PLANE DETECTION IN POINT CLOUD VIA RANSAC

A. Makendi
TU Berlin, Institute of Geodesy and Geoinformation Science, Berlin, Germany
amos.makendimanonbo@campus.tu-berlin.de

KEY WORDS: Terrestrial Laser Scanning, Point Clouds, Segmentation, RANSAC, Planes

ABSTRACT:

The detection of planes is a significant step to develop substantial applications in various vision tasks. Therefore, the use of the RANdom SAmple Consensus (RANSAC) is commonly used to detect basic shapes for 3D-reconstruction and scene analysis. RANSAC is used to segment planes of building facades and roofs in terrestrial laser scans. Meanwhile, the challenge is to avoid the misdetection of planes caused by the complex geometry of the 3D point cloud. Despite that, we get successful results to a small practical dataset consisting of two planar surfaces while struggling on another slightly trickier and large scene.

1. INTRODUCTION

3D point clouds obtained by terrestrial laser scans are generally noisy and redundant, and do not easily provide semantics of the scene. Due to their importance for compact and semantic modelling of 3D scenes, primitive fitting to point cloud attracts many research interests. In this work, we are interested in finding the best plane from point cloud. The Random Sample Consensus (RANSAC) algorithm was therefore preferred as a simple algorithm to detect planes in point cloud. As a result, planes could be detected in both high and low density point cloud by changing RANSAC parameters. Furthermore, the threshold depends on the point cloud density and highly influence on the number of detected planes.

2. RELATED WORK

There are many algorithms available for plane detection from 3D point clouds in the scientific literature. RANSAC-based methods have been widely used (Schnabel et al., 2007). Since RANSAC is an iterative process that also requires removing points belonging to the found largest consensus set, it is a time consuming approach. Therefore, for random plane-model selection and their comparison different methods were developed. Methods based on octrees (Su et al., 2016) could be used to improve the efficiency of plane segmentation.

3. RANSAC PLANE DETECTION

3.1 RANSAC description

The current session describes the RANdom SAmple Consensus (RANSAC) algorithm, used to detect planes in terrestrial laser scans. The RANSAC algorithm was introduced by (Fisher and Bolles, 1981) and consists to generate a hypothesis and to verify it iteratively in a given point cloud. RANSAC starts by randomly selecting a minimum subset of n points and then hypothesize the respective shape-model. For instance, a plane needs three points to estimate its model. After the selection of the points and hypothesizing the shape-model, the remaining points in the point cloud are assessed against the candidate shape-model to find out the points that belong to it. Furthermore, RANSAC assumes that a model generated from a contaminated minimal sample will have low support, thus making it possible to distinguish between correct and incorrect models (Yang and Förstner, 2010). Then, the process requires several iterations in order to find and to remove the largest consensus set of points in the point cloud. The process is repeated to the remaining points in the point cloud.

3.2 RANSAC parameters

The plane detection using the RANSAC algorithm was implemented for 3D terrestrial laser scans on both a small set, which consists of two planar surfaces and on a large dataset. Components to be estimated in RANSAC algorithm are normal vectors that compose the planes. Besides this, the parameters to configure in the RANSAC algorithm are:

- ε: Probability that a point is an outlier.
- α : Minimum probability of finding good set.
- initial random set of points $X = \{X_{1,} X_2, \ X_3\}$
- tolerance ($distance$)
- N: Number of samples.
- threshold: Decide if points are part of a plane.

3.3 Experiment and results

RANSAC algorithm was applied to two different point clouds. In the former, we have a small set of point cloud, which consists of $\mathbf{30336}$ points representing two planar surfaces. We choose for our implementation the uniform subsampling as method for the random selection of the minimum subset of points. This method is used for it allows to uniformly select three random points distributed on a plane. After that, the tolerance distance is selected as a variable, and was conducted for $\boldsymbol{tolerance} = \mathbf{4}\, \boldsymbol{mm}$ in this experiment. This value was empirically found based on trials and visualization of results. The number of samples is computed based on formula developed by (Yang and Förstner, 2010). For the number of samples $\boldsymbol{N} = \mathbf{14}$, we got the best detection of plane in the small dataset. Besides this, the minimum probability of finding that best consensus set is $\boldsymbol{\alpha} = \mathbf{0.99}$. In addition, we acknowledge that the increase of the minimum probability can decrease the number of samples. This inverse proportionality has an influence onto the amount of points found in different consensus sets. A point is set to be in a consensus set if its distance to the plane is less than the threshold. The RANSAC algorithm stops searching for candidate consensus sets whenever the iterations reach the number of samples. At this stage, the candidate consensus set with respectively the highest number of best support points and the minimum standard deviation of distances to plane is considered as the largest consensus set. For the low point cloud density, we found that the best support points is $\mathbf{SupportPoints} \leq \mathbf{16432}$.The visualization of results was performed using CloudCompare, which is a 3D point cloud processing software as shown in the figure1.

