Implementation of Improved RANSAC Algorithm for 3D Point-Clouds using Normal Distribution Transformation Cells

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Keywords: *RANSAC, 3D Point-Cloud, Normal Distribution Transformation*

1 Introduction and Motivation

Plane segmentation plays a crucial role in automatically reconstructing indoor and urban settings from disorganized point clouds gathered by laser scanners. The standard Random Sample Consensus (RANSAC) is a widely used plane-segmentation technique that sequentially identifies planes. However, it encounters the issue of false planes when noise and outliers are present due to the random sampling of the minimum subset containing three points.

To overcome this challenge, a refined RANSAC method utilizing Normal Distribution Transformation (NDT) cells has been suggested for 3D point-cloud plane segmentation. In this method, a planar NDT cell is chosen as the minimal sample during each iteration, ensuring accurate sampling on the same plane surface. The 3D NDT expresses the point cloud using a collection of NDT cells and models the observed points with a normal distribution inside each cell. The geometric features of NDT cells are employed to categorize them into planar and non-planar groups.

The implementation of this technique is derived from the paper "An Improved RANSAC for 3D Point Cloud Plane Segmentation Based on Normal Distribution Transformation Cells." [1]

2 Related works and Definitions

2.1 Point-Cloud

A point cloud is a set of data points in space that often represents a 3D shape or object. Each point in the collection has its own X, Y, and Z coordinates, indicating its position. Point clouds are commonly created by 3D scanners or specialized software that measures numerous points on the outer surfaces of objects.

These point clouds have multiple uses, such as creating 3D computer-aided design (CAD) models for manufactured parts, which helps engineers and designers visualize and refine their designs. They are also used in quality inspection processes to ensure that products meet the required specifications. Additionally, point clouds play a role in visualization, animation, and rendering applications, contributing to various forms of digital media like movies, video games, and virtual reality experiences.

2.2 RANSAC

Random Sample Consensus (RANSAC) is a repetitive technique for estimating the parameters of a mathematical model from a dataset that includes outliers, ensuring that these outliers don't impact the estimation. As such, RANSAC can be viewed as an outlier detection method. This algorithm is non-deterministic, meaning it generates a reasonable outcome with a specific probability, which increases with more iterations. Fischler and Bolles first introduced the algorithm at SRI International in 1981, using RANSAC to address the Location Determination Problem (LDP) by identifying points in space that project onto an image with known landmarks. [2]

RANSAC employs continuous random sub-sampling and assumes that the data is composed of ”inliers” (data points that can be explained by a set of model parameters, potentially with some noise) and ”outliers” (data points that don’t fit the model). Outliers might result from extreme noise, inaccurate measurements, or incorrect data interpretation assumptions. RANSAC also presumes that, given a small group of inliers, there’s a method for estimating the parameters of a model that optimally fits or explains the data.

RANSAC is indeed a versatile algorithm that can be applied to various types of primitive models, not just planes in 3D or lines in 2D. As long as there is an evaluation function (such as distance) available, the algorithm can be used with the same procedure for different primitives. For instance, spheres can also be utilized in RANSAC by randomly sampling the center point and radius. This adaptability makes RANSAC a valuable tool for a wide range of applications and model types.

2.3 Related works

Point-cloud data contains abundant geometric information, but neighboring points must be considered during point-cloud processing. This is because point features, such as normal, curvature, and roughness, are typically calculated based on the surrounding points. To improve the efficiency of plane segmentation, voxel grids and octrees have been commonly used [3, 4]. However, the proposed method employs Normal Distribution Transform (NDT) cells, which offer a discrete representation of the point-cloud space. Unlike methods that handle each point individually, NDT features consider each cell. In other words, NDT is akin to super-voxels and sub-windows, but offers a more comprehensive approach to point-cloud data.

