Stairway Detection from Point Cloud Data for Robot Operation in Nuclear Facilities

Sungmoon Joo *, Dongseok Ryu
Korea Atomic Energy Research Institute, Daedeok-daero 989-111, Yuseong-gu, Daejeon, Korea
Corresponding author: smjoo@kaeri.re.kr

1. Introduction

Robotic systems have become increasingly popular for performing tasks in hazardous environments such as nuclear facilities. These systems can reduce the risks associated with human intervention and provide more accurate and reliable results. However, navigation and obstacle avoidance remain critical challenges for robots operating in these environments. In particular, detecting and navigating stairs is crucial for robots to access different levels of the facility [1][2][3][4].

In this paper, we present a stairway detection method using point cloud data acquired by a laser scanner mounted on a robot. Our approach leverages unsupervised point cloud segmentation with refinement using Euclidean clustering to identify planes comprising stairways and estimate their geometries.

The remainder of this paper is organized as follows. Section II provides an overview of out method on stairway detection using point cloud data, and presents the experimental results. Section III concludes the paper and discusses future directions for this research.

2. Methods and Results

In this section methods for stairway detection and estimation of stairway parameters are summarized, and a preliminary test result is presented.

2.1 Plane and Line Segmentation

Stairway detection involves the segmentation of point clouds into planes, followed by the estimation of parameters describing the stairway's geometry using line segmentation. To achieve this, we employ two key and efficient techniques for plane segmentation: RANSAC and Euclidean clustering through DBSCAN. RANSAC, an acronym for RANdom SAmple Consensus, is a highly effective algorithm suitable for datasets that have outliers. In real-world scenarios, data collected from sensors is often not perfect and tends to be affected by outliers. RANSAC is a probabilistic trial-and-error method that partitions data points into two groups, an inlier set, and an outlier set. By disregarding outliers, we can focus on the inliers and perform further analysis.

First, we generate a plane from the data by randomly selecting three points from the point cloud to determine a plane. We then assess the number of remaining points that appear to lie on the plane within a certain threshold. This evaluation generates a score for the plane proposal. We repeat this process by selecting three new random points and analyzing how well they match the data until we obtain optimal candidate values. The resulting inlier point set comprises the supporting points plus the initially sampled three points, while the remainder is the outlier point set.

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm analyzes each point in the dataset to determine its density-based reachability. The process involves identifying the set of points reachable from the analyzed point based on their density. Specifically, the algorithm computes the neighborhood of the point and checks if it contains more than a certain number of points. If the threshold is exceeded, the point is considered part of the cluster. The algorithm repeats the same process for each neighboring point until it can no longer expand the cluster. Any points that fail to meet the threshold and are not part of an interior point are labeled as noise. This characteristic enables DBSCAN to be resilient to outliers by isolating them.

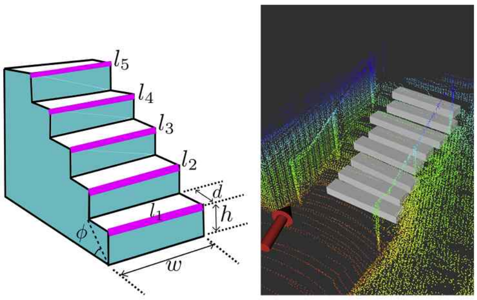
The segmented point cloud is organized into a 2D array structure, where each row index corresponds to a segmented plane, and the column indices represent each point on the plane [5]. To split N points on a plane, we initially fit a line between the first and last points. Next, we identify the point that has the greatest distance from this line. If the distance exceeds a given threshold, we split the points into two groups until the number of points in each set exceeds a specific limit or if all the points are within the threshold distance. The process stops and returns the line if all the points are close to the line. To improve this approach, we modify the behavior by using weighted line fitting, which employs the uncertainty of a point as weights. Weighted line fitting is a version of least square line fitting[5].

2.2 Stairway Geometry Estimation

To estimate stairway parameters, we iterate over the segmented lines obtained in the previous step. First, we describe the model of our stairway as follows[5],

•Stairway Height, h
•Stairway Depth, d
•StairwayWidth, w
•List of Lines L, each line l_i is described by 3D start point p_s, 3D end point p_e on a segmented plane, and it's orientation α_i in the XY plane

•Stair Slope, φ = tan−1(h/d)



(a) Staircase model with (b) Detected staircase, each

Fig. 1. Stairway Geometry [5]

After detection, we estimate the model parameters as shown below[5],

$$h = \frac{\sum_{n=1}^{k-1} ||\bar{p_s}^{(i+1)} - \bar{p_s}^{(i)}||_z + ||\bar{p_e}^{(i+1)} - \bar{p_e}^{(i)}||_z}{2k}$$

$$d = \frac{\sum_{n=1}^{k-1} ||\bar{p_s}^{(i+1)} - \bar{p_s}^{(i)}||_{xy} + ||\bar{p_e}^{(i+1)} - \bar{p_e}^{(i)}||_{xy}}{2k}$$

$$w = \frac{\sum_{n=1}^{k} ||\bar{p_s}^{(i)} - \bar{p_e}^{(i)}||}{k}$$

where $||p_1 - p_2||_z$ *is the 1D distance in z axis*

where $||p_1 - p_2||_{xy}$ *is the euclidean distance in xy plane*

2.3 Test and Preliminary Result

We have tested the segmentation method on a scan data of stairway [6] as shown in Fig. 2.

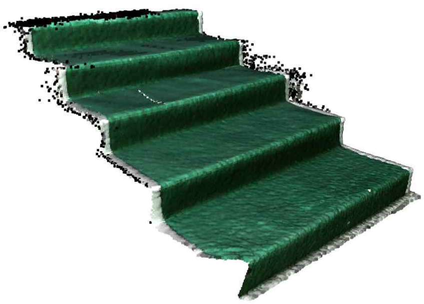
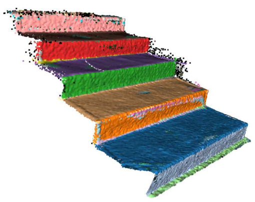


Fig. 2. Stairway Scan Data (Point Cloud)

Fig.3 displays a segmentation result and estimated parameters. Each segmented point is properly clustered and colored for visualization purpose.



	True (m)	Estimated(m)
Stairway Height	0.110	0.121
Stairway Depth	0.280	0.275
Stairway Width	0.920	0.929

Fig. 3. Stairway Detection Result

3. Conclusions

In this research, we presented an approach for plane segmentation in the context of stairway detection and geometry estimation. The proposed method utilized the RANSAC algorithm for plane matching and DBSCAN algorithm for segmentation refinement, resulting in promising segmentation results.

Our work has demonstrated that accurate stairway detection and geometry estimation can be achieved through plane segmentation of point cloud data. However, further investigation is needed to robustify the segmentation and improve its reliability in more challenging environments.

Future research could explore alternative segmentation methods, such as deep learning-based approaches, to enhance the segmentation's robustness and accuracy. Additionally, incorporating more sensors, such as RGB-D cameras, could potentially improve the segmentation and estimation performance.

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