface and the object is exposed highly, the pose of the metal object estimates accurately using our proposed method. It is expected that the object pose be estimated accurately since the principal axis of the object are estimated more accurately.

The value of evaluation function of matching to the model approximated to the pillar does not change, since the model of the object is matched to the range data. It is useful to use of the end of the model is applicable to the pose identification to solve this problem.

7   CONCLUSIONS

This paper describes an automated identification method of type and pose of partially exposed metal objects based on the range image data. Experimental results show feasibility of the type and pose identification of the partially exposed object. Object orientation about the horizontal axis is inaccurate. We show that the object pose are accurate if the principal axis of the target objects is estimated with high accuracy.

The evaluation of type identification is future work. The estimated pose of the object has to be more accurate in order to apply the practical excavation task.

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