https://doi.org/10.2352/ISSN.2470-1173.2019.7.IRIACV-452

Automatic Estimation of the Position and Orientation of the Drill to Be Grasped and Manipulated by the Disaster Response Robot Based on Analyzing Depth Camera Information

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Abstract

Towards the actualization of a disaster response robot that can locate and manipulate a drill at an arbitrary position with an arbitrary posture in disaster sites, this paper proposes a method that can estimate the position and orientation of the drill that is to be grasped and manipulated by the robot arm, by utilizing the depth camera information acquired by the depth camera. In this paper's algorithm, first, using a conventional method, the target drill is detected on the basis of an RGB image captured by the depth camera, and 3D point cloud data representing the target is generated by combining the detection results and the depth image. Second, using our proposed method, the generated point cloud data is processed to estimate the information on the proper position and orientation for grasping the drill. More specifically, a pass through filter is applied to the generated 3D point cloud data obtained by the first step. Then, the point cloud is divided, and features are classified so that the chuck and handle are identified. By computing the centroid of the point cloud for the chuck, the position for grasping is obtained. By applying Principal Component Analysis, the orientation for grasping is obtained. Experiments were conducted on a simulator. The results show that our method could accurately estimate the proper configuration for the autonomous grasping a normal-type drill.

Introduction

Once severe disasters such as large scale earthquakes and nuclear power plant accidents occur, the disaster sites are extremely dangerous for people. In particular, after the disasters, tasks such as repairs of collapsed buildings and destroyed plants etc. and rescues of victims are very difficult and dangerous. To solve this issue, disaster response robots are desired to be actualized. The DARPA Robotics Challenge (DRC) [2], which is a contest for disaster response robots, was held in the US. The authors' group also have developed a disaster response robot called WAREC-1 [1], which has four arms, two of which can work also as legs. Among various tasks after the disasters, the disaster response robot is expected to drill holes or cut objects such as walls using a drill to repair broken facilities and/or buildings. Using a drill is included in the DRC. In disaster sites, even if drills were put back to the proper place such as store rooms, the drills could not stay at the original positions: e.g. fall down to the floor. The disaster response robot needs to find a drill placed at an arbitrary position with an arbitrary pose. In addition, the robot needs to estimate the proper configuration for grasping the drill and to manipulate it to execute the task.

Conventional disaster response robots participating in the DRC detect the objects (tools), with which the tasks are completed, by exploiting 3D point cloud data obtained by depth cameras. In many cases, the operators detect the objects by fitting 3D models to the captured 3D point cloud data through graphical user interfaces. Obviously, it is clear that such a system is not autonomous enough for detecting the drill and estimating the information on the proper position and pose for grasping the drill; in addition, in unknown environments, the robots have difficulty in detecting target objects that do not necessarily fit the 3D model due to differences in their shapes, even if they are of the same category (tool). As Norton et al indicated in [3], the robots participating in the DRC strongly depended on 3D models such as 3D CAD models, supplied by the contest organizers in advance to complete the required tasks, in which they needed to use some objects or tools; should be more general when applying them in unknown environments in real disaster sites. For these reasons, a method for recognizing or detecting a drill without a precise 3D model of the target is obviously required.

In this paper, we propose a method for autonomously detecting a drill and estimating information on the position and orientation for properly grasping the drill with the disaster response robot called WAREC-1 based on the information captured by a depth camera, without a detailed 3D model such as 3D CAD information.