Biber and Strasser first proposed the concept of Normal Distribution Transform (NDT) in 2013 for 2D point-cloud registration [5]. Later on, NDT was extended to three dimensions [6]. Despite its potential, few works have used NDT for point-cloud segmentation [7]. NDT involves dividing the space occupied by the scan into a grid of cells (squares in 2D and cubes in 3D) and computing a Probability Density Function (PDF) for each cell based on the point distribution within it. In contrast to point-based features that take into account the neighbors of a point, NDT features are based on points within a cell, which distinguishes them from point-based features.

3 Method

The proposed method comprises four main parts.

Firstly, NDT cells are created by dividing the point-cloud space into a grid of cells, and the features of each cell are identified based on the distribution of points within it. This process helps to capture the underlying structure of the point-cloud data in a discrete manner.

Secondly, the appropriate plane is identified for the planar cells. This involves using the eigenvectors of the points in each cell, which allows us to determine the orientation and extent of the plane.

Thirdly, the RANSAC algorithm is used to refine the plane estimation by randomly selecting planar cells and extending their plane to other nearby cells. The objective of this step is to find the best possible plane that fits the data, while minimizing the effect of outliers.

Finally, and additionally to the paper’s work, a network is incorporated into the procedure to locate neighboring cells that share similar features. I think that this network-based approach can help in creating meshes or selecting objects within point clouds, as it allows us to identify the underlying relationships between different parts of the data.

3.1 NDT Features

The primary objective of this project is to incorporate local information into the RANSAC algorithm. To achieve this, the 3D NDT method is utilized, which involves discretizing the point cloud using a set of cells and modeling the observed points within each cell. Each cell in the grid contains a group of points with a mean of μ and a covariance matrix Σ, which is a positive definite matrix that describes the shape of the cell. For each cell, the eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3$ and corresponding eigenvectors e_1, e_2, e_3 of the covariance matrix Σ are computed. This information is then used to enhance the RANSAC algorithm by incorporating local information about the shape of each cell.

After computing the eigenvalues and eigenvectors of the covariance matrix Σ for each cell, there are three possible scenarios based on the values of the eigenvalues.

The first scenario is when $\lambda_1/\lambda_2 \geq te$, indicating that the points in the cell are almost in a line.

The second scenario is when $\lambda_2/\lambda_3 \geq t3$, indicating that the points in the cell are co-planar. This is the primary focus of this project.

The third scenario is when neither of the above conditions is met, indicating that the points in the cell form a sphere. This scenario does not provide much information and is ignored in this project.

To better understand the analysis of the covariance matrix, it is helpful to visualize the eigen vectors, which create a basis for the space.

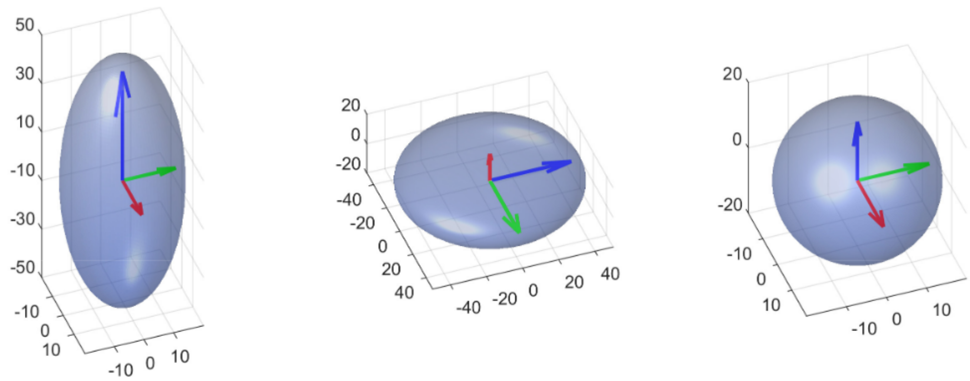

Figure 1: Visualization of NDT cells covariance eigen analysis. source: [1]

Based on the paper, the value $te = 25$ is a good threshold.