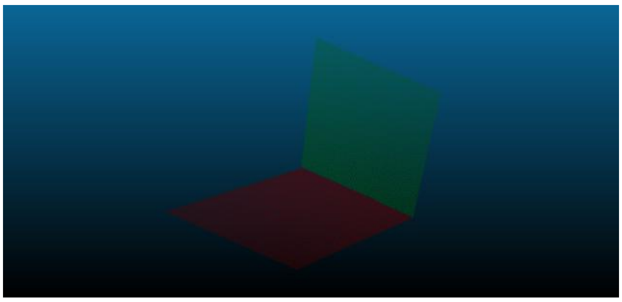

Figure 1. RANSAC two planar surfaces detection

The number of detected planes is two, and the respective parameters were recorded in the table 1.

Table 1. Two Planar surfaces detection hyper parameters

Min Probability (α)	Best Support Point	Best Standard Deviation	Number of Samples (N)	Tolerance Distance
0.99	**16387**	**0.0001937m**	**14**	**0.004 m**

In the second, we have a large and tricky set of point cloud, which consists of $\mathbf{227492}$ points representing an unknown number of planes to detect. As for the detection of the two planar surfaces, the selection of the three random points was done based on the uniform subsampling. We acknowledged that the tolerance distance for high density point cloud significantly differs from the one in low density point cloud. The value of the distance tolerance was empirically set to $\boldsymbol{tolerance} = \mathbf{5}\, \boldsymbol{cm}$. Meanwhile, the abort criterion of the algorithm was based on comparing the remaining points in the point cloud to a defined minimum support points. Therefore, the algorithm will stop whenever the remaining points become less than the minimum support points, which represents the minimum points our algorithm needs in order to validate the existence of a plane. This value is not optimal for it depends on assumptions defined based on the visual inspection of the point cloud on CloudCompare. The root causes of the challenges we faced while implementing the RANSAC Algorithm on a large scene were to define the adequate setting values of essential parameters. This lack of efficient definition of coefficients has resulted to the detection of spurious-planes found in so many cases.

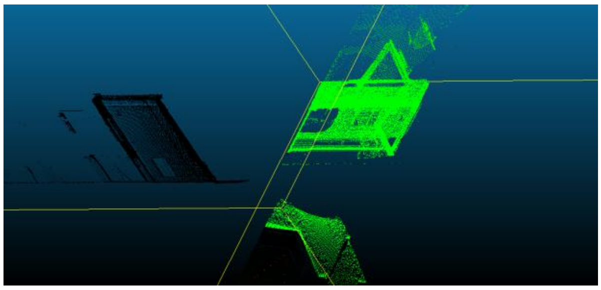

Figure 2. RANSAC Plane detection on large dataset

4. CONCLUSION

In this paper, we conducted an experiment to evaluate the plane detection method using RANSAC algorithm by changing the threshold, tolerance distance, and minimum probability in both high and low point density. As a result, the threshold of RANSAC algorithm should be changed according to point density in order to detect planes without false detections. In other words, low point density data is enough to detect planes by changing the threshold appropriately with is not the case for high point density that requires additive criteria such as the minimum support point well defined for the algorithm to converge. The results achieved while extracting planes in a large point cloud were not good. Therefore, we explored methods that can help to deal with spurious-planes detection problems and to improve the robustness of the RANSAC algorithm; for example, it could be benefic to evaluate the contribution of the inliers based on the point-to-plane distance by optimizing a loss function than to fix thresholds. In addition, to define a self-voting function based on two weights function to improve the segmentation quality of the RANSAC algorithm.

Last but not the least, octree can be used to establish spatial proximity among samples and to test only local subset of samples based on a scoring function.

REFERENCES

R. Schnabel, R. Wahl, and R. Klein, “Efficient RANSAC for pointcloud shape detection,” Computer Graphics Forum, vol. 26, no. 2, pp. 214–226, June 2007.

Su, Y.-T.; Bethel, J.; Hu, S. Octree-based segmentation for terrestrial LiDAR point cloud data in industrial applications. ISPRS J. Photogramm. Remote Sens. **2016**, 113, 59–74.

Yang, M., Förstner, W., 2010. Plane Detection in Point Cloud Data. Technical Report, Institute of Geodesy and Geoinformation, Department of Photogrammetry. University of Bonn, Germany.