Proposed Method

Fig. 1 shows the algorithm that can estimate the position and orientation of the drill for grasping. Note that the blocks that

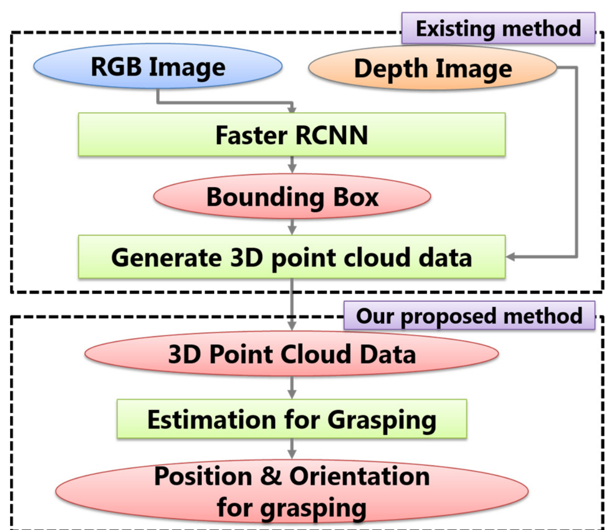


Fig. 1. The entire flow of estimating the position and orientation of the drill.

correspond to the conventional (existing) method [4] and our proposed method are discriminated by the dotted lines. As shown in the existing method in Fig. 1, first the target drill in the 2D RGB image captured by the depth camera is detected using Faster RCNN [5]. Second, 3D point cloud data is generated by combining the depth image captured by the depth camera and a bounding box which encloses the target in the RGB image, which is obtained from the detection result of Faster RCNN. In our proposed method shown in Fig. 1, we process the obtained point cloud data on the basis of a category from the detection result of Faster RCNN because the proper configuration for grasping which enables robots use the tools or objects, is heavily depending on the category, therefore, the processing methods for 3D point cloud data are different from each category for achieving properly grasping the objects in the category. In this paper, we assume that a drill which should be detected can be split into three parts; the chuck, handle, and battery. Therefore we exploit k-means to classify the point cloud data representing the drill into each cluster representing each part mentioned above. In addition, for grasping, we define the position as the 3D centroid of the point cloud representing the handle in the drill and the orientation as the direction of the chuck, which means the first eigenvector obtained by applying the principal component analysis (PCA) to the point cloud data representing the chuck.

Faster RCNN for detecting a drill in a 2D RGB image

To detect a drill serving as the target object without a precise 3D model, such as a 3D CAD model, we utilize Faster RCNN [5] which detects a drill in the RGB image captured by the depth camera. To design Faster RCNN for detecting a drill, we use VGG_CNN_M_1024 as the feature extractor in the network architecture, which is initialized with a pre-trained model on ImageNet, and we fine-tune it with our own dataset. We created the dataset by gathering RGB images of five different types of valves and one type of drill which are available in the Internet and manually annotating. The reason why we gathered not only images of drills but also those of five different types of valves and fine-tune this framework with them is that we will exploit this detection system which generates the 3D information about other objects necessary to be detected in a disaster site without any detailed 3D model, in order to be more general to an unknown environment. We also conducted data augmentation of our original dataset to increase the robustness against changes on orientation and scale by mirroring, rotating and scaling the images. In this paper, because we exploit this fine-tuned framework to detect only one category, which is a drill.

Generating 3D point cloud data representing target

To estimate the position and orientation for grasping in the 3D coordinate system, 3D point cloud data by combining the depth image captured by the depth camera and the bounding box output from the fine-tuned Faster RCNN, which is a rectangle enclosing the detected object as [4]. Concretely, the pixels in the area enclosed by the bounding box in the given RGB image are recorded and the corresponding pixels from the depth image whose resolution is equivalent to that of the given RGB image are extracted. After that the extracted pixels in the depth image are projected to the 3D coordinate system to obtain the point cloud data represents the target and objects close to it.