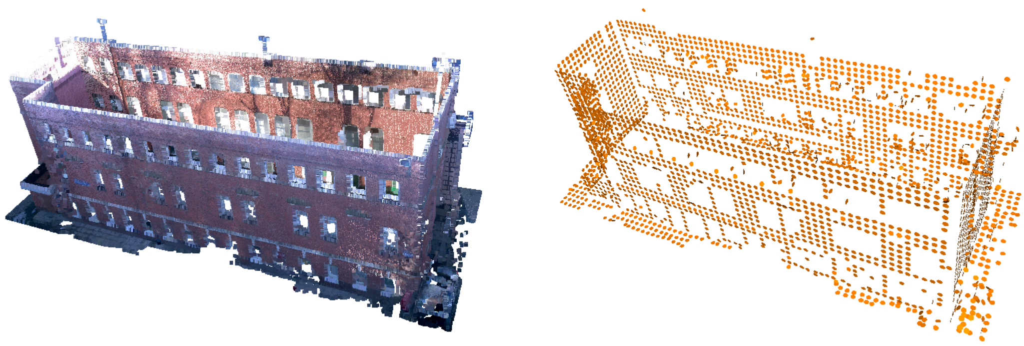

Figure 2: A sample facade point-cloud and its NDT features. Each circle is a planar cell.

3.2 Cells' plane fitting

As is well-known, planar cells in a point cloud have two larger eigenvalues that correspond to the two eigenvectors on the plane, and one smaller eigenvalue that corresponds to the eigenvector perpendicular to the plane. This information can be used to easily determine the normal vector of the plane. In order to find a point on the plane, taking the mean of all the other points in the cell is a reasonable initial estimate. However, this approach may not be optimal as it can lead to an optimization problem with only one parameter. The typical method for addressing this issue is to use least squares, but this approach is sensitive to outliers. To overcome this limitation, the proposed method employs the iterative reweighted least-squares (IRLS) [1] algorithm.

The proposed method involves minimizing the weighted distance between the points and the plane, rather than minimizing the summation norm 2 of the distance. The weight is determined by $w(r_i^{k-1})$, which is updated in each iteration of estimation. To solve this constrained least-square problem, the Lagrange multiplier method is used.

This constraint using weight w helps to reduce the effect of outliers.

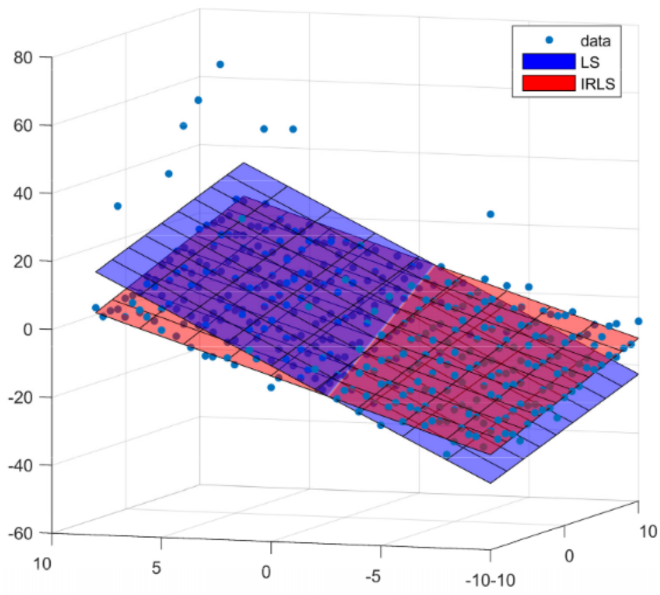

Figure 3: IRLS vs LS. source: [1]

3.3 NDT RANSAC

The NDT-RANSAC algorithm starts by randomly selecting a minimal subset of planar NDT cells and uses the normal of the cell as the plane parameter. Two thresholds are applied to consider both the gravity distance from the point to the plane and the angular differences of the cells' normals to the plane, ensuring that only candidate cells are selected. Traditional RANSAC assumes that inliers and outliers can be distinguished by fitting a model to the data. However, if the randomly selected minimal set contains outliers, spurious planes may appear. Using NDT cells as the minimal subset improves reliability since points within the same cell are likely from the same plane. Moreover, the NDT-cell-based method is faster than point-based methods since it doesn't require estimating the normal of every point, and the time consumption depends on the cell size and point density.

