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# An Automated Generation of 3D Point Cloud Training Data for Object Recognition using Depth Cameras Mounted on Robotic Arms

Ki Hong Im*, Jongwon Park, Jinyi Lee and Yun Jun Nam
*Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daegeon, 04535, Rep. of Korea*
**Corresponding author: khim@kaeri.re.kr*

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## 1. Introduction

The increasing demand to handle various objects has prompted significant developments in the utilization of robotic arms with object shape recognition capabilities. Various strategies have been employed to meet this demand, with some studies proposing plans for effective object grasping using robotic arms. A prominent solution to address this challenge involves the widespread exploration of methods utilizing 3D Point Cloud Data for object recognition [1-3]. In order to train deep neural networks for object recognition in a volumetric manner, it is necessary to generate 3D model data for multiple objects. However, manually carrying out this process is time-consuming and labor-intensive, emphasizing the need for preliminary research to automate as much of the data generation process as possible. In this paper, we present a method and process for creating a 3D Point Data Set using a robotic arm and depth camera for the types of objects we aim to handle.

## 2. Methods and Results

A manipulator and a depth camera are employed to capture images and 3D shapes of the target object from diverse perspectives. For this test environment, hardware and software components are chosen as Table I below. A custom bracket is designed and 3d printed to mount a depth camera on robot manipulator's wrist. Intel realsense D405 depth camera is chosen and used since it provides a closer look capability than other depth cameras and the close capture of a detailed 3d point cloud to be achieved by D405 will play a crucial role for this study. The posture of the depth camera is determined through simulation studies that can visualize the FoVs of the depth camera while it operates with various posture of robot arm that moves in front of target objects. Fig. 1 shows the simulation studies visually. From the results of the simulation study, we designed a custom camera bracket like in Fig. 2.

Table I: Test Environment

| | |
|---|---|
| Depth Camera | Intel Realsense D405 |
| Manipulator | Universal Robot UR10 |
| Bracket (custom) | PLA (3D printed) |
| Objects | Apple, Elephant, etc. (including a Calibration Tip) |
| Simulation/Control | Matlab/ROS2 |
| Post processing | Meshlab |

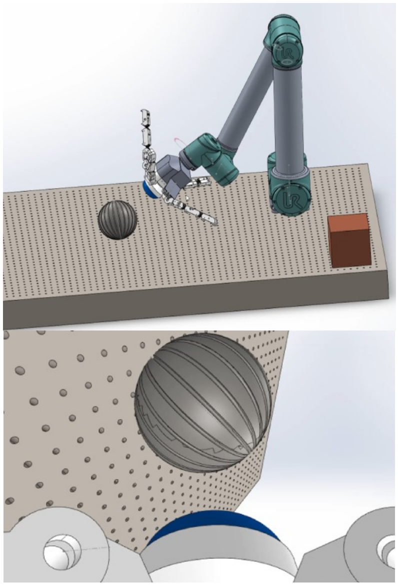

Fig. 1. Simulation study for determining camera posture.

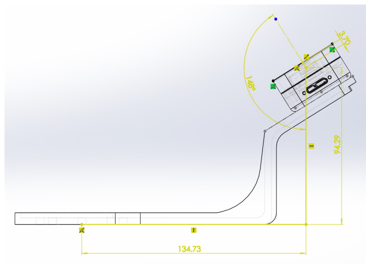

Fig. 2. Design of depth camera bracket.

The robot manipulator used in this study has 1.2m max. reach and this makes it possible to achieve 360 scanning and the point cloud of 10 to 20cm sized objects lying in front of the robot arm. In this phase we recorded 3d point cloud of each target object from 5 different perspectives, such as top, left, right, front, and back. Fig.3 depicts a test conducted to achieve the point cloud of an apple object.

When we achieved a 3d point cloud of an object, we found there exist nonnegligible amount of posture mismatch and discontinuity between the point clouds from each perspective.

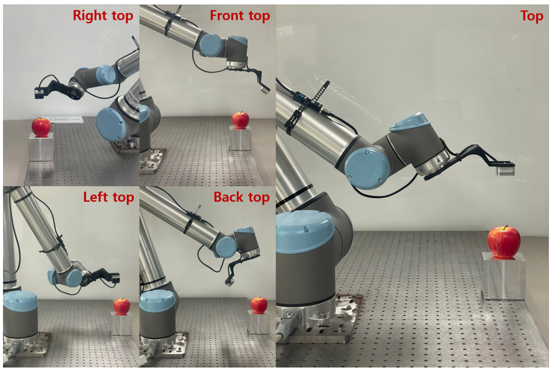


Fig. 3. Achieving point clouds of an apple from 5 camera perspectives.

In order to compensate for this uncertainty, we also custom designed a prism shaped calibration tip in Fig. 4 and collected five point clouds as described above.

Fig. 4. Examples of the target objects.

The point clouds are postprocessed in meshlab and we found the transformation matrix for the point cloud from each perspective. The compensation matrices are applied to other point clouds for other objects like in Fig. 5. We can find the whole-body 3D objects postprocessed in this study shows desirable results. This whole body 3d point cloud model for each target object can be used as reference 3d training data for a 3D object detection and recognition networks.

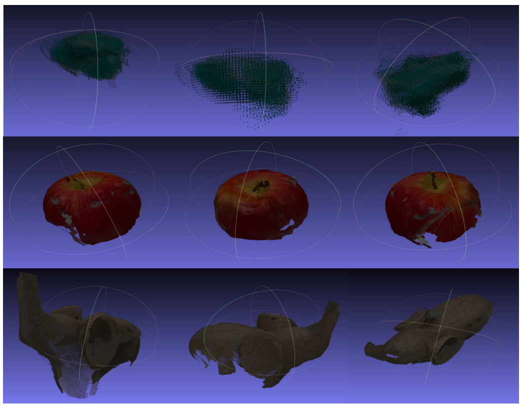

Fig. 5. Postprocessed 3d point model of target objects.

## 3. Conclusions

In this study 3D point cloud models are achieved by using a robot manipulator and a depth camera, which can automate the scanning and postprocessing object's point clouds to build up a whole body point cloud model. For an upcoming study, we will use this data to train 3d object detection/recognition network.

## ACKNOWLEGEMENT

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