Processing 3D point cloud data on the basis of a category

After obtaining the generated 3D point cloud data by exploiting the part of the method proposed in [4], we process the data to

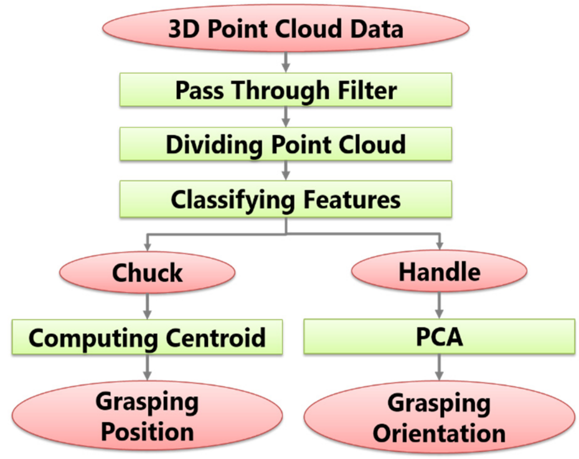


Fig. 2. The flow of processing 3D point cloud data

estimate the information for properly grasping a drill, such as the position and orientation for grasping. The entire flow of the processing method is shown in Fig. 2, which corresponds to the originality of this paper. In general, how to process the generated point cloud data depends on the “category” which output from the detection in a 2D image shown in Fig. 1. in our proposed method. In this case the “category” is “a drill”, so we choose the method for estimating the position and orientation for grasping.

Preprocessing point cloud data using Pass through filter

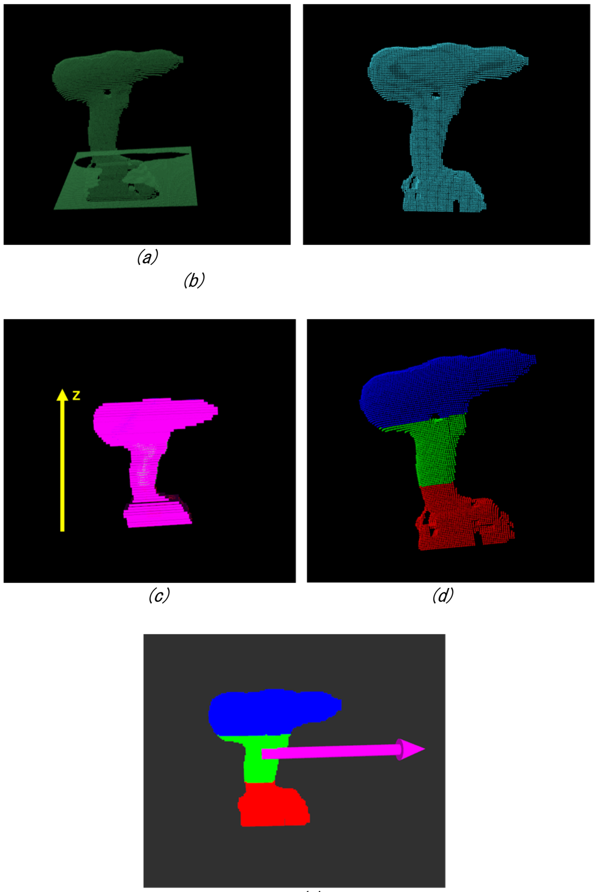
In this paper, we assume that a drill which should be detected is standing on a floor or ground plane, and an optical axis of a depth camera which is mounted on the robot is parallel to the floor. Therefore we simply remove the point cloud data representing a plane such as the floor or ground plane with Pass through filter [6]. This filter removes the point cloud data which is not belonging to the specified rectangular area. First, the 3D box minimally enclosing the entire point cloud data is computed. Second, we increase the height of the bottom surface so as to recreate the 3D box which does not contain the point cloud representing the floor or ground plane. By doing this, the point cloud data only representing the drill is obtained. The generated point cloud data and the processing result by Pass through filter is shown in Fig. 3(a) and (b), respectively.

Dividing preprocessed point cloud data along z-axis

A drill which should be detected consists of three parts; chunk, grasping part, and battery. Therefore, the point cloud data representing a drill also consists of the three parts. To divide the point cloud data, we divide it along z-axis in a resolution. The z-axis means the axis whose direction is parallel to the normal of the plane which the drill stands on. After the division, we compute the minimum 3D box enclosing each divided point cloud data and extract a feature that is four dimensional vector, using each box. The feature consists of the 3D center coordination of the box and the area of the surface of the bottom. The process for the division is shown in Fig. 3(c).