3.4 Connectivity Network

The addition of the connectivity network of the cells is a my novel contribution to this paper. By considering the neighbours of the cells in the same surface, which are likely to have similar

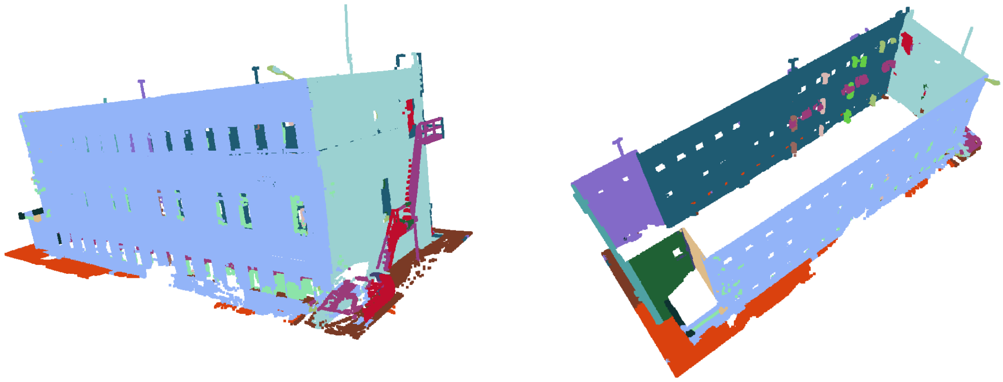

Figure 4: NDT RANSAC result of the same facade in figure 2.

normal vectors with slight variations in the angles, a network is created based on the cosine similarity of the normal vectors. The network connects the neighbouring cells that have less than 20 degrees difference in their normal angles. This network visualization can reveal critical parts of the point cloud, which can be useful for object selection or mesh mapping in the future.

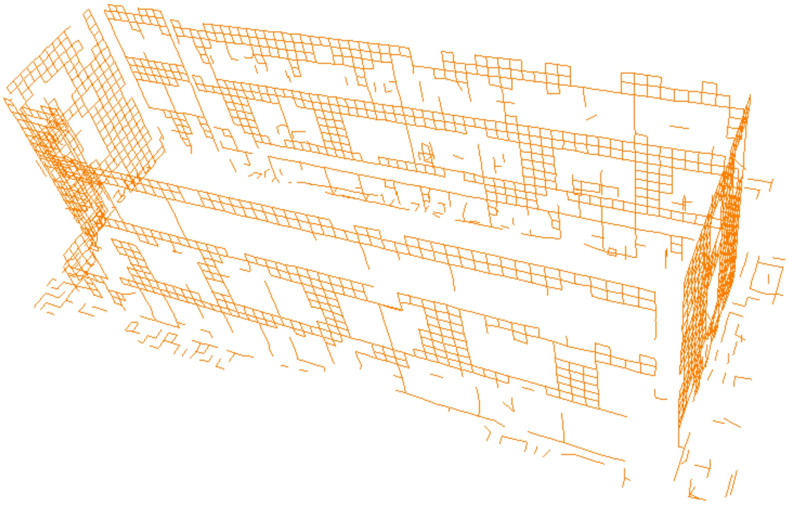

Figure 5: The connectivity network of the same facade in figure 2.

4 Results

The performance of the proposed NDT-RANSAC method was evaluated on three additional point cloud models besides the example presented earlier. These models consisted of a LIDAR scan of a campus yard, a residential property with interior walls and furniture, and a boat. The obtained results are summarized in this section, providing insights into the effectiveness of the algorithm in different scenarios.

Figure 6: Campus yard point cloud and its NDT cells.

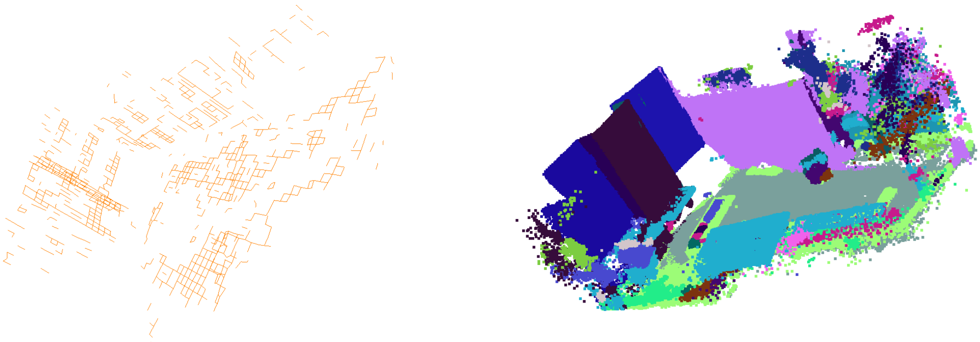

Figure 7: Campus yard connectivity network and NDT-RANSAC plane segmentation.

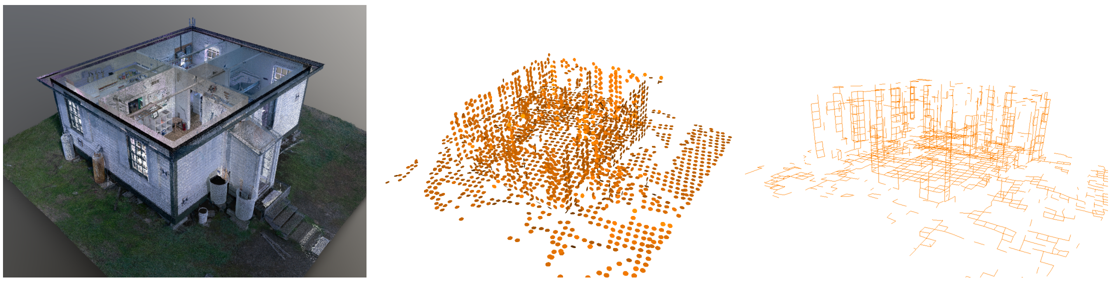

Figure 8: Residential building point cloud, its NDT cells, and its connectivity network.

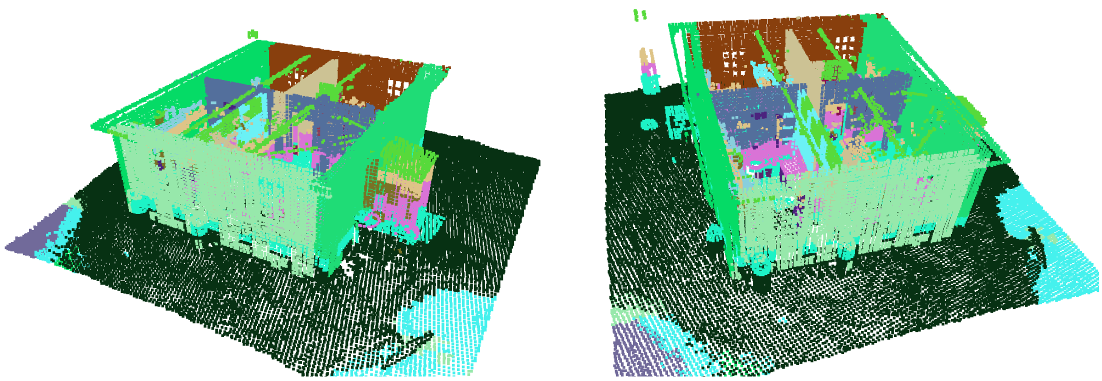

Figure 9: Residential building NDT-RANSAC plane segmentation from two point of views.

