

Comparison of Point Cloud Segmentation Methods for Calibration of 3D Environment Scanning System

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1. Introduction

Robotic technologies have been applied to address unique needs in decommissioning of nuclear facilities. Recently, for example, an integrated robotic dismantling system has been proposed, where precise three-dimensional (3D) as-built information is required [1]. An accurate environment mapping system plays a key role in these robotic decommissioning systems, because planning for the safe and controlled decommissioning of highly contaminated nuclear facilities requires that engineers and managers fully understand the 3D work space in which personnel and equipment will operate [2].

Extrinsic calibration is a process of identifying extrinsic parameters of a 3D measurement system, and it is a critical process in order to get precise measurements. Authors proposed a practical extrinsic calibration method that uses a simple geometric object (i.e. sphere) as a target [3]. Fig. 1 shows the test setup using a 3D scanner attached to a robot manipulator.



Fig. 1. Test Setup for Extrinsic Calibration.

Identifying the target object from the point clouds measured by a scanner is a well-studied yet challenging task. It is a two-step process. First step is segmentation that is a process of classifying the point cloud into multiple homogeneous groups. Then we compare each segmentation with reference models to find out the closest match. This study compares two segmentation methods: conventional filtering approach and a deep learning approach, and discuss pros and cons.

2. Extrinsic Calibration System

The extrinsic calibration is to identify the transformation from the tool flange frame to the sensor frame, i.e.,

$${}^{Tool\ Flange}_{Sensor}T = {}^{Tool\ Flange}_{Scanner}T {}^{Scanner}_{Sensor}T$$

The coordinate frames are described in Fig. 2. The transformation from the (reference) world coordinate frame to the tool flange frame, ${}^{World}_{Tool\ Flange}T$, can be identified through a separate kinematic calibration process, and is assumed to be known. The position of a target object (i.e., the center of the sphere), ${}^{World}P$, is also known.

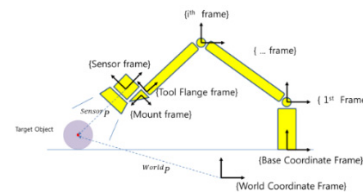


Fig. 2. Coordinate Frames for Extrinsic Calibration.

Extrinsic parameters are identified through the following steps:

Step 1. Identify points that belong to the surface of the target sphere

Step 2. Identify the geometric parameters of the points from Step 1, such as the radius and center position in the sensor coordinate frame, ${}^{Sensor}P$

Step 3. Solve the following for ${}^{Tool\ Flange}_{Sensor}T$ [6]

$${}^{Tool\ Flange}_{Sensor}T \cdot {}^{Sensor}P = [{}^{World}_{Tool\ Flange}T]^{-1} {}^{World}P$$

3. Point Cloud Segmentation Methods

Point cloud is a set of data points in some coordinate system. In a 3D coordinate system, these points are usually defined by X, Y, and Z coordinates, and often are intended to represent the external surface of an object. Fig. 3 shows a photo of the target on a table and the point cloud measured by a 3D scanner.

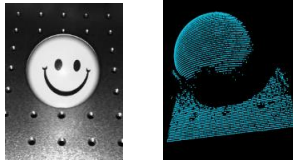


Fig. 3. Sphere Target on Table: Photo vs Point Cloud.

3.1 Classical Filtering Approach using PCL

If we know what to expect (e.g. sphere on table), we can efficiently segment our data. In Point Cloud Library (PCL), several extensions of randomized geometry modelling algorithm, called RANSAC, exist such as MSAC, MLESAC, or PROSAC. We can model several types of geometric shapes using PCL including plane, cone, cylinder, sphere, line and circle. In the sphere on table scenario for the extrinsic calibration, we can (i)create a SAC model to detect a plane, (ii)create a RANSAC algorithm, then (iii)compute the best model. Finally, we can retrieve the best set of inliers that represent the table.

Once we have a plane table model, we can find objects standing on the plane, i.e. sphere target, by computing the convex hull of the planar points and extruding this outline along the plane normal. Fig. 4 shows the segmentation results. The point cloud in Fig. 3 is segmented into two groups: table and sphere.



Fig. 4. Segmentation Result using PCL.

3.2 Deep Learning Approach

An alternative and more general method for point cloud segmentation is to use a deep learning network. The baseline network chosen in this study is PointNet [4]. PointNet directly consumes point clouds and provides a unified architecture for applications ranging from object classification, part segmentation, to scene semantic parsing. Fig.5 shows the architecture of PointNet [4].

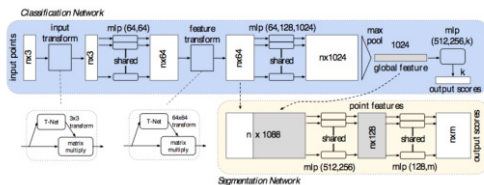


Fig. 5. PointNet Architecture [4].

Using PointNet, we can segment the point cloud

data into two groups. The result is similar to the PCL approach described in the previous section.

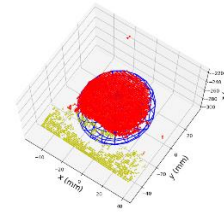


Fig. 6. Segmentation Result using PointNet.

4. Conclusion

This study applies two different approaches to segment point cloud. The segmentation results are similar, and both of them can be used for calibration introduced in [3]. The filtering approach using PCL can be applied to the cases when we know what to expect exactly. On the other hand, the deep learning approach is more general in the sense that, once we train the network using a model database, the deep neural network can segment a point cloud into groups even in the case we don't know the objects in the captured scene a priori. This implies that it is more flexible in the choice of target shape for calibration.

ACKNOWLEDGEMENT

This work was supported by the nuclear research and development program (2017M2A8A5015146) through the national research foundation of Korea funded by the Ministry of Science and ICT.

REFERENCES

- [1] I. Kim, B. Choi, D. Hyun, J. Moon, J. Lee, K. Jeong, S. Kang, "Integration of the Unit Modules of the Nuclear Facility Dismantling Simulation System", Proc. of the KRS 2017 Spring Conference, pp. 297-298, May 24-26,2017, Busan.
- [2] S. Joo, J. Lee, I. Kim, D. Hyun, S. Kang, "Preliminary Study on Environment Mapping for Nuclear Reactor Dismantling", Poster Presentation at the KRS 2017 Autumn Conference, Oct. 18-20,2018, Changwon, Korea.
- [3] S. Joo, D. Hyun, I. Kim, J. Lee, "Extrinsic Calibration of Robotic Laser Scanning System using Spherical Target", to be presented at 2018 ICCAS, Oct. 17 ~ 20, 2018, PyeongChang, Korea.
- [4] C. R. Qi, H. Su, K. Mo, L.J. Guibas, "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation", CVPR 2017, arXiv: 1612.00593.