Classifying point cloud data based on extracted features

To obtain the point cloud data which is divided into three parts, we classify all of the obtained boxes into each class which corresponds to each part in a drill on the basis of the features extracted from the boxes. For classifying the features, we exploit k-



(a) (b)

(c) (d)

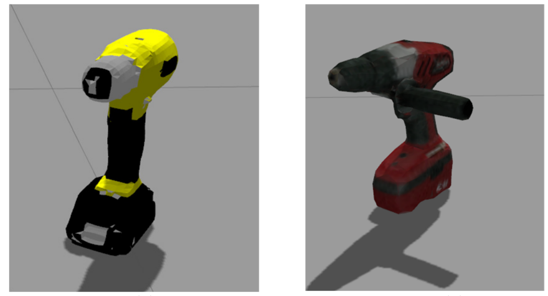
(e)

Fig. 3 The processing of the 3D point cloud data
(a) The generated point cloud data
(b) The result of Pass through filter.
(c) The division of the point cloud data along z-axis. Each pink-colored box contains each divided point cloud data.
(d) The point cloud data classified into three parts; The blue part is the chuck, green part is the handle, and red part is the battery.
(e) The position and orientation for grasping. The point is the starting point of the pink-colored arrow, and the direction of arrow is the orientation.

means. In our proposed method, we specify the three features as initialing vector when applying k-means method for classifying the boxes to make the classification stable. Those three features are selected from the one of the box whose center coordination is highest, middle, and lowest in z-axis. After classifying all the boxes, the three clusters containing the classified boxes are obtained. To assign each cluster to each part of a drill, these clusters are sorted on the basis of the z-value of the center coordination of the box because a drill has its parts in the ascending order of the battery, handle, and chuck. The classified point cloud data is shown in Fig. 3(d).

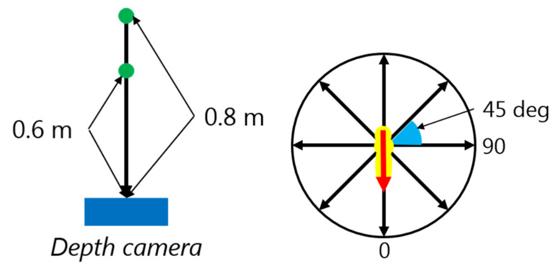
Estimating position and orientation for grasping

After the classified point cloud data is obtained, the position and orientation for grasping are estimated. For estimating the position, we compute a centroid of the point cloud data representing the handle of the drill. For estimating the orientation for grasping, we apply the PCA to the point cloud data representing the chuck of the drill and regard the vector which the first eigenvector is projected



(a) (b)

Fig. 4 The drills used for our experiments
(a) type-A (b) type-B



(a)

(b)

Fig. 5 The patterns of the positions and orientatins of a drill
(a) The positions of a drill. Each green point indicates each position.
(b) The orientations of a drill. The red arrow indicates the orientation of

in x-y plane. The visualized result of the estimated orientation for grasping a drill is shown in Fig. 3(e).

Experiments and Discussion

Experimental Environment

We conducted our experiments on the GAZEBO simulator [7]. We used an ideal depth camera already prepared in the simulator, whose calibration had already been completed. We prepared two-types drills. The one of the drills used for our experiments was also prepared in the simulator in advance, and the other was prepared by downloading 3D CAD models from the free download website called GrabCAD [8]. The drills for our experiments are shown in Fig. 4. The patterns of the position and orientation of the drills for our experiments are shown in Fig. 5(a) and (b), respectively. The ground-truth of the position for grasping is manually specified. In both of the drills used for our experiments, the ground truth of the positions are corresponding to the position of the drills and that in the direction of the normal to the ground is -0.12 meter from the sensor coordination.