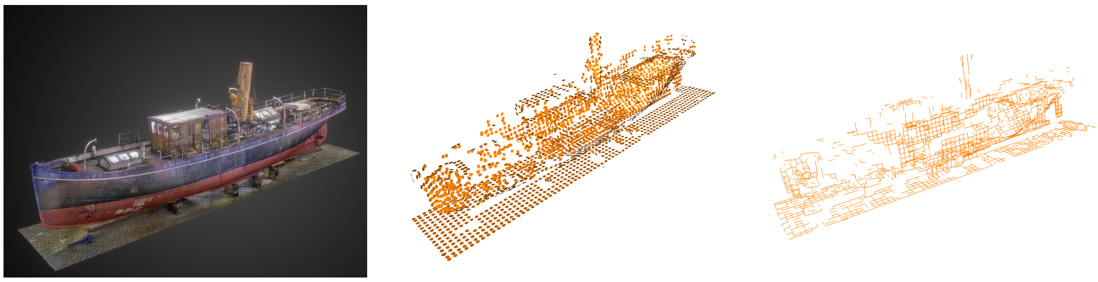

Figure 10: Boat point cloud, its NDT cells, and its connectivity network.

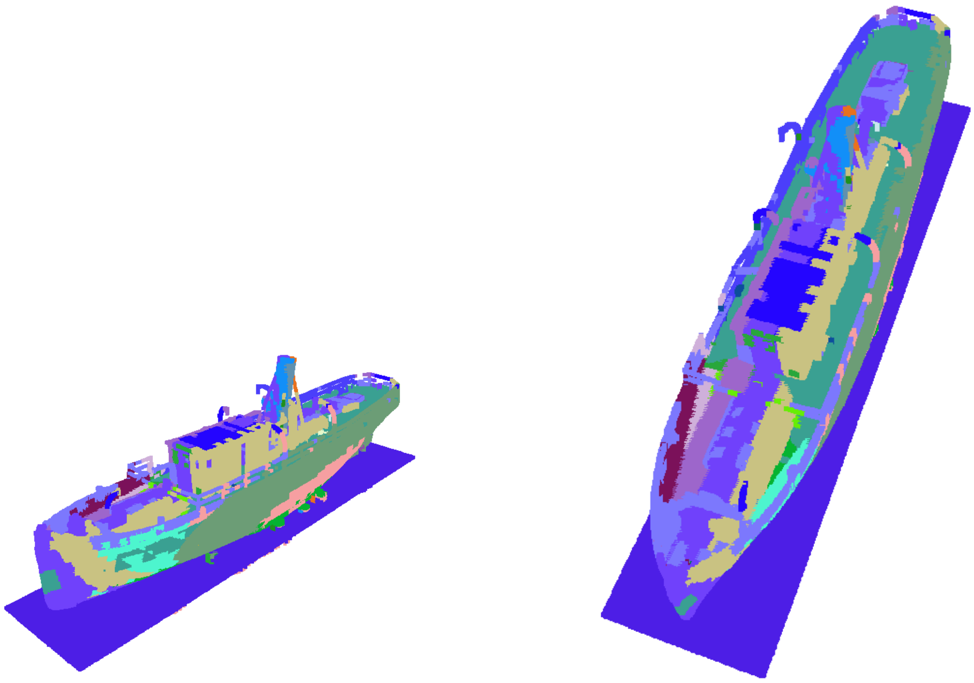

Figure 11: Boat NDT-RANSAC plane segmentation from two point of views.

5 Code and Environment

The implementation of the proposed method was done in Python 3 programming language, utilizing the Open3D library. The mathematical computations were performed using the NumPy library, and the code was developed in a Jupyter Notebook format. The notebook containing the code is attached for reference. Additionally, the resulting models obtained from the application of the proposed method on the point clouds are provided as attachments.

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