Experimental Results

Detection in 2D images

We show both successfully detected patterns and failures in the detection phase on the supplied 2D image. The result of the detection on each pattern is shown in Table 1 and 2 on both of prepared drills. In Table 1 and 2, S indicates that the detection was successful, and F indicates the detection failed.

Error in estimation of the position and orientation for grasping

We chose the drills that were successfully detected in the phase of detection on the 2D image. The errors in estimating the position and orientation are show in Table 3, 4, 5 and 6. We computed the error in position, e_p, as follows:

$$e_p = \|\boldsymbol{c}_e - \boldsymbol{c}_g\| \quad (1)$$

where $\boldsymbol{c}_e$ the estimated 3D centroid coordinate position for grasping, $\boldsymbol{c}_g$ is the ground truth of the position for grasping, which we specify in advance. Equation (1) compute the Euclidean distance between given two points in the 3D coordinate system. Also, we computed the error in orientation, e_o as follows:

$$e_o = 180 \times \arccos(\boldsymbol{o}_e \cdot \boldsymbol{o}_g)/\pi \quad (2)$$

where $\boldsymbol{o}_e$ the estimated orientation vector for grasping, $\boldsymbol{o}_g$ is the ground truth of the orientation vector for grasping. Both of above vectors are unit vectors. Equation (2) computes the angle between given two vectors. The units in Table 3 and 4 are meter and, in Table 5 and 6 are degree, respectively. In these tables, patterns for which detection failed or failed processing the 3D point cloud data for estimation, even if the detection in 2D image, was successful are indicated by diagonal lines.

Discussion

Detection in 2D images

According to Table 1 and 2, 31 out of 32 patterns were successfully detected using fine-tuned framework of Faster RCNN. However, at the same time, there was also a pattern for which detection failed. The results of both failed detection and successful one are shown in Fig. 6 for comparison. The failed pattern is shown in (a), and the successful ones are shown in (b). In our experiments, we regard a successful detection as one whose confidence is greater than 80 %. However, the confidence in the failed detection was about 50 %. To increase the confidence in detection in 2D image, it is reasonable that the data augmentation about an image of a drill whose orientation is 0 degree as shown in Fig. 5 and fine-turning a framework for detection in 2D image should be executed.

3D point cloud data processing for estimating the position and orientation for grasping

As shown in Tables 3, and 5, in the case of type-A drill, the estimation error of the position and orientation is small. In [9], they target robotic grasping of a drill for their disaster response robot and evaluate how their prepared 3D model of a drill fit to the point cloud data representing their target drill which is 60 cm away from their sensor. Their acceptance criteria for the alignment is the error in the position is less than 5 cm and that in the orientation is less than 10 degree. In our results, the almost cases are close to their acceptance criteria even in the situation where we did not use any prior-detailed 3D information such as 3D CAD model of a drill, in the situation where the drill is both 60 and 80 cm away.

(a)

(b)

Fig. 6 The detection result in both of a failed pattern and successful one. (a) The detection was failed. The numerical value in this figure is the confidence in detection. (b) The detection was successful. The confidence in detection is higher than that of (a).

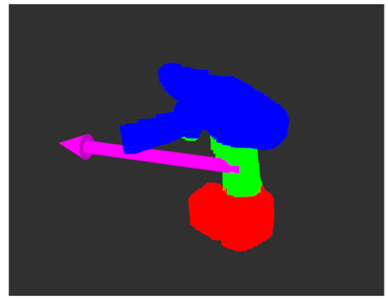


Fig. 7 The estimation error of the orientation of type-B drill. The pink colored arrow indicates the estimated orientation of a drill. The blue part is the chuck of the drill.

As shown in Tables 4, and 6, in the case of type-B drill, the almost cases in the estimation of the position were accurate, even if our results were compared with the acceptance criteria. There were, however, some cases where the estimation error of the orientation was larger than 60 degree. In addition, the range of error was from about 20 to 60 degree. It seems to be relatively wide. The reason why this occurred was because type-B drill had the handle not only between the chuck and the battery, but also on the side of the chuck. If the handle on the side of the chuck is observable in both of a 2D RGB image and a depth image captured by a sensor, the point cloud data representing it can be appeared. After obtaining the point cloud data above mentioned, we use the data to compute the PCA for estimating the orientation. The PCA outputs eigenvector on the basis of the covariance of the supplied point cloud data. Therefore it is reasonable that point cloud data representing the handle on the side of the chuck has the variance in the direction which is perpendicular to the dominant direction of the chuck and this affects to accurately estimating the dominant axis as shown in Fig. 7. To increase the robustness against the variance of the shape of the targeted drill, it is necessary to take applying a clustering algorithm to the obtained point cloud data and computing the density or the dominating space of extracted clusters into our consideration to distinguish the parts of drill, because those features are largely different from each parts.

Conclusion

In this paper, we proposed a method for estimating the position and orientation for grasping a drill on the basis of a depth camera information without using any detailed 3D model information about a target such as 3D CAD model. In our proposed method, along the part of the conventional method, we detected the drill in an RGB image captured by a depth camera by using Faster RCNN and combined the detection result and a depth image to generate 3D point cloud data representing our target and objects close to it. After obtaining the point cloud data, we processed the point cloud data to classify it into three parts of the drill which are the chuck, handle, and battery on the basis of classifying extracted feature vectors by

Table 1: The result of detection in 2D image in drill type A

Orientation pattern	Position pattern	
	0.6	0.8
0	S	S
45	S	S
90	S	S
135	S	S
180	S	F
225	S	S
270	S	S
315	S	S

Table 2: The result of detection in 2D image in drill type B

Orientation pattern	Position pattern	
	0.6	0.8
0	S	S
45	S	S
90	S	S
135	S	S
180	S	S
225	S	S
270	S	S
315	S	S

Table 3: The error in estimation of the position in drill A

Orientation pattern	Position pattern	
	0.6	0.8
0	0.01293	0.01239
45	0.02987	0.03439
90	0.04215	0.04344
135	0.05802	0.05958
180		0.05354
225	0.05471	0.05081
270	0.03592	0.03595
315	0.02706	0.02722

Table 4: The error in estimation of the position in drill B

Orientation pattern	Position pattern	
	0.6	0.8
0	0.01066	0.02858
45	0.02677	0.02722
90	0.04822	0.04443
135	0.06747	0.06906
180	0.05644	0.05713
225	0.04578	0.04740
270	0.02021	0.03565
315	0.02679	0.01925

Table 5: The error in estimation of orientation in drill A

Orientation pattern	Position pattern	
	0.6	0.8
0	0.000	0.7239
45	7.050	7.302
90	4.536	4.501
135	1.781	1.851
180		0.1481
225	2.023	2.226
270	4.360	4.542
315	7.092	6.895

Table 6: The error in estimation of orientation in drill B

Orientation pattern	Position pattern	
	0.6	0.8
0	68.27	59.14
45	8.120	13.83
90	3.706	3.747
135	1.239	1.025
180	36.71	41.50
225	19.51	23.90
270	30.74	5.622
315	80.7	10.25

using k-means. We estimated the position and orientation for grasping by computing the centroid of the point cloud data representing the handle of the drill and the first eigenvector by applying the PCA to the point cloud data representing the chuck. In our experiments, we confirmed that the estimations in the almost patterns of the position and orientation were accurate in the case which one of the drills we prepared for the experiments was used. However, in the case which the other one which has the handle on the side of the chuck was used, though the estimation errors of the positions were so small, those of the orientations were not small. To increase the robustness against the variance of the shape of the target, we will take a clustering algorithm into a method for processing the 3D point cloud data.

Acknowledgement
The authors of this paper acknowledge to the support of Toshiki Kurosawa, Kazuya Miyakawa and Kanaki Nakao of Waseda